Cross-modal perception for industrial robots

Guest Editors: Huaping Liu and Yuan Yuan
Guest editorial

Special issue on cross-modal perception for industrial robots

Cross-modal perception means learning knowledge from some modality (e.g. vision) and using this knowledge to understand the environment with another modality (e.g. touch). The key to cross-modal perception is to establish a unified representation between multi-modal data sources. Cross-modal learning has been extensively used in Web search and human–computer interaction, but it finds little application in industrial robots. Currently, we can find several sensors in industrial robots, but the multi-modal integration and cross-modal transferring problems are still difficult. The first challenge stems from the heterogeneous gap: there exists significant feature space difference between modalities, and direct comparison or matching between them is difficult. The second challenge stems from the weak pairing: it is difficult to establish the sample correspondence relationship between modalities. These challenges incur many unsolved problems worthy of research.

This special issue mainly focuses on cross-modal perception and learning technology for modern industrial robots, solving both original theoretical development and engineering applications of cross-modal learning and transferring. We received many high-quality submissions, and only 15 have been finally accepted for publication after several rounds of peer review. They can be divided into three categories: sensing, perception and applications.

A few papers solve some basic sensing problems for cross-modal perception tasks. In “A cross-modal tactile sensor design for measuring robotic grasping forces,” a cross-modal tactile sensor design for measuring robotic grasping forces has been developed. In “The perceptually-inspired model of tactile texture sensor based on the inverse-magnetostrictive effect” has described the development of a new perceptually inspired model of tactile texture sensor based on the inverse-magnetostrictive effect. The paper “An investigation of stimuli-current thresholds on the non-steady contact condition” describes the investigation of the stimuli-current thresholds on the non-steady contact condition. In addition, the authors of “Incorporating artificial skin signals in the constraint-based reactive control of human-robot collaborative manipulation tasks” incorporate artificial skin signals in the constraint-based reactive control of human-robot collaborative manipulation tasks. All of these works provide strong support for the cross-modal perception technology.

In few papers, various challenging cross-modal perception problems are tackled. In “An effective multifocus image fusion method using guided filter, multifocus image fusion based on coefficient significance of redundant discrete wavelet transform,” two representative image fusion methods are developed. “Road segmentation of cross-modal remote sensing images using deep segmentation network and transfer learning” and “Radar and vision fusion for the real-time obstacle detection and identification” are concerned with the perception of road using vision and radar. In “Online weakly-paired similarity learning for surface material retrieval,” an online weakly paired similarity learning for surface material retrieval is developed. “Natural teaching for humanoid robot via human-in-the-loop scene-motion cross-modal perception” investigates the natural teaching of a humanoid robot via human-in-the-loop scene-motion cross-modal perception.

The third part, which focuses on the applications, contains five papers. This part addresses various application problems including satellite attitude control (“Model-based deep reinforcement learning with heuristic search for satellite attitude control”), lower-limb exoskeleton systems (“Learning and planning of stair ascent for lower-limb exoskeleton systems”), bilateral-wheeled cable-climbing robot (“Dynamic obstacle-surmounting analysis of a bilateral-wheeled cable-climbing robot for cable-stayed bridges”), autonomous vehicles (“Research on decision-making of autonomous vehicle following based on reinforcement learning method) and welding systems (“A welding seam identification method based on cross modal perception”).

We are glad to see that the papers included in this special issue cover different aspects of sensing, perception and applications. In particular, we can find lots of promising results using different perception modalities including vision, tactile, radar, etc.

We have to acknowledge that many submissions to this special issue exhibit high quality, but we were not able to accept them because of space limitations. During the review process, reviewers contributed a lot to the quality of this special issue by thoroughly evaluating the papers and providing a great deal of constructive comments. Last, but not the least, the completion of this special issue cannot be separated from the strong support from the Editor-in-Chief Dr Clive Loughlin. We would like to thank him for his great support.

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The current issue and full text archive of this journal is available on Emerald Insight at: www.emeraldinsight.com/0143-991X.htm
Strong prospects for robots in retail

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Abstract
Purpose – This paper aims to illustrate the rapidly growing use of robots in the retail sector by considering a range of products and applications.
Design/methodology/approach – Following a short introduction, this paper discusses robotic products and deployments in the following applications: inventory management, the provision of customer assistance, cleaning and hazard detection and product delivery. It concludes with a brief discussion.
Findings – Robots are rapidly making inroads in the retail sector. They have been shown to reduce manpower requirements, improve efficiency, reduce costs and speed-up deliveries. As applications grow and the technologies mature, retail is expected to become a major robot user and will offer significant business opportunities.
Originality/value – This study provides a detailed insight into the emerging and rapidly developing retail robotics business.

Keywords Robots, Retail, Delivery, Cleaning, Customer assistance

Paper type Technical paper

Introduction
The retail sector comprises businesses and individuals selling products directly to consumers and includes shops, supermarkets, department stores, market stalls and internet retailers. It has a global value of around US$23tn (thousand-billion) and represents approximately 30 per cent of the world’s gross domestic product. It is highly labour intensive; for example, in 2017, the UK retail sector had 2.8 million employees and retail giant Walmart has over 1.5 million workers in the USA alone and 2.2 million globally. Retail employees conduct a wide variety of tasks, including stocking and re-stocking, assisting customers to locate products, providing product advice, product demonstrations, checking prices, store cleaning and maintenance, packaging, dispatch, delivery and taking payments.

As yet, robots have had little impact on this industry, but recent deployments and trials show that this situation is rapidly changing, and in 2018, the first conference devoted to retail robotics and artificial intelligence (AI) was held at Northwestern University. In view of the size of this sector, future business opportunities could be very significant.

Inventory management
Inventory distortion (out-of-stock and overstocking) costs US retailers over $250bn per year, and the global figure is estimated at nearly $1.1tn. Simbe Robotics, a venture-backed company based in San Francisco and founded in 2014, is one of the number of companies to have recently developed robotic solutions to address this problem. The mobile Tally robot (Figure 1) was developed through collaboration with SoftBank Robotics America. It is aimed specifically at store inventory management and can autonomously traverse large retail environments to capture, report and analyse the state and availability of merchandise and help to ensure compliance with the store’s planogram – the optimal product placements to maximise sales. Using Radio-frequency identification (RFID) and computer vision it can identify out-of-stock, low stock and misplaced items and pricing errors and is equipped with a charging dock that it autonomously navigates back to between scans. The robot includes a suite of vision and other sensors which allow safe operation in retail environments and the data captured are sent to the cloud for processing and analysis. Additionally, it can be integrated into the retailer’s existing IT systems. Tally uses the open source Robot Operating System (ROS), stands 38 inches tall, weighs approximately 30 lbs and has an adjustable mast for capturing shelf data. Since its launch in 2015, it has been deployed by 11 leading international retailers and in October 2018 grocery chain Schnuck Markets announced they would expand its use to at least 15 further stores. Previously, the robots operated at three Schnuck locations and traversed store floors three times each day, scanning approximately 35,000 products on each run. By increasing this to 15 stores, the robots will scan over 1.5 million products in an average day. A Schnuck spokesperson stated that this will give them “more accurate, frequent and comprehensive insights into product flow and in-store operations”. In late 2018, Simbe announced a partnership with Decathlon, the world’s largest sporting goods retailer, operating over 1,400 stores in 45 countries and will deploy the robots at its first US store, opened in San Francisco in early 2018.

A similar mobile robot, the AdvanRobot, has been developed by Spanish RFID specialist Keonn Technologies. It is an autonomous, robotic RFID reader system that automatically performs the inventory in a retail store or warehouse. It is equipped with a 12-antenna RFID reader, a navigation system and anti-collision sensors and weighs 64 kg. Prior to autonomous deployment, an operator guides it around its environment with a
smartphone or tablet as shown in a video clip at https://youtu.be/V72Ep4s9T4o. A further company operating in this market is US-based Bossa Nova Robotics. Its system (Figure 2) uses 2D and 3D vision rather than RFID, and lidar is used both to navigate and to measure a shelf’s depth to determine whether it is fully or partially stocked. It can image 80 feet of isle in two minutes, capturing 2 TB of raw data. The company is working with five retailers across the US and Europe and Walmart is testing the robots at 50 of its US stores. The company opened a European office in Sheffield, UK, in 2018 and talks are underway with further retailers.

Providing customer assistance

Locating products in large stores can be time-consuming and also difficult for the aged, infirm or disabled and can cause customers to make fewer or no purchases. Accordingly, robotic solutions are being developed which offer customer assistance. An example is the LoweBot which was introduced in 2016 and developed by Fellow Robots for Lowe’s, an American retailer specialising in home improvements. It is mobile and battery powered and equipped with high resolution monitors and a multi-lingual speech recognition capability and creates a verbal response or visual display in response to customer questions regarding products or their location (Figure 3). Navigation is autonomous and the battery life between charges is 8-10 h. The robot is also equipped with three high resolution cameras allowing it also to conduct inventory management by using machine learning, vision and AI to determine out-of-stocks, price discrepancies and misplaced items and can assist in maintaining a store’s planogram (Figure 4). A rapidly growing purchasing trend is “buy online and pick up in store” and the...
robot’s knowledge of each product’s exact location and the optimal picking route allows employees to fulfill customers’ online orders quickly and efficiently.

SoftBank’s humanoid Pepper (Figure 5) is one of the best known service robots and has been used in numerous applications, including a number of trials and real deployments in the retail sector where it greets customers, provides directions and helps with their enquiries. It is a sophisticated device and features IR sensors, bumper sensors, an inertial navigation unit, gyroscopes, 2D and 3D cameras and sonar for omnidirectional and autonomous navigation. Touch sensors, LEDs and multiple microphones allow multimodal interactions and speech recognition and dialogue is available in 15 languages via cloud services. Applications in retail customer assistance are growing: for example in Japan the Amazushi restaurant chain has deployed a Pepper robot in each of its 400 outlets; in Europe 100 units are acting as concierges for Renault dealership customers and 14 Carrefour grocery stores in Spain have a Pepper guiding shoppers to the right products; and in the US and Canada the robots are being deployed in several airport restaurants where they greet travellers, provide menu details and even offer menu recommendations. Nicolas Boudot, SoftBank Europe’s sales and marketing director, argues that the first European mass deployment of Pepper robots will be in retail.

In early 2019 Samsung, the world’s largest manufacturer of consumer electronics by revenue, demonstrated three pre-production service robots at the Consumer Electronics Show in Las Vegas. These include the “Bot Retail” which can provide directions and features a touchscreen for ordering and trays at the rear for delivering food and other purchases (Figure 6). According to Samsung it “streamlines ordering and payments and offers a personalised retail experience”. It is still at an early stage of development and no technical details have been disclosed or release dates announced. The ability to deliver food suggests that the company may be targeting the robotic waiter market which is developing very rapidly in the Far East, particularly in China. These robots are perhaps best viewed as part of the hospitality industry rather than the retail sector and will be covered in a future issue of this journal.

Store cleaning and hazard detection

Cleaning is a vital but monotonous and time-consuming task and large stores generally use manually operated cleaning machines which scrub and dry the floors and aisles. Typically, 20 per cent of an overnight employee’s time at a large retail outlet is dedicated to floor cleaning. Allied to cleaning is hazard detection which is a concern for many food retailers as the simplest of solid or liquid spills can expose them to major liability claims.

Robotic cleaning solutions are now being developed and a company pioneering this technology is Brain Corporation who specialises in autonomous navigation systems and their applications to conventional, non-robotic machines. These systems are based on their proprietary BrainOS technology which uses lidar, 3D vision and AI to confer this capability. This technology has been applied to several industrial floor cleaning products from a number of manufacturers and the company has recently collaborated with Intelligent Cleaning Equipment (ICE), one of the world’s leading industrial cleaning equipment manufacturers. The resulting robot, the Auto-C (Figure 7), combines a traditional ICE floor cleaning product with BrainOS technology and can operate autonomously with a maximum speed of 2 mph once it has been manually trained to navigate routes in the store. It is equipped with safety and obstacle avoidance sensors and has a run time of up to 4 h from its four 6V 360 Ah lead-acid batteries. In late 2018, it was announced that Walmart will deploy 360 of these units in hundreds of its stores. The BrainOS technology is also being used by SoftBank who has unveiled a new robot designed to clean commercial floors. Named the Whiz, the robot will be manufactured using Chinese parts and is being promoted by
Figure 7 The Auto-C floor cleaning robot

Source: Courtesy of Walmart

SoftBank as a potential remedy to Japan’s chronic labour shortage.

In early 2019, US-based Giant Food Stores announced that it would be deploying an autonomous, mobile robot dubbed Marty in all of its 172 stores to identify hazards such as liquids, powders, cardboard, shrink wrap and bulk food item spills and provide reporting that enables quick, corrective action to be taken. This application is part of a larger plan by Giant’s Dutch parent company Ahold Delhaize which intends to deploy robots in nearly 500 stores including Giant, Martin’s and Stop & Shop. This is one of the largest, if not the largest, roll-out of autonomous robots in the grocery retail industry. The robot was developed by Badger Technologies, a division of Jabil, a $22bn global company. As with similar, autonomous robots, it uses multiple cameras and lidar for store mapping and navigation. It is a multi-function robot, and in addition to hazard detection, it can conduct inventory management by reading unit tags and recognising if items are out-of-stock, as well as determining planogram compliance and checking prices.

Robotic delivery

Robotic delivery has attracted much recent attention, largely due to Amazon’s declared intention in 2013 to deploy drones for this function but while the technology exists, many regulatory, legal, safety and societal hurdles remain unresolved, at least in the West. Nevertheless, several other retail and delivery companies have since expressed an interest in the technology and conducted limited trials, including Google, FedEx, DHL, UPS and others and UPS has experimented with the deployment of drones from the rooves of its delivery vans.

Despite the many factors presently restricting the widespread deployment of delivery drones in Europe and the USA, a European commercial service has recently been launched in Iceland. Since August 2018, Flytrex Mule autonomous drones have been delivering groceries, clothing, medication and other items from AHA, one of Iceland’s largest e-commerce companies, to customers in the city of Reykjavik. The drones use a patented and unusual wire-drop delivery mechanism. Dubbed InAir, the system uses a tethered cord that gently lowers packages to the ground after delivery recipients confirm their proximity and safety to deploy using Flytrex’s app. AHA is now delivering goods between two parts of the city that are separated by a wide river, thereby dramatically cutting delivery times and costs and a short video clip of the system in operation can be viewed at https://youtu.be/I8NGrpO6sc.

While still little known in the West, China’s largest e-commerce company, JD.com, has over 300 million active customers and generated revenue of US$55.7bn in 2017. The company invests heavily in advanced technology and has approximately 12,000 engineers and scientists and operates a global R&D centre in Santa Clara, CA. In 2016, it started drone delivery trials (Figure 8) and now has seven different drone models operating on over 100 routes in several provinces. These have payloads ranging from 5 to 30 kg, operating ranges of 7-100 km and maximum speeds of 54-100 km/h and use proprietary technology developed at JDX, the company’s logistics innovation lab. The drone programme seeks to address the problems facing rural and isolated communities which have poor infrastructure and are currently underserved by the e-commerce industry. It operates by dispatching orders from regional delivery stations to JD’s network of dedicated “village promoters” in each village, who then distribute the orders directly to customers, significantly shortening delivery times and reducing logistics costs. The company currently has more than 300,000 village promoters across the country and is the world leader in high technology delivery through the use of drones and terrestrial robots (see below), and possesses the largest robotic delivery system, infrastructure and capability.

Land-based delivery robots face fewer restrictions than drones and are the topic of intensive development activity. Most companies are concentrating on “last mile delivery” which is responsible for much of the overall cost and UPS has estimated that cutting just one mile off the routes taken by each of its 66,000 delivery drivers would amount to $50m in savings. A company pioneering this strategy is US-based Starship Technologies which was founded in 2014 by two of Skype’s co-founders. The company has developed a small, autonomous, six-wheeled robotic delivery vehicle (Figure 9) which weighs 20 kg, has a payload of 10 kg and a top speed of 4 mph. A key design issue was to minimise cost which ruled out the use of lidar. Instead the robots use neural networks combined with multiple cameras, ultrasound sensors, radar and GPS for navigation. It is a multi-function robot, and in addition to hazard detection, it can conduct inventory management by reading unit tags and recognising if items are out-of-stock, as well as determining planogram compliance and checking prices.

Figure 8 A delivery drone taking off in Suqian

Source: JD.com
navigation and obstacle avoidance. Security is another important issue and the robot is equipped with a siren and ten cameras. It is constantly connected to the internet and knows its precise location with an accuracy of 2 cm and can also be tracked by the delivery recipient who can take control at any time. During trials, the robots have covered over 125,000 miles in 20 countries and in over 100 cities around the world, and pilot delivery programmes have been conducted US, UK, Germany, Switzerland and Estonia. In the UK, the company has been running a fleet of around 20 robots in Milton Keynes for food delivery, working with the Cooperative, and in 2018, it launched what it claims to be the first commercial robotic delivery service, again in Milton Keynes. Parcels and groceries are delivered from stores or specialised hubs within a two mile radius at a time the customer requests via a mobile app and arrive in between 5 and 30 min. The company announced that the service will soon be available to residents in the Bay Area, CA.

While Starship is perhaps the best known it is just one of an ever-growing number of mostly US-based, early stage companies aiming to enter the market. An example is Nuro which was founded in 2016 by two former engineers from Google’s self-driving car project. The company is developing a small van-sized delivery robot which, unlike the Starship product, will operate on public roads and has raised $92 million in two rounds of fundraising and is in talks with a number of retailers and delivery providers about possible partnerships. Another company aiming to enter this market is Robby Technologies. Founded in 2015, it is developing a small, six-wheeled delivery robot, Robby 2, which has a range of about 20 miles between charges and resembles Starship’s robot. It is equipped with a suite of infrared cameras, allowing it to operate at night. The company has partnered with Doordash, Instacart and Postmates and its test robots have logged over 4,000 miles delivering food. A further company is Marble which was also founded in 2015, by three former Carnegie Mellon University graduates. Describing themselves as “the last-mile logistics company”, Marble has raised $15m in start-up funding. Yet another early-stage start-up is Dispatch, again founded in 2015. The robot (Figure 10) named Carry exploits computer vision and machine learning techniques and has a payload capacity of 100 lbs.

In contrast to the above, several companies are aiming to exploit more conventional driverless/autonomous vehicle technology for delivery. For example, Udely, a self-driving delivery vehicle start-up founded in 2016 recently announced that it was teaming up with Walmart to trial an autonomous grocery delivery service in Arizona and Ford has announced it is also partnering with Walmart, as well as Postmates, in an autonomous vehicle delivery pilot scheme. Udely states that it has completed 1,200 deliveries and up to 100 of its autonomous vans will be delivered to customers in 2019.

In addition to its drones, JD.com has developed ground delivery robots and released an initial fleet of 20 from its logistics base in Changsha, Hunan Province in late 2018 (Figure 11). The four-wheeled robot travels at up to 20 kph and has 22 compartments giving a total payload capacity of 300 kg. The compartments are unlocked by a password or face recognition and a surveillance centre monitors the robots’ locations through the data and video they transmit. They are equipped with cameras, radar and a suite of sensors, together
with AI technologies for navigation and have a range of 5 km. The operate in non-motor vehicle lanes and their use has reduced unit delivery cost by 80 per cent and is helping the company to cope with labour shortages and rapidly rising wages in China’s logistics industry.

While all of the above deliver specific products to customers from a store or distribution centre, Robomart, founded in 2017, is developing an autonomous vehicle which effectively takes the store to the customer. Still at an early stage, the concept is for customers to summon the closest Robomart unit, effectively a mobile grocery store, and select the required products. Robomart tracks what customers have taken using a patent pending “grab and go” checkout-free technology and will charge them and send a receipt.

**Discussion**

The retail industry faces many challenges. Traditional “bricks and mortar” retailers often have difficulties in recruiting and retaining staff, profit margins are being eroded while operating costs continue to rise, and they face ever-growing competition from the fast growing e-commerce sector, although this is not immune to challenges: competition is intense, and it is under pressure to speed-up delivery times while minimising the costs.

These issues are being addressed and many of the functions listed in the Introduction are being streamlined and modernised through the use of IT, automation and AI by both the traditional and on-line sectors, as illustrated well by the activities of major retailers such as Walmart and JD.com. Robots are playing a critical role in this process but the market is still at an early stage of development and products and strategies will inevitable evolve. Future generations of in-store robots will most likely offer combined capabilities. They would greet customer and offer directions and advice, conduct inventory management, determine planogram compliance, detect hazards and perhaps also perform other functions such as covertly detecting shoplifters. Once driverless vehicles become commonplace, they will inevitably play a central role in delivery. In addition to operating alone, as in some of today’s applications, a large autonomous vehicle could cover most of a route and then deploy multiple small robots to deliver over the last few miles where there is good infrastructure; in rural areas with poor access they could be replaced by drones. Both of these strategies have already been investigated.

Even at this early stage, robots have been shown to reduce manpower requirements, improve efficiency, reduce costs and speed-up deliveries. As applications grow and the technologies mature, retail is expected to become a major user of robots and will offer significant business opportunities.

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COMMERCIAL INTERVIEW

The Pransky interview: Dr Maja Matarić, Professor, University of Southern California; Pioneer, field of socially assistive robotics; co-founder of Embodied

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Abstract

Purpose – The following paper is a “Q&A interview” conducted by Joanne Pransky of Industrial Robot Journal as a method to impart the combined technological, business and personal experience of a prominent, robotic industry PhD and innovator regarding her pioneering efforts and the challenges of bringing a technological invention to market. This paper aims to discuss these issues.

Design/methodology/approach – The interviewee is Dr Maja Matarić, Chan Soon-Shiong Distinguished Professor in the Computer Science Department, Neuroscience Program, and the Department of Pediatrics at the University of Southern California, founding director of the USC Robotics and Autonomous Systems Center (RASC), co-director of the USC Robotics Research Lab and Vice Dean for Research in the USC Viterbi School of Engineering. In this interview, Matarić shares her personal and business perspectives on socially assistive robotics.

Findings – Matarić received her PhD in Computer Science and Artificial Intelligence from MIT in 1994, MS in Computer Science from MIT in 1990 and BS in Computer Science from the University of Kansas in 1987. Inspired by the vast potential for affordable human-centered technologies, she went on to found and direct the Interaction Lab, initially at Brandeis University and then at the University of Southern California. Her lab works on developing human–robot non-physical interaction algorithms for supporting desirable behavior change; she has worked with a variety of beneficiary user populations, including children with autism, elderly with Alzheimer’s, stroke survivors and teens at risk for Type 2 diabetes, among others.

Originality/value – Matarić is a pioneer of the field of socially assistive robotics (SAR) with the goal of improving user health and wellness, communication, learning and autonomy. SAR uses interdisciplinary methods from computer science and engineering as well as cognitive science, social science and human studies evaluation, to endow robots with the ability to assist in mitigating critical societal problems that require sustained personalized support to supplement the efforts of parents, caregivers, clinicians and educators. Matarić is a Fellow of the American Association for the Advancement of Science (AAAS), Fellow of the IEEE and AAAI, recipient of the Presidential Awards for Excellence in Science, Mathematics & Engineering Mentoring (PAESMEM), the Anita Borg Institute Women of Vision Award for Innovation, Okawa Foundation Award, NSF Career Award, the MIT TR35 Innovation Award, the IEEE Robotics and Automation Society Early Career Award and has received many other awards and honors. She was featured in the science documentary movie “Me & Isaac Newton”, in The New Yorker (“Robots that Care” by Jerome Groopman, 2009), Popular Science (“The New Face of Autism Therapy”, 2010), the IEEE Spectrum (“Caregiver Robots”, 2010), and is one of the LA Times Magazine 2010 Visionaries. Matarić is the author of a popular introductory robotics textbook, “The Robotics Primer” (MIT Press 2007), an associate editor of three major journals and has published extensively.

Keywords Artifical intelligence, Education, Healthcare robots, Robot design, Robotics, Humanoid robots

Paper type Case study

Pransky: Since a socially assistive robot (SAR) does not require physical interaction, even in a non-humanoid form, do you think a SAR needs a torso, or is a “face”/head enough, and within the head, what features has your research found to be important to the user (e.g., eyes, mouth), etc.? (Figure 1)

Matarić: We actually just published a review paper www.nowpublishers.com/article/Details/ROB-056 where we reviewed 65 studies and compared different aspects of embodiments – on-screen and physically embodied. Physically embodiment does not only mean physically interacting with the environment to perform tasks; embodiment also has to do with non-verbal communication, including proxemics (social use of space, such as how far people feel they should stand from others), oculesics (eye-gaze related non-verbal communication), posture and gestures, to enhance communication and the perception of being trustworthy, helpful and engaging.

Everything about the robot’s body communicates something at all points in time, even when the robot isn’t moving. What we found is that people typically ascribe a face or a head to a robot, even if there isn’t one. It’s just how we
Pransky: What robot behavior gave you as a scientist the most unexpected response?

Matarić: One of the things that I find really interesting and important for the way we’re developing technology today is the notion of perfection. Technologists are really obsessed with trying to create the perfect robot or agent that knows all the answers and behaves perfectly. However, that’s really not what people want from a companion (though it is what we want from a surgeon; so context is important). In everyday life, people do not accept function alone if they can’t engage with it in a social way, because we are social creatures (Figure 2).

One example where I learned this was about ten years ago from our humanoid robot, Bandit. http://rasc.usc.edu/bandit.html Bandit, built by BlueSky Robotics, was quite sophisticated for those days and it’s still quite sophisticated today. It has a simple actuated mouth that sometimes did not work because of a servo motor problem. Sometimes the mouth “froze” so the robot was talking but the mouth was not moving. We decided to control the conditions and programmed Bandit to say at the beginning of an interaction with a user: “Sometimes my mouth just doesn’t work. I’m sorry about that.” To our surprise, we discovered that people were so much more forgiving about everything Bandit did for the remainder of the interaction. Because Bandit apologized up front, users effectively gave it a break, and allowed it to be imperfect. In fact, they liked it that way, because it was more relatable. The robot’s open vulnerability made people much more forgiving and they enjoyed the interaction more (Figure 3).

Pransky: Speaking of lessons, what is the greatest lesson that you’ve learned in your long and distinguished career?

Matarić: Oh, there are so many lessons … The lesson I’d like to share with people now is that while deep learning and big data can do narrow, well-defined things well,
interactions with people are exactly the opposite. They’re not narrow at all; they’re more broad and complex, fluid and ever-changing. The data we collected in our research has been highly personal and differs from participant to participant. What the field of human–robot interaction (HRI) really needs is more research with real multi-modal human interactions in the real world, to personalize to each individual’s changing needs.

**Pransky: What lessons do you think can be learned from say, Jibo?**

Matarić: Cynthia Breazeal, who founded Jibo, is a grad school friend of mine. She is a trailblazer who put a spotlight on social robotics and its promise on the consumer market. But I think there were two major challenges with Jibo. One was the timing of Jibo relative to Amazon Alexa, which came out earlier (via the Echo) and had so much more content.

The other thing with Jibo, and also Mayfield Robotics’ Kuri, another beautifully designed robot, is their lack of specific purpose. Jibo was supposed to be a platform that people would program to do interesting things. But consumers want a product that can do things and be useful in a way that is commensurate with its cost. Unfortunately for Jibo, the much cheaper Amazon Echo (and other Alexa products as well as Google Home) could do more (because of having much more content). The adorable Kuri could only take photos. But users want more out of a robot; they want it to have some useful purpose. The purpose does not have to be a physical function, but it has to be something it can do better (more enjoyably) and more cheaply than other devices and technologies.

**Pransky: What has been your favorite robot of all the ones you’ve worked with and why? (Figure 4)**

Matarić: I can’t pick a favorite robot; it’s like picking a favorite child or student, and that can’t be done. Let me tell you about a recent one, Kiwi. In our National Science Foundation Expedition in Computing grant, a large multi-university research effort with Yale, USC, MIT and Stanford, we used table-top squash and stretch robots, because we needed them to be safe and affordable for in-home use. http://robotics.usc.edu/interaction/sponsors/expeditions That was a revelation for me because eight or ten years ago I hadn’t really worked on anything that was just on a tabletop. But a tabletop robot is still very much a robot, and it can be very expressive, engaging, and effective. I came to appreciate that more because I realized how much one can do with an embodiment that is much lower cost and higher safety (Figure 5).

**Pransky: How did you become part of the startup Embodied that you co-founded? Did they approach you or was it a long-term goal of yours?**

Matarić: I was part of the small group of researchers who pioneered the field of SAR back in 2005. I am proud to say that my research team named it; specifically, in a paper published by David Feil-Seifer and me. We are very happy...
that the name has stuck! http://robotics.usc.edu/publications/media/uploads/pubs/442.pdf

Based on my lab’s work in SAR, I was inspired to see if we could transition the research insights to real-world use. I had a sabbatical in 2016, so that was the time to do a startup. I said, “Let’s get this out to real people”, and I teamed up with my former postdoc Paolo Pirjanian; we talked about various possible applications of SAR for about six months, identified one that had a business proposition, and then went on to incorporate Embodied, Inc. www.embodied.me and raised seed and A rounds of financing. I was Chief Science Officer of Embodied until November 2018, and now I serve in an advisory role. Embodied is currently in stealth; I believe it will come out of stealth in 2020. Though I’m not involved in the daily operations of the company anymore, I’m hoping that it will be a successful instance of a robot with a purpose.

Pransky: How did you like being in a startup compared to being in academia?

Matarić: In academia, you get to do the fun stuff (if you can raise the funds to do it); explore interesting open problems and discover and develop new things. Nobody is your boss; the professor or researcher is the ultimate authority on what is done and how it is done and if you can fund your research, you can do it. That is not the case in startups. In a startup, the funders have a great deal of influence on what is done and how it is done: the company has to have growing value so they can get a return on their investment.

In academia, we can develop prototype systems without great concern about component costs, as we are focused on running experiments and discovering things; not developing affordable products. In academia, we think nothing of putting a 3D $90 camera on a robot, but such a camera on a mass-produced consumer robot means that it’s driving the cost to likely a $900 final product. Those realities are not something that one would ever learn in academia and I’m really grateful that I’ve had the opportunity to learn so much by starting a company. I’m interested in staying involved and who knows what my next step will be?

That is truly an amazing quality of being in academia – we can explore many things and find various ways to have an impact. We teach and train young people, which I find tremendously rewarding. We invent new fields and frontiers. We can start companies and transition technologies from research to the consumer. The flexibility of academia allows us to have the best of multiple worlds. It’s great to be able to do that. Of course, you have to juggle, you are busy and things are crazy, but it’s so satisfying. I also think it is important to be able to speak from experience to my engineering and computing students who are interested in entrepreneurial endeavors. I think it makes me a much better advisor. I hope to inspire them to focus on products with a real purpose; hopefully those that make the world a better place.

Pransky: If something happened and you had to make a lot of money for your own research to carry on, how would you do it?

Matarić: I’m incredibly grateful to the National Science Foundation (NSF) which has been my main source of research support over the years. NSF’s mission is basic research, but it also supports the Small Business Innovation Research (SBIR) program and I’ve collaborated with a lot of small businesses over the years to take our research to that next step. It is incredibly important to have that first, basic research support. After that, however, how do you get supported to do that next step? How do you scale up to go from research to products?

When it comes to products in human health and wellness, the area I am focused on, it is not enough to just jump from basic research to a company. Typically there is a need for scaling up the work, showing evidence that the approach really works, because without such evidence, consumers may not buy the product, or may be disappointed. The National Institutes of Health (NIH) funds health-related research, but not much of the kind that involves technology and behavior change. Some support can be found from non-profit philanthropic organizations and foundations. But we need much more of that type of support that bridges basic research and translation to the real world and the marketplace. Much of venture-backed innovation is poorly suited to this type of impact; making a real disruptive difference in difficult problems in human health and behavior (just like other societal-scale problems such as sustainable energy and climate), requires patient, long-term study, investment and evaluation. Finally, in robotics, in both the short and long term, we need to focus more on augmentation – technologies that make people better at having skills and purpose, rather than just automation.
About the author

Joanne Pransky has been an Associate Editor for *Industrial Robot Journal* since 1995. Joanne was also one of the co-founders and the Director of Marketing of the world’s first medical robotics journal, *The International Journal of Medical Robotics and Computer Assisted Surgery*. Joanne served as the Senior Sales and Marketing Executive for Sankyo Robotics, a world-leading manufacturer of industrial robot systems, for more than a decade. Joanne, also known around the globe as the World’s First Robotic Psychiatrist®, has consulted for some of the industry’s top robotic and entertainment organizations including: Robotic Industries Association, Motoman, Staubli, KUKA Robotics, STRobotics, DreamWorks, Warner Bros., as well as for Summit Entertainment’s film “Ender’s Game” in which she brought never-seen-before medical robots to the big screen. Joanne Pransky can be contacted at: joannepransky@gmail.com
A cross-modal tactile sensor design for measuring robotic grasping forces

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Abstract
Purpose – The purpose of the paper is to present a novel cross-modal sensor whose tactile is computed by the visual information. The proposed sensor can measure the forces of robotic grasping.

Design/methodology/approach – The proposed cross-modal tactile sensor consists of a transparent elastomer with markers, a camera, an LED circuit board and supporting structures. The model and performance of the elastomer are analyzed. Then marker recognition method is proposed to determine the movements of the marker on the surface, and the force calculation algorithm is presented to compute the three-dimension force.

Findings – Experimental results demonstrate that the proposed tactile sensor can accurately measure robotic grasping forces.

Originality/value – The proposed cross-modal tactile sensor determines the robotic grasping forces by the images of markers. It can give more information of the force than traditional tactile sensors. Meanwhile, the proposed algorithms for forces calculation determine the superior results.

Keywords Force, Cross-modal, Elastomer, Marker, Tactile, Tactile sensor, Three-dimension force

Paper type Research paper

1. Introduction

In recent years, the new generation of robots has entered into our lives with the development of robotic technology, such as humanoid robots, bionic robots, medical robots and so on. Their working environment is different from the traditional industrial robot. In most cases, the robots execute tasks in the uncertain environment. Hence, perception becomes important for the robots. Like humans, tactile is also indispensable for robotic grasping (Dahiya et al., 2010). Certain mechanical properties of the object, such as shape, friction, hardness and texture, which are obtained through tactile (Liu et al., 2017). If there is not enough tactile feedback information, it is very difficult or even impossible to achieve the common tasks of operating (Tapomayukh et al., 2018). Hence, the robot tactile has become a hot research topic (Liu and Sun, 2018).

At present, there are many kinds of tactile sensors, including resistive, capacitive, optical, piezoelectric, etc. (Luo et al., 2017). The resistive tactile sensor measures the contact force by changing the resistance of the sensing material (Weiss and Worn, 2005). Capacitive sensors are widely used in robots (Schmidt et al., 2006). They can be made into high-density arrays (Huang et al., 2017). The sensor array consists of row electrodes and column electrodes, which are separated by an elastic dielectric to form a capacitive array. The optical sensor measures the pressure by changing the optical density in different refractive index media. Reference (Heo et al., 2006) introduces a tactile sensor based on optical fiber, which can measure the normal force. Optical-based sensors are not affected by electromagnetic interference and have the advantages of flexibility, sensitivity and speed, but are often cumbersome. Piezoelectric sensors measure the charge generated by the piezoelectric material in proportion to the applied pressure (Yu et al., 2016). Piezoelectric materials such as PZT and PVDF are suitable for dynamic tactile sensing.
However, piezoelectric materials are susceptible to temperature. Most tactile sensors can only measure the magnitude of the normal force, but they cannot measure the tangential force. When the force is applied to the skin’s surface, the human touch can detect not only the magnitude of the force but also the direction of the force output. Tangential force plays an important role in slip detection and stable grasp, hence it is necessary to measure tangential force. Nowadays, the cross-modal tactile sensor that using visual information is a potential solution to measure the three-dimension force (Fang et al., 2018). The principle of the vision-based tactile sensor is printing markers on the elastic body, and then measure the forces by the movements of the markers that determined by the images.

This paper designs a cross-modal tactile sensor based on visual information. It includes elastomer, micro camera, LED circuit and supporting structure. The mechanical model of the elastomer was proposed. The simulation of the elastomer was implemented by ANSYS, including the simulation of the surface deformation of the elastomer under normal load, tangential load and torque. Then the method based on the connected domain is proposed to obtain the position of the marker, and determine the movements of all markers. The BP neural network is designed to compute the three-dimensional force. Finally, the experiments are designed and implemented to prove the effectiveness of the proposed cross-modal tactile sensor.

2. Cross-modal tactile sensor design

The sensor designed in this paper consists of a transparent elastomer, camera, LED circuit board, acrylic board, shell and the supporting structures, as shown in Figure 1. The 3D printing structures are low-cost and lightweight. The effect of structures are supporting and positioning the elastomers, cameras and LED circuit boards so that the relative positions of the three are kept unchanged and the camera can take a stable picture regardless of the interference of the overall motion or vibration of the sensor. The shell isolates the outside light. The only source of illumination for the elastomer is from the LED circuit board. A constant light source ensures the performance of the sensor. A piece of transparent acrylic board is used to enter the elastomer. Hence, the light on the elastic body is uniform, and the image quality is greatly improved. The sensor structure designed in this paper, as shown in the figure, is a fingertip shape with an external dimension of $24 \times 33 \times 25$ mm, which can be installed at the fingertip of a dexterous hand.

The sensor designed in this paper obtains the tactile information by analyzing the deformation of the elastomer. Hence, it is a critical part of the sensor. The characteristics of the elastomer include hardness, thickness and transmittance that affect the performance of the sensor. The softer elastomer is easier to deform, so it is more sensitive. A harder elastomer can withstand heavy loads, and the range of measurable force is greater. The viscosity of the elastomer should be as small as possible, which can shorten the time needed to restore the original shape of the elastomer and improve the dynamic response speed. The absolute displacement of the thick elastomer is greater, so it is easier to detect the deformation of the elastomer, but it will increase the size of the sensor. The elastomer should also be as transparent as possible, with high transmittance and no air bubbles or other impurities in the interior, so that the camera can clearly capture the state of the marking point. In addition, the adhesion between the elastomer and the marking points should be very strong to avoid the marking points falling off during the use. In generally the elastomer should have good elasticity and low viscosity. The transparent elastomer used herein uses polydimethylsiloxane (PDMS).

The marking point array is attached to the surface of the elastomer. When a contact force acts on the elastomer, the marking points move as the surface of the elastomer deforms. To get contact force information, the state of the surface of the elastomer is obtained by the displacement of the marker points. The marking points are produced by magnetron sputtering of aluminum. The color of aluminum differs greatly from the background and is highly adherent to PDMS. Aluminum does not have a strong metallic luster, so there is no problem such as reflection. The mask with $16 \times 16$ circular holes is placed on the surface of the elastomer to make markers by sputtering.

3. Elastic mechanics modeling and simulation analysis

3.1 Elastic mechanics modeling

For elastic objects, when the stress is less than the extreme limit of elastic proportional, the relationship between stress and strain is linearly elastic, then the elastic constitutive relation is:

\[ \sigma = \frac{E \epsilon}{1 - \nu^2} \]

where $\sigma$ is the stress, $\epsilon$ is the strain, $E$ is the Young’s modulus, and $\nu$ is the Poisson’s ratio.
Cross-modal tactile sensor design

Bin Fang, Hongxing Xue, Fuchun Sun, Yiyou Yang and Rensiang Zhu

\[
\sigma_x = \frac{E}{(1 + \nu)(1 - 2\nu)} \left[(1 - \nu)\epsilon_x + \nu(\epsilon_y + \epsilon_z)\right],
\]
\[
\tau_{xy} = \frac{E}{2(1 + \nu)} \gamma_{xy} = G\gamma_{xy}
\]
\[
\sigma_y = \frac{E}{(1 + \nu)(1 - 2\nu)} \left[(1 - \nu)\epsilon_y + \nu(\epsilon_x + \epsilon_z)\right],
\]
\[
\tau_{yx} = \frac{E}{2(1 + \nu)} \gamma_{yx} = G\gamma_{yx}
\]
\[
\sigma_z = \frac{E}{(1 + \nu)(1 - 2\nu)} \left[(1 - \nu)\epsilon_z + \nu(\epsilon_x + \epsilon_y)\right],
\]
\[
\tau_{zx} = \frac{E}{2(1 + \nu)} \gamma_{zx} = G\gamma_{zx}
\]

where \(\sigma_x, \sigma_y, \sigma_z\) represent stresses in the x, y, and z directions, \(\epsilon_{x_0}, \epsilon_{y_0}, \epsilon_{z_0}\) represent strains in the x, y, and z directions, and \(\gamma_{x_0}, \gamma_{y_0}, \gamma_{z_0}\) represent shear strains in the x, y, and z directions, respectively, E is Young’s modulus of the material, and \(\nu\) is the Poisson’s ratio of the material.

For the linear elastic model, the stress and strain are linear, and the stress and strain are independent of time. When an external force is applied to the elastic material, the deformation is instantaneous, and when the external force is removed from the elastic material, it recovers instantaneously.

Commonly silica gel is considered as an isotropic elastic material, but silica gel is also viscous. One of the main features of viscoelastic materials is that the stress state depends not only on the strain at the current moment but also on the history of previous strain rates. The strain–stress relationship of a linear viscoelastic model is:

\[
\epsilon(t) = \int_0^t \mathcal{J}_0(t-\tau)\dot{\epsilon}(\tau)d\tau + \int_0^t \mathcal{J}_1(t-\tau)\dot{\sigma}(\tau)d\tau
\]

where \(\mathcal{J}_0(t)\) is a creep flexibility function that changes over time.

The stress–strain relationship is:

\[
\sigma(t) = E_r(t)\epsilon(0) + \int_0^t E_r(t-\tau)\dot{\epsilon}(\tau)d\tau
\]

where \(E_r(t)\) is the stress relaxation function.

The viscoelastic model can describe the mechanical behavior of rubber materials at lower strain rates, but in the case of high strain rate and large deformation, such as impact load, the viscoelastic model is quite different from the actual situation. The sensor is designed for dexterous hand operation. During the using process, the rate of contact force changes is not high, the size is less than 10 N, and the maximum strain of the elastic body does not exceed 0.2, which conforms to the assumption of the viscoelastic model. Therefore, the viscoelastic model can be used for the mechanical model of the elastomer.

3.2 Simulation analysis

To understand the surface deformation of the elastomer, the mechanical properties were simulated by finite element software ANSYS (Huang et al., 2007). A simulation model is built based on the actual dimensions of the elastomer. It is mainly used to study the quasi-static response of the elastomer, regardless of the change of the stress and strain state of the elastomer with time. The normal forces, tangential forces and torques are applied to the elastomer. The size of the elastomer is the same as the one used in the experiment, 13 mm × 13 mm × 7 mm. The entire model contains more than 220,000 nodes with a side length about 0.29 mm of each grid.

In the normal indentation simulation, the indenter diameter is 3 mm and the normal displacement is 1 mm. The vector diagram of the surface of the elastomer deformed in the x-y plane is shown in Figure 2(a). The radial displacement of each point on the surface of the elastomer is shown in Figure 2(b). It can be seen that under the action of the normal force, the surface of the elastomer has a tendency to expand outward in a two-dimensional space. Because the indenter is axisymmetric, the displacement field is also axisymmetric, and the center of symmetry is the axis of the indenter. The radial displacement at the center of symmetry is 0. From the center of symmetry, the radial displacement of each point becomes larger first, reaching the maximum near the boundary of the indenter and then decreasing. The simulation results show that the displacement of each grid point is linear with the normal load.

In the pure shear load indentation simulation, the indenter diameter is 3 mm, the tangential displacement is 0.1 mm, and the direction is the x positive direction. The deformation of the surface of the elastomer in a two-dimensional plane is shown in Figure 3(a). The radial displacement of each point on the surface of the elastomer is shown in Figure 3(b). The radial

![Image](328x259 to 565x404)

**Notes:** (a) Elastomer surface radial displacement vector; (b) elastomer surface radial displacement
displacement field is symmetric up and down, i.e. symmetric about the x-axis. It shows that the displacement is mainly concentrated in the shear direction. The displacement field in the shear direction is symmetric along the x-axis and the y-axis (where the x-axis should be in the horizontal direction, which is the shear direction, and the y-axis is in the vertical direction), and the displacement component decreases the slowest in the shear direction. The vertical displacement field is centrosymmetrical along the origin. The displacement field of a pure shear load is similar to the fluid flow through a narrow valve.

In the torque load simulation, the indenter has a diameter of 3 mm and a torque of 10 N·mm. The vector of the elastomer surface deformed in the x-y plane is shown in Figure 4(a). The radial displacement of each point on the surface of the elastomer is shown in Figure 4(b). It can be seen that under the action of the torque load, the surface of the elastomer is counterclockwise in a two-dimensional space, the displacement field is axisymmetric, and the center of symmetry is at the axis of the indenter. The radial displacement at the center of the symmetry is 0. From the center of symmetry, the radial displacement of each point becomes larger first, reaching the maximum inside the boundary of the indenter and then decreasing. The simulation results show that the displacement of each grid point is linear with the magnitude of the torque load.

It can be seen from the simulation results that the displacement field of the surface of the elastomer has superposition. When a composite load of normal, tangential and torque is applied, this composite load can be regarded as a superposition of normal load, tangential load and torque, and the displacement field of the composite load is also equal to normal load, tangential load and torque. The superposition of the displacement fields when acting separately. An example of a resultant force displacement field is shown in Figure 5.

4. Contact forces measuring

4.1 Marker recognition

In this section marker recognition algorithm is proposed. The basic idea of the method is to preprocess the image and perform binarization, then identify the connected domain, eliminate the connected domain that does not meet the requirements. The remaining connected domain corresponds to the marked point and then finds the centroid of the connected domain. The position of the centroid is the location of the center of the marker. The base steps are as follows.

4.1.1 Convert the original RGB image to the grayscale image

The original image captured by the camera is an RGB color image, as shown in Figure 6(a). Color information has little effect on marker recognition, so the RGB image is converted into a grayscale image, as shown in Figure 6(b).

4.1.2 Perform high-profile filter on the grayscale image and adjust image brightness

The image captured by the camera is not very uniform, so preprocessing is required. Here, no common Gaussian filtering is applied to eliminate noise, because Gaussian filtering will blur the image, making it difficult to accurately distinguish the edges of the markers. To reduce the influence of uneven illumination, a high-hat filter is used to enhance the contrast of the image. An important use of the high and low hat transform is to reduce the effects of uneven illumination. The high-hat transform is used for bright objects on a dark background, while the low hat transform is used for dark objects on a bright background. After the high-hat filter processes the image, the brightness of the image is enhanced. For example, the original image and the high hat filtered image are shown in Figure 6(c).

Figure 5 Deformation of the elastomer under three loads

Notes: (a) Elastomer surface radial displacement vector; (b) elastomer surface radial displacement

Figure 6 The process of mark recognition

Notes: (a) The original image; (b) grayscale; (c) high hat filtering; (d) binarization; (e) connected domain processing; (f) looking for the center of mass
image is adjusted to improve the contrast of the image so that it is easier to recognize the mark from the image, as shown in Figure 6(c).

4.1.3 Binarization

Binarization is the comparison of all pixels on an image to a selected threshold. When it is greater than the threshold, it takes 255, which is white. If it is less than the threshold, it takes 0, which is black. This converts the 256-order grayscale image into an image with only 0 and 255 values. Here we use a fixed threshold. It is found through experiments that when the threshold is chosen to be 150, the effect of binarization is better, as shown in Figure 6(d).

4.1.4 Connected domain search and markup

The binarized image contains a plurality of regions, the black regions correspond to the background while the white regions correspond to the markers and some regions of binarized anomalies caused by uneven illumination. The white areas need to be extracted separately by marking. A simple and effective way to mark regions in a segmented image is to check the connectivity of each pixel to its neighboring pixels. Pixels within the same connected domain are labeled with the same value, and pixels in different connected domains are labeled with different values. The value of the pixel in the background area is 0, and the pixel value of the target area is 1. The binarized image is searched using an eight-connected rule.

4.1.5 Select the connected domain that meets the requirements

Owing to the uneven illumination and the influence of noise, some areas of the background are binarized into white areas. Compared with the connected domain of the marker, the area of the connected domain of the white region generated by the above influences is usually very small or large, so the erroneous connected domain can be eliminated by limiting the area of the connected domain. It is larger than a certain threshold and smaller than another threshold. The connected domain is culled, and the area of the connected domain of the markers is within this range, as shown in Figure 6(e).

4.1.6 Looking for the center of mass

Take a square window to calculate the centroid. If the sensor does not touch the object, the diameter of the marker is D, and the spacing of the markers is L. The length W of the square window is greater than D and less than \(2 \times L - D\). Such a window can have exactly one marker inside. The image outputted in step 5 is progressively scanned. When the pixel value is 1, the pixel is the edge of the marked point, and the pixel whose distance is offset from the radius of the marked point is taken as the scanning center, and a \(W \times W\) field is taken, that is, the window calculates the coordinate mean of the corresponding mark point, obtains the centroid coordinate, and assigns the scanned mark point pixel to 0. Loop through the above process until the entire image is traversed, and the centroid coordinates of all the points can be obtained, as shown in Figure 6(f).

4.2 Forces calculation

Although the displacement field of the elastomer’s surface has superposition, it is difficult to decompose three kinds of forces or moments by the combined displacement field of the normal force, the tangential force and the moment. To solve this problem, we design the BP neural network to fit the three-dimensional contact force by the displacements of the markers. The input-output relationship of neurons reflects the nonlinear mapping relationship. Considering that the displacements of the markers are coupled to each other, it is a great advantage to establish an input-output relationship through the MLP (multilayer perceptron). In this paper, the three-layer BP neural network is proposed as shown in Figure 7.

Using the BP neural network to fit the relationship between force and displacement:

\[
h_I^i = \sum_{k=1}^{32} (x_{ik} \omega_{ik}^{1}) - b_{hi}^i \quad (i = 1, 2, \ldots, n)
\]

\[
h_O^i = f(h_I^i) = \frac{1}{1 + e^{-a h_I^i}} \quad (i = 1, 2, \ldots, n)
\]

where \((x_{11}, x_{12}, \ldots, x_{12})\) is the displacement vector of the \(4 \times 4\) marker point \((x, y)\), \(\omega_{ik}^1\) is connected to the \(k\)-th of the input layer and the weight of the \(i\)-th neuron of the hidden layer, \(b_{hi}^i\) is the \(i\)-th neuron input offset of the hidden layer, \(f(h_I^i)\) is a sigmoid function. The random sample of the above sample training set calculates the alpha value. \(f(h_I^i)\) and \(f(h_O^i)\) are the inputs and outputs of the hidden layer of the three-layer neural network. The output is a three-dimensional resultant force.

The mapping relationship between the hidden layer and the output layer of the three-layer neural network is:

\[
\dot{f}_x = f\left(\sum_{i=1}^{n} (h_O^i \omega_{2i}^2) - b_x\right)
\]

\[
\dot{f}_y = f\left(\sum_{i=1}^{n} (h_O^i \omega_{2i}^2) - b_y\right)
\]

\[
\dot{f}_z = f\left(\sum_{i=1}^{n} (h_O^i \omega_{2i}^2) - b_z\right)
\]

where \(\dot{f}_x, \dot{f}_y, \dot{f}_z\) are the predicted values of the force component, \(\omega_{2i}^2\) is the connection weight of the \(i\)-th neuron of the hidden layer and the \(x\)-th neuron of the output layer, and \(b_i\) is the input offset of the hidden layer \(x\) neuron. Other variables use the same rules.

Any optimization process of a neural network is a process of solving parameters using existing samples. In this process, we will set an optimized objective function, also called the cost function. The setting of the objective function will affect the convergence and convergence speed of the network training. At

![Figure 7 The three-layer BP neural network](image-url)
the same time, to avoid over-fitting, especially in the dexterous hand grabbing the experimental scene, the dexterous hand’s motion posture is limited to a specific motion pose. The data of the dexterous hand of the sampling sensor is very scarce, so over-fitting is likely to occur when the neural network is trained with the sample. To avoid over-fitting, we added a network parameter item to the objective function. The specification and objective function are as follows:

$$e = \frac{1}{2} (\hat{f}_x - f_x)^2 + \frac{1}{2} (\hat{f}_y - f_y)^2 + \frac{1}{2} (\hat{f}_z - f_z)^2 + \beta \| \omega \|^2$$

(6)

where $\hat{f}_x, \hat{f}_y, \hat{f}_z$ are the predicted values of the force components, and $f_x, f_y, f_z$ are the actual values of the force components.

5. Experiments and results

The experimental calibration platform is shown in Figure 8(a). The top of the platform is a three-dimensional force sensor. We convert the three-dimensional force to three sets of analog voltage by the differential amplification circuit. Then we can calculate the magnitude of the three-dimensional force by linear conversion. A number of indenters of different materials, shapes and sizes were used in the experiment, as shown in Figure 8(b). There are two kinds of indenter materials: one is an aluminum alloy and the other is resin. The shape of the indenter is cylindrical and hemispherical. The cylindrical indenter has diameters of 5, 10 and 20 mm, and the hemispherical indenter has a diameter of 5 mm. Then the several experiments are implemented to prove the effectiveness of the proposed tactile sensor.

5.1 Stress-strain experiment

An elastomer sample of a cubic structure having a size of $13 \times 13 \times 10$ mm and a cylindrical indenter having a diameter of 20 mm can completely cover the surface of the elastomer. The elastic body is fixed, and the normal deformation amount of the elastic body is changed. The axial load displacement is controlled by a moving table based on a spiral micrometer. The deformation range of the elastic body is from 0 to a thickness of 2 mm, and the step of the load change is 0.2 mm. To reduce the influence of stress relaxation, after each change of the deformation amount, to make the elastic body reach a stable state, after each loading/unloading, the $z$-axis force of the three-dimensional force sensor is measured after 3 min, and the normal force is basically stable. The loading and unloading stress-strain curves of the elastomer are obtained.

During the loading and unloading process, each time the load is changed, wait about 3 min to measure the normal force, so that the elastic body is in a state of near static. Figure 9 shows the normal stress of the elastomer sample during loading and unloading. Strain relationship curve. It can be seen from the figure that the stress-strain curves of the loading and unloading do not coincide, and the unloading stress is significantly lower than the loading stress, which is caused by the viscoelasticity of the material.

5.2 Normal force indentation experiment

The indentation tests of cylindrical indenter normal and tangential loads were carried out. The experimental device can load the normal and tangential loads separately. It measures the head displacement with a spiral micrometer. A force sensor connected to the indenter measures the real-time force in three directions of the load.

The experiment only tested the quasi-static response of the elastomer. Because of the viscoelastic properties of the elastomer, it takes an infinite time for the elastomer to reach equilibrium, but the stress relaxation process decreases exponentially, so after a period of time, the stress will remain in a relatively stable state. It has been found that in the incremental load test, the elastomer reaches a quasi-static state of no more than 3 min. The indenter is a cylindrical one with a diameter of 5 mm and the indenter is pressed against the central

![Elastomer mechanics experimental device](image)

**Figure 8** Elastomer mechanics experimental device

![Axial stress and strain during loading and unloading](image)

**Figure 9** Axial stress and strain during loading and unloading

Notes: (a) Experimental platform; (b) indenters
region of the elastomer. The size of the elastomer is $13 \times 13 \times 10$ mm. Control the load-displacement during the test. When loaded, the deformation range of the elastomer is from 0 to 2 mm of thickness, and the step of load change is 0.2 mm. Figure 11 shows the change in normal force with time during the experiment. It can be seen that after each loading, the normal force will reach a peak and then slowly decrease until it is stable, showing viscoelasticity. Figure 10 also shows that the force sensor readings fluctuate because of errors and external disturbances. The average of the last normal force of each loading phase is approximated as the final loading normal force. Figure 11 shows the relationship between normal force and load displacement. The red line is the fitted line of the data. It can be seen that for a small-sized flat-end circular indenter, there is a good linear relationship between the normal load and the load-displacement in a relatively large range. The slope of this experiment is 36.51.

5.3 Tangential force experiment

In the shear indentation experiment, the shear displacement is controlled by a helical micrometer, and the shear force is measured by a force/torque sensor on the indenter. The motion accuracy at this horizontal stage is 0.02 mm. The indenter is a cylindrical indenter with a diameter of 5 mm and the indenter is pressed against the central region of the elastomer. The size of the elastomer is $13 \times 13 \times 10$ mm. Control the tangential load displacement during the test. Because the tangential force cannot be loaded when there is no normal force, in the experiment, firstly, the normal direction is loaded, and then the tangential loading is performed. The deformation range of the elastic body is from 0 to 0.8 mm, and then the normal force and the tangential force are unloaded. The corresponding position of the tangential displacement only loads the normal force. Similarly, only the quasi-static response of the elastomer response was considered in the experiment, so we waited for about 3 min for each load increase until the elastomer reached a substantially steady state.

Because the normal force and the tangential force act together on the elastic body in the tangential force test, to obtain the deformation of the elastomer surface under the action of the individual tangential force, it is necessary to remove the effect of the normal force. The displacement of the position of the marked point when the position of the marked point is normal force to the corresponding normal force and tangential force is considered to be the displacement under the tangential force.

Figure 12 shows the shear force as a function of time during the experiment. Figure 13 shows the relationship between quasi-static tangential force and load displacement. The red line is the fitted line of the data. It can be seen that for a small-sized flat-end circular indenter, there is a good linear relationship between the tangential load and the tangential displacement in a relatively large range. The slope of this experiment is 1.31.

5.4 Evaluation

Finally, the evaluation experiment is implemented. The images of the sensor are acquired by the camera in real time and three-dimensional forces acquired by the force sensor. The samples are
divided into three parts, including training sets, validation sets, and test sets. An iterative mapping function formula (5) can be generated by training. The coefficients in equation (5), the connection weight \( W \) and the input offset \( b \), have been obtained during the training. As can be seen from Figure 14, the neural network regression algorithm used in this paper, the measurement error of most samples is in the range of 0.05 N, which can meet the needs of robotic hand operation (Figure 14).

6. Conclusions

In this paper, a vision-based tactile sensor is designed, which uses the camera to capture the marking points on the surface of the elastomer to obtain the deformation of the surface of the elastomer. It has the simple structure and low cost. The mechanical model of the viscoelasticity of the elastomer was established. The deformation of the elastomer under normal load, tangential load and moment were simulated by ANSYS.

The connected domain method is deduced to find the position of the marker point and obtain the movements of the markers. The BP neural network is proposed to obtain the three-dimensional contact force by the movements of the markers. The experiments are implemented to prove that the proposed cross-modal sensor can be used for measuring the robotic grasping forces.

References


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The perceptually-inspired model of tactile texture sensor based on the inverse-magnetostrictive effect

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Abstract
Purpose – The purpose of this study is to develop an output model to extract surface microstructure characteristics of different objects, so as to predict the response of the output voltage obtained from tactile texture sensor.

Design/methodology/approach – The model is based on the consideration of the inverse-magnetostrictive effect, the flexure mode, the linear constitutive equations and the strain principle.

Findings – This research predicts and investigates the effect of the texture properties on the tactile texture sensor output characteristics.

Originality/value – The surface texture characteristic is regarded to be important information to evaluate and recognize the object.

Keywords Roughness, Tactile texture sensor, Deflection function, Inverse-magnetostrictive effect

Paper type Research paper

1. Introduction

With the development of online shopping and intelligent industry, tactile perception has become the focus of attention and research. This sensitive texture detection of human is realized by characteristics of skin structure and several kinds of highly sensitive tactile capacitors in skin (Noda et al., 2010). The surface texture characteristic is regarded as important information to evaluate and recognize the object (Liu et al., 2018; Pestell et al., 2017). Tactile sensors are necessary to mimic the human touch sensing ability in many areas, such as virtual environment, e-commerce, robotic telemanipulation and so on. Most of tactile sensors are based on piezoresistive or capacitive principles. They can provide some tactile or touch information, which includes weight, stiffness, elasticity and friction. At present, the cost-effective measurement of fine geometric texture is still a challenging task because the nonvisual texture sensors are relatively difficult to design. The magnetostrictive material has the characteristics of a small saturated magnetic field, good ductility and high tensile strength, so that it can withstand a variety of mechanical loads, such as pressure, tension and impact. The inverse-magnetostriction effect indicates that the permeability of a magnetostrictive material can be changed by an external impact. Therefore, the tactile sensor can be designed, based on the inverse-magnetostrictive effect. However, the relationship between the output voltage and the external impact is still unclear on the tactile sensor, based on the inverse-magnetostrictive effect, and the theoretical model of the output voltage for the tactile texture sensor has not been founded. Therefore, it is necessary to investigate the perceptually inspired model of the tactile texture sensor based on the inverse-magnetostrictive effect. At the same time, the perceptually inspired model can also predict surface texture and classification by mimicking the active texture perception process of a human finger.

2. Principle and structure of tactile texture sensor

The fingertip pushes the object surface with slight pressure and repeats a back-and-forth motion at speeds within 2-10 cm/s (Song et al., 2014). Smith et al. (2010) studied the texture surface exploration process of humans by the fingertip and showed that the mean normal contact force exerted by human being on the texture surface is 1.54 ± 0.50 N. By imitating the...
above process of human active texture perception, a novel texture sensor system for object surface texture measurement using Galfenol sheet is designed and the prototype of tactile texture sensor has been manufactured in Figure 1.

Figure 1(a) shows the structure of the proposed texture sensor. The main part of the tactile texture sensor consists of Galfenol sheet, permanent magnet, strain gauge, rigid contact, silica coat, amplifier circuit and detecting coil. In addition, the system platform of the texture tactile sensor for simulating human touch samples also consists of a support frame, DC motor with encoder, conveyor belt connected with the motor shaft, power supply and computer in Figure 1(b). The Galfenol material used in this study is a <100> oriented sheet. The sheet sample is prepared from a directional solidified rod, with the length of 69.67 mm, width of 5 mm and thickness of 0.7 mm. A cone-shape tip is fabricated onto the free of the Galfenol sheet to contact the sample. An ultrasensitive strain gauge is bonded on the upper surface of the cantilever to monitor the contact force, as well as the vibration responses under sample texture excitation. To get large detection sensitivity, the velocity of the sample is determined by the speed of the dc motor. Firstly, a strip piece of sample fabric with the same width as the conveyor belt is fixed onto the upper surface of the conveyor belt using the adhesive. Before measuring the sample surface texture, the support frame supporting the tactile texture sensor is turned to move up and down along the vertical bar so as to keep the tactile texture sensor in contact with the sample surface at a certain distance or depth. Then the DC motor is controlled by an encoder through the drive circuit to move at a certain constant speed, so that the tactile texture sensor slides along the surface of sample placed on the conveyor belt. The sample surface texture property can be obtained by measuring the output voltage of tactile texture sensor, which is induced by the height and the width of the sliding sample surface bump.

3. Perceptually inspired model of the tactile texture sensor

The output characteristics of tactile texture sensor are mainly caused by the deflection of the cantilever beam and the inverse-magnetostrictive effect, which is the phenomenon by which a sample of magnetic material is magnetized when it is under the effect of a mechanical pressure (Zhang et al., 2015). The height from the contact sample texture rotates the magnetic domains of the Galfenol sheet along the cantilever direction. The rotation of the magnetic domain causes the magnetic induction intensity to be changed, and then, an output voltage will be generated in the detecting coil. Using Faraday’s law of electromagnetic induction, the voltage induced in the coil is:

\[ e(t) = -N \frac{\partial \phi}{\partial t} = -NS \frac{\partial B}{\partial t} \]  

where \( N \) is the turns of detecting coil, \( S \) is the cross-sectional area, \( \phi \) is the magnetic flux in the Galfenol sheet, \( B \) is the magnetic induction intensity in detecting coil and \( t \) is the time.

The linear constitutive equations for Galfenol are:

\[ \sigma = \frac{E}{1 + \frac{\nu}{C_0}} \frac{dH}{dt} + d^2 H \]  

\[ B = d\sigma + \mu H \]  

where \( \sigma \) is the stress, \( d \) is the piezomagnetic coefficient, \( \mu \) is the permeability under constant stress, \( H = H_b \) is the total magnetic field, which is a bias magnetic field provided by the permanent magnet. The combination of equations (2) and (3) yields:

\[ B = dEe + (\mu - d^2 E)H_b \]  

For a one-dimensional texture tactile sensor, the mechanical part of the strain can be treated as a simple cantilever beam structure with a rectangular cross section. As shown in Figure 2, the detecting coil is installed on the cantilever beam (upper and lower surface). The left end of the beam is fixed, and its right end can be pushed upward or downward by a load sample in the direction perpendicular to the plane of the surface.

For the cantilever beam, the test point \( Q \) in Figure 2 is at the central of the detecting coil and the Galfenol sheet along vertical direction. Based on the principle of transverse bending, \( \sigma_Q \) at the point \( Q \) can be computed as follows:

\[ \sigma_Q = \frac{M(x)}{I} = \frac{h}{2} M(x) \]  

where \( M(x) \) is the bending moment of the cantilever beam, \( y \) is the vertical distance from point \( Q \) to the natural axis of the cantilever beam \( (y = \frac{h}{2}) \), \( I \) is the cross-sectional area moment of inertia of the beam about the axis passing the fixed end and perpendicular to the side surface plane, \( x \) is the horizontal distance between the any point of Galfenol sheet and the fixed end of the cantilever beam and \( h \) is the thickness of Galfenol sheet.
Based on Hooke’s Law $\sigma = E\varepsilon$, and Kuang et al. (2018), the strain acting on the cross section of Galfenol sheet wrapped in the detecting coil can be assumed to be uniform. The average strain can be obtained through equation (6). Substituting $M(x) = EI\omega^{(2)}(x)$ into equation (6) yields:

$$\varepsilon = \frac{h}{2IE} EI\omega^{(2)}(x) = \frac{h}{2}\omega^{(2)}(x)$$

(7)

where $\varepsilon$ is the average strain, $\omega(x)$ is the deflection function and $L_1$ is the length of Galfenol sheet wrapped in the detecting coil.

From equation (7), the $\varepsilon$ value of Galfenol sheet at any point is related to the deflection of the cantilever beam at that point. The deflection responses the amplitude of cantilever beam, and the amplitude is determined by the texture of the tested sample.

When the rigid contact touches the sliding sample surface, the Galfenol sheet moves up and down with the characteristics of the sample surface texture. The texture features are characterized by texture height, bump width and spatial period. Nakamoto et al. (2015) stated that the perception of texture is intimately related to the trajectory traced by the probe. In particular, they identified the value of texture spacing at which the probe can exactly fall between two texture dots as drop point.

For a spherical contact, in the absence of dynamic effects, the surface traced by the contact during exploration constitutes on the deflection of Galfenol sheet on the tactile texture sensor, as shown in Figure 3.

The tactile expression of texture is established based on the specific mathematical model and geometric constraints. The offset surface tracked by the rigid contact of the tactile texture sensor is approximately a sinusoidal curve, which can be expressed as:

$$\gamma_{end} = A\sin \left( \frac{2\pi}{T} t \right)$$

(8)

where $\gamma_{end}$ is the deflection value of the contact position at the Galfenol sheet, $A$ is the amplitude of the sinusoidal curve and represents the height of the texture bump of the sample. $T$ is the time of the contact sliding the distance between the adjacent bump on the texture surface, which can reflects the width of the texture bump and $h_1$ is the depth at which the contact touches the texture surface of the sample.

The offset vibration of the texture sensor contact drives the vibration of the end point of the cantilever beam, that is, equation (8) is the deflection at the free end of the cantilever beam, and the deflection of any point can be obtained from the relationship between the deflection and stress of the cantilever beam. The deflection function can be written as:

$$\omega(x, t) = \frac{3}{2T^3} \left( 3h_2^2 - x^2 \right)$$

(9)

Based on the Faraday law, the voltage for infinitesimal portion $\Delta l$ of the coil can be expressed as:

$$\Delta u(t) = \frac{3\pi A h d}{2T^3} \left( l - x \right) \cos \left( \frac{2\pi}{T} t \right)$$

(10)

Based on the inverse-magnetostrictive effect, the flexure mode, equations (1)-(10), and the detecting coil are fixed on Galfenol sheet, and the total induction voltage is:
In equation (11), $A$ and $T$ are related to the texture of contacted sample, which represent the height and the width of the surface bump, respectively, when the moving speed of a rigid contact fixed on the texture tactile sensor is constant. With the different texture samples, the above two parameters are variables. $L_0$ indicates that the detecting coil is installed on the position of Galfenol sheet. In addition, the perceptually inspired model includes some parameters that related to the detecting coil, and the cantilever material. The three variables, $A$, $T$ and $h_1$, are the most important factors that affect the sensor output characteristic. According to equation (11), we can calculate the output voltage under the texture sample when the detecting coil and the cantilever material are determined. The model can provide important guidance for designing tactile texture sensor.

4. Results and analysis

The output voltage of the tactile texture sensor can be derived according to the calculation process of the proposed model above. Here, considering the Galfenol sheet, $l = 69.67$ mm, $b = 5$ mm, $h = 0.7$ mm, $E = 70$ MPa, $d = 34$ T/GPa. For the detecting coil, $N = 200$, $S = 3.5$ mm$^2$ (Nakamoto et al., 2015; Zheng et al., 2018; Wan et al., 2017). For the other parameters, the speed of conveyor belt, $v = 2$ cm/s, and $h_1 = A$.

Figure 4 shows the calculated and experimental peak of output voltage versus parameter of $[A:(TV)]$. The output voltage is linear relation with the parameter (less than 0.10) of $[A:(TV)]$. The sample of different roughness is contacted by the tactile texture sensor, the cantilevered Galfenol sheet moves up and down to make the magnetic domain of the sheet rotate. With increasing the parameter of $[A:(TV)]$, more magnetic domains in Galfenol sheet rotate and then lead to the increase of the output voltage peak.

Based on the experimental data, the peak of output voltage increases linearly with increasing parameter of $[A:(TV)]$ at a speed of $2$ cm/s. The calculated curve agrees with the experimental one, and it means that the theoretical analysis coincides with experimental result. However, the error exists between the calculated result and the experimental one, and it may come from the parameters, which are relative to the Galfenol sheet material properties, the depth value of rigid contact for the sample and the speed of the dc motor. Therefore, the roughness parameter of sample has a large effect on the peak of output voltage of tactile texture sensor.

In the experiment, denim, nylon ribbon, gossamer, gauze and rough cloth are selected as the test samples, and the roughness properties of these materials are shown in the Table I.

From the experimental results in Figure 5, the tactile texture sensor moves up and down with the height of bump and spatial period of fabric when the tactile sensor comes in contact with the fabric surface at a speed of $2$ cm/s. The output voltage in Figure 5(a) and 5(b) is mostly below $5$ mV, but their average voltage and period are different. Both voltage amplitude in Figure 5(c) and 5(d) is mostly between $5$ and $10$ mV, but the period of the voltage wave is relatively longer in Figure 5(d), which is related to the distance between adjacent bump on fabric $d$. The peak of the output voltage in Figure 5(e) is obviously the largest, which is more than $10$ mV. Therefore, we speculate that the output voltage can represent the surface texture of the object.

The roughness is related to the pellet feeling of the texture surface (Zheng et al., 2018; Wan et al., 2017; Sell et al., 2016; Hoelscher et al., 2015; Meier et al., 2011), which can be described by peak average. Figure 6 shows the peak average voltage of five vibration signals. The experimental peak average voltage increases with increasing roughness. The experimental peak average voltage is barely influenced by roughness (less than 6.5). When the roughness increases from 6.5 to 9, the peak average voltage rapidly increases. The results in Figure 6 indicate that the texture sensor has a higher sensitivity and can reach $150$ mV/mm when the roughness of samples is larger than 6.5. Based on the result in Figure 6, the designed tactile sensor can accurately distinguish the texture of sample with greater roughness.

Each sample was tested six times under the same conditions. The measurements have been recorded by a Tektronix DPO3014 oscilloscope. In the output signal of each test result, 10,000 uniform sampling points are selected and divided into $500 \times 20$ matrices. The maximum value is extracted from every

<table>
<thead>
<tr>
<th>Sample</th>
<th>Name</th>
<th>Roughness</th>
</tr>
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<tbody>
<tr>
<td>a</td>
<td>medical gauze</td>
<td>$5.35 \pm 0.9$</td>
</tr>
<tr>
<td>b</td>
<td>gossamer</td>
<td>$6.05 \pm 0.5$</td>
</tr>
<tr>
<td>c</td>
<td>rough cloth</td>
<td>$6.55 \pm 0.9$</td>
</tr>
<tr>
<td>d</td>
<td>denim</td>
<td>$7.4 \pm 1.0$</td>
</tr>
<tr>
<td>e</td>
<td>nylon ribbon</td>
<td>$8.56 \pm 0.9$</td>
</tr>
</tbody>
</table>
column of the matrix, and the relation between the peak value of output signal and the sampling sequence number is obtained, as shown in Figure 7.

Figure 7 shows that the experimental peak voltage decreases gradually according to the order of nylon ribbon, denim, rough cloth, gossamer and medical gauze. In other words, the roughness of sample increases with the increasing peak voltage. An experimental peak voltage up to 12.6 mV can be reached when the roughness equals 8.56. The calculated curve agrees with the experimental one in Figure 4, so the theoretical
analysis coincides with the experiment results. However, a discrepancy exists between the calculated and the experimental one. In fact, the trajectory curve of the rigid contact in equation (8) is approximate, and the depth measurement of the rigid contact is inaccurate. In addition, the weight of permanent magnet and the speed of DC motor influence the experimental results.

5. Conclusion

In conclusion, this paper makes contributions by developing a perceptually inspired model of tactile texture sensor based on the inverse-magnetostrictive effect, the flexure mode, the Jiles–Atherton model and the signal processing theory. Specifically, relations between the output voltage and the information of sample texture are tested theoretically and experimentally. The results revealed that output peak voltage increases with an increasing roughness parameter. Five kinds of fabric samples are detected by the tactile texture sensor, and the results show that the texture sensor has higher sensitivity and can reach 150 mV/mm, when the roughness of samples is larger than 6.5. Furthermore, the peak voltage for the experiment or the model is more than 12 mV when the roughness reaches 8.56. The experimental result and calculated one have proved that the roughness has a large effect on the output voltage of tactile texture sensor. The future work is that the cross-modal sensing between vision and tactile sensing is being applied on the robot to realizing the perceptual accuracy required for precise control (Liu et al., 2017, 2018).

References


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An investigation of stimuli-current thresholds on the non-steady contact condition

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Abstract

Purpose – This paper aims to investigate the perception threshold (PT) of electrotactile stimulation under non-steady contact condition (NSCC) which is rarely considered in previous reports mainly because of the difficulty with experimental control. Three factors of NSCC are involved, including the current alternating frequency, the tapping interval of stimulation and the stimulating area of skin. The study is aimed at providing the basic PT data for design and application of wearable and portable electrotactile device.

Design/methodology/approach – The up-down method was selected to assess PT, and 72 experimental scenarios were constructed. During the study, we developed an experimental platform with the function of data record and programmable current stimulation. With psychophysical experiment, more than 10,000 data were collected. Furthermore, statics analysis and ANOVA test were opted for exploring the main factor influencing PT.

Findings – NSCC has different PTs on each body location, and PT has a positive correlation with frequency. In general, PT in NSCC is significantly lower than that in SCC. In some cases, it can be lower by more than 60 per cent. In addition, women have a lower PT than men across all age groups, and the younger is generally more sensitive than the older in electro-sensation.

Research limitations/implications – Limited factors of NSCC were considered in this study. Contact time and break interval should be investigated in the future work.

Practical implications – The paper includes implications for the development of smart electrotactile device.

Originality/value – This paper fulfills a challenge in assessing the PT under NSCC.

Keywords Virtual reality, Current frequency, Electrotactile, Non-steady contact condition, Perception threshold

Paper type Research paper

1. Introduction

The tactile display technology plays a central role in human device interaction and virtual reality. The device of this display technology can provide edge, shape, signal, roughness, color, and force information, which can make user feel the virtual object through the tactile channel. The options for tactile stimulation include electrical, mechanical, pneumatic, ultrasonic, water-jet stimulation and so on. Among them, the latter four types of stimulation require large size tactile display devices, which limit their daily use. Recently, electrical stimulation has been more frequently used in many applications. Electrical stimulation enables small, flexible and low-cost tactile pattern presentation due to its high integration density and powerful rendering ability.

For vision substitution, Kajimoto et al. (2006) and Kajimoto et al. (2014) developed an electric tactile display device with 512 electrodes covering an area of 81.28 mm by 40.64 mm, driven by half-bridge switches. At any moment, a single electrode was set as an anode and all the other electrodes worked as cathodes by high speed scanning. The system aimed...
to enable the vision impaired to “see” the surrounding environment. For high spatial resolution, Kitamura et al. (2013), designed a micro-needle electrode array for electric tactile display. This device allowed subjects to feel tactile sensation by lower voltage than a flat electrode array with good repeatability. Multimodal perception is the expectation of researchers for multi-dimensional tactile display so as to express powerfully real or artificial information. Kaczmarek et al. (2017) manipulated both current and frequency to produce two dimensional electrotactile perception, perceptual frequency and intensity, which were strongly correlated with the two stimulus variables, frequency and current.

Electric stimulation has become one of the most important and useful tool in information representation, tactile augmentation, sense substitution, virtual reality and so on (Seps et al., 2011; Altinsoy and Merchel, 2012; Isaković et al., 2016). With the advance of technology, these devices are becoming more miniature, portable, and comfortable. The development of these devices is often coupled with the basic study of electrical stimulation applications. Buma et al. (2007) proposed that intermittent stimulation signal may delay adaptation to electrotactile sensory feedback. Robineau et al. (2007) developed a 6 × 6 stimulation matrix on the tongue for providing tactile sensation. A comparative study of continuous or discontinuous waveform and patterns with two or four electrodes on the sensory threshold was investigated, and the results suggested that for energy saving and to improve the yield, it would probably be better to use discontinuous stimulation with two electrode patterns. Lozano et al. (2009) focused on estimating the ability of tongue’s sensory system. They indicated that the average DR (Dynamic Range) of a tongue was 17dB which was generally larger in comparison with other tactile loci and of a relatively constant magnitude among subjects. Electrical stimulation also has the ability of simulating different material properties, such as roughness, hardness, temperature and friction (Germani et al., 2013).

From the perspective of applications, current perception threshold (PT) or perceptible current is a basic parameter of electrotactile applicable device. The perceptible current is important for assessing the touch experience of electrotactile display applications and the safety of electric appliances, hand tools, or other electric equipment (Dalziel and Mansfield, 1950). Although some parameters employed in the different application studies are different, the sensation caused by current stimulation is quite similar. The perception is generally considered annoying if it is unexpected, because it may produce a sudden shock and cause subsequent agitation as the secondary effect. PT is the current intensity which just evokes sensation in psychophysics. A current slightly over the PT is useful since it can transmit contact, force and shape information as an option of tactile display. However, an excessive current over the PT may produce apprehension, fear and other adverse reaction, which might result in an involuntary movement, and consequently, it might incur a loss of balance, a fall or other serious injuries.

In the first half of 20th century, Professor Dalziel and his partners investigated the perceptible current considering stimulation location, contact type of electrode-skin, supply frequency, wave-form, and so on (Dalziel and Mansfield, 1950 and Dalziel, 1954). Results showed that, at very low electric frequencies, the perception produced by alternating current may be a little sharp. With increasing frequency, the sensation became smooth, soft and less piercing, and it may spread out from the initial locus under the electrode to a big area. Besides, the contact type also played an important role in PT. Three different modes of contact situation were involved in the study, i.e. Holding with the palm, Touching with the middle finger and Tapping at a rate of once to twice per second. Among them, Holding and Touching were belonging to steady contact condition (SCC) while Tapping was non-steady contact condition (NSCC). Experiments showed that Tapping leads to the lowest PT and Holding leads to the highest threshold of perception current.

With time, skin structure features, human gender, age, and other subject’s factors are also considered in PT investigation under SCC (Edelberg, 1977). In 1989, Irmich and Batz (1989) demonstrated that the voltage PT for males and females were practically identical, while the current PT for males was much higher than that for females. From 2002 to 2005, Leitgeb and Schrötter (2002), Schrötter and Leitgeb (2003) and Leitgeb et al. (2005) conducted the study of electric safety limit considering body size, age, and gender with a great deal of samples. Results showed that the perception variability among the general population may be 100-fold higher than what was estimated by the previous studies and that the currently used estimate of the threshold was more than 10-fold higher than estimated before. In 2010, Leong et al. (2010) further demonstration showed that there was a gender difference in PT across all ages. In particular, woman presented higher PTs in advanced age than man.

Previous reports concerned many types of factors in PT evaluation and obtained a good deal of valuable data. However, NSCC, especially incipient contact, has not been fully investigated. The NSCC is very important and should be emphasized because experiencing a sudden contact is very normal in touching with the electric equipment. In addition, with the development of mobile phone, portable pad, and virtual reality device, chances are that non-steady contact is common in touching a portable electronic device.

In the primary experiments, we found that a very small current, seemingly absolutely senseless with our prior knowledge, may evoke an electric sensation on the condition of a sudden touch. This indicates that the electric perception may change significantly with the contact conditions.

There is little report on current perception of NSCC except for Dalziel’s early findings (Dalziel and Mansfield, 1950; Dalziel, 1954). This paper will investigate the current thresholds in NSCC with psychophysical experimentation methods. Based on the literature review, the three key factors selected in this investigation are current frequency, tapping interval and stimulation location. In addition, the difference of PT on NSCC will be compared with that on SCC to evaluate the influence by contact mode. During the data analysis, the gender and age factor are also intentionally considered.

2. Methods

2.1 Participants

A total of 600 healthy adults of age 18-56 were recruited to participate in the experiment that lasted about three hours per
The demographics of participants

<table>
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2.2 Technique

A computer-controlled device has been developed to provide programmable stimulation current. It can generate constant-current, biphasic sine-wave pulses, and adjustable output voltage. The highest output voltage is ±72 V in peak value. Two separated electrodes are designed to serve as the stimulators, which are circular, gold-plated, and with the diameter of 10 mm. Concentric electrodes are not used because using them in NSCC may incur asynchronous touch, due to the arc shape of skin surface.

In the NSCC experimentation, the anode E0, is placed at a fixed location with conducting gel as the stimulation baseline. It is kept steady during the whole experiment process. The cathode E1 serves as the stimulator tapping the skin intermittently. The distance between the two electrodes is about 10-12 mm. For manipulation convenience, E1 has been welded to a stick in advance.

However, in the SCC cases, both E1 and E0 directly adhere to the skin surface in a similar way to that of NSCC. The key factors for NSCC experimentation may be the tapping interval. As shown in Figure 1, \( t_1 \) is the time of stimulator touching the skin, and \( t_2 \) is the break interval between the previous tapping and the following one. For assessing the influence of different \( t_2 \), two different levels are set as 0.5 and 1 s, while \( t_1 \) is a constant of 0.5 s. To better control the tapping interval variable, a robotic arm (Figure 2) is designed to clamp E1 to tap a participant cyclically.

"Touching" indicates that the cathode E1 is contacted with skin surface, and "Interval" indicates E1 is taken away from the skin surface. The anode E0 has been kept a good touch status during the procedure. The touching time \( t_1 \) is 0.5 s, a constant, while the tapping interval \( t_2 \) is set as two different levels, 0.5 s and 1 s. Accordingly, we get one tap each at 1 or 1.5 s in NSCC. However, in SCC, both E1 and E0 are kept a good touch status with skin, and only the current is pulsed with a switch based on the same rule, i.e. each pulse at 1 or 1.5 s.

As shown in the Figure 2, “0” is the flexion position. In practical operation, E1 is initially located at “1” to ensure the “Touching” locus, and then, the participant is asked to confirm a good contact of E1 without visible deformation. Several toggles between “1” and “0” are necessary to ensure the consistent stimulating area of E1. Once confirmed, the subject will be instructed not to move throughout the experiment. For each level, there are six repetitive taps.

2.3 Preliminary experiment

All subjects are asked to perform a pilot study to get familiar with the experiment procedure, and to understand how to differentiate the mechanical only touch (without current stimulation) from the real current stimulation.

2.4 Experimental design

In a full-factorial design, we manipulate five parameters, two contact conditions CC (SCC & NSCC), two time intervals (0.5 and 1 s) which are called pulse interval (PI) for SCC and tapping interval (TI) for NSCC, three body locations BL (left cheek, palm of left hand, the left finger pad), and six electric current frequencies \( f \) (10, 20, 50, 100, 1,000 and 2,000 Hz). Consequently, a total of 72 experimental scenarios are yielded.

In each scenario, the only adjustable parameter is the current, and some ascending and descending stimulation sequences are programmed for the 1-up 1-down method (Hanley and Zerbolio, 1964), as depicted in Figure 3. Practically, the up-down stimulation sequences are interleaved.

Figure 1 The stimulation mode of tapping in NSCC.

Figure 2 The six-axis robotic arm is manipulating the stimulator to stimulate the cheek.
The ascending sequence begins with a current level close to zero where each participant cannot get any current sensation, while the descending sequence should start from the stimulation intensity where each participant can obviously obtain a current sensation. The choice of ascending or descending at the very beginning is random, so that the subjects are not able to predict stimulation signals.

If a distinct but weak current sensation is perceived, the participant is instructed to say “YES” or gesture with “OK” to let the operator know, and the data will be recorded. If the participant does not speak or gesture, it implies there is “NO” current sensation.

When the ascending sequence is chosen, it will not stop until a “YES” is confirmed, and a reversal sequence (a decreasing sequence) from the “YES” level is followed. The reversal is controlled by a touch button which is connected to the stimulation device operated by the technician tester based on the subject response. In addition, the descending sequence will not stop until “NO” appears. One up and one down complete a stimulation cycle.

The step size may be larger in the first several cycles to quickly bring the stimulus level close to the threshold being estimated. Then, the step size gradually decreases in the remaining ascending–descending cycles to improve the accuracy in estimation (Jones and Tan, 2013). A step size can be $c/n$ where $c$ is a constant and $n$ is the number of stimulation cycles.

The mean PT of this trial is estimated by first calculating $m$ averages from the Crest and Trough corresponding to the stimulus values of the last $2m$ reversal amplitudes, as shown in equation (1).

$$PT_i = \frac{1}{2m} \sum_{j}^{n} (Crest_{ij} + Trough_{ij})$$

(1)

where $j$ is the $j_{th}$ stimulation cycle of all the $n$ cycles, and $i$ means the $i_{th}$ trial of a subject. Accordingly, Crest$_{ij}$ means the $j_{th}$ “YES” level of the $i_{th}$ trial and Trough$_{ij}$ is the $j_{th}$ “NO” level of the $i_{th}$ trial.

If each participant is tested $q$ times, then the estimated PT of this subject under this experimental scenario is,

$$PT = \frac{1}{q} \sum_{i=1}^{q} PT_i$$

(2)

Each participant completes eighteen sessions selected randomly. A typical session lasts approximately 10 minutes. To avoid measuring errors resulting from fatigue or boredom, at least a five minutes break is required between two experiment sessions.

3. Results

For each case, the mean PT values ±SDs are determined from the total number of readings. The response of current stimulation closely approximates a normal distribution. Figure 4 shows the PT curves depicted under different experiment scenarios.

3.1 Difference between steady contact condition and non-steady contact condition

From Figure 4, we can see that there is an obvious span between two clusters of curves. The upper cluster of three curves is the mean values of PT in SCC cases, while the lower cluster is in NSCC’s. Repeated measures ANOVA shows a statistically significant difference ($p < 0.01$) between the two clusters.

The PT of the three body locations in each frequency are all influenced by the factor of contact mode. The consistent result shows that the intermittent contact mode results in a lower PT in all the scenarios.

Furthermore, cheek presents a prominent sensitivity to the factor of contact mode, with an approximate 60 per cent drop, while PT’s at palm and finger only decrease moderately.
3.2 Difference among body locations
From Figure 4, we can also see that the lowest PT is found at the cheek, while the highest PT is found at the palm. Moreover, finger and cheek are relatively close in PT means.

3.3 Difference in frequency
An obvious positive correlation between PT and frequency can be observed from Figure 4. The slopes of PT in low frequencies are relatively sharp and become moderate as frequency increases. An abrupt change in the response occurs between 1,000 and 2,000 Hz.

In addition, different types of sensation are described by experiment subjects. Under SCC, participants tend to feel obvious current pulsation at low frequencies at 10 and 20 Hz, even without mechanical vibration. With higher frequencies, 50 and 100 Hz, the feeling becomes a sense of tingling accompanying slight pulsation sensation. When the frequency continues to increase, the feeling becomes difficult to describe, like pricking or sting. Interestingly, some subjects describe the sensation at 2,000 Hz as a stream of vibration floating on the skin surface. However, under NSCC, the sensation is not so complex like that under SCC. At low frequencies, from 10 to 100 Hz, most of the subjects say the feeling is like tingling and not too bad to bear. At 1,000 and 2,000 Hz, the perception current makes people boring and feeling anxious about that.

3.4 Difference in tapping cycle
There are two tapping intervals investigated in the NSCC experiments, 0.5s and 1s, respectively.

The PT’s of the three body locations are averaged in each current frequency and tapping interval, and then twelve statistical data are obtained, as presented in Figure 5. The left bar of each cluster represents the case of TI = 1 s, and the right bar, TI = 0.5 s.

It shows that the longer TI produces a bigger PT, although the difference of PT for the variation of the parameter TI is not significant. Furthermore, we can find that the difference between the two modes is relatively visible at low frequency levels, while modest at high levels. In particular, at 2,000Hz, the two levels are almost the same.

3.5 Difference in age group
Four age groups are considered, including AG1 (22.3 ± 2.3), AG2 (29.2 ± 2.3), AG3 (40 ± 3.7), and AG4 (49.6 ± 4.1). Under NSCC, the mean PT values on the three locations in each age group are summarized as shown in Figure 6. In general, the advanced group has higher PTs than those of the younger. In particular, the AG1-AG3’s PTs have clear and almost monotonous spans. However, there is an unexpected drop of AG4’s PT in comparison with AG3’s. The average values of AG4 are close to AG2’s PT average statistically. Along the frequency axis, the AG4’s PT shows a sharp increase.

Notes: Each dot is the mean value of one body location. Each curve denotes the PT of the different age group with the variation of current frequency.
from 1,000 to 2,000 Hz after a fluctuation with local peak value at 50 Hz.

3.6 Difference in gender
In all, 324 male and 276 female’s PTs are obtained respectively. The two-tailed t-test is used to evaluate the difference between the groups of the male and female. Repeated measure ANOVA is conducted on mean PT values to identify group differences. The results show that the female across all ages have lower group mean PTs than the male ($p < 0.1$). Especially, in the AG2 and AG3 groups, there is a significant difference ($p < 0.05$) between women and men.

4. Discussion
Our study reveals that the PT values are significantly related to the contact mode of electrode-skin. NSCC produces much lower PTs than SCC under almost same conditions. The drop seen in the non-steady contact can be over 60 per cent. This result is quite counter-intuitive. Let us look into this phenomenon.

Skin is multi-layered tissue consisting of epidermis, dermis and subcutaneous tissue, which can vary in thickness depending on the body location. The epidermis is mainly composed by stratum corneum which is a lipid-corneocyte matrix arranged in a flattened fashion (Reilly, 1992) crosslinked with skin appendages (Chizmadzhev et al., 1995). The latter two layers have a stable environment that is rich in free moving ions, and provide low and stable impedance levels, which can be regarded as a pure resistor $R_s$. It is known that the stratum corneum acts as a barrier to hydrophilic and ionized-species movement and consequently, represents the biggest resistive portion of the skin impedance. Some studies have localized the non-linear variations of body impedance in the stratum corneum (Luna et al., 2015) They modeled a parallel network of resistance and capacitance. The resistance includes two types of resistors. One of them is for the stratum corneum matrix and the other is for the appendage. In addition, the capacitance is mainly for the current flow in appendage.

Let us model the impedance of epidermis using $R_s$ and $C_{ps}$ which represents the resistance and capacitance, respectively, and the global impedance of skin can be equivalent to a RC network as shown in Figure 7.

Among them, $R_s$ is defined by the impedance variations due to the electroporation of ionic pathways in both stratum corneum matrix and appendages. The time constant for the lipid-corneocyte matrix is less than 1 $\mu$s (Chizmadzhev et al., 1998). So, the capacitive performance of $C_p$ is mainly influenced by the appendages.

4.1 Non-steady contact condition factor
The drop of current threshold for the change of contact mode is mainly relevant to the instantaneous effect of the impedance of skin-electrode interface under electrical stimulation.

The instantaneous effect of skin impedance is mainly attributed to the electroporation of skin (Luna et al., 2015) which is the phenomenon when the membrane permeability to ions and macromolecules is increased by being exposed to a high electrical field (Ivorra, 2010).

From the point of electric circuit, when the touch initiates, $C_p$ may be almost short-circuited, and the total impedance of skin $Z$ is determined only by $R_s$. Over time, $C_p$ is charged, and $Z$ becomes bigger with the more prominent role of capacitance. When $C_p$ is fully charged and stable, the final available impedance $Z$ is much bigger than the initial condition $R_s$. We can imagine that, within the initial several milliseconds of stimulation, current should be easier to go through skin and evoke response of the receptors, which may account for the lower PT values of NSCC.

There is still a warm-up effect of skin impedance (Akhtar et al., 2018; Kajimoto, 2012). The impedance tends to be dropped from 10-15 k$\Omega$ to 5-7 k$\Omega$ within dozens of seconds, which may be a result of vasodilatation or activation of sweat glands due to the passage of current. The process is slower and goes through longer interval than the instantaneous change of skin impedance. In general, the warm-up effect can be seen only in SCC condition.

The instantaneous effect is not the same as the warm-up effect. The instantaneous effect happens before the full charged state, while the warm-up effect occurs after the stable state. In addition, the instantaneous effect may last only several milliseconds, while the warm-up effect can go through several or even dozens of seconds. In addition, the instantaneous effect increases the impedance sharply from several hundreds of Ohm to several dozens of Mega-Ohm, while the warm-up effect gives rise to a gradual decrease.

4.2 Body location factor
At the three body locations, palm is associated with the highest PT and the cheek the lowest in both SCC and NSCC cases. This is because the skin can vary in thickness depending on the body region, from 0.5mm at the eyelid up to more than 4mm at the foot sole. Finger and cheek skin thicknesses are approximately 1-2 mm, while palm skin thickness is about 4 mm.

Under electric stimulation, skin can be seen as a RC medium, and the resistance and capacitance at a given location can be described by the equations (3) and (4).
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\[ R = \frac{\rho(t)L}{S} \]  
\[ C = \frac{\varepsilon S}{4\pi kL} \]

where:
- \( \rho(t) \) - the electrical resistivity of skin at a given time \( t \);
- \( L \) - the thickness of some body area;
- \( \varepsilon \) - the dielectric coefficient of skin;
- \( k \) - the electrostatic constant; and \( S \) means the area that the current flow through.

Therefore, it can be expected a bigger \( R_s R_i \), and a smaller \( C_p \) are at palm area, which may be the primary reasons for the higher PT.

As for cheek and finger, the impedances of them are close, while finger presents less PT than cheek. This is because PT is dependent on not only the impedance but also the afferent fiber types projecting from the cutaneous site stimulated (Davey et al., 2001). It is known that there are four types of tactile corpuscles in the skin, i.e., Merkel cell (SAI), Ruffini ending (SAII), Meissner corpuscle (RA), and Pacinian corpuscle (PC). Each type of receptor selectively receives and matches the adaptive stimulation (Delmas et al., 2011). Among them, RA and PC are the two most important types of tactile sensors for alternating current stimulation, especially for low frequency cases. Kajimoto et al. (2004) also showed that RA and PC’s adaptive current frequency were 30 and 250 Hz, respectively. It is notable that finger area has dense receptors. Consequently, it makes sense that finger presents a relatively lower current threshold.

4.3 Frequency factor

Regarding the factor of frequency, we get positive correlation of PT-\( f \) under both SCC and NSCC, which is consistent with the reports of (Dalziel and Mansfield, 1950; Dalziel, 1954).

It is documented that skin impedance has an obvious negative correlation with current frequency. That is to say, much less impedance at high frequencies can be seen than that at low frequencies. However, the PT becomes higher than expected in the condition of less impedance. We should consider this phenomenon from the touch performance of electrode-skin with frequency.

It is well known that there is some kind of skin effect in conductor. When alternative current flows from one point to another across the conductor, the current is not distributed homogeneously. It is mainly concentrated on the surface of the conductor. The AC current density \( J \) in a conductor decreases exponentially from its value at the surface \( JS \) according to the depth \( d \) from the surface, as follows (Demarest, 2012).

\[ J = J_s e^{-(1+j)d/\delta} \]

where \( \delta \) is called the skin depth.

Similar skin effect may exist in human’s skin. The skin depth is thus defined as the depth below the surface of the skin at which the current density has fallen to \( 1/e \) of \( J_s \). In general, \( \delta \) can be formulated as,

\[ \delta = \sqrt{2\rho(t)/\omega \mu} \]

where:
- \( \rho(t) \) - the resistivity of the skin, which is relevant to the ionic flow under electric field;
- \( \omega \) - is called the angular frequency of current, which is equal to \( 2\pi f \) and \( f \) is the frequency of current stimulation;
- \( \mu \) - is the magnetic permeability of skin, which may be associated with the skin thickness.

From equation (6), we can see that \( \delta \) is mainly concerned with the current frequency at a given skin area. High frequency current may expect a low current density under the same current intensity. It can speculate that high frequency current has less penetration ability across skin. A higher current intensity is needed to compensate the reduction of current density of the inner skin. As a result, higher PTs are observed under high frequencies.

In addition, Merkel corpuscles, thermal and pain spots are mainly located in the outer layer of skin, which easily react to high frequency stimulation. This structure performance of skin combined with the skin effect may help explain why subjects feel prickling at high frequencies.

4.4 Tapping interval factor

The results in Figure 5 show that tapping interval has an impact on PT values. The small intervals will produce a small PT under NSCC. We hope to explain this phenomenon in the physiological field.

It is known that the current perception mainly includes three stages, the sensation of tactile corpuscles, the evoked potential transmission by nerves, and the perception in the cerebral cortex. In physiology, the nerve works like a voltage-gated ionic channel. When stimulation is equal to or over the threshold, the channel will open for the potential transmission, which is dependent on the ionic movement of the charged Ca2+ and Na+ (Woo et al., 2015).

Each tapping may evoke a convergence of the charged ionic. It is reasonable to imagine that two available tapping may produce a combined effect. That is to say, an overlap effect may be expected with less tapping interval, and it is possible to trig a sensation by a small stimulation with fast speed.

4.5 Age and gender factor

Under NSCC, the elder group has a higher PT than the younger which is almost consistent with the findings that in SCC (Leong et al., 2010). Analysis of the four age groups show that there is an initial increase from AG1 to AG3 and followed by a slight decrease after AG3. It is easy to understand the uptrend of PT with the age, while the inversion at AG3 is beyond the expectation.

From the above analysis, we know that the skin impedance is a dynamic variable and may be relevant to the number of free ion. With age, the water content of skin may diminish and one of the important parameter \( \rho(t) \) in equation (3) can become large. Consequently, skin impedance may have a positive effect with age based on the normal biological change. Under consistent environment, it is reasonable to see a higher PT in the aged group.
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However, we also find that the youth and the middle-aged are faced with social stress in the harsh environment. Therefore, they have to work hard and may be easy to form thick callus resulting in bigger impedance. The elder group, people more than 45 years of age, tends to enjoy a relaxing job and comfortable family, and it is reasonable to see a relative younger skin state in comparison with their real age. These phenomena may account for the drop of PT after AG3.

As far as the gender factor considered, women totally have a less PT than men. In addition, the span between them is bigger in the AG2 and AG3 groups than the other two age groups, which may result from the same reason as that for the age factor.

5. Conclusion

In this work, we have investigated current PT considering five types of factors, i.e. contact mode (NSCC and SCC), tapping interval of NSCC, pulse interval of SCC, body location, and current frequency. The results show that the contact mode has an obvious impact on current perception. Under NSCC, PT drops almost 60 per cent compared to that under SCC. The tapping interval factor of NSCC also plays an important role on the current perception. A shorter tapping interval leads to a lower PT value. In addition, current frequency and body locations present similar impact on PT under both SCC and NSCC.

Besides, the gender and age factor are also considered during the NSCC’s data analysis. Generally, the aged group has a higher threshold which can be explicable using the variation of impedance with age. The female’s PT tends to be lower than the male’s across all the age groups, which may result from the less skin impedance of women.

In the future, accurate control of intermittent stimulation mode may be explored, such as contact time, break interval and the ratio of them, which can be meaningful in investigating the perception characteristics of the transition process systematically. Under NSCC, we mainly focus on the instantaneous effect in this paper. For the transient process, the initial impedance of the skin is very small, and the response of electric stimulation is so sensitive that the PT is about one-half in SCC. Our future work on PT under NSCC will explore a more adequate description of the transient process.

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Incorporating artificial skin signals in the constraint-based reactive control of human–robot collaborative manipulation tasks

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Abstract
Purpose – The purpose of this paper is to develop a control strategy for human–robot collaborative manipulation tasks that can deal with proximity signals from 373 interconnected cells of an artificial skin.

Design/methodology/approach – The robot and the operator accomplish an industrial task while interacting in a shared workspace. The robot controller detects and avoids collisions based on the information from the artificial skin. Conflicting constraints can be handled by prioritizing between hard and soft constraints or by weighing the different constraints.

Findings – Weak soft constraints (low weight) are specified to command the robot to move along a nominal path with constant velocity. Stronger soft constraints (higher weight) prevent collisions by means of either moving the end effector backward along the path or circumventing an obstacle. The proposed approach is validated experimentally.

Originality/value – As a first contribution, this paper proposes a discrete optimization algorithm activates an a priori selected maximum number of cells. The algorithm selects the appropriate distribution based on the amplitude of each signal and the spatial distribution of the proximity measurements. A second contribution is the specification of a human–robot collaborative application as an optimization problem using eTaSL (expression graph-based task specification language), which provides reactive control.

Keywords Human–robot interaction, Constraint-based task specification and control, Artificial robotic skin

Paper type Research paper

1. Introduction

More and more robots are not only deployed in large industries such as the car industry but also in small- and medium-sized enterprises (SMEs). To be successful in SMEs, the deployment of a robot application needs to be faster and cheaper. Conditioning the environment or the product input flow to a specific robot application by building fences and using conveyor belts with accurately positioned work pieces has become unaffordable. The Factory-in-a-Day project (Factory in a Day, 2014) proposed an extended collaboration between human and robots, in which robots perform tasks that require high power and/or a minor level of decision-making, while humans perform tasks where there is a need for a high level of dexterity and the ability to discern between non-trivial options.

This calls for new sensors and control strategies to enable safe cooperation in shared workspaces. One of the most common strategies used nowadays in industry, and already incorporated in the new generation of collaborative robots such as UR10, KUKA LWR, ABB Yumi (Bélanger-Barrete, 2015), consists of detecting collisions by means of monitoring the currents fed to the motors. When these motor currents are not consistent with a dynamic model of the robot and its load, a stop signal is issued. In a related approach, Haddadin et al. (2018) developed an artificial skin that provides only tactile feedback enabling the controller to detect collisions. These methods have in common that they are able to react only after the collision has occurred.

Zanchettin et al. (2016) used a more proactive approach based on the perception of the scene through a point cloud reconstruction acquired with a Kinect sensor and human motion tracking using OpenNI drivers. They proposed to decrease the velocity of the robot joints in function of the minimum distance between the robot and the obstacle (e.g. human arms); once the measurement is under a lower threshold the robot maintains its position, and the robot only restarts its motion when the distance increases above the threshold. A similar approach of velocity reduction was tested in simulation by Shin et al. (2018). The velocity reduction proposed by both methods occurs even when objects are close enough but not interfering with the robot motion. As a result, unnecessary stops are induced.
Dumonteil et al. (2015) proposed a method to command the robot to move between two points with the capability of circumventing obstacles. They continuously monitor the workspace with a Kinect sensor. The collision detection is done by the Kineo Collision Detector (KCD) module, which takes as an input an OctoMap representation (Hornung et al., 2013) of a filtered point cloud. Once a surface section of an obstacle along a nominal trajectory is reconstructed, the KineoWorks software replans a new trajectory to circumvent the reconstructed surface. As the method is based on a scene representation using a Kinect sensor, it is very sensitive to scene occlusions. Zeestraten et al. (2016) tested a method in simulation, which enables a robot to adapt to human motions. However, their algorithm needs prior human demonstrations to generate new trajectories.

Luo et al. (2017) described a control strategy that uses partial observations of human reaching motions to predict the remainder of the trajectories. Their unsupervised on-line learning approach uses Gaussian mixture models, requires no off-line training or manual labeling, and can build prediction models for the reaching motions of the human operator. This information allows the system to avoid possible collisions by either stopping the robot motions or re-planning a trajectory towards a new target. The poses of the human are captured by placing markers on the human limbs and tracking them with a VICON tracking system. In a similar approach, Sadrfaridpour and Wang (2018) developed a trajectory selection algorithm based on human intention prediction and included a method to measure and include human trust in their model. As in Luo et al.’s (2017) study, human motions are tracked by using a VICON system, which can be sensitive to occlusions when the environment is not conditioned enough.

Similarly as in this work, Buizza Avanzini et al. (2014) developed a human–robot collaboration strategy based on the perception of a human in the robot workspace using proximity sensors. In all, 20 sensors placed in the robot body feed a controller which considers three scenarios based on the intensity of the proximity signal:

1. change the robot configuration without affecting the task performance when the signals report a low value i.e. large distance;
2. alter the robotic task when the value of the proximity signals is medium; and
3. stop the robot motion when the signals report a high value, i.e. small distance.

Therefore, this strategy does not allow having a close human robot collaboration behavior, and it requires sensor systems that are able to detect objects from far away.

In this paper, the presence of an obstacle that appears in the scene is sensed by proximity sensors embedded in an artificial robotic skin (Mittendorfer et al., 2015); this skin covers the last links of an industrial robot UR10 and contains 373 interconnected cells (Figure 1).

The robot behavior and its interaction with the operator are specified using a constraint-based reactive control strategy. Several constraint-based frameworks are found in literature, such as iTaSC (De Schutter et al., 2007) stack-of-tasks (Mansard et al., 2009) and expression-based task specification language (eTaSL) (Aertbeliën and De Schutter, 2014; Aertbeliën, 2016). These modular approaches are able to combine constraints related to the task, the robot and the environment that are specified separately. eTaSL is chosen as the constraint-based framework since it offers an easy and compact way to specify a great variety of constraints involving signals coming from different types of sensors. eTaSL uses a reactive velocity-resolved control strategy. It can deal with conflicting constraints by either prioritizing the constraints or by weighting them.

However, it is infeasible to add a constraint for each of the cells, due to the large number of cells in the robotic artificial skin. Therefore, as a first contribution, this paper proposes an additional discrete optimization algorithm to activate an a priori selected maximum number of cells. The algorithm selects the appropriate distribution based on the amplitude of each signal and the spatial distribution of the proximity measurements.

The second contribution of this work is a modular methodology by which a human–robot collaborative task can be specified as an optimization problem subject to constraints. The task is specified as a set of (weighted) constraints. An additional set of constraints involving the input of skin cells is defined such that collisions are avoided. These two sets of constraints are combined to perform a human–robot collaborative task. Section 2 describes the skin hardware. Section 3 describes the underlying concepts of the eTaSL framework. Section 4 describes the optimization-based cell selection algorithm. Section 5 explains the reactive control strategy for human–robot collaboration. Section 6 describes the test setup inspired by an industrial use case. The experimental validation is described in Section 7 and Section 8 contains the discussion and conclusions.

2. Artificial robotic skin

The artificial robotic skin, consisting of a modular arrangement of cells that can sense multi-modal tactile stimuli, was developed by Mittendorfer et al. (2015). Multiple sensors are embedded in each cell:

- a 3D acceleration sensor;
- three capacitive force sensors able to measure normal forces;
- two temperature sensors; and
- one optical proximity sensor.
A micro controller embedded in each cell collects, filters and sends the most recent signals in packages over the network of sensor cells. Cells are arranged in patches. Patches are flexible and can be mounted on curved surfaces.

The artificial robotic skin comes with a self-calibration procedure (Mittendorfer and Cheng, 2012). The 3D acceleration sensors measure gravity while the robot link is put in different poses. This information is used to determine the transformation from each cell to a reference frame attached to that robot link. The skin used in the experiment is depicted in Figure 2.

In this work, only the distance sensor is used. Distance sensing is based on a photo-emitter that sends out modulated light, paired with a photo-receiver and filter. The power of reflected light is evaluated and normalized between 0 and 1. While this measurement principle enables to build a very compact cell, the signal is strongly non-linear with respect to the distance and is influenced by the reflecting surface.

The relation between the proximity measure and the distance is calibrated by moving a patch of seven cells on a known trajectory while measuring the proximity to a reflective white surface. As can be seen in Figure 3, there is only a noisy non-linear relationship between the proximity measurements and the actual distances. This makes it infeasible to accurately estimate geometrical properties of the perceived objects or even to detect objects beyond 20 - 25 mm. Therefore, distances will not be directly used to formulate collision constraints. Instead, the proximity values will be used to generate a reference velocity, as detailed in Section 5.

3. Expression graph-based task specification language framework

eTaSL is a task specification language for reactive control of robot systems. It describes how a robotic system has to move and interact with sensors such as distance, position or force sensors.

eTaSL uses a constraint-based methodology in which a robotic task is specified as an optimization problem subject to constraints. Two priority levels for the constraints are introduced, giving the possibility to specify hard and soft constraints. Besides priorities, the constraints can be also weighted, allowing conflicting constraints.

In contrast to the Task Frame Formalism (Bruyninckx and De Schutter, 1996) or iTaSC (De Schutter et al., 2007), the control is not performed in a frame or using variables of a virtual kinematic tree. Instead, arbitrary expressions are used to describe the constraints. These expressions are specified using expression graphs (Aertbeliën, 2012), which encapsulate geometric expressions (e.g. positions, orientations and trajectories), allowing mathematical operation on them. eTaSL incorporates automatic differentiation, allowing the calculation of Jacobians and higher-order derivatives of these expressions.

A task expression is a function of the following three types of variables:

1. a time variable $t$
2. $n_r$ robot joint variables $q_j$ contained in a vector $q \in \mathbb{R}^{n_r\times1}$; and
3. $n_f$ feature variables $x_{i,3}$ contained in a vector $x_f \in \mathbb{R}^{n_f\times1}$, used to facilitate the formulation of the task.

While constraints take away motion freedom, feature variables add degrees of freedom to the system.

In this work, two types of constraints are introduced.

3.1 Position constraint

This type of constraint commands a task expression $e_{i}(q, x_f, t) \in \mathbb{R}^1$, which represents the difference between an expression and a desired target, to evolve towards zero value. This is written as:

$$e_{i}(q, x_f, t) \xrightarrow{w_i} 0,$$

(1)

where the term $w_i$ is defined to weight the constraint. The velocity-resolved controller enforces the position constraint to evolve towards its target as a first-order system with a time constant $1/k_i$; this behavior is described as:
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\[ \frac{d}{dt} e_i(q, \dot{q}_f, t) = -k_i e_i(q, \dot{q}_f, t). \]  

3.2 Velocity constraint

This type of constraint commands the time derivative of an expression \( g_i(q, \dot{q}_f, t) \in \mathbb{R}^1 \) to follow a specific velocity. This is written as:

\[ \text{Time derivative} \left\{ g_i(q, \dot{q}_f, t) \right\} \overset{\text{w}}{=} v. \]  

Note that the behavior of this constraint is influenced only by the weight \( w_i \). This type of constraint can be transformed into a position constraint, where \( k_i \) equals zero, in the following form:

\[ \frac{d}{dt} \left( g_i(q, \dot{q}_f, t) - v t \right) = 0. \]  

Although in this paper both types of constraints are introduced only as equality constraints, eTaSL also supports the definition of inequality constraints, which are defined in a very similar way to equations (2) and (4).

Multiple constraints of the above type are used to formulate the robot control as a quadratic programming (QP) optimization problem:

\[
\begin{align*}
\text{minimize} & \quad y^T \mathbf{H} y \\
\text{subject to} & \quad \mathbf{L}_A \leq \mathbf{D} y \leq \mathbf{U}_A
\end{align*}
\]  

The optimization variable \( y \) is a vector that corresponds to \( [\dot{q} \ \dot{\dot{q}} \ \ldots \ s] \) where \( \dot{q} \) contains the time derivative of the robot joints, \( \dot{\dot{q}} \) corresponds to a vector with the time derivative of the feature variables, and vector \( s \) contains the slack variables \( e_i \).

Position constraints, equation (1), are translated into the QP constraints, equation (5b), by expanding the left term in equation (2) into its partial derivatives; as a result, the equation becomes:

\[ \begin{bmatrix} J_i & \mathbf{L}_f \\ \mathbf{L}_f^T & \mathbf{I} \end{bmatrix} \begin{bmatrix} \dot{q} \\ \dot{\dot{q}} \end{bmatrix} = -\mathbf{A}_i e_i - \frac{\partial \mathbf{G}_i}{\partial \mathbf{H}} + e_i \]  

In this equation, \( k_i e_i \) corresponds to the feedback control term, while \( \frac{\partial \mathbf{G}_i}{\partial \mathbf{H}} \) can be seen as the feed-forward contribution.

For the velocity constraints, the same approach as with the position constraints is used; therefore, expanding the left term in equation (4) yields:

\[ \begin{bmatrix} \mathbf{J}_i & \mathbf{L}_f \end{bmatrix} \begin{bmatrix} \dot{q} \\ \dot{\dot{q}} \end{bmatrix} = v - \frac{\partial \mathbf{G}_i}{\partial \mathbf{H}} + e_i \]  

The task function Jacobian \( \mathbf{J}_i \in \mathbb{R}^{1 \times (n + m)} \) in equations (6) and (7) contains the partial derivatives of the task with respect to the robot joint positions and feature variables. This expression is automatically calculated by eTaSL. In case of constraints with a low priority, the slack variable \( e_i \) is added to relax the constraint. For constraints with high priority (hard constraints) this term is left out.

4. Optimization of cell selection based on spatial distribution and proximity

As hinted before, it is not feasible to impose a collision constraint for each cell, as this will increase the size of the optimization problem drastically. If a fixed subset of cells has to be selected, the most intuitive solution would be to pick cells measuring the highest values. On each cell will be defined a constraint that enforces a velocity applied to the cell center location and directed inward and perpendicular to the cell surface. However, this simplistic policy can result in limit cycles when the skin surface is (almost) parallel with an obstacle. In such a case, a very small motion of the robot can cause the set of selected cells to change drastically, resulting in a radically different control action at each time step.

Therefore, another approach is chosen. The activation value \( a_i \) of a cell \( i \), where \( 0 \leq a_i \leq 1 \) corresponds to 1 when an obstacle is touching the cell and corresponds to 0 when there is no obstacle or it is outside the measurement range. Cells with an activation value above a given threshold are called active.

To avoid limit cycles, we seek a policy that selects a subset of the activated cells in such a way that not only the sensor values, but also the subset’s spatial distribution is considered. The proposed solution solves an optimization problem that selects a subset of cells that maximizes the activation value of cells and the summed distance along the surface between the selected cells.

As a preprocessing step, a distance map is computed corresponding to the distance along the surface of the skin between each of the cells. Geodesic distance is considered: each patch is unrolled on a flat surface, and the Cartesian distance on this surface is considered. In case of a close-to-cylindrical patch, as for the one encasing the upper arm, geodesic distance on a cylinder is used. The distance map from one cell to all other cells of the same patch is illustrated in Figure 4. The patch in Figure 4 is mounted on the last link of the robot (the one touched in Figure 6).

The optimization problem is then formulated as follows: Given \( A \) the set of active cells, with cardinality \( N_A \), \( N_s \) the number of cells to select; \( d_{ij} > 0 \) as the distance between cells, find the subset \( S \subseteq A, \text{card}(S) = N_s \), that satisfies the following optimization problem:

\[
\begin{align*}
\max \quad & \nu \sum_{i \in S} a_i + \sum_{i,j \in S, i \neq j} d_{ij} \\
\text{s.t.} \quad & S \subseteq A, \text{card}(S) = N_s
\end{align*}
\]  

where \( \nu \) is a tradeoff factor between highest activation and spatial distribution.

This problem can be re-formulated as a binary linear programming problem, in the form:
The state vector $\mathbf{x}$ contains a binary variable for each activated cell, plus a variable for each possible pair of cells. The number of pairs $N_c$ is given by $0.5N_s(N_s - 1)$. $N = N_s + N_c$ corresponds to the size of $\mathbf{x}$.

The cost vector $\mathbf{c}$ can be formalized as:

$$
\mathbf{c} = \left[ \nu \cdot a_1 \cdots \nu \cdot a_{N_s}, d_{1,2} \cdots d_{1,N_s}, d_{2,3} \cdots d_{2,N_s}, \ldots d_{N_s-1,N_s} \right]^T
$$

(10)

where the second part contains $N_c$ elements. The equality constraints take care that exactly $N_s$ cells and $N_c$ cell couples are selected:

$$
\mathbf{A}_x \mathbf{x} = \mathbf{b}_s,
$$

$$
\mathbf{A}_x \mathbf{x} \leq \mathbf{b}_c
$$

The inequality constraints enforce the relation between the selected cells (first part of $\mathbf{x}$) and the pairs (second part of $\mathbf{x}$), and impose the following $N_s$ inequalities for all $i$ and $j$:

$$
x_i + x_j - x_{i} x_{j} \leq 1,
$$

with

$$
z = i \cdot N_s - i \cdot \frac{i-1}{2} + j - i
$$

(12)

To illustrate the structure of the matrix, the inequalities in matrix form for $N_s = 4$ are given below:

$$
\mathbf{A}_i = \begin{bmatrix}
1 & 1 & 0 & 0 \\
1 & 0 & 1 & 0 \\
1 & 0 & 0 & 1 \\
0 & 1 & 1 & 0 \\
0 & 1 & 0 & 1 \\
0 & 0 & 1 & 1
\end{bmatrix}
$$

$$
\mathbf{B}_i = 1_{N_s \times 1}
$$

(13)

An optimization problem is solved for every patch independently. Time execution varies depending on the number of active cells, and can be slower than the frequency at which cell measurement data is gathered by the interface. The index of selected cells is maintained until a new solution is computed, while the values of the selected cells are updated every time new data is made available by the cell interface. The optimization problem is implemented with the qp_solve library (Berkelaar et al., 2004).

An example solution of the described problem is reported in Figure 5, where the activation of eight cells is depicted, from which three are selected.

### 5. Reactive robot motion control

This section presents four motion control laws, specified in the constraint-based methodology described in Section 3. These constraints allow human–robot collaboration in a robotic task in which the end effector moves between two points following a nominal trajectory.

#### 5.1 Task execution: trajectory following

##### 5.1.1 Constraint 1: move along path

The trajectory followed by the end effector to perform the desired task is composed of a nominal path from an initial position, toward a desired target, and a corresponding orientation of the end effector along the path. This orientation is calculated by a linear interpolation between the orientation of the end effector at the initial point, and its desired orientation at the target.

To describe the motion of the end effector along the path, first, a position vector $\mathbf{C}(\chi_{1,1}) \in \mathbb{R}^{3 \times 1}$ is defined on the nominal path (Figure 6). Note that $\mathbf{C}$ is defined in function of the path coordinate $\chi_{1,1}$, which is specified as feature variable in eTaSL.

A trapezoidal velocity profile $v_i$ is designed in function of this path coordinate $\chi_{1,1}$: (i) at the starting section of the path, $v_i$ rises at a constant rate $a_{\text{max}}$ until reaching $v_{\text{max}}$; (ii) in the middle section, $v_i$ keeps a value of $v_{\text{max}}$; (iii) during the final section, $v_i$ decreases at a constant rate $-a_{\text{max}}$ until it reaches zero velocity at the specific target. The motion of point $\mathbf{C}(\chi_{1,1})$ is constrained to follow the velocity profile $v_i$ using a velocity constraint [equations (3) and (4)]:

$$
\mathbf{F}_i \mathbf{v}_i = \mathbf{0},
$$

where $\mathbf{F}_i$ is a constraint matrix.

### Figure 4

Distance value, computed from the most left cell to other cells of the patch.

**Note:** Distance is normalized in such a way neighboring cells have a distance of 1.

$$
\begin{align*}
\max & \quad \mathbf{c}^T \mathbf{x} \\
\text{s.t.} & \quad \mathbf{x} \in \{0, 1\}^N \\
& \quad \mathbf{A}_s \mathbf{x} = \mathbf{b}_s \\
& \quad \mathbf{A}_s \mathbf{x} \leq \mathbf{b}_c
\end{align*}
$$

(9)

### Figure 5

Simulated activation of cells.
Incorporating artificial skin signals
Cristian Alejandro Vergara et al.

Figure 6 Robot behavior along the trajectory

Note: The green dashed line corresponds to a nominal path

\[ g_1 := x_{f,1} \quad \text{and} \quad v := v_c. \] (14)

If a constraint with higher weight \( w_i \) is conflicting with \( g_1 \) (e.g., an object detected near to the robot) the velocity of \( C \) can still be adapted because this is a soft constraint. This velocity can decrease towards zero or even take negative values, causing the robot to move backward.

5.1.2 Constraint 2: remain on path

To command the motion of the robot end effector, a position vector \( T(q) \in \mathbb{R}^{3 \times 1} \) is defined in the tool as depicted in Figure 6. To attach \( T(q) \) to \( C(x_{f,1}) \), a position constraint [equations (1) and (2)] is specified:

\[ e_2 := T(q) - C(x_{f,1}). \] (15)

In this case \( e_2 \in \mathbb{R}^{3 \times 1} \). Hence, each element of \( e_2 \) is included as a separate constraint in equation (5b).

5.2 Reactive behavior: collision avoidance

5.2.1 Constraint 3: avoid collisions

The discontinuous change between active/non-active cell \( j \) can cause instabilities/limits/cycle.

To improve the behavior caused by the transition between active and non-active cells, an improved selection procedure is proposed based on the weight \( w_{3,j} \) assigned to each cell:
- all the weights \( w_{3,j} \) are initialized in zero;
- after a cell is selected by the optimization problem (Section 4), its weight \( w_{3,j} \) rises proportionally to the time it has been selected. If a cell is rejected, \( w_{3,j} \) decreases at the same rate;
- then, a number up to \( N_j \) cells with the highest nonzero weights are selected; and
- the weights \( w_{3,j} \) are normalized dividing their value by the number of nonzero weights.

Velocity constraints are defined using the selected cells \( j \) with their corresponding weight \( w_{3,j} \). The control law is designed based on a damping force controller described in Bruyninckx and De Schutter (1996). While in the damping force controller the correcting velocities are function of the force errors, in the proposed method these velocities \( v_{p,j} \) are proportional to the sensed proximity signals \( S_{p,j} \) as follows:

\[ v_{p,j} := C_p S_{p,j}, \] (16)

where \( C_p \) is a proportional constant.

The motion of the position vector \( D(j) \in \mathbb{R}^{3 \times 1} \) located in the center of a selected cell is constrained to follow a velocity \( v_{p,j} \) directed inward and perpendicular to the cell surface (i.e., \( v_p \) is projected on \(-\hat{n}_j\)). In eTaSL, this is implemented as a velocity constraint [equations (3) and (4)]:

\[ g_{3,j} := D(j) \quad \text{with} \quad v_j := v_{p,j} \cdot \hat{n}_j. \] (17)

Similarly to (15), \( g_{3,j} \in \mathbb{R}^{3 \times 1} \) and each of its elements is included separately in equation (5b).

5.2.2 Constraint 4: remain on normal plane

A soft position constraint [equations (1) and (2)] is set to restrict \( T(q) \) to the normal plane of the trajectory at point \( C(x_{f,1}) \). The desired behavior of \( e_4 \) is given by:

\[ e_4 := (T(q) - C(x_{f,1})) \cdot t_{traj}. \] (18)

where \( t_{traj} \) is the tangent vector of the trajectory at point \( C(x_{f,1}) \) (Figure 6).

6. Use case

This section describes a use case involving human–robot collaboration inspired by an industrial application.

The complete manual assembly operation consists of retrieving five solenoids from a rack. Subsequently, the solenoids are inserted and fixed to a main hub. Each solenoid is fixed to the hub by two screws positioned at opposite sides of its body. The workstation for the application is shown in Figure 1. The assembly sequence for one solenoid is summarized in Table I.

The high load on the insertion operation is strenuous for the human operator when executed repetitively. This combined with the relatively low level of dexterity required makes the solenoid manipulation suitable for robotic automation. On the other hand, the screw handling operations require a higher level of dexterity and precision. The small size of the handled objects presents a bigger challenge to grasp and align them. Moreover, there can be a slight misalignment between the screw holes of the solenoid and their counterparts in the hub. During a

Table I Manual assembly sequence for one solenoid

<table>
<thead>
<tr>
<th>Object</th>
<th>Tools</th>
<th>Step</th>
<th>Operation</th>
<th>Requirements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solenoid</td>
<td>Gripper</td>
<td>1</td>
<td>retrieve</td>
<td>grip 3cm</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>transport</td>
<td>carry 260 g</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>align</td>
<td>&lt;5mm and &lt;1&quot;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4</td>
<td>insert</td>
<td>push 100 N</td>
</tr>
<tr>
<td>Screw x2</td>
<td>Human hand</td>
<td>5</td>
<td>take</td>
<td>grip 5mm</td>
</tr>
<tr>
<td></td>
<td></td>
<td>6</td>
<td>transport</td>
<td>carry 4g</td>
</tr>
<tr>
<td></td>
<td></td>
<td>7</td>
<td>align</td>
<td>&lt;0.5mm</td>
</tr>
<tr>
<td>Screw driver</td>
<td></td>
<td>8</td>
<td>insert</td>
<td>turn &gt; 10 times</td>
</tr>
</tbody>
</table>
manual screw handling, these issues could be easily resolved by an operator.

Therefore, to reduce assembling time and increase production efficiency for both human and robot, we propose to perform the manual and automated operations simultaneously. In the proposed scenario, as soon as the robot finishes the solenoid insertion, the operator starts to insert the screws to fix the inserted solenoid to the hub. While the operator performs these operations, the robot continues with the subsequent tasks: retrieve, transport and align the next solenoid. If the robot approach to insert a solenoid while the operator still is in the workspace performing his task, the operator can interrupt the robot motion by placing his hand in front of the robot’s end effector (Figure 1). Once the operator finishes his task leaving the workspace, the robot continues its motion to insert the next solenoid.

7. Experimental results

This section first describes how to configure the control parameters for the collaborative controller. Secondly, an isolated experiment is described where the robot avoids an obstacle. Finally, the results of human–robot collaboration in a laboratory mock-up of an industrial environment are presented.

7.1 Tuning control parameters

The constraint parameters are summarized in Table II.

The behavior of a robotic application is influenced by the relation between the constraint weights \( w_i \) in particular for this application:

- The robot motion along the path must react fast enough in case a potential collision is perceived. To this end, \( w_1 \) is set with a small value.
- Constraint 3 determines the reaction of the robot when a collision is sensed by the artificial skin. The gain \( C_p \) is set to assure that the maximum reacting velocity takes a value of \( 0.1 \text{m/s} \). The weights \( w_{3,j} \) of each selected cell are set to have a maximum combined value of 1. The rate at which they increase/decrease is tuned to have a fast response to avoid collisions.
- The relation between constraints 2 and 3 influences the robot behavior when deviating from the nominal path (Figure 6). Parameters \( w_2 \) and \( k_2 \) are set to let the robot deviate from the nominal path if a collision is detected, while driving the robot back to the nominal path fast enough if a collision is not perceived.
- Constraint 4 does not affect directly the robot behavior.

7.2 Circumventing an obstacle

In this isolated experiment, the robot must follow a nominal path (Figure 7). An object, with a convex shape, is placed close enough to the nominal path to interfere with the end effector motion. The robot avoids collision while circumventing the obstacle based on the readings of the proximity sensors. Once the obstacle is avoided, the end effector continues its motion towards the target.

This task can be divided into five phases (Figures 7 and 8):

1. In the first phase, the robot follows the trajectory with a trapezoidal velocity profile. Constraint 3 (Table II) is disabled, because there are no selected cells (the associated weights \( w_{3,j} \) are equal to zero).

Table II: Control parameters

<table>
<thead>
<tr>
<th>Constraint</th>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: Move along path</td>
<td>( v_{\text{max}} ) for ( v_c )</td>
<td>0.22</td>
<td>m/s</td>
</tr>
<tr>
<td></td>
<td>( a_{\text{max}} ) for ( v_c )</td>
<td>0.5</td>
<td>m/s²</td>
</tr>
<tr>
<td></td>
<td>( k_1 )</td>
<td>0</td>
<td>s⁻¹</td>
</tr>
<tr>
<td></td>
<td>( w_1 )</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>2: Remain on path</td>
<td>( k_2 )</td>
<td>0.55</td>
<td>s⁻¹</td>
</tr>
<tr>
<td></td>
<td>( w_2 )</td>
<td>0.5</td>
<td></td>
</tr>
<tr>
<td>3: Avoid collisions</td>
<td>( C_p )</td>
<td>0.1</td>
<td>m/s</td>
</tr>
<tr>
<td></td>
<td>( k_{3,j} )</td>
<td>0</td>
<td>s⁻¹</td>
</tr>
<tr>
<td></td>
<td>( w_{3,j} )</td>
<td>0–1</td>
<td></td>
</tr>
<tr>
<td>4: Remain on normal plane</td>
<td>( k_4 )</td>
<td>1</td>
<td>s⁻¹</td>
</tr>
<tr>
<td></td>
<td>( w_4 )</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

Figure 7: 3D path followed by a solenoid tip to circumvent an obstacle located along a nominal path

Figure 8: Experimental result of robotic end-effector circumventing an obstacle located along a nominal path

Note: The solenoid tip deviates 50 mm from a nominal path to avoid collisions
As soon as the cells of the artificial skin sense an object, the signals $S_{p,j}$ increase rapidly, hence the associated weights $w_{3,j}$ start to increase. Consequently, the velocity along the path reverses its sign, resulting in the end effector moving backward along the path to avoid collision with the obstacle. At the same time, the end effector starts to deviate from the nominal path.

In this phase, the end effector is far enough from the obstacle. The resulting behavior is a tradeoff between constraint 1 pushing the robot further along the path (i.e. trying to increase $x_{f,1}$), constraint 2 trying to keep the robot on the trajectory and constraints 3 trying to avoid collisions. The proximity signals $S_{p,j}$ are still active with a lower value compared with the previous phase.

The fourth phase starts when the end effector finishes circumventing the obstacle. There are no more signals $S_{p,j}$ reported from the skin, the weights of the cells start to decrease until they reach zero. The distance between the solenoid tip and the nominal path decreases, leading the end effector towards the nominal path.

In the final phase the path coordinate $x_{f,1}$ has reached its maximum value leading $C$ to the end of the path. However, the tool point $T$ (solenoid tip) has not yet arrived at the desired target. Immediately after the weights $w_{3,j}$ reach zero value, the distance between the solenoid tip and the nominal path decreases according to a first-order system parameterized by the control constant $k_2$. As a result, $T$ evolves towards the target.

### 7.3 Use case

Experimental results from a full sequence of the use case, described in Section 6, are presented here.

In Figure 9, the left column presents the results of the first solenoid insertion; in this case, there is no human intervention, therefore, the path coordinate follows the trapezoidal velocity profile $v_c$. In the insertion of the four subsequent solenoids, the operator interrupts the robot motion by placing his hand against the end effector to interrupt its motion. After finishing his task, the operator removes his hand, letting the robot continues its task.

In contrast to the previous experiment, in this cases, the velocities computed from the proximity signals lead the robot to avoid collisions going backward in a first phase and then maintaining its position. In Figure 9, it is shown that the maximum deviation of the end effector from the path is 10 mm, which is not enough to circumvent the operator’s hand. The path coordinate presents the following behavior:

- first $x_{f,1}$ has a slight decrement immediately after the proximity signals are activated, therefore, the end effector moves backward along the path;
- subsequently $x_{f,1}$ maintains its value until the operator removes his hand from the path;
- at this stage, the weights $w_{3,j}$ decrease until they reach zero, deactivating constraints 3; and
- finally constraints 1 and 2 drive the end effector towards the desired target.

### 8. Conclusions

This paper discusses a new framework for the specification of robotic tasks where human–robot collaboration is involved. A strategy is presented to deal with a large number of proximity signals and selecting the appropriate input to a constraint-based reactive controller.

The cell selection algorithm showed to be an effective method to deal with signals coming from 373 cells embedded in an artificial robotic skin. A discrete optimization algorithm provides this selection by considering a threshold between the intensity reported by each cell and the spatial distribution of the activated cells. This strategy was validated both in simulations and in real experiments.

An interaction modeled by four conflicting constraints results in a task execution scenario where a robot advances...
along a nominal path while offering the ability to avoid collisions by stopping, moving backward along the path or deviating from a nominal path to circumvent obstacles. This behavior is independent of the end effector orientation.

A first experiment demonstrates a case where a robot is able to circumvent a convex obstacle, deviating 50 mm from a nominal path to later reach a desired target. A second experiment tests the framework in a use case inspired by an industrial application. The robot is commanded to insert five solenoids in a main hub, while the human interrupts the robot motion to fix the solenoids.

In the current framework, only collisions with the surfaces covered by the artificial skin can be avoided, however, it is not possible to perceive and avoid collisions with the tool or the solenoid. Future work will extend our methods to combine other types of sensors with an extended perception range, such as tracking devices and point cloud sensors.

References


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An effective multifocus image fusion method using guided filter

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Abstract
Purpose – The more precise decision map is important to generate better-fused image. Guided filter can preserve edge information effectively. The purpose of this study is to use guided filter to form the precise decision map and highly informatively fused image.

Design/methodology/approach – The dual tree complex wavelet transform is adopted to decompose the source images into high frequency and low frequency coefficients. Sum of modified Laplacian method is introduced as the focus metric in dual tree complex wavelet coefficients. The guided filter is guided by the dual tree complex wavelet coefficient when the sum of modified Laplacian is used as the input image. The output image of guided filter is used to produce the decision map to fuse dual tree complex wavelet coefficient of source images.

Findings – The sum of modified Laplacian of dual tree complex wavelet coefficient can be used as the guided image in guided filter to generate better decision map. Comparison with the other state-of-the-art methods illustrates that the proposed approach is more effective in fusing the multifocus images both visual performance and objective evaluation.

Originality/value – The sum of modified Laplacian of dual tree complex wavelet coefficient is introduced to be used as the guided image in guided filter to generate better decision map. This method is fast and effect to fuse the source images. Comparison with the other state-of-the-art methods illustrates that the proposed approach is more effective in fusing the multifocus images both visual performance and objective evaluation.

Keywords DTCWT, Guided filter, Multifocus image fusion, SML

Paper type Research paper

1. Introduction

Image fusion can be defined as the process that a set of images is merged as a new image that combines complementary, multitemporal or multiview information from the sources (Liu et al., 2018). The fused image is more suitable for image segmentation, feature extraction and target recognition. Multifocus image fusion plays an important role in the area of image fusion since many approaches can be naturally extended to other applications such as remote sensing images, multimodal medical images, and visible-infrared images. Generally, multifocus image fusion algorithms are divided into two categories: spatial domain methods (Liu et al., 2017) and multiscale decomposition domain methods. The spatial domain methods combine pixels or regions from source images to fused images in spatial domain (Liu et al., 2017). The other methods adopt the sparse transforms such as traditional wavelets, curvelet, contourlets (Yang et al., 2010), nonsubsampled contourlet transform and shearlets (Zhang et al., 2016). Furthermore, there are other image fusion methods (Shahdoosti and Mehrabi, 2018; Kim et al., 2016) based on sparse representation in recent years. The main idea of sparse representation theory lies in the fact that an image can be represented as a linear combination of the fewest possible atoms or transform basis primitives in an over-complete dictionary. The dictionary learning (Nejati et al., 2015) from local patches of images is adopted to fuse source images based on sparse represent. The correlation between the sparse representation of the input images and the pooled features obtained in the dictionary learning phase is used as the decision map for the fusion. The non-negative sparse representations (Jinyepeng et al., 2014) of the source images are obtained by learning the non-negative dictionary. The feature of sparse coefficients is used to fuse the source images. The robust sparse representation (Zhang and Levine, 2016) is introduced to replace the conventional least-squared reconstruction error with a so-called sparse reconstruction error to fuse multifocus images. The sliding window method is often used to decrease spatial artifacts of fused results in image fusion method based on sparse representation (Zhang et al., 2017). This causes the loss of image information in fused result and increases the computation complexity. On the other side, only the maximum selecting rule is...
Multifocus image fusion method
Peng Geng and Jianhua Liu

adopted in most of the existing image fusion methods based on sparse represent. The fusion performance only depends on different sparse representation models. Hence, this research work turn to find an effective image fusion method based on transform domain to obtain both better performance in image quality and lower computation complexity. The contourlets lack of shift-invariant (Yang et al., 2010). Although nonsubsampled contourlet transform, and shearlets (Zhang et al., 2016) are shift-invariant, a large number of redundancy decompositions in these transforms lead to the high computational-complexity. It is well known that discrete wavelet transform (DWT) suffers from the poor direction and is lack of shift-invariance. The shift dependency occurs as a result of the aliasing that is introduced by the down-sampling that follows each filtering operation in DWT. Complex wavelet transforms (CWT) (Rakvongthai and Orantara, 2013) provides a method to overcome these two drawbacks of DWT. However, CWT based on wavelets of compact support cannot exactly posses the Hilbert transform/analytic signal properties, and this means that CWT will not perfectly overcome the DWT’s shortcomings. Because the energy with each sub-band signal at any given level remains constant regardless of shift, the DTCWT (Selesnick et al., 2005) is therefore shift-invariant. The DTCWT treats positive and negative frequencies separately and produces six sub-band images at each level. Each sub-band contains wavelet coefficients whose magnitude is proportional to one of the $\pm 15^\circ, \pm 45^\circ$ and $\pm 75^\circ$ directional orientations of the input signal. Because positive and negative orientations are treated separately, the DTCWT provides greater directional selectivity than the DWT. Hence, the dual-tree 2-D CWT (DTCWT) for images can more effectively overcome these drawbacks of DWT owing to the DTCWT’s shift-invariant and more direction selectivity. DTCWT is able to effectively express the geometric features of image. In this paper, DTCWT is introduced into decomposing the source multifocus images. Furthermore, guided filter guided by the DTCWT coefficient is adopted to create the decision map to combine the source images. The experiments are executed on five pairs of multifocus images to illustrate that the proposed method is more effective to select the well-focus pixels in source images than the other art-of-state fusion approaches.

2. Guider filter

The guided filter is a recently proposed edge-preserving filter, and the computing time of which is independent of the filter size. Based on a local linear model, the guided filter is qualified for image processing such as image matting and image fusion. Guided filter is a type of edge-preserving smoothing operator, which filters the input image under the guidance of another image (Tariq, 2014; Bauszat et al., 2011). The guided filtering algorithm includes the guiding image $I$, the input image $p$, and the output image $q$. Theoretically, the guided filtering assumes a linear relationship between the input image and the output image in the local window centered at pixel $k$. The output image $q$ can be expressed as:

$$q_i = a_k I_i + b_k, \quad \forall i \in w_k$$  

(1)

where $a_k$ and $b_k$ are constant in the window $w_k$, respectively. The $r$ decides the size of the window. The cost function of minimizing the difference between the output filtering $q$ and input filtering $p$ is shown following:

$$E(a_k, b_k) = \sum_{i \in w_k} \left[ (a_k I_i + b_k - p_i)^2 + \varepsilon a_k^2 \right]$$  

(2)

In this equation, $\varepsilon$ is a regularized parameters to avoid $a_k$ being too big. The equation (2) can be calculated through linear regression adopting the following two equations (Pang et al., 2011):

$$a_k = \frac{1}{w} \sum_{i \in w_k} I_i p_i - \mu_k \bar{p}_k \quad \sigma_k^2 + \varepsilon$$  

(3)

$$b_k = \bar{p}_k - a_k \mu_k$$  

(4)

where $\sigma_k^2$ and $\mu_k$ denote the variance and mean of $\omega_k$ in $I$, respectively. $|\varepsilon|$ represents the number of pixels in $\omega_k$, $\bar{p}_k$ is the mean of $\omega_k$. The final filtering output is given by:

$$q_i = \frac{1}{w} \sum_{i \in w_k} (a_k I_i + b_k) = \sigma_k I_i + \bar{p}_k$$  

(5)

3. Dual tree complex wavelet

DTCWT proposed by Kingsbury (1998) provides better shift-invariance and more directional selectivity than the DWT does. The core idea of DTCWT is two parallel trees: the first represents the real part while the second represents the imaginary part. These parallel trees provide the signal delays necessary for every level to eliminate aliasing effects and achieve translation-invariance (Ng et al., 2012). Compared with DWT and CWT, DTCWT has the advantage of shift invariance, directional sensitivity without aliasing effects. DTCWT can represent the line singularities and plane singularities of image more effectively than DWT. In theory, DTCWT can overcome the pseudo-Gibbs phenomena appear in DWT. There is lower compute complexity in DTCWT than in NSCT and Shearlet. Figure 1 illustrates the decomposition framework of 1-D DTCWT. With regard to 1-D input signal $x$, $h_0(n)$ and $g_0(n)$ stand for the lowpass filter for the upper filter bank and the lower filter bank, respectively. Similarly, $h_1(n)$) and $g_1(n)$ represent the highpass filter for the upper filter bank and the lower filter bank, separately. 1-D DTCWT can easily be extended to the 2-D DTCWT when we parallelly perform 1-D DTCWT on rows and columns of an image (Minamoto and Ohura, 2013), respectively. The horizontal and vertical subbands are separated into six directional subbands such as $\pm 75^\circ, \pm 45^\circ, \pm 15^\circ$. Therefore, DTCWT can more effectively represent the line singularities and plane singularities of image than DWT can.

4. Fusion process

In theory, the image fusion methods are based on an image clarity measure, namely a focus measure. There are many focus measure methods such as Energy of Laplacian of the image, Tenenbaum’s algorithm, Energy of image gradient and so on. In Huang and Jing (2007), all of these focus measure method are compared and shown that the sum of modified Laplacian (SML) can provide better performance than other focus measures. The
modified Laplacian (ML) adopts the absolute values of the second derivatives in the Laplacian to avoid the cancelation of second derivatives in the horizontal and vertical directions that have opposite signs. The ML is calculated as follows:

\[
ML_l^k(m, n) = \frac{1}{C_1^2} D_l^k(m, n) - \frac{1}{C_0} D_{l-1}^k(m - \text{step}, n) + \frac{1}{C_1^2} D_l^k(m + \text{step}, n) - \frac{1}{C_0} D_{l+1}^k(m, n + \text{step})
\]  

(6)

where \(D_l^k(m, n)\) is the coefficient located at \((m, n)\) in the \(l\)-th scale and \(k\)-th direction subband of the DTCWT coefficients. The SML (Huang and Jing, 2007; Stanciu et al., 2011), as the focus measure of image, can be calculated as following in a window around the center point when “step” is set to 1 in equation (6):

\[
SML_l^k(m, n) = \sum_{o=-O}^{O} \sum_{p=-P}^{P} [ML_l^k(m + o, n + p)]^2
\]  

(7)

where the parameters \(O\) and \(P\) determine the window with size of \((2O + 1) \times (2P + 1)\) in the image. The SML can effectively be used as the focus performance of the source image. Furthermore, the focus performance metrics of SML can be optimized by the guided filter method guided by source images. Figure 3 shows the decision map of the “book” images in Figure 2(a) and (b) produced by the SML and the guided filter guided by source images, separately. It is clear that the decision map created by the guided filter guided by source images is closer to the ideal decision map than it by SML method. That is to say, white region of the left part in Figure 3(a) means that the corresponding region in the left part in Figure 2(a) will be selected into the final merged image. In a similar way, black region of the left part in Figure 3(a) means that the corresponding region in the left part in Figure 2(b) will be selected into the final merged image. However, it is obvious that the left part of book image in final merged image should entirely come from the left part of Figure 2(a). The SML method cannot make the decision map with white region in the vast majority of left part. On the contrary, the left part in Figure 3(b) is able to effectively select the left book of Figure 2(a) into final fused image.

On the other hand, the SML can be applied to the transform domain to distinguish the contrast and clarity of multiscale transform coefficients. Similarly, the guided filter method can be introduced into the DTCWT coefficients. Furthermore, different guidance image in guided filter can be used in different application. If SML of DTCWT coefficients as focus measure metric used as the guidance image in guided filter and at the same time, the DTCWT coefficients is used as input image, the output of guided filter can be thought as the better focus measure metric than SML and create the more precise decision map. That is to
say, the DTCWT coefficients $D^h_{l}(m, n)$ at $l$-level and $d$-direction are adopted as the guide image in guided filter. Meanwhile, the SML value of DTCWT coefficients $D^h_{l}(m, n)$ is adopted as the input image in guided filter. On the basis of Formula (5), the output of the guided filter can be modified as:

$$q^k(m, n) = \frac{1}{|\mathcal{E}|} \sum_{k \in \mathcal{E}} (a_k D^h_{l}(m, n) + b_k) = \alpha_k D^h_{l}(m, n) + \beta_k$$

(8)

where the $a_k$ in equation (8) according to equation (3) should be calculated as:

$$a_k = \frac{\sum_{l \in \mathcal{E}} I_l SML^h_{l}(m, n) - \mu_{l} \beta_k}{\sigma_k^2 + \epsilon}$$

(9)

Hence, the decision map can be obtained as follows according to equation (8):

$$Map^h_{l}(m, n) = \begin{cases} 1, & \text{if } q^h_{A_{l}}(m, n) > q^h_{B_{l}}(m, n) \\ 0, & \text{if } q^h_{A_{l}}(m, n) < q^h_{B_{l}}(m, n) \end{cases}$$

(10)

Finally, the new fused DTCWT coefficients $D^h_{f_{l}}(i, j)$ can be merged on the basis of the following:

$$D^h_{f_{l}}(m, n) = \begin{cases} D^h_{A_{l}}(m, n), & \text{if } Map^h_{l}(m, n) = 1 \\ D^h_{B_{l}}(m, n), & \text{if } Map^h_{l}(m, n) = 0 \end{cases}$$

(11)

5. Experiments result analysis

To certify the effectiveness of the proposed scheme, the experiments have been executed on five pairs of multifocus images. The source multifocus images shown in the Figure 2 can be named as “Book”, “Lab”, “Disk”, “Clock”, and “Pepsi” images by convention. In these experiments, the proposed method is compared with the cross bilateral filter method (Shreyamsha Kumar, 2013), the multiscale geometry analysis method based on Ripplet transform and cycle spinning (Geng et al., 2014), and the statistical sharpness measure in the wavelet domain (Tian and Chen, 2012). The parameters in the paper Shreyamsha Kumar (2013) are adopted in the Kumar’s method based on the cross bilateral filter. Based-Ripplet method is proposed in paper (Geng et al., 2014). For convenience, we name this method as Peng’s method. In the Peng’s method, the source images are decomposed by the three scales in which directions are set to 1, 2 and 4. The four times of cycle spinning are adopted along the row and column, separately. Based-wavelet method is proposed in paper (Tian and Chen, 2012). For convenience, we name this method as Tian’s method. The one level of “Daubechies” wavelet decomposition is used in Tian’s method based on the statistical sharpness measure of the wavelet coefficients. The window size
is set to 5 in the weight of the approximation subband. Because the proposed method is based on DTCWT, the decomposition level is very important to the performance of this fusion method. Table I shows the mutual information (MI) (Li et al., 2013) value of the fused image by different decomposition level in the DTCWT. The italic data means they are best value in different metric performance. The other tables are same to Table I in this paper. The MI metric can compute how much information from source images is converted into the fusion result. The bigger the MI is, the better this fusion image. Hence, the larger the MI value is, the better the decomposition level is. Because the MI value by one level decomposition is the bigger than the MI values by two, three, four and five levels decompositions, one level decomposition of DTCWT is adopted in the proposed approach. There are the local window radius \( r \) and regularization parameter (named as Eps) in the guided filter. The edge information criteria \( Q^{ABF} \) (Xydeas and Petrović, 2000) is employed to evaluate the performance of different parameters. \( Q^{ABF} \) can measure the amount of edge information transferred from the source images to final fused image. The larger the objective criteria values are, the better the fusion performance of the method is. The left part of Table II is the different \( Q^{ABF} \) values by different Eps value and \( r \) is set to 16. The right part of Table II is different \( Q^{ABF} \) values by different \( r \)-value and Eps is set to 0.04. There is not obvious difference by using the different \( r \) and different Eps. In this paper, the local window radius and regularization parameter of guided filter are set to 16 and 0.04, separately. The window size of SML is set to \( 3 \times 3 \) which is often used in other fusion methods such as (Geng et al., 2014).

### 5.1 Fusion rule comparisons

For proving the effectiveness of the proposed fusion rule, the “Max” rule, SML rule and the proposed rule by the guided filter are adopted to fuse the five pairs of multifocus images shown in Figure 2. In this comparison, the one level decomposition of DTCWT is used. In the “Max” rule, the larger value of the DTCWT coefficients will be selected into the final fused coefficients. This means that if the DTCWT coefficient value of one source image is larger than the DTCWT coefficient value of other source image in same location, the larger coefficient will be select as the DTCWT coefficients value of fused image and the smaller one will be discarded. The SML rule selects DTCWT coefficients with larger SML value into the merged image. The Figure 5 demonstrates the Mutual information (MI) (Li et al., 2013) value of the fuses image by the three rules in the DTCWT domain. It is obviously concluded that the MI value by the proposed fusion rule is superior to those by the “Max” rule and SML rule.

### 5.2 Visual performance comparisons

For the purpose of verifying the effectiveness of the proposed approach, five pairs of multifocus images shown in Figure 2 are used in the experiments on these four methods. The images in the first row of Figures 6-10 are the fused images by four different methods, separately. Focusing on the enlarged and labeled regions in first row of Figures 6-10, it is clear that Tian’s approach produces artifacts around boundaries. There are the obvious blurred edges in fused images by Peng’s and Kumar’s approach. However, there are clearer image edge and less artifacts in the fused images by the proposed methods than in the other fused results. On the other hand, the difference images between source images and the fused images are illustrated to unambiguously express the difference among the four methods. According to the imaging theory of multifocus image, the

<table>
<thead>
<tr>
<th>Different level Decomposition</th>
<th>Lab</th>
<th>Book</th>
<th>Disk</th>
<th>Clock</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level = 1</td>
<td>8.4135</td>
<td>9.1019</td>
<td>8.0289</td>
<td>8.0656</td>
</tr>
<tr>
<td>Level = 2</td>
<td>8.318</td>
<td>8.8197</td>
<td>7.9821</td>
<td>7.8936</td>
</tr>
<tr>
<td>Level = 3</td>
<td>8.2683</td>
<td>7.5215</td>
<td>7.8258</td>
<td>7.6895</td>
</tr>
<tr>
<td>Level = 4</td>
<td>8.086</td>
<td>7.1407</td>
<td>7.4932</td>
<td>7.3192</td>
</tr>
<tr>
<td>Level = 5</td>
<td>7.6413</td>
<td>7.0558</td>
<td>6.0493</td>
<td>6.9059</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Eps</th>
<th>( Q^{ABF} )</th>
<th>( r )</th>
<th>( Q^{ABF} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eps = 0.01</td>
<td>0.7042</td>
<td>( r = 1 )</td>
<td>0.7032</td>
</tr>
<tr>
<td>Eps = 0.04</td>
<td>0.7051</td>
<td>( r = 4 )</td>
<td>0.7048</td>
</tr>
<tr>
<td>Eps = 0.08</td>
<td>0.7038</td>
<td>( r = 8 )</td>
<td>0.7039</td>
</tr>
<tr>
<td>Eps = 0.16</td>
<td>0.7031</td>
<td>( r = 12 )</td>
<td>0.7029</td>
</tr>
<tr>
<td>Eps = 0.20</td>
<td>0.7101</td>
<td>( r = 16 )</td>
<td>0.7051</td>
</tr>
<tr>
<td>Eps = 0.24</td>
<td>0.7022</td>
<td>( r = 20 )</td>
<td>0.7043</td>
</tr>
<tr>
<td>Eps = 0.27</td>
<td>0.7018</td>
<td>( r = 24 )</td>
<td>0.7039</td>
</tr>
</tbody>
</table>
The difference image between source images and the fused image should be zero for the well-focused regions. Therefore, the lower residue information in the difference image there is, the better the fusion method transfers information of the source images to fused image. For obviously demonstrating the residual information, several white rectangles are labeled in the second row of Figure 6-10. There are maximum residues in the difference images in Figure 6(e)-Figure 10(e) by Kumar's method. The residue information in Figure 6(f)-Figure 10(f) by Peng’s method and Figure 6(g)-Figure 10(g) by Tian's method can be seen by carefully observation, separately. However, there is very little residue in the counterpart by the proposed method. The difference images in Figures 6-10 indicate that the proposed method can extract most of the good-focused parts of source images and preserve the detailed information better than the other three methods.

5.3 Objective performance analysis
To fair comparisons, the edge information criteria $Q^{AB/F}$ (Xydeas and Petrović, 2000) and MI are employed to objectively evaluate the performance of the four approaches. $Q^{AB/F}$ can measure the amount of edge information transferred from the source images to final fused image. The larger the objective criteria values are, the better the fusion performance of the method is. Tables III and IV show the MI and $Q^{AB/F}$ values of the multifocus images fusion by different approaches, separately. It is obvious that different methods lead to different MI and $Q^{AB/F}$ values. As listed in Tables III and IV, the largest MI and $Q^{AB/F}$ values of the proposed method in every fused image demonstrate that the proposed method can not only preserve the most abundant image edges, but also provide the most consistent fused images to the source images.

5.4 Computation time comparison
Table V demonstrates the computation time of all methods. This comparison is executed on a laptop computer with 2 Cores 2.5 GHz CPU and 4 GB RAM. Tian’s method is the slowest because the complexity in the fusing the three high

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**Table III** Evaluation of fusion results by mutual information (MI) performance

<table>
<thead>
<tr>
<th>Methods</th>
<th>Book</th>
<th>Lab</th>
<th>Clock</th>
<th>Disk</th>
<th>Pepsi</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kumar’s method</td>
<td>6.3534</td>
<td>7.4774</td>
<td>7.4139</td>
<td>6.6735</td>
<td>7.2282</td>
</tr>
<tr>
<td>Peng’s method</td>
<td>7.4672</td>
<td>7.8562</td>
<td>7.2665</td>
<td>7.1422</td>
<td>7.2556</td>
</tr>
<tr>
<td>Tian’s method</td>
<td>8.6443</td>
<td>8.0415</td>
<td>8.0441</td>
<td>7.5498</td>
<td>7.3136</td>
</tr>
</tbody>
</table>

**Table IV** Evaluation of fusion results by $Q^{AB/F}$

<table>
<thead>
<tr>
<th>Methods</th>
<th>Book</th>
<th>Lab</th>
<th>Clock</th>
<th>Disk</th>
<th>Pepsi</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kumar’s method</td>
<td>0.6566</td>
<td>0.7321</td>
<td>0.6873</td>
<td>0.6952</td>
<td>0.7867</td>
</tr>
<tr>
<td>Peng’s method</td>
<td>0.7163</td>
<td>0.7381</td>
<td>0.6806</td>
<td>0.7071</td>
<td>0.7771</td>
</tr>
<tr>
<td>Tian’s method</td>
<td>0.7219</td>
<td>0.7412</td>
<td>0.6931</td>
<td>0.7153</td>
<td>0.7425</td>
</tr>
<tr>
<td>Proposed method</td>
<td>0.7299</td>
<td>0.7536</td>
<td>0.7051</td>
<td>0.7325</td>
<td>0.7895</td>
</tr>
</tbody>
</table>

---

---
frequency coefficients. Owing to the four times cycle spinning along the row and column, respectively, Peng’s method will take you 16 times as long as the Rippet method without cycle spinning does. The proposed method is the fastest in the four methods. Furthermore, the SML and the consistency check need 85 per cent time to calculate the focus measure value of the images in DTCWT domain. The guided filter needs only less than 8 per cent time. In the whole, the proposed method is better in effectively reducing time cost than the other methods.

6. Conclusion
To get the more precise focus measure method to make the precise decision map in fusing process, a new and effective focus measure method is proposed to create the better decision map which is very important in fusing the multifocus images. The sum of ML is used as the input image in the guided filter. At the same time, the DTCWT coefficients are used as the guided image of the guided filter. Because the output of the guided filter can distinguish the well-focused part from the ill-focused part than the traditional sum of Laplacian energy can. Hence, the more precise decision map is made by this method. The experiments result show that the guided filter rule is able to accurately transfer the DTCWT coefficients into the fused coefficients. Therefore, the proposed approach based on DTCWT can extract the well-focused pixels and integrate them into the fused image. The experiment analysis about merged five pairs of multifocus images demonstrates the superior performance of the proposed fusion approach from both the objective criteria and subjective evaluation.

References


Multifocus image fusion based on coefficient significance of redundant discrete wavelet transform

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Abstract
Purpose – This study aims to obtain the more precise decision map to fuse the source images by Coefficient significance method. In the area of multifocus image fusion, the better decision map is very important the fusion results. In the processing of distinguishing the well-focus part with blur part in an image, the edge between the parts is more difficult to be processed. Coefficient significance is very effective in generating the better decision map to fuse the multifocus images.

Design/methodology/approach – The energy of Laplacian is used in the approximation coefficients of redundant discrete wavelet transform. On the other side, the coefficient significance based on statistic property of covariance is proposed to merge the detail coefficient.

Findings – Due to the shift-variance of the redundant discrete wavelet and the effectiveness of fusion rule, the presented fusion method is superior to the region energy in harmonic cosine wavelet domain, pixel significance with the cross bilateral filter and multiscale geometry analysis method of Ripplet transform.

Originality/value – In redundant discrete wavelet domain, the coefficient significance based on statistic property of covariance is proposed to merge the detail coefficient of source images.

Keywords Sensors, Machine vision, Image processing, Image fusion, Coefficient significance, RDWT, Energy of Laplacian, Covariance

Paper type Research paper

1. Introduction

Data fusion techniques combine data from many sensors and related information to achieve improved accuracy and more specific inferences with the goal of improving the performance of surveillance, diagnosis, prediction and soon (Liu et al., 2018, 2017). Image fusion is an important technique of data fusion for various image processing and computer vision applications such as feature extraction and target recognition (Sun et al., 2016). Through image fusion technology, different images of the same scene can be combined into a single fused image. The fused image can provide more comprehensive information about the scene which is more useful for human and machine perception. Optical lenses are widely mounted in imaging devices (Cossairt et al., 2010). A lens with long focal lengths suffers from the problem of limited depth of field, and only few objects with the depth of field are focused and others are blurred (Zhu et al., 2018; Ghassemian, 2016). Besides solutions making use of specialized optics and computational imaging, the multi-focus fusion process is highly desirable to create a single image where all objects are in focus. A good image fusion method has the following properties. First, it can preserve most of the useful information of different images. Second, it does not produce artifacts. Third, it is robust to imperfect conditions such as mis-registration and noise.

Multiscale transforms are generally used for image fusion to estimate image sharpness in transform domain and select informative coefficients. Burt et al. firstly used Laplacian pyramid for image fusion (Wang and Chang, 2011), later Toet used contrast pyramid (Jin et al., 2007). The discrete wavelet transform (DWT) is used mainly owing to its good localized time frequency characteristics and its ability to deal with abrupt changes, spikes, drifts and trends. Owing to good localized time frequency characteristics of DWT, Yang et al. (2014) proposed the maximum sharpness focus measure and neighboring energy to select low and high frequency sub-bands coefficients in DWT domain. However, the DWT needs a great deal of convolution calculations, and it either consumes much time or occupies memory resources, which impedes its real-time application. Relative to the DWT, the lifting wavelet transform (LWT) can overcome its shortcomings. Multifocus image fusion method (Wang et al., 2009) based on the LWT are proposed. Whereas

Conflict of interests: The authors declare that there is no conflict of interests regarding the publication of this paper.

Received 9 November 2018
Revised 22 November 2018
28 February 2019
21 March 2019
Accepted 26 March 2019
lifting-based wavelets are computationally simpler but with similar performance in some cases and poor performance in other cases with DWT (Kumar, 2013). The discrete cosine harmonic wavelet transform (DCHWT) was proposed for image fusion to obtain the performance similar to that of convolution-based wavelets with a reduced computational complexity. However, the major disadvantage of LWT, DHCWT and DWT is the shift variant. This occurs due to the downsampling process after each level of filtering, which causes a significant change in the wavelet coefficients of the image even for minor shifts in it. This leads to inaccurate selection of the wavelet coefficients when the source images are not rigorously registered. Redundant discrete wavelet transform (RDWT) is established to overcome that problem because it is shift invariant. Furthermore, the RDWT sub-band maintains the same size as the original image, and keeps the important texture of an original image at the same spatial location in each sub-band. In this paper, the statistical property of the covariance of RDWT coefficients as the coefficient significance fusion rule are introduced to fused the RDWT coefficient of source multifocus images.

2. Redundant discrete wavelet transform

The RDWT has been developed for some image processing applications such as denoising, texture classification, fusion, and watermarking (Guo and Prasetyo, 2014). On the other side, the advantage lies in the pixel-wise analysis, and corresponds to an over-complete representation. There are multiple methods to implement the RDWT, and multiple methods to represent the resulting overcomplete set of coefficients. The original implementation is in a form of the átrous algorithm, which eliminates the downsampling operator from the usual implementation of the DWT (Karthikeyan and Palanisamy, 2018). To describe RDWT, the decomposition and reconstruction process of 1D DWT and the inverse RDWT are illustrated in Figure 1. Where f[n] and f'[n] are the input signal and reconstructed signal, respectively. h[k] and h'[-k] are denoted as the corresponding low pass synthesis filters and low pass analysis filters, respectively. g[k] and g'[-k] represent the high pass synthesis filters and high pass analysis filters, respectively. c_j and d_j are the low-band and high-band output coefficients at level j, respectively. RDWT decomposition and reconstruction are given as follows:

\[ c_j[k] = (c_{j+1}[k] * h_{j}[-k]) \]
\[ d_j[k] = (c_{j+1}[k] * g_{j}[-k]) \] (1)

\[ C_{j+1}[k] = \frac{1}{2} (c_j[k] * h_j[-k] + d_j[k] * g_j[-k]) \] (2)

where * represents convolution operation. RDWT eliminates down sampling and up sampling of coefficients during each filter-bank iteration. Redundant representation of the input sequence is obtained by eliminating down sampling in the RDWT decomposition. Since frame expansion increases robustness with respect to misregistered multifocus image, RDWT based image fusion is more robust than DWT method.

3. Fusion rule

3.1 Approximation coefficient fusion rule

Because energy of Laplacian (EOL) (Zhan et al., 2015) is a lower time-consuming process than the sum-modified Laplacian, EOL is used to distinct the coefficient in clear region with coefficients in the blurred region in this paper. The Laplacian is given by sum of second partial derivatives of the redundant discrete wavelet approximation coefficient \( M^a(i, j) \) of two variables with respect to each independent variable. \( a \) represents the approximation RDWT coefficient instead of the detail RDWT coefficient:

\[ \nabla^2 M^a(i, j) = \frac{\partial^2 M^a(i, j)}{\partial x^2} + \frac{\partial^2 M^a(i, j)}{\partial y^2} \]
\[ = M^a(i+1, j) + M^a(i-1, j) + M^a(i, j+1) + M^a(i, j-1) - 4M^a(i, j) \] (3)

This equation can be implemented as \( M^a(i, j) \) convoluted with the filter mask \( L \).
According to equation (4), the four diagonal coefficients around the window size of $3 \times 3$ are not used to compute the second partial derivatives of $M^d(i, j)$. In fact, all the eight coefficients can together be adopted to judge whether the center coefficient around the window belongs to clear part or not. Therefore, the filter mask can be set to:

$$L = \begin{bmatrix}
1 & 4 & 1 \\
4 & -20 & 4 \\
1 & 4 & 1
\end{bmatrix}$$

(5)

The EOL focus measure of $M^d(i, j)$ can be computed by:

$$\text{EOL} = (M^d(i, j) \ast L)^2$$

(6)

where $\ast$ denotes the convolution. In the spatial domain, the pixel with the larger EOL should belong to the clear region in the image. On the contrary, the pixel with the smaller EOL should belong to the blurred region in the image. Similarly, approximation RDWT coefficient with the larger EOL will be selected as the fused coefficient and approximation RDWT coefficient with the smaller EOL will be discarded. Furthermore, if the center coefficient comes from $M^d_B(i, j)$ while the majority of the surrounding coefficients come from $M^d_A(i, j)$, the center coefficient value is switched to that of $M^d_B(i, j)$. Before fusing the approximation coefficient of source multifocus image A and B, The majority filter is utilized in window-based consistency verification.

### 3.2 Detail coefficient fusion rule

It is concluded that the eigenvalue of covariance matrix of an image block depends on the strength of edges (Wee and Paramesran, 2007). Because the high pass coefficients contain contour and detail information of image, eigenvalue of covariance matrix of an coefficients region can be used as the coefficients significance to distinct the coefficients in the clear part of source images with coefficients in blurred part of source images. The significance of coefficient can be defined as sum of eigenvalue of RDWT coefficient’s covariance in a given region instead of the detail information by cross bilateral filter like (Kumar, 2015). In essence, the fusion rule based on coefficient significance is a kind of weighted fusion method which adopts the weight value to decide to how percentage the source multifocus image account for in final fused coefficients.

For any matrix $X$, each row of $X$ is treated as an observation and column as a variable to compute the unbiased estimate $X$ of its covariance matrix.

$$\text{covariance}(X) = E[(X - E(X))(X - E(X))^T]$$

(7)

It can be concluded that the covariance of the RDWT coefficient $M^d(i, j)$ should be expressed as:

$$M^d(i, j) = \sum_{k=1}^{w} \left( M^d_k - \bar{M}^d \right) \left( M^d_k - \bar{M}^d \right)^T$$

(8)

where $M^d(i, j)$ is denoted as the value at $i$-th row and $j$-th column in detail coefficient of source image. Superscript $d$ denotes the detail coefficient instead of approximation coefficient. $M^d_k$ represents the $k$-th observation of $w$ dimensional variable around the $w \times w$ window centered at detail coefficient $(i, j)$. $\bar{M}$ denotes as the mean vector of observation location the same window region. The horizontal edge strengths $S_{hd}(i, j)$ can be calculated by the sum of eigenvalues of $M^d(i, j)$ around $w \times w$ window centered at detail coefficient $(i, j)$:

$$S_{hd}^d(i, j) = \sum_{k=1}^{w} \text{eigen}_k(M^d_{hd}(i, j))$$

(9)

Similarly, the unbiased covariance estimate $M^d_{hd}(i, j)$ in vertical direction can be obtained by introducing each column of RDWT coefficient $M^d(i, j)$ as observation and row as a variable. The vertical edge strength $S_{vd}^d(i, j)$ can be computed as following by sum of eigenvalue of $M^d_{vd}(i, j)$:

$$S_{vd}^d(i, j) = \sum_{k=1}^{w} \text{eigen}_k(M^d_{vd}(i, j))$$

(10)

Now we take the sum of edge strength $S_{hd}^d(i, j)$ and $S_{vd}^d(i, j)$ as the significance $S$ to be given to the pixel into consideration as shown below. Hence, the significance depends on the strength of the edges and not on the actualintensity values.

$$S^d(i, j) = S_{hd}^d(i, j) + S_{vd}^d(i, j)$$

(11)

According to equations (7)-(11), $S_{hd}^d(i, j)$ and $S_{vd}^d(i, j)$ can be computed as the weights for the detail coefficients of $M^d_A(i, j)$ and $M^d_B(i, j)$ corresponding to source images A and B, respectively. The weighted average of the source images will result in a fused detail coefficients in RDWT domain. The fusion process can be expressed as following:

$$F^d(i, j) = \frac{M^d_A(i, j) \cdot S_{hd}^d(i, j) + M^d_B(i, j) \cdot S_{vd}^d(i, j)}{S_{hd}^d(i, j) + S_{vd}^d(i, j)}$$

(12)

where $F^d(i, j)$ is denoted as the fused detail coefficient located at $i$-th row and $j$-th column.

### 4. Experiments and analysis

To certify the effectiveness of the presented fusion method, experiments were carried out on various standard test pairs of multifocus images shown in Figure 2. The images in first column of Figure 2 are focused on the left part. The right part is in clear in the images in second column of Figure 2. In the experiments, the proposed method is compared with the pixel significance method with cross bilateral filter method (Wee and Paramesran, 2007) region energy based on discrete cosine harmonic wavelet transform (DCHWT) (Kumar, 2013), the multiscale geometry analysis method based on Ripplet transform and cycle spinning (Kumar, 2015). The parameters
in the paper (Wee and Paramesran, 2007) are adopted based on the cross bilateral filter and we named this method as CBF method. Three levels of DCHWT decomposition are adopted to decompose the source multifocus images and the fusion rule based on pixel significance adopted the region energy of children and grandchildren coefficients in DCHWT subbands.

We named this method as DHCWT method in this paper. The fusion rule is described in the paper (Kumar, 2013). Finally, the fusion method based on Ripplet, named as Ripplet-SML, is introduced to be compared with the presented method because Ripplet transform is a kind of multiscale geometry analysis method like the MDWT and the sum-of-Laplacian fusion rule is adopted. In this method, the source images are decomposed by the three scales in which directions are set to 1, 2, and 4, respectively.

A fusion artifact introduced into the fused image in the fusion process could lead to a benign object being classified as a threat or a valid target. So, an efficient fusion method is one that introduces minimum artifacts. Performance evaluation of fusion is a challenge as in most of the applications, ground truth is not available. Table I lists the conventional performance measures of mutual information (MI) and \( Q^{AB/F} \) (Geng et al., 2016; Guo et al., 2015) on fused images with the four different fusion methods. \( Q^{AB/F} \) can measure the amount of edge information transferred from the source images to the final fused image. The larger the objective criteria values are, the better the fusion performance of the method is. In Table I, the higher values are bolded for clearly displaying better fusion results among the different methods. It is obvious that different methods lead to different MI and \( Q^{AB/F} \) values. As listed in Table I, the MI value of “book” image with the Ripplet-SML method is larger than that with other methods and proposed method. However, the MI and \( Q^{AB/F} \) value of other four pairs of images by the proposed is largest among the four methods. According to the definition of MI and \( Q^{AB/F} \), it can be concluded that the proposed method can not only preserve the most abundant image edges, but also provide the most consistent fused images to the source images except of special case.

In addition to the quantitative analysis, the visual analysis is also very important because the goal of image fusion method is to enhance comprehensive, accurate and stable information so that the fused image is more suitable for human perception. The first column of Figures 3, 4 and 5 show the fused images with different methods. Generally, the fused images with proposed method are more clear than other three methods. For clearly displaying the distinct of the fused results, the residual images in the second column of Figures 3, 4 and 5 are shown to demonstrate the difference among the four methods. Although the MI and \( Q^{AB/F} \) value of “book” image by the Ripplet-SML method is largest among the three methods, there are more residual information in right part of the residual image in Figure 3(f) than in corresponding region of Figure 3(h). The residual information in the Figure 4(e) and (g) is more clear than the Figure 4(f) and (h). By carefully observing Figure 4(f) and (h), there is minimum residual information in the right part.

Table 1 Objective criteria comparison on different methods

<table>
<thead>
<tr>
<th>Image</th>
<th>Criteria</th>
<th>DCHWT</th>
<th>Ripplet-SML</th>
<th>CBF</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Book</td>
<td>MI</td>
<td>7.0406</td>
<td>7.4672</td>
<td>6.3534</td>
<td>7.8119</td>
</tr>
<tr>
<td></td>
<td>( Q^{AB/F} )</td>
<td>0.6942</td>
<td>0.7163</td>
<td>0.6566</td>
<td>0.7215</td>
</tr>
<tr>
<td>Lab</td>
<td>MI</td>
<td>7.0348</td>
<td>7.8562</td>
<td>7.4774</td>
<td>7.7060</td>
</tr>
<tr>
<td></td>
<td>( Q^{AB/F} )</td>
<td>0.6959</td>
<td>0.7381</td>
<td>0.7321</td>
<td>0.7386</td>
</tr>
<tr>
<td>Clock</td>
<td>MI</td>
<td>6.7403</td>
<td>7.2665</td>
<td>7.4139</td>
<td>7.5774</td>
</tr>
<tr>
<td></td>
<td>( Q^{AB/F} )</td>
<td>0.6481</td>
<td>0.6806</td>
<td>0.6873</td>
<td>0.6885</td>
</tr>
<tr>
<td>Pepsi</td>
<td>MI</td>
<td>6.8542</td>
<td>7.2556</td>
<td>7.2282</td>
<td>7.6250</td>
</tr>
<tr>
<td></td>
<td>( Q^{AB/F} )</td>
<td>0.7568</td>
<td>0.7771</td>
<td>0.7798</td>
<td>0.7804</td>
</tr>
<tr>
<td>Disk</td>
<td>MI</td>
<td>6.0930</td>
<td>7.1422</td>
<td>6.6735</td>
<td>7.1478</td>
</tr>
<tr>
<td></td>
<td>( Q^{AB/F} )</td>
<td>0.6542</td>
<td>0.7071</td>
<td>0.6950</td>
<td>0.7121</td>
</tr>
</tbody>
</table>

Note: The best value of metric performance is set as the italic format.
of Figure 4(h) among Figure 4(e)-(g). The same analysis result may be reached by the second column of Figure 5.

In the overwhelming majority of cases, the minimum MI and $Q^{AB/F}$ and maximum residual information by the DHCWT method verify that the pixel significance base on the region energy among the children and father coefficient of DHCWT is not effective to select the coefficient in clear region of source images to fuse image. The larger MI and $Q^{AB/F}$ and less residual information by the CBF method than the DHCWT method demonstrate that the coefficient significance based on the statistical property of covariance is effective than the region energy. Because the EOL and coefficient significance are introduced in the different RDWT coefficient, the best fusion result are produced. To sum up, just as Table I and Figures 4 and 5, we may objectively draw the conclusion that the proposed algorithm can preferably extract focused image part and discard the defocused region in the source images according to both visual performance and objective criteria among the four methods. The better performance of the presented approach can be owed to two sides. One is the better RDWT’s shift-variance. On the other hand, EOL and coefficient significance fusion rules in the different RDWT coefficient can competitively separate the focus region from defocused part of source images.

5. Conclusion

According to the different feature in the detail coefficient and the approximation coefficient of RDWT, the different fusion
rules are used to merge the source images. By measuring the of horizontal strength and the vertical strength of details coefficient’s covariance, the weights in detail coefficients of source images are computed to merged the corresponding coefficients. The EOL is introduced into merging the approximation coefficients of source images. Several pairs of multifocus images are adopted to evaluate the performance of the proposed method. Through the experiments on several pairs of multifocus images, the proposed method has shown superior performance as compared to other methods in terms of quantitative analysis and visual quality analysis.

References


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Road segmentation of cross-modal remote sensing images using deep segmentation network and transfer learning

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Abstract

Purpose – The purpose of this paper is to study the road segmentation problem of cross-modal remote sensing images.

Design/methodology/approach – First, the baseline network based on the U-net is trained under a large-scale dataset of remote sensing imagery. Then, the cross-modal training data are used to fine-tune the first two convolutional layers of the pre-trained network to achieve the adaptation to the local features of the cross-modal data. For the cross-modal data of different band, an autoencoder is designed to achieve data conversion and local feature extraction.

Findings – The experimental results show the effectiveness and practicability of the proposed method. Compared with the ordinary method, the proposed method gets much better metrics.

Originality/value – The originality is the transfer learning strategy that fine-tunes the low-level layers for the cross-modal data application. The proposed method can achieve satisfied road segmentation with a small amount of cross-modal training data, so that is has a good application value. Still, for the similar application of cross-modal data, the idea provided by this paper is helpful.

Keywords Remote sensing, Deep learning, Autoencoder, Cross-modal, Road segmentation, Transfer learning

Paper type Research paper

1. Introduction

Automatic road segmentation contributes much to many different fields, including but not limited to urban planning, Geographic Information System (GIS) and navigation. Over the past decades, people have tried many methods to detect the road targets from aerial imagery (Hu et al., 2007; Steger et al., 1995; Wu and Hu, 2010). Most of these methods obey a pattern of designing the common features and connecting the detected road seeds. Since many threshold parameters should be elaborately given, and the parameters may be varied in different images, these traditional methods cannot work well on large-scale application (Mnih and Hinton, 2010).

Benefiting from the development of deep segmentation networks (Badrinarayanan et al., 2017; Long et al., 2015; Ronneberger et al., 2015) and the growing data scale in recent years, the technology of road segmentation has also been improved. Mnih (2013) and Mnih and Hinton (2010) have explored to segment the roads and buildings by artificial neural network methods, and established a corresponding large-scale dataset, the Massachusetts roads and buildings dataset. Some methods that combine the convolutional neural networks and the sliding window approach have achieved breakthroughs (Alshehhi et al., 2017; Wang et al., 2015), but their speed is limited because of the sliding window approach. Based on the fully convolutional network architecture (Long et al., 2015), the end-to-end road segmentation methods have been further developed (Panboonyuen et al., 2017a, 2017b; Wei et al., 2017). These methods have made the road segmentation results reach state-of-the-art.

There are usually many different formats of available data in remote sensing field, such as multispectral, infrared, and visible light. Even the images collected from the same formats are varies depending on the sensors, as illustrated in Figure 1. However, as a supervised machine learning problem, the performance of the networks relies on the training data much and may not generalize well on a new data domain. To solve the generalization problem, transfer learning methods have been studied to improve the learned models (Dou et al., 2018; Ghafoorian et al., 2017; Huang et al., 2017; Tsai et al., 2018). Because of the various data formats, the cross-modal remote sensing imageries bring more challenges.

In this paper, a transfer learning approach for cross-modal remote sensing imagery road segmentation is proposed. First, a deep segmentation network for visible light data under an improved U-net (Ronneberger et al., 2015) architecture is pre-trained. Second, the first two layers of the pre-trained model are fine-tuned by using the cross-modal data, while the parameters of the higher layers are frozen. To adapt to the cross-modal data with different band, an autoencoder is trained to transform the data to 3-band, to come up with the input layer of the pre-trained model. The experimental results on visible light data (produced by different sensors with the original training data), panchromatic data and multi-spectrum data
show that the proposed method performs well without large-scale cross-modal training data. Furthermore, the proposed method can be used simultaneously to segment the road from different cross-modal remote sensing imagery.

2. Methodology

2.1 Problem formulation

As a transfer learning problem, the network is first trained on the data from the source domain \( D_S \). The sample in \( D_S \) can be denoted as \( X' = \{ (x'_i, y'_i), \ldots, (x'_n, y'_n) \} \), where the \( x'_i \) represents the sample of the input image (a pixel of a patch) and the \( y'_i \) represents the corresponding category annotation. When the pre-trained model is applied to different data in the target domain \( D_T \) where its sample \( X_T = \{ (x'_i, y'_i), \ldots, (x'_{n'}, y'_{n'}) \} \) has a different distribution, the features learned from \( D_S \) should be used so that the model can be applied quickly with a satisfied performance. To the cross-modal remote sensing road segmentation problem, the label space (binary label of road/background) is common for \( D_S \) and \( D_T \). Therefore, the problem can be described as the effective representation of the data from \( D_T \) by using the knowledge learned from the data of \( D_S \).

2.2 The proposed method

Based on the improved U-net segmenter, the baseline network is pre-trained on the visible light data, which is easy to obtain relatively. Then, the pre-trained model is fine-tuned by using the cross-modal training data. In addition, the autoencoder is used to make the cross-modal data available for the pre-trained model. The architecture of the proposed network is shown in Figure 2.

The improved U-net architecture is used as the baseline network, as illustrated in Figure 3. It consists of an encoder path (left side) and a decoder path (right side). The encoder follows the typical architecture of a convolutional network. It consists of the repeated application of two \( 3 \times 3 \) convolutions with stride 1 and padding 1. Each convolution is followed by an exponential linear unit (ELU) (Clevert et al., 2016) and a batch normalization layer (Ioffe and Szegedy, 2015). Each repeated application is followed by a \( 2 \times 2 \) max pooling operation with stride 2 for down sampling. At each max pooling step, the number of feature channels is doubled. Every step in the decoder path consists of an up-sampling of the feature map followed by a \( 2 \times 2 \) convolution that halves the number of feature channels, a concatenation with the correspondingly feature map from the encoder path, and two \( 3 \times 3 \) convolutions that followed by an ELU and a batch normalization at the final layer. A convolution is used to map each 64-component feature vector to the desired number of classes, which is 1 in this network. As a binary segmentation task, the sigmoid function is used for the probability of the pixels.

The model is pre-trained under the data from the source domain by minimizing the loss \( L_{seg} \) that composed of binary cross-entropy loss function and Jaccard index function. Formally, the \( x_i \) represents the \( i \)th input pixel, \( y_i \) is its truth and \( \hat{y}_i \) is its prediction. The binary cross-entropy is defined as:

\[
L_{BCE}(y, \hat{y}) = - \frac{1}{n} \sum (y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i))
\]

(1)

To get a better Jaccard metric, an objective function \( J \) is added:

\[
J(y, \hat{y}) = \frac{1}{n} \sum \frac{y_i \hat{y}_i}{y_i + \hat{y}_i - y_i \cdot \hat{y}_i}
\]

(2)

Therefore, the joint loss function is defined as:

\[
L_{seg} = L_{BCE} - \log(J)
\]

(3)

As an unsupervised method, the autoencoder is used to retrieval cross-modal data (Feng et al., 2014). Inspired by this, a simple fully convolutional network is raised as the
autoencoder to convert the cross-modal data into an accessible format for the baseline network, especially, 3-band in this paper. The reason for converting to 3-band is that, the baseline network is pre-trained on the easily accessible RGB data (3-band). To make the baseline network serve as a common module, the output of the autoencoder is set to 3-band to access the baseline network. The architecture of the proposed autoencoder is shown in Figure 4.

When the 3-band RGB images to the same area are available, the N-band images can be used as the input and the 3-band image as the ground-truth to train the autoencoder, so that the other N-band data can be transformed into the distribution of the 3-band data. The mean square error (MSE) is used as the loss function to train the autoencoder. The MSE is shown in equation (4):

$$L_{MSE} = \frac{1}{n} \sum_{i=0}^{n-1} (y_i - \hat{y}_i)^2$$

where, the $\hat{y}_i$ represents the prediction probability of the $i$th pixel, and $y_i$ represents the value of the corresponding pixel on the 3-band image.

### 2.3 The fine-tuning strategy for cross-modal imagery

To the problem of road segmentation application, the higher semantic features are common but the local features are quite different because of the variety of the cross-modal input data. Therefore, a strategy to fine-tune the lower layers is raised to adapt the input data, while the higher layers are frozen.

#### 2.3.1 Cross-modal data with the same band

Because the target data are different from the source data in value distribution, the pre-trained model cannot extract the basic local features from the target data. However, the semantic features for the road are common, meaning that the parameters of the higher layers in the pre-trained model are still useful. Therefore, the fine-tuning strategy is to freeze the parameters expect those in the first convolutional stack. The parameters just in the first two convolutional layers are fine-tuned under the data from the target domain. The network uses very few target samples to learn the low-level local features of the target domain but need not relearn the complex semantic features about the road. The loss function of equation (3) is used to fine-tune the network.

#### 2.3.2 Cross-modal data with a different number of channels

Because the structure of the first several layers cannot be used directly, the problem becomes more complicated when the data from the target domain have a different number of channels with the source data. Therefore, an autoencoder is raised to transform the cross-modal data into an accessible format. In this way, the parameters of the first several layers of the baseline network can be fine-tuned as initial parameters without changing the structure of the first layers.

For the same area, several different types of remote sensing data may be available, while the data of visible light is the most common one. Based on the transformed data, the proposed fine-tuning strategy can be applied and the network can be adapted for cross-modal data. It should be noted that the parameters of the autoencoder are not frozen during the fine-tuning process, because the autoencoder is also used to extract the local features that should be learned from the target data.

### 3. Experiments and analysis

In this section, experiments and analysis on the results are presented to demonstrate the validity of the proposed method. Before the experiments of segmenting roads from the cross-modal remote sensing data, the dataset and the preprocessing process are explained. Then, the details of the pre-training process on source data and the training of the mentioned autoencoder are presented. Based on these works, the first two convolutional layers are fine-tuned to extract the local features from the cross-modal data of 16-bits RGB imagery (3-band), panchromatic imagery (1-band) and multispectral imagery (8-band). To demonstrate the advantages of the proposed method, the baseline network is also trained only on the target training data to compare with the proposed method.

#### 3.1 Evaluation

As the road extraction is studied as a problem of semantic segmentation, the metrics of recall rate, precision, F1-score and IOU (intersection-over-union) are used to evaluate the extraction results. Define TP as true-positive predictions, FP as false-positive predictions, TN as true-negative predictions and FN as false-negative predictions, the metrics are as follows:

$$\text{recall} = \frac{TP}{(TP + FN)}$$

$$\text{precision} = \frac{TP}{(TP + FP)}$$

$$F1 = \frac{2TP}{(2TP + FN + FP)}$$

$$\text{IOU} = \frac{TP}{TP + FN + FP}$$

#### 3.2 The dataset and preprocessing

The baseline network is trained under the source training dataset. The source dataset contains 6626 satellite images with annotation. Each image is an 8-bits RGB image with size $1,024 \times 1,024$ and resolution 0.5 m/pixel, as shown in Figure 5. These images are randomly divided into training dataset with...
6035 images and testing dataset with 591 images. To facilitate
the segmentation network, these images are zoomed into 512×
512, with a resolution of 1 m/pixel.

The target dataset consists of multi-modal remote sensing
images that captured by the WorldView-3 satellite. All these
public images are in a format of 16-bits. Except the 3-band
traditional RGB natural images, the 8-band multispectral
(400-1,040 nm) and the 1-band panchromatic (450nm-
800nm) images for the same area are provided. Each image
covers a 1 km × 1 km area. The RGB images and
panchromatic images are about 3,348 × 3,392 with a
resolution of 0.31 m/pixel, and the multispectral images are
about 849 × 837 with a resolution of 1.24 m/pixel. Totally
25 images that contain road objects are selected to form the
target dataset. According to the scale of the road targets,
these images are resized into 1,024 × 1,024 (about 1m/
pixel). These selected images are cropped as training dataset and 15 as
testing dataset. The other cropped images that do not
contain road targets are abandoned.

All the images are preprocessed by 0-1 normalization, as
present in equation (9):
\[ V_n = \frac{(V - \min(V))}{(\max(V) - \min(V))} \]  
(9)
where the \( V \) represents the input values, and the \( V_n \) represents
the normalized values. It is easy for the source data, but not for
the target data. The extreme values in the target images
increase the denominator in equation (9), and reduce the range
of the other pixels. Therefore, the top 2 per cent values and the
bottom 2 per cent values of the target images are removed to
make the 0-1 normalization usable.

3.3 The pre-training of the baseline network
To train the baseline network, the training source data is
augmented by rotating (90°, 180°, 270°) and flipping
(horizontal and vertical). An advanced optimizer of Adam
(Kingma and Ba, 2015) is used, and the parameters are set as
the learning rate \( \alpha = 10^{-4} \), \( \beta_1 = 0.9 \) and \( \beta_2 = 0.9 \).
Finally, the trained network gets metrics of recall rate 74.2 per cent,
precision 76.4 per cent, F1-score 74.3 per cent and IOU 61.0 per cent on the testing source dataset. Some examples of
visualization result are shown in Figure 6.

3.4 The pre-training of the autoencoder
In this paper, two autoencoders should be trained to transform 1-
band data and 8-band data to 3-band data respectively. The
architecture of the two autoencoders is almost the same except
for the channels of the input layer. Using the 1-band data and 8-
band data as the input of the autoencoders, and the
corresponding 3-band data as the ground-truth, the
autoencoders are trained by minimizing the loss of equation (4).
Some examples of the visualization results are shown in Figure 7.

3.5 Fine-tuning for cross-modal road segmentation
Based on the pre-trained baseline network and the
autoencoders, the first two layers of the pre-trained network

Figure 5 Some examples of the source data

Figure 6 The examples of the visualization results of the baseline
network

Figure 7 Some visualization examples of the trained autoencoder

Original

Multispectral to RGB

Panchromatic to RGB

(a) (b) (c)
can be fine-tuned for cross-modal road segmentation. The RGB images can be used directly for fine-tuning the network after the preprocessing, while the panchromatic and multispectral images should be converted by the autoencoder. In the fine-tuning process, the loss function in equation (3) is used. As discussed before, the parameters of the autoencoder part are also fine-tuned in this stage.

3.6 Analysis of the results

Through the proposed fine-tuning strategy, the experiment gets fine road segmentation results with very limited training data. To compare with the proposed method, the baseline network is also trained only by using the target dataset. Under the same parameter settings, the baseline network is trained by using 3-band, 1-band and 8-band. The experimental metrics of the proposed method and the compared method are shown in Table I.

Table I Results on testing data of RGB, panchromatic and multispectral band

<table>
<thead>
<tr>
<th>Data format</th>
<th>Recall (%)</th>
<th>Precision (%)</th>
<th>F1 (%)</th>
<th>IOU (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Baseline network</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-band RGB data</td>
<td>67.6</td>
<td>49.5</td>
<td>55.6</td>
<td>39.6</td>
</tr>
<tr>
<td>1-band panchromatic data</td>
<td>64.6</td>
<td>42.0</td>
<td>49.3</td>
<td>33.3</td>
</tr>
<tr>
<td>8-band multispectral data</td>
<td>61.7</td>
<td>40.1</td>
<td>47.8</td>
<td>32.1</td>
</tr>
<tr>
<td><strong>Proposed method</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-band RGB data</td>
<td>63.3</td>
<td>63.9</td>
<td>62.8</td>
<td>46.8</td>
</tr>
<tr>
<td>1-band panchromatic data</td>
<td>57.5</td>
<td>62.7</td>
<td>58.9</td>
<td>43.2</td>
</tr>
<tr>
<td>8-band multispectral data</td>
<td>56.2</td>
<td>51.1</td>
<td>52.4</td>
<td>36.1</td>
</tr>
</tbody>
</table>

With the limited amount of training data, the proposed method got the IOU metric of 46.8, 43.2 and 36.1 per cent on the 3-band, 1-band and 8-band data, respectively. The panchromatic data have fewer channels and the resolution of the multispectral data is insufficient, so that their road segmentation results are not as good as the RGB data. Because the scale of the training data is too small, and there are too many parameters to train an entirely new network, the compared method of simply training the baseline network did not work well, got the IOU metric of 39.6, 33.3 and 32.1 per cent on the 3-band, 1-band and 8-band data, respectively.

Some examples of the visualization results are shown in Figure 8. The “RGB” represents the target testing visible light images, the “P” represents the panchromatic images and the “M” represents the multispectral images. It is obvious that the proposed method performs better than the compared method in every example. For all showed images in Figure 8, the proposed method gets much less false positive pixels, and predicts the edges of the road more clearly. Because our method spends all the training target data on leaning the first two layers, it is stronger in representing the local features. At the same time, the pre-trained model of the proposed method is also better than the newly trained model in representing higher semantic features, resulting in that the proposed method performs much better than the compared method.

The metrics and the visualization results show that the proposed autoencoder and fine-tuning strategy perform well on cross-modal remote sensing road segmentation. Although the ultimate effect of transfer learning method may not be better than that of training on large-scale data directly, it can be used...
quickly when the available cross-modal data are limited and large-scale trained cannot be achieved.

4. Conclusion

In this paper, a method for road segmentation of cross-modal remote sensing images is proposed.

First, a road segmentation network based on an improved U-net architecture is pre-trained under the source data. Based on the pre-trained baseline network, a fine-tuning strategy is raised to updates the parameters of the first two convolutional layers. Additionally, an autoencoder that consists of two convolutional layers is proposed to convert the cross-modal data into an accessible format.

The baseline network is pre-trained on a dataset of RGB remote sensing images and fine-tuned on the target cross-modal data. The experimental results show that the proposed method can effectively segment the roads on the cross-modal remote sensing images. The proposed method needs only a small amount of training data to achieve a similar performance with large-scale data training. Compared with the method of training the baseline network on the target data directly, the proposed method gets much better results, with about 7, 10 and 4 per cent higher IOU on RGB data, panchromatic data and multispectral data, respectively. The experimental results also demonstrate that our inference about the higher semantic features is correct, which means that the parameters of high layers are still useful for cross-modal data. Therefore, the experience can work on other similar cross-modal applications.

The limitation of the proposed method is that annotations are still needed, so that immediately applications are not accessible. For more convenient application that without annotated data, the unsupervised method will be explored, such as domain adaption, for the further researches.

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Radar and vision fusion for the real-time obstacle detection and identification

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Abstract
Purpose – The purpose of this paper is the presentation and research of a novel sensor fusion-based system for obstacle detection and identification, which uses the millimeter-wave radar to detect the position and velocity of the obstacle. Afterwards, the image processing module uses the bounding box regression algorithm in deep learning to precisely locate and identify the obstacles.

Design/methodology/approach – Unlike the traditional algorithms that use radar and vision to detect obstacles separately, the purposed method of this paper uses radar to determine the approximate location of obstacles and then uses bounding box regression to achieve accurate positioning and recognition. First, the information of the obstacles can be acquired by the millimeter-wave radar, and the effective target is extracted by filtering the data. Then, use coordinate system conversion and camera parameter calibration to project the effective target to the image plane, and generate the region of interest (ROI). Finally, based on image processing and machine learning techniques, the vehicle targets in the ROI are detected and tracked.

Findings – The millimeter wave is used to determine the presence of an obstacle, and the deep learning algorithm of the image is combined to determine the shape and the class of the obstacle. The experimental results indicate that the detection rate of this method is up to 91.6 per cent, which can better implement the perception of the environment in front of the vehicle.

Originality/value – The originality is based on the combination of millimeter-wave sensors and deep learning. Using the bounding box regression algorithm in RCNN, the ROI detected by radar is analyzed to realize real-time obstacle detection and recognition. This method does not require processing the entire image, greatly reducing the amount of data processing and improving the efficiency of the algorithm.

Keywords ADAS, Bounding box regression, Millimeter wave radar, Obstacle detection, Radar and vision fusion

Paper type Research paper

1. Introduction
The perception system is the premise and foundation for acquiring the interior and surrounding information of the vehicle to implement an autonomous driving system. To ensure that the system can collect information safely, efficiently, in real time and with precision, autonomous vehicles often require to provide multiple sensors for the perception system (Liu et al., 2014). Such as a camera, Millimeter Wave Radar, LIDAR, and ultrasonic radar, who is responsible for collecting information on pedestrians, traffic signs and vehicles. Either a GPS or inertial measurement unit is for the precise positioning and planning of vehicles.

The detection and identification of obstacles are the most significant parts of the perception system, and they are one of the key technologies of self-driving vehicles and advanced driver assistance systems. Accurate and real-time obstacle detection and identification technologies can be used for autonomous driving assistance such as forward collision warning, adaptive cruise control and auto emergency braking. This system provides decision-making basis to avoid the occurrence of a collision accident and improve the driving safety and driving comfort of the vehicle.

In recent years, many sensors for the environmental perception have been developed and equipped in automobiles to implement obstacle detection and recognition (Liu et al., 2018a). These sensors exhibit high performance in the safety and security of vehicle driving. However, they still have certain hardware and software defects. For instance, the stability, instantaneity and cost factors for the hardware, the processing speed and result accuracy of the software, and the mutual constraints between different performances. On the other hand, the information collected by a single sensor cannot achieve accurate perception of the surrounding environment. Therefore, to ensure the integrity of the collected information and the safety of automatic driving, various devices are required to collect and fuse data (Liu et al., 2018b).

This paper takes the road environment perception technology in the vehicle's autopilot system as the research object, and develops a front obstacle detection and recognition
system. A camera and millimeter-wave radar installed on the vehicle are used to obtain road information in real time, and the data reception, processing, and fusion algorithms of each sensor are studied. The fusion system outputs real-time, accurate, reliable and environmentally adaptive front vehicle information for the autonomous driving system, which is of great significance for avoiding vehicle collision accidents and improving traffic safety.

2. Related work

Millimeter-wave radar and machine vision have their own advantages in environmental perception. Machine vision has the advantages of wide detection range and large amount of information. However, machine vision is affected by weather and light changes, and it is difficult to obtain depth information. Millimeter-wave radar has many advantages such as wide detection range, good adaptability, penetration of rain and fog, and direct access to depth information. Whilst millimeter-wave radar cannot perceive features such as target texture and shape. Consequently, the fusion detection based on millimeter-wave radar and machine vision is considered to be an effective means to reduce environmental noise and improve detection accuracy (Chavez-Garcia et al., 2011). Purposed to obtain richer and more timely access to road environment information, several methods based on millimeter-wave radar and visual fusion are increasingly used for the environmental perception of autonomous vehicles.

Toyota Motor Corporation of Japan proposed an obstacle classification system that incorporates a camera and millimeter-wave radar. First, the millimeter-wave radar selects the most effective candidate image from a large number of images obtained by the camera and establishes a region of interest (ROI). Then, the vehicle within the ROI is identified based on a neural network (Raschhofer and Gresser, 2005). The Fiat company in Italy uses far-infrared cameras and millimeter-wave radar to detect and track obstacles, front vehicles and pedestrians through a centralized data fusion method (Polychronopoulos et al., 2004). However, these methods have low detection accuracy and low real-time performance (Haselhoff et al., 2007).

As one of the machine learning methods, the Adaboost-based classification method has the characteristics of good real-time performance and high recognition rate. It is suitable for the detection of “basic rigid” objects (faces, cars, bicycles, humans). Many researchers (Wang, 2013) and (Huang, 2010) used a combination of millimeter-wave radar and machine vision to detect vehicles in front and used the Adaboost algorithm to identify vehicles. However, this literature focuses on the detection and recognition of vehicles by machine vision and does not discuss the synchronization of multiple sensors in depth. In fact, using the method of combining millimeter-wave radar and machine vision to detect obstacles, accurate mapping and deep integration of different domain information are both important and difficult. For this reason, Zhai et al. (2017) studied deeply the space-time synchronization between radar and machine vision, and on this basis, proposed an obstacle detection method based on millimeter-wave radar and machine vision information fusion, using information from different domains.

Jin et al. (2016) proposed the fusion approach of millimeter-wave radar and machine vision for the vehicle detection by using Dempster-Shafer Evidential Theory. The effect of the calculation amount and the subjective threshold on the detection accuracy is reduced, and the execution speed and accuracy of vehicle positioning are improved. Zeng et al. (2017) proposed a detection method using the Harri-like feature classifier combined with the shadow feature rectangle at the bottom of the vehicle. A classifier based on Harri-like rectangular features is used to detect the entire image, and the ROI region of the image is segmented to determine the coincidence degree of the same target ROI region between the radar and the vision detection.

In general, the current fusion method requires the detection of regions of interest for millimeter-wave and image processing (such as inter-frame difference or shadow detection). Furthermore, the two regions of interest are merged and further analyzed. There are two problems:

1. Millimeter wave and vision are detected after fusion, a large amount of calculation.
2. Normally, the size of the ROI from radar is set based on prior knowledge.

The size and position of the ROI are estimated values, which may lead to incomplete information or excessive information and increase the difficulty of analysis.

3. Fusion model

This paper studies the obstacle detection and recognition technology of the environment perception module in the autonomous vehicle driving, and uses the method of millimeter-wave radar and machine vision data fusion. First, the information of the obstacles can be acquired by the millimeter-wave radar, and the effective target is extracted by filtering the data. Then, use coordinate system conversion and camera parameter calibration to project the effective target to the image plane, afterwards generate the ROI. Finally, based on image processing and machine learning techniques, the vehicle targets in the ROI are detected and tracked. The entire workflow of the system is as shown in the Figure 1, and the data fusion model is introduced in this section. This data fusion
model of radar and vision can be divided into two categories, spatial and time fusion, which represent different aspects of data fusion.

### 3.1 Spatial fusion

The spatial fusion of the millimeter-wave radar and the camera can realize the unification of the millimeter-wave radar coordinate system, the camera coordinate system, the three-dimensional world coordinate system and the image coordinate system (as shown in Figure 2). By this means, the target position information from the radar can be converted to the image acquired by the camera, and the ROI can be generated.

First, the obstacles detected by the millimeter-wave radar are represented as two-dimensional information in polar coordinates. Therefore, it requires to convert this two-dimensional information of the obstacle $P$ into a rectangular coordinate system. Assuming that the $X_R0Y_RZ_R$ plane of the radar coordinate system is parallel to the $XOZ$ plane of the world coordinate system, and the distance between these two planes is. Assume the distance $R$ and angle $\alpha$ of the point $P$ with respect to the radar, the coordinates of the point in the world coordinate system can be determined as follows:

\[
\begin{align*}
    x_R &= R \cdot \sin \alpha \\
    y_R &= -H \\
    z_R &= R \cdot \cos \alpha
\end{align*}
\]

According to the positional relationship between the radar and the camera, and the camera calibration results, the conversion relationship between the world coordinate system and the image coordinate system is shown in equation (2):

\[
\begin{bmatrix}
    x_p \\
    y_p \\
    1
\end{bmatrix} = 
\begin{bmatrix}
    \frac{1}{d_x} & 0 & x_{p0} \\
    0 & \frac{1}{d_y} & y_{p0} \\
    0 & 0 & 1
\end{bmatrix} 
\begin{bmatrix}
    f & 0 & 0 & 0 \\
    0 & f & 0 & 0 \\
    0 & 0 & 1 & 0
\end{bmatrix} 
\begin{bmatrix}
    x \\
    y \\
    z \\
    1
\end{bmatrix}
\]

where $(x_{p0}, y_{p0})$ is the coordinates of a projection point $P$ in the image coordinate system; $d_x, d_y$ are the physical dimensions of each pixel in the $x$-axis and $y$-axis directions respectively; $(x_{p0}, y_{p0})$ represents the main point offset of the camera and $f$ is the focal length; $R$ is the camera external parameter rotation matrix, which is a $3 \times 3$ orthogonal unit matrix; $T$ is a column vector of length 3, which represents the camera external parameter conversion vector. Among the above parameters, $d_x, d_y, (x_{p0}, y_{p0})$ and focal length $f$ are the internal parameters of the camera. $R$ and $T$ are external parameters of the camera. Hence, these parameters can be acquired offline by the camera calibration method.

### 3.2 Time fusion

In the actual perception process, environmental information at different times is also discrepant due to vehicle movement and environmental changes. Especially for vehicles that are moving at a high speed, the momentary differences in time may cause environmental information to vary widely. Consequently, it is required that the environmental information detected by different sensors must be simultaneous to perform data fusion.

To achieve time synchronization, radar threads, camera threads, and data fusion processing threads are created in the program. When the data fusion processing thread is triggered, the system acquires radar data from the buffer queue that consistent with the image data in time. The spatial fusion was then performed using the coordinate transformation, and the millimeter-wave radar and camera data fusion at a certain time can be implemented.

### 4. Obstacle detection and identification

#### 4.1 Obstacle detection based on millimeter wave radar

The radar used in this article is Delphi’s ESR77GHZ millimeter-wave radar, and the range of the radar scanning area is shown in Figure 3. Millimeter-wave radar analyses the relative angles, distances, relative speeds of sixty-four objects, and other information in accordance with a parsing protocol after acquiring data. According to the requirements of self-driving vehicles, the 64 targets detected by the millimeter-wave radar are divided into left-, middle-, and right-lane targets with vehicle distance and angle. Since the main threat of changing lanes or following cars comes from vehicles whose lanes are closest to the vehicle, the target of radar detection is reduced to...
the goal of the three lanes closest to the vehicle. Based on the National Highway Standard, the width of each lane is 3.75m. As the visually recognized vehicle range effective distance R is less than 60 m, the target within this range is regarded as an effective fusion target. Figure 4 shows the projections of vehicles in the pixel space detected by millimeter-wave radar at a certain moment.

Integrated with the equations in Section 3.1, the effective target point of radar can be projected into the image. However, to specifying the shape of the obstacle, the detected target point can be expanded to a ROI. Based on the prior knowledge, such as the aspect ratio of vehicles and the distance, a dynamic ROI is generated for the corresponding point. By this method, it can reduce the search time and the amount of calculations on the image.

4.2 Bounding box regression
The concept of bounding box regression is proposed firstly by Girshick et al. (2014), which can be construed as part of machine learning. The main role of this algorithm in this paper is to accurately locate the ROI and identify the class of obstacles in this region. Each region can be represented by a four-dimensional vector \((x, y, w, h)\), which respectively indicate the center point coordinates, width and height of the region. As shown in Figure 5, the red frame represents the region proposal, as the ROI generated in previous step; whilst the green frame shows the ground truth of the target. Through the

![Figure 4](image-url) An example of the projections of vehicles (the red points) in the pixel space detected by millimeter-wave radar

![Figure 5](image-url) The ROI of a vehicle from radar and its ground truth

mapping of the original window \(P\), a regression window \(\hat{G}\) that is more coincide with the real window \(G\) is obtained.

To express in mathematics: Given a four-dimensional vector \((P_x, P_y, P_w, P_h)\), search for a mapping relationship \(f_t\) such that

\[
f_t(P_x, P_y, P_w, P_h) = \begin{pmatrix} G_x, G_y, G_w, G_h \end{pmatrix}
\]

and

\[
\hat{g}_t(P_x, P_y, P_w, P_h) \approx \begin{pmatrix} G_{\hat{x}}, G_{\hat{y}}, G_{\hat{w}}, G_{\hat{h}} \end{pmatrix}
\]

As explained in pervious paragraph, this kind of projection can be understood as a linear transformation, which may include translation and scaling transformations. Thus, the objective function can be expressed as:

\[
d_t(P) = w^T \Phi_5(P)
\]

where \(\Phi_5(P)\) is the eigenvector of the region proposal \(P\), and \(w\) represents the parameter to learn (* indicates the transformation of \(x, y, w, h\)), \(d_t(P)\) is the predicted value of this regression process.

According to the definition, the purpose is to minimize the difference between the predicted value and the ground truth, which is denoted as \(t^* = (t_{x^*}, t_{y^*}, t_{w^*}, t_{h^*})\). Consequently, the optimum objective function can be summarized in equation (4)

\[
\hat{w} = \arg\min_{\hat{w}} \sum_i \left( t_{i} - \hat{w}^T \Phi_5(P)^i \right)^2 + \|\hat{w}\|^2
\]

5. Experimental verification
To further verify the proposed fusion algorithm, a series of experimental verifications are proceeded. The millimeter wave radar is the main sensor and the camera is used for sensor fusion. The radar is installed under the front bumper of the vehicle, and the camera is located inside the windshield of the vehicle. Several video data are collected on Beijing Fifth Ring Road and Tsinghua University campus roads, and the fusion system is equipped for the environmental perception. The testing results are shown in Table I, and an example of obstacle recognition is shown in Figure 6. The red frame is the generated ROI from radar, and the blue frame represented the revised region after the regression processing.

After comparing some of the video with the subjective judgments of the researchers, it contains 1170 frames of vehicle images. The proposed system has identified 1143 frames of vehicles including 813 cars, 143 trucks and 187 vans, with an average accuracy rate of 91.6 per cent.

6. Conclusion
In this paper, a sensor fusion-based approach is proposed for the obstacle detection and identification. A millimeter-wave radar is used to detect the position and speed of the obstacle, and the effective target is extracted after filtering the returned target information. Through the transformation of the coordinate system, the target position is projected in the road image collected by the camera at the same time, and the detection ROI is generated. The image processing module uses the bounding box regression algorithm in deep learning to precisely locate the ROI. Afterward, the detection and identification of the obstacles can be easily realized by analyzing this precisely ROI. The experimental results indicate that the detection rate of this method is up to 91.6 per cent, which can
better implement the perception of the environment in front of the vehicle.

Comparing with the state-of-art approaches, the innovations of the proposed approach are as following: the millimeter-wave radar is proposed to locate the detection target and generate the ROI. Thus, the image processing module only concentrate on the ROI, which greatly reduces the amount of program calculation; Furthermore, the use of deep learning for bounding box regression can implement accurate positioning and reduce the scope of image identification. The false detection probability of the image processing module is reduced to a great extent, and the accuracy of obstacle perception is further improved.

References


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Online weakly paired similarity learning for surface material retrieval

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Abstract

Purpose – For robots to more actively interact with the surrounding environment in object manipulation tasks or walking, they must understand the physical attributes of objects and surface materials they encounter. Dynamic tactile sensing can effectively capture rich information about material properties. Hence, methods that convey and interpret this tactile information to the user can improve the quality of human–machine interaction. This paper aims to propose a visual-tactile cross-modal retrieval framework to convey tactile information of surface material for perceptual estimation.

Design/methodology/approach – The tactile information of a new unknown surface material can be used to retrieve perceptually similar surface from an available surface visual sample set by associating tactile information to visual information of material surfaces. For the proposed framework, the authors propose an online low-rank similarity learning method, which can effectively and efficiently capture the cross-modal relative similarity between visual and tactile modalities.

Findings – Experimental results conducted on the Technischen Universität München Haptic Texture Database demonstrate the effectiveness of the proposed framework and the method.

Originality/value – This paper provides a visual-tactile cross-modal perception method for recognizing material surface. By the method, a robot can communicate and interpret the conveyed information about the surface material properties to the user; it will further improve the quality of robot interaction.

Keywords Online similarity learning, Robotic cross-model perception, Surface material retrieval, Weak pairing

Paper type Research paper

1. Introduction

When interacting with the surrounding environment in object manipulation tasks or walking, robots need to understand the physical attributes of objects and surface materials they encounter before performing certain actions (Yuan et al., 2017; Zheng et al., 2018). Based on these properties information, a robot can select a suitable movement strategy or interaction mode during interaction with the target object (Burka et al., 2017). If a robot can interpret the conveyed information about the surface material properties to the user, it will further improve the quality of robot interaction. Hence, how to effectively convey and interpret the surface material properties becomes a problem that needs to be solved for human–machine interaction, particularly in a remote unstructured environments.

For perceiving material properties, dynamic tactile sensing can provide rich information about material properties (Kroemer et al., 2011). Nowadays, various tactile sensors have been widely used for material recognition. Kerr et al. (2018) collected tactile information by the BioTAC sensor and used this information to classify the material. Liu and Sun (2018) used tactile information to identify materials by dictionary learning. On the other hand, induced vibration signal also

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Industrial Robot: the international journal of robotics research and application 46/3 (2019) 396–403
© Emerald Publishing Limited [ISSN 0143-991X] [DOI 10.1108/IR-09-2018-0179]

This work was supported by the National Natural Science Foundation of China under Grant 61673238; in part by the Key Project of Natural Science Foundation of Hebei Province No. E2017202035; and in part by Joint Doctoral Training Foundation of HEBUT 2017GN0006.

Received 9 November 2018
Revised 20 January 2019
Accepted 25 January 2019
contains relevant tactile information about material properties of the surface during sliding contact with an object surface (Ji et al., 2015). There are many studies using induced vibration signals to recognize surface material. For example, Strese et al. (2015) used three-axes acceleration signals recorded during free sliding for surface materials classification. In addition, the robotic finger with a built-in three-axes accelerometer is used to distinguish different surface materials by detecting vibrotactile signals (Sinapov et al., 2011).

From the above works, these dynamic tactile information delivering material properties are usually high-dimensional time-series data. The users cannot intuitively obtain information related to material properties from this high-frequency information during interaction, particularly in the case of interacting with unfamiliar objects. In this respect, it is necessary to interpret these dynamic tactile-sensing information for observing the material properties of an object. However, the interpretation of dynamic tactile data has yet been fully taken into consideration. Therefore, how users use dynamic tactile information to observe material properties is still an open question.

In fact, humans can estimate the material properties of an object from its images through imagining tactile perception. This is mainly because the human brain can use the shared model obtained to transfer knowledge about material properties from tactile modality to visual modality after obtaining sufficient experience (Kerr et al., 2018). This sharing and transfer mechanism of information is especially useful when one sensing modality cannot be used or suitable in some application. Inspired by this mechanism, we seek to enable robots to use a tactile sensor to autonomously explore objects and report back a list of images describing the characteristics of the material. In other words, we use relevant tactile data of an unknown surface to retrieve perceptually similar surface images from an available known surface sample set to estimate material properties of an unknown surface.

Similar to other cross-modal retrieval, visual-tactile cross-modal retrieval also faces the problem that similarity of data from different modalities cannot be directly calculated because data of different modalities usually have very different representations (Liu et al., 2017). How to effectively measure similarities between data of heterogeneous modalities has become a core issue in visual-tactile cross-modal surface material retrieval. Therefore, it is necessary to explore an effective method for similarity measurement. However, the high heterogeneity between visual modality and tactile modality makes it a non-trivial problem that requires careful consideration.

Most of existing methods of cross-modal pairwise correlation learning require one-to-one samples as training data to discover cross-modal correlation (Kuang and Wong, 2015). Namely, any two training samples from different modalities are paired samples or unpaired samples. However, obtaining absolutely paired vision and tactile samples is very difficult or even impossible in real-world applications. It is more suitable to adopt weakly paired relation than absolutely paired relation in visual-tactile cross-modal retrieval. For instance, given an input query of tactile data, the robot will return a list of more-likely-paired surface images with the input tactile data, rather than absolutely paired image. In fact, weakly paired is a general form of absolutely paired. Triplet loss network (Wen et al., 2016) can be used to capture cross-modal relation of weakly paired samples.

Since differences between pairwise similarities may vary from triplet to triple, it results in that a fix margin used in existing methods may be not beneficial for relative similarity learning (Wu et al., 2017). Moreover, it requires high computational complexity when we perform triplet sampling in the whole sample space or in batch styles, which also greatly limits its application.

In this paper, we propose an online low-rank similarity learning method for cross-modal surface material retrieval, which adopts relative pairwise similarity and adaptive margin to learn a cross-modal similarity function between visual modality and tactile modality through an efficient online learning technique. Different from most existing works, our method relies on neither prior distribution assumption nor statistics calculation. Moreover, unlike batch training methods involving high computational complexity, online learning be able to improve the scalability in larger-scale data sets. To further improve the efficiency of training, we enforce the low-rank constraint on the online learning process of similarity function. The main contributions of this work can be summarized as follows:

- A low-rank similarity learning method is proposed for cross-modal surface material retrieval through an efficient online learning technique.
- We use relative pairwise similarity and adaptive margin to learn a cross-modal similarity model between visual modality and tactile modality, which is suitable for visual-tactile weakly paired problem.
- Experiments results conducted on the Technischen Universität München (TUM) data set show the effectiveness of the proposed cross-modal retrieval framework and the online low-rank similarity learning method.

The remainder of the paper is organized as follows: Section 2 provides some related works of cross-modal retrieval and online similarity learning. In Section 3, we formulate the problem of cross-modal surface material retrieval. Section 4 details low-rank relative similarity learning method and online learning optimization algorithm. Experimental results and evaluations are presented in Section 5.

2. Related work

2.1 Cross-modal retrieval

The mainstream method of cross-modal retrieval is to seek a low dimension latent common subspace. By projecting features from different modalities into a shared subspace, the similarity of the transformed features can be directly computed using common distance metric. Canonical correlation analysis (CCA) (Hardoon et al., 2004) is the naive method of common subspace learning, which uses a pair of matrices to project original features of pairwise samples from different modalities into a lower-dimensional common subspace, and gets the same dimension shared representation. Sharma et al. (2012) proposed generalized multiview analysis for cross-view classification and retrieval which is a supervised extension of CCA. In addition, Kroemer et al. (2011) presented weakly paired maximum covariance analysis (WMCA), which aims at
finding a latent space to maximize the covariance between transformed features of cross-modal pairwise samples by alternatively finding element pairs.

Recently, deep learning, which can effectively learn complex nonlinear correlation by deep neural network (DNN), has been proposed for cross-modal retrieval. Kim et al. (2013) used a pair of deep belief network to learn high-level features of two languages, and then used CCA to learn representation in a common subspace. Andrew et al. (2013) developed deep CCA to model complex correlation of the two different modalities data. Feng et al. (2015) adopted a deep correspondence restricted Boltzmann machine to model the correlation between cross-modal data for retrieval.

Although these methods have been successfully employed in some cross-modal retrieval tasks, they either explicitly or implicitly assume the transformed features of different modalities have similar distribution and they are indiscriminate for modalities in a latent common subspace. When real data does not meet the assumptions, the final result will be unreliable. Moreover, optimization objectives of these methods are not directly learned for information retrieval.

2.2 Online similarity learning
Online learning learns models from data in a sequential manner. Unlike batch learning methods that often suffer from high computational complexity when new training samples are collected sequentially (Wu et al., 2016), online learning provides an efficient updates method for each new training sample, making it scalable to large-scale learning problems in practice. Due to the efficiency and scalability of online learning, it has been widely applied to similarity measurement. For example, Grangier and Bengio (2008) proposed using the online PA model to directly learn a similarity model for retrieval by adopting a learning criterion associated with the retrieval performance. Chechik et al. (2009) developed an online learning algorithm OASIS for pairwise similarity learning in single modality.

3. Problem formulation
The framework of cross-modal surface material retrieval using cross-modal similarity learning is illustrated in Figure 1, which consists of training stage and retrieval stage. In training stage, training samples of visual and tactile modalities are used to learn a similarity model by cross-modal correlation. In the retrieving phase, the similarity score between given tactile sample and each sample from gallery visual sample set can be computed by the learned model.

Given training set of two modalities, \( U = [u_1, u_2, \ldots, u_n] \in \mathbb{R}^{d_v \times n} \) and \( T = [t_1, t_2, \ldots, t_n] \in \mathbb{R}^{d_t \times n} \), respectively, denote visual features and tactile features. The number \( d_v \) and \( d_t \) are the corresponding dimension numbers of the feature vector, and the number \( n \) denotes the numbers of the training visual samples and tactile samples. Each visual and tactile sample is assigned with a corresponding category one-hot label \( y_i \in \mathbb{R}^C \), where \( C \) is the category number of the data set.

Due to modal discrepancy, visual features and tactile features usually have different feature dimension, namely, \( d_v \neq d_t \), so their similarity cannot be directly measured. Even if \( d_v = d_t \), it is still difficult to effectively measure their similarity since visual modality and tactile modality are highly heterogeneous data.

In addition, as visual samples and tactile samples are collected separately, there is no one-to-one absolutely paired relation between \( u_i \) and \( t_j \), for \( i = 1, 2, \ldots, N_v \) and for \( j = 1, 2, \ldots, N_t \). We only can use the category label of samples to construct the class pair, which is classical weakly paired problem (Kroemer et al., 2011). Therefore, the problem of visual-tactile cross-modal retrieval is how to learn a similarity model from weakly paired samples. The main challenging problems of visual-tactile cross-modal retrieval are summarized as followings:

- Since visual and tactile modalities are heterogeneous data, which usually exhibit different distribution and representation, their similarities are difficult or even impossible to be effectively measured by conventional distance metric.
- For the visual-tactile cross-modal retrieval, how to effectively learn a similarity measure model with weakly paired visual and tactile samples is still a challenging issue.

4. The proposed method
4.1 Low-rank relative similarity learning
To address the aforementioned problems, it is critical to learn an effective similarity function to measure the pairwise relevance between weakly paired samples. In this work, instead of explicitly finding a common subspace, we adopt the triplet network to express cross-modal relative similarity relations of tactile and visual modalities, which can be represent by two types of triplets \( (t_i, u_j^+, u_j^-) \in \prod_v \) and \( (u_i, t_j^+, t_j^-) \in \prod_v \). Considering the fact we use tactile modality to retrieval visual modality, we only use \( (t_i, u_j^+, u_j^-) \) to illustrate the model in the direction of tactile-to-visualization. In \( (t_i, u_j^+, u_j^-) \), \( u_j^- \) is a matching sample and \( u_j^+ \) is a mismatching sample for \( t_i \), and \( u_j^- \) is more relevant than \( u_j^+ \) and \( t_i \).

The goal of the relative similarity learning to find a similarity function \( s(t_i, u_j) \), which needs to satisfy the following the triple constraint conditions:
The similarity of visual-tactile heterogeneous modalities $s(u_t, t_j)$ can be formulated by a asymmetric bilinear function:

$$s(t_i, u_j) = t_i^T W u_j,$$  

(2)

where $W \in \mathbb{R}^{d \times d}$ is the similarity measure model. Since this bilinear function can be seen as a linear projection on joint feature of $t_i u_j^T$, interaction between visual modality and tactile modality can be measured (Wu et al., 2017). The advantage of our model over distance metric is that the dimension of features does not need same. Although our similarity function only considers inter-modal samples, the cross-modal correlations also affect the relation in one modality.

To further improve performance of the model, we introduce a margin $\delta$ into the relative similarity constraint as:

$$s(t_i, u_j^+) > s(t_i, u_j^-) + \delta,$$  

(3)

However, for different triples $(t_i, u_j^+, u_j^-)$ and $(t_i, u_j^-, u_j^+)$, the difference $s(t_i, u_j^+) - s(t_i, u_j^-)$ and $s(t_i, u_j^-) - s(t_i, u_j^+)$ may be very different. An example is shown in Figure 2, given a tactile sample $t_i$ describing carpet belonging to fibers, image $u_j$ depicting carpet, image $u_k$ depicting jeans belonging to fabrics, image $u_{k'}$ depicting beech belonging to wood, the difference $s(t_i, u_j) - s(t_i, u_k)$ should be larger than $s(t_i, u_j) - s(t_i, u_{k'})$, since physical properties similarity of carpet and jeans is more-like larger than those of carpet and beech.

As shown in Figure 2, although both visual samples $u_j$ and $u_{k'}$ belong to different class with a given tactile sample $t_i$, image $u_j$ is more relevant to a given tactile sample $t_i$ than image $u_{k'}$ and the margin $\delta$ should be more small. Therefore, we define an adaptive margin function of $u_i$ and $u_j$, where label information and feature similarity are considered simultaneously. The function can be expressed as:

$$s(t_i, u_j^+) > s(t_i, u_j^-) + \delta.$$

(4)

$$\delta(u_i, u_j) = \beta \left( \alpha ||u_i - u_j||^2 + (1 - \alpha) ||y_i - y_j||^2 \right),$$  

(4)

where $||.||^2$ represents Euclidean distance, $\alpha$ is weight coefficient determining the relative importance of label information and feature similarity, and $\beta$ is used to adjust suitable margin.

Then, the constraint function of the model can be defined by hinge loss function, which is formulated as:

$$l(W, t_i, u_i^+, u_j^-) = \max \left( 0, s(t_i, u_i^+) - s(t_i, u_j^-) + \delta(u_i, u_j) \right),$$  

(5)

The objective function of overall training set $D_{train}$ is modeled as:

$$L(W) = \sum_{D_{train}} l(W, t_i, u_i^+, u_j^-)$$  

(6)

Please note that computing a similarity score with full rank $W$ in equation (2) need $O(d^2 \times d^2)$ operations. When the feature dimension $d^2$ and $d^2'$ are high, the computation is quite complex. When enforcing a low-rank constraint on matrix $W$, the computation complexity of $s(.)$ can be dramatically improved. If rank of the matrix $W$ is $k$, operations of computing a similarity score will reduce to $O((d^2 + d^2')k)$. Moreover, low-rank constraint also provides a regularization for the model. Adding a low-rank constrain into the matrix $W$, the formally optimization function of the model can be formulated as

$$W = \arg\min_{W} L(W), \quad s.t. \ rank(W) = k$$  

(7)

### 4.2 Online learning optimization algorithm

Considering the efficiency and scalability of online learning, we adopt online learning scheme to optimize low-rank constrain objective function. The low-rank constraint is not convex, and it makes the online learning optimization difficult. The two naive methods of low-rank matrices learning, which are repeated singular value decomposition and optimizing a factored representation of the low-rank matrix, are either involved high computational complexity or numerically unstable. Fortunately, Shalit et al. (2012) proposed an iterative online optimization algorithm for low-rank matrices learning. In the following, we will respectively denote $d^2$ and $d^2'$ as $m$ and $n$ for convenience.

Following this work (Shalit et al., 2012), we perform stochastic gradient descent to optimize the loss function $L(W)$ over the manifold of low-rank matrices $M_k^{m \times n}$.

$$W = \arg\min_{W} L(W), \quad s.t. \ W \in M_k^{m \times n}$$  

(8)

where $M_k^{m \times n}$ is the set of $n \times m$ matrices of rank $k$. Since the common projection operation during gradient step involves singular value decomposition, it is too costly to calculate the embedded manifold of low-rank matrices. To reduce the computational complexity, reactions operation is introduced for low-rank matrices embedded manifold as an alternative to projection operation, which can capture the gradient direction
of a point on the manifold. The mathematically ideal retractions are the exponential mapping, while second-order retractions perform a second-order approximate of exponential mapping. It has been demonstrated that second-order retraction on the embedded manifold can be used to perform projection-like operations (Absil and Malick, 2012).

Based on the illustration described above, the model $W$ acts as bilinear form of $u_i$ and $t_b$ and the loss $L(W)$ is a linear function of $u_i^T W t_b$. At every iteration, the gradients of the loss function in the equation (5) is:

$$
\frac{\partial L(W, t_b, u_i^*, u_j^*)}{\partial W} = t_b (u_i^* - u_j^*)^T.
$$

(9)

Obviously, the gradients are a rank-one matrix. Given rank-one gradients, we use rank-one stochastic gradient descent algorithm (Wu et al., 2017) to learn the similarity matrix model $W$. The online low-rank similarity learning model for visual-tactile cross modal retrieval is summarized in Algorithm 1:

**Algorithm 1 Online Low-rank Similarity Learning Model for visual-tactile cross modal retrieval**

**Input**: $W_n \in M^{m,n}$, $A_0 \in R^{m \times k}$, $B_0 \in R^{n \times m}$ s.t. $W_0 = A_0 B_0^T$. $U = \{u_1, u_2, \ldots, u_n\}$ and $T = \{t_1, t_2, \ldots, t_m\}$. Rank $k$.

**Output**: The final low-rank matrix $W \in M^k_{m,n}$

1. Generate a set of triplet training samples $\prod = \{(t_i, u_i^*, u_j^*)\}$ using uniform sampling technique
2. Initialize $A_k$ as $m \times k$ matrix with mean 0 and standard deviation 1.
3. Initialize $B_k$ as $n \times k$ matrix with mean 0 and standard deviation 1.
4. for all $(t_i, u_i^*, u_j^*) \in \prod$
5. $p = \eta \varepsilon_i$, $q = u_i - u_j$, where $\eta$ is the size of gradient descent step.
6. $a_3 = A_{k-1}^* p$, $b_1 = B_{k-1}^* q$, where $\dagger$ denotes the pseudo-inverse.
7. $a_2 = A_{k-1}^* a_1$.
8. $s = b_1^T a_2$.
9. $a_3 = a_2 - \frac{1}{2} + \frac{1}{2} s + p (1 - \frac{1}{2} s)$
10. $A_k = A_{k-1} + a_1 b_2^T$.
11. $b_2 = (q^T B_{k-1}) B_{k-1}^* q (1 - \frac{1}{2} s)$
12. $b_3 = b_2 - \frac{1}{2} + \frac{1}{2} s + q^T (1 - \frac{1}{2} s)$
13. Rank-one Update $(A_{k-1} a_3 b_1) \rightarrow A_{k}^\dagger$
14. Rank-one Update $(B_{k-1} b_3^T a_1) \rightarrow B_{k}^\dagger$
15. end for
16. return $W = A_k^\dagger B_k^{\dagger T}$

5. Experiments

5.1 Data set

We use the TUM Haptic Texture Data set (Strese et al., 2017) to evaluate cross-modal surface material retrieval framework and the online low-rank similarity learning (OLRSL) model. The TUM data set is composed of tactile acceleration traces and texture images for 108 different texture surface material instances. Based on the material attribute, these surface materials were divided into nine categories, which are meshes, stone, glossy, wood, rubber, fibers, foams, foils and papers, textiles and fabrics. The number of surface material instances in each category is between 5 and 17. The data set includes a training set and a testing set, where each set includes 108 texture surface material instances and every instance has ten tactile acceleration traces and ten surface images (Strese et al., 2015).

In this work, we reorganize the TUM data set and combine the training set and testing set for each material instance. According to the reorganization way, we can obtain 20 tactile traces samples and 20 image samples for each surface material, respectively. Then, we randomly select an image and a tactile trace from 20 corresponding samples for 108 surface materials as gallery visual samples set and tactile query set, and the remaining surface material samples as training sample.

5.2 Feature extracting

Tactile modality: In the TUM data set, tactile signals are three-axes acceleration signals. We use a 10 Hz-1kHz band-pass filter to remove the effect of noise on the signals (Strese et al., 2014). Then the filtered three-axes acceleration signals are combined into one-dimensional signal using DFT321 algorithm (Kuchenbecker et al., 2010). This method preserves temporal and spectral properties of the three axes components and reduces the dependency of the signal on the device inclination toward the surface. Then, we use power spectrum density (PSD) to extract feature of the 1-D DFT321 acceleration signals, where these parameters of PSD can refer to (Zheng et al., 2016). The top 5000 values are used as the features of tactile samples, and then reduce the dimensionality of PSD features into 200-dimension for nonlinear transformation by principal components analysis (PCA).

Visual modality: We choose the set of images without conditional light as the visual samples from two image sets. Recently, deep convolutional neural networks (CNN) are considered as the efficient tool for extracting image feature. What’s more, there are some pretrained CNN models on ImageNet which can directly be used to extract image features. In this work, we use the pretrained VGG16 (Simonyan and Zisserman, 2014) model to extract 4096 dimension image features for the visual samples and employ PCA to reduce it into 512 dimension.

5.3 Evaluation metric

In this experiment, the mean average precision (MAP) (Rasiwasia et al., 2010) is used as the major metric to evaluate the retrieval performance of the model. Given a tactile query, the average precision (AP) can be computed by:

$$
AP = \frac{\sum_{k=1}^{R} P(k) r(k)}{\sum_{j=1}^{R} r(j)}
$$

(10)

where $R$ is the number of samples in the retrieval set, $P(k)$ is precision at position $k$, $r(k)$ denotes the relevance of $k$-th result (if relevant $r(k) = 1$, otherwise $r(k) = 0$). A retrieved item is considered as relevant if it has the same class label with the query sample. The MAP is computed by averaging AP of all the
queries. In addition, we use precision-scope curve and precision-recall curve (Wang et al., 2016) for more comprehensive evaluation.

5.4 Comparison methods
In this experiment, we compare our proposed OLRSL method with five cross-modal retrieval methods on the TUM data set to verify the effectiveness of our method. The comparison methods are CCA, MCCA, CCCA, WMCA and DCCA. These compared methods are briefly presented as follow:

- CCA (Hardoon et al., 2004) projects two different modalities features into a shared subspace, where the pairwise correlations of projected feature is maximized by a couple of linear projections.
- MCCA (Rasiwasia et al., 2014) is the most intuitive way to handle weakly paired multi-modal data. It performs a CCA operation on the average mean of the same class samples between the two modalities.
- CCCA (Rasiwasia et al., 2014) uses class-labels to learn a common feature space, where all samples from one modality within a class label are paired with all samples from the other modality in the same class labels and thereafter the projections are learned using CCA.
- WMCA (Kroemer et al., 2011) aim at find a latent space to maximize the covariance between transformed features of pairwise samples from different modalities by alternatively finding element pairs. Class label information is imposed into the covariance matrix.
- DCCA (Andrew et al., 2013) is a method to learn nonlinear transformations to project two modality paired data into a common space using two separated DNNs, where the correlations of their outputs is maximized.

CCA and DCCA are the classical methods which use pairwise information to learn a common shared subspace, while MCCA, CCCA and WMCA are supervised methods which exploit the class label information to learn common feature representation. Considering that the supervised methods can learn discriminative shared feature using the label information, they may be more suitable for weakly paired matching.

5.5 Experimental results
In this section, we show experimental results on the TUM data set. The performance of our proposed model OLRSL and the compared methods are evaluated, where query samples are tactile modality and the retrieval set is visual modality. Table I summarizes the best values of MAP scores and average precision (top-5) of different methods.

<table>
<thead>
<tr>
<th>Model</th>
<th>MAP</th>
<th>Average precision (top-5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCA (Hardoon et al., 2004)</td>
<td>0.234</td>
<td>0.267</td>
</tr>
<tr>
<td>MCCA (Rasiwasia et al., 2014)</td>
<td>0.166</td>
<td>0.146</td>
</tr>
<tr>
<td>CCCA (Rasiwasia et al., 2014)</td>
<td>0.172</td>
<td>0.261</td>
</tr>
<tr>
<td>WMCA (Kroemer et al., 2011)</td>
<td>0.268</td>
<td>0.261</td>
</tr>
<tr>
<td>DCCA (Andrew et al., 2013)</td>
<td>0.321</td>
<td>0.343</td>
</tr>
<tr>
<td>OLRSL</td>
<td>0.4258</td>
<td>0.4526</td>
</tr>
</tbody>
</table>

As shown in Table I, it can be found that the proposed model OLRSL achieves the highest MAP and average precision (top-5). It means that the proposed model can get more relevant objects than other methods when checking the same number of search results. These results demonstrate that our method is effective in weak-paired cross-modal surface material retrieval.

Compared with CCA, the supervised methods CCCA and MCCA fail to achieve class discrimination. Since MCCA ignores feature discrepancy of different instances from same class, it is not suitable to weak-paired matching of different instance within same class label. Due to that the number of pairwise correspondences in CCCA grows quadratically with the number of samples per class, it is difficult to capture their complex correlations for by linear projection matrices. By adopting the DNNs to model complex correlation, DCCA shows superior performance than CCA. As DCCA only maximizes cross-modal correlation and ignores label information, DCCA is not able to learn the class discrimination shared features. The proposed OLRSL method achieves significant improvement than compared methods, which combine the weak-paired pairwise and low-rank constraints in a similarity learning process.

For further analysis, the precision-scope curves and precision-recall curves of all approaches are shown in Figure 3. From the precision-scope curves in Figure 3, we can observe that our method obtains more correct matching visual sample in the returned top k ∈ [1, 100] retrieval results. It is clear that the precision-recall curve of our method is almost always above those of the compared methods, as shown in Figure 3. It means that our method ranks more relevant objects in front of the retrieval results list.

5.6 Parameter sensitivity analysis
The parameters α and β are important parameters for the OLRSL model. α controls the relative importance of label information and feature similarity, and β controls margin. To analyze the impacts of these parameters α and β on the performance of the OLRSL model, we do grid search for the parameters α within the set [0, 0.1, 0.2, 0.4, 0.6, 0.8, 1.0], and β within the set [0.01, 0.1, 1, 10, 100] to determine the optimal value through cross validation in the model. Figure 4 depicts the relationship between MAP and α and β. It can be seen that MAP is sensitive to the parameter α and β, and the model achieve optimal performance when α is 0.8 and β is 0.01.

From the above, the margin function δ of the proposed OLRSL model includes two components. Please note that α = 0 represent the margin δ with label information only, and α = 1 represent the margin δ with feature similarity only. As shown in Figure 5, adopting adaptive margin, which integrates label information and feature similarity into a margin function, is beneficial to improve retrieval accuracy.

In addition, we further conduct experiments to study the roles of the rank k in the model. Figure 5 shows the MAP of the OLRSL model with different rank k in the range of {5, 10, 15, 20, 25, 30, 35, 40}. When the rank k is set to 25, the model can achieve optimal retrieval performance.
6. Conclusion

In this work, we adopt a visual-tactile cross-modal retrieval framework to convey and interpret tactile information of surface material for perceptual estimation. To this end, we propose an online OLRSL method, which can effectively and efficiently capture the cross-modal relative similarity between visual and tactile modalities. Experimental results demonstrate the effectiveness of the proposed cross-modal retrieval framework and the low-rank similarity learning method. The cross-modal perception provides a useful method to improve the quality of robot interaction.

References


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Natural teaching for humanoid robot via human-in-the-loop scene-motion cross-modal perception

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Abstract

Purpose – This paper aims to present a human-in-the-loop natural teaching paradigm based on scene-motion cross-modal perception, which facilitates the manipulation intelligence and robot teleoperation.

Design/methodology/approach – The proposed natural teaching paradigm is used to telemannipulate a life-size humanoid robot in response to a complicated working scenario. First, a vision sensor is used to project mission scenes onto virtual reality glasses for human-in-the-loop reactions. Second, motion capture system is established to retarget eye-body synergic movements to a skeletal model. Third, real-time data transfer is realized through publish-subscribe messaging mechanism in robot operating system. Next, joint angles are computed through a fast mapping algorithm and sent to a slave controller through a serial port. Finally, visualization terminals render it convenient to make comparisons between two motion systems.

Findings – Experimentation in various industrial mission scenes, such as approaching flanges, shows the numerous advantages brought by natural teaching, including being real-time, high accuracy, repeatability and dexterity.

Originality/value – The proposed paradigm realizes the natural cross-modal combination of perception information and enhances the working capacity and flexibility of industrial robots, paving a new way for effective robot teaching and autonomous learning.

Keywords Humanoid robot, Cross-modal perception, Human-in-the-loop, Motion imitation, Natural teaching

1. Introduction

In recent years, demands for industrial robots with high intelligence have shown a tremendous growth in military, medicine, manufacturing and social life. Industrial robots are increasingly faced up with challenges of executing complicated tasks in unstructured environments, such as welding tracking on a curved surface, sorting and placing of scattered workpieces with surfaces of multiple types, like...
three-way valves and flanges and so on. Many paradigms are adopted to improve the ability of robots to perform complex tasks based on data-driven methods (Deisenroth et al., 2013; Bohg et al., 2014; Mnih et al., 2015; Levine et al., 2018). However, with limited data, those data-driven methods alone tend to have a poor performance. Under such a circumstance, the combination of teaching and machine learning to cope with the lack of data has achieved good results (Koenig and Mataric, 2017; Finn et al., 2017; Michini et al., 2013; Kassahun et al., 2016; Osentoski et al., 2012). As a direct way to endow industrial robots with human’s knowledge, teaching renders the intelligence development of robots more than possible.

As a matter of fact, traditional teaching methods are faced with multiple difficulties. First, when teaching is performed for complicated motions with multiple degree of freedom (DOF), an expert is necessary for demonstration and the effect of teaching highly depends on his knowledge. The numerous frames of continuous movements will cause a sharp increase in the amount of teaching information, thus placing a heavy burden on the expert (Silver et al., 2012; Laskey et al., 2016; Koert et al., 2016). Second, to facilitate robots to understand human’s teaching information and to develop intelligence, behavior recognition and semantic classification are necessary, while conventional demonstration methods often neglect the transmission of semantic information (Wächter and Asfour, 2015; Lim, 2016; Rozo et al., 2016; Alibeigi et al., 2017). Third, the ability to make decisions based on multiple kinds of sensory information is an important manifestation of human intelligence while conventional demonstration methods generally overlook or misunderstand the relations between different sensory information (Lim and Okuno, 2014; Noda et al., 2014).

Considering children’s learning process, they observe the behavior of adults and then reproduce it (Riley et al., 2003). Such a process is always natural and effective because human beings share the same way to comprehend scenes and the same behavioral language. Inspired by this, natural teaching is the key to overcoming obstacles to the exchange of teaching information between human and robots. Natural teaching is actually a branch of human-robot interaction (HRI) technology, representing a kind of teaching paradigm which is user-friendly and coordinates human and robot in scene comprehension. Aimed at completing tasks with specified human semantic information, natural teaching is an end-to-end and highly efficient method for interaction with surroundings or complicated movements. Moreover, fulfilling such tasks is conducive to establishing a deep understanding of potential implications from training data through subsequent intelligence algorithms, thus achieving a high level of intellectual development.

Scene-motion cross-modal perception constitutes a critical component of natural teaching. Enlightened by role-playing in E-sports, the demonstrator is provided with visual information to perceive the mission scenario of the robot and then implements movements. The demonstrator’s eye-body synergic movements are collected as motion information. Thanks to VR (Virtual Reality) and HRI technology, the robot and the demonstrator can share the common visual and motion information during the whole teaching process. Through such a perception system, the robot can achieve the cross-modal combination of scene and motion information, while the demonstrator can have an overall cognition of the surroundings from first person view (FPV), analyze complicated information and make movement decisions. Furthermore, the recording of intricate multi-DOF movements, as well as the live video stream, provides the robot with comprehensive scene-motion information so that the robot can be gradually endowed with the ability to repeat the same process. In the near future, the robot can even develop the capability of making autonomous decisions through such a natural teaching paradigm.

Employing humanoid robots as a platform to verify the natural teaching paradigm with scene-motion cross-modal perception can provide numerous advantages. First, since humanoid robots possess human-like structures and scales that have evolved for millions of years, the abundant DOF and the complex joints between links of a humanoid can represent an industrial robot with an extremely complicated structure. Second, the excellent mobility potential of humanoid robots renders it possible for them to be assigned with different tasks (Koenemann et al., 2014). Third, humanoids can serve as a direct and natural platform for natural teaching. As they can completely reflect human motion, demonstrators can easily assess the difference between human motion and robot imitation during motion synchronization. Demonstrators can further consider the conversion of postures from human to the robot and optimize the conversion rules against corresponding problems (Argall et al., 2009).

Herein we report a human-in-the-loop natural teaching paradigm with motion-scene cross-modal perception on a life-size humanoid robot. The robot is established based on InMoov, an open-sourced 3D printing humanoid robot. It possesses 29 DOF, 22 of which are controlled in this system. The following is the natural teaching process. First, a vision sensor is employed to project the mission scene onto the VR glasses. Second, motion perception captures the motion of human with a set of wearable sensors and presents the collected motion data in BVH (BioVision Hierarchy) format. The motion data are transmitted to an industrial PC (IPC) through TCP/IP and parsed according to BVH format. Next, the parsed Euler angles are converted to corresponding joint angles through a fast mapping algorithm and encapsulated in a communication protocol. At last, IPC sends joint angles to the slave controller to control the robot. The whole system has paved a novel, real-time and accurate way for a natural teaching paradigm on humanoid robots.

This paper is organized as follows. In Section 2, the scene-motion cross-modal perception system is introduced. Section 3 discusses the setup of the humanoid robot. Section 4 presents the scheme of real-time motion imitation on the humanoid. Section 5 performs several experiments based on the proposed natural teaching paradigm. Finally, section 6 deals with the conclusion about our work.

2. Scene-motion cross-modal perception

The framework of the cross-modal perception system is shown in Figure 1. Scene perception makes it possible for the demonstrator to remotely perceive the complicated surroundings around the robot, while motion perception passes back real-time human motions to the controller. The combination of scene and motion perceptions takes full advantage of human’s intelligence because
each movement in the loop is determined by human and reflected on the robot.

2.1 Scene perception

Scene perception is achieved through a remote video stream and multiple display terminals. Figure 2 shows its principle and the video stream. The main function of scene perception is to stream the live video recorded by Raspberry Pi Camera to the demonstrator. Since the camera is installed in one eye of the robot, the demonstrator wearing VR glasses can make decisions about movements from FPV. Besides, multiple display terminals make it possible for users to watch the same video stream on different electrical devices.

2.1.1 Remote video stream

Raspberry Pi is selected as the processing unit to drive the Pi camera for remote live video monitoring. The video obtained from Raspberry Pi is encoded in H.264 format, which is barely supported in browsers. Hence, FFmpeg (Fast Forward mpeg) is adopted to convert the H.264 format to the MPEG1 format. The video stream is then uploaded to an HTTP server through ws4py. Decoding is completed with JSMpeg, an excellent MPEG1 video and MP2 audio decoder defined in JavaScript. At most 30 fps video with a resolution of 1280 × 960 can be decoded by JSMpeg. Since JSMpeg is based on JavaScript, the video stream works in most modern browser (i.e. Firefox, Edge, Chrome, etc.). Moreover, the decoder has a low latency via WebSockets, thus achieving the real-time feature of our work.

2.1.2 Multiple display terminals

Display terminals include VR glasses and webpages. The type of VR glasses we adopt is Royole Moon, a combination of a headset, vari-focusing glasses, and a control terminal. The operating system of Royole Moon is Moon OS developed based on Android. What’s more, it provides free access to the external network, which means users can access the live video stream and perceive the mission scene at a distance. However, since the video capture is accomplished using one camera, all videos are two-dimensional. It is inevitable that some necessary information will be lost if the demonstrator watches the screen alone. Therefore, some external assistance is required to improve the user experience. For webpage terminals, the principle is basically the same with VR glasses. Any devices which have installed a modern browser are accessible to the low-latency live video stream through a specified URL.

2.2 Motion perception

To capture motion information, several methods have been adopted. Gobee et al. (2017) fixes IR sensors and accelerometer motion sensors to human legs and achieves real-time control of gaits on a biped humanoid robot. Durdu et al. (2014) attaches potentiometers to human joints and then collect motion data. Furthermore, vision sensing technology is also employed. Several articles (Yavşan and Uçar, 2016; Ding et al., 2014; Bindal et al., 2015) utilize Kinect for gesture recognition and then perform similar actions on robots through diverse algorithms. Herein motion recording is achieved through wearable sensors. The motion capture system is composed of a motion sensor to capture real-time human motion and a human motion retargeting method.

2.2.1 Motion sensor

A modular system composed of 32 9-axis sensors is adopted as the motion sensor. It is a set of wearable sensors designed by Noitom Technology Ltd. to deliver motion capture technology. It contains 32 IMUs (Inertial Measurement Unit), each of which is composed of a 3-axis gyroscope, 3-axis accelerometer, and 3-axis magnetometer. The static accuracy of each IMU is ±1 degree for roll/pitch angle and ±2 degree for yaw angle. The system is operated with Axis Neuron Pro (ANP) running on Windows OS for calibration and management. In addition, a skeleton model is visualized in ANP to reflect real-time human motion. Another important feature of ANP is the function to broadcast BVH data through TCP so that other programs can obtain and analyze these data.

2.2.2 Human motion retargeting

Motion retargeting is a classic problem which aims to retarget motion from one character to another while keeping styles of the original motion (Meng et al., 2017). With this method, real-time human motion can be displayed on the skeletal model in ANP through BVH data. As a universal file format for human feature animation usually adopted in skeleton models, it can store motion for a hierarchical skeleton, which means that motion of the child node is directly dependent on the motion of the parent one (Dai et al., 2010). As shown in Figure 3, a normal BVH file will consist of several parts as follows.

- HIERARCHY signifies the beginning of skeleton definition.
- ROOT defines the root of the whole skeleton.
**Figure 3** An Example of BVH Format

Hierarchical Structure:

```
HIERARCHY
ROOT Hips
{
    OFFSET 0.00 0.19 0.00
    CHANNELS 6 Xposition Yposition Zposition Rotation Xrotation Zrotation
    JOINT RightHips
{
    OFFSET -0.19 0.00 0.00
    CHANNELS 6 Xposition Yposition Zposition Rotation Xrotation Zrotation
    JOINT RightLeg
{
    OFFSET 0.00 -0.19 0.00
    CHANNELS 6 Xposition Yposition Zposition Rotation Yrotation Zrotation
    End Site
{
    OFFSET 0.00 -1.81 1.80
    }
    }
    }
    }
    }
    CHANNELS contains several parameters. The first parameter indicates the number of DOF. Usually, only the root joint has both position data and rotation data. The rest ones only contain rotation data in the form of Euler angles. The sequence of rotation hinges on the sequence mentioned in CHANNELS, i.e. the rotation is carried out in YXZ order in the example.

- **OFFSET** specifies the deviation of the child joint from its parent joint, which remains constant.
- **CHANNELS** contains several parameters. The first parameter indicates the number of DOF. Usually, only the root joint has both position data and rotation data. The rest ones only contain rotation data in the form of Euler angles. The sequence of rotation hinges on the sequence mentioned in CHANNELS, i.e. the rotation is carried out in YXZ order in the example.
- **End Site** is only tagged in the definition of an end-effector and describes the lengths of bones through OFFSET.
- **MOTION** represents the beginning of another section which describes the states of each joint at each frame.
- **Frame Time** is the duration of each frame. The rest data are real-time states of each joint described sequentially in the HIERARCHY section. Hence, the number of these data is equal to the that of channels defined in the HIERARCHY section.

We adopt BVH with no position channels since position values keep constant. Hence, three rotation values are obtained for each joint. Accordingly, we can describe human postures through these Euler angles based on the assumption that wearable sensors keep fixed with respect to human body.

### 3. Setup of the humanoid robot

To realize real-time motion imitation, a humanoid robot is assembled since it possesses human-like design and is able to mimic human motion (Rodriguez et al., 2006). However, due to the complicated structure of the robot and various constraints of conventional manufacturing methods, it is difficult to fulfill an elegant design of a dexterous humanoid robot. Fortunately, with the rapid advancement in additive manufacturing, 3D printing turns to be more cost-effective. Moreover, 3D printing element is also becoming stronger, more accurate and therefore more reliable. 3D-printed humanoid robots like InMoov, Flobi and iCub have been created to serve as experiment platforms where research on HRI is conducted.

Here a 3D-printed life-size humanoid robot is established based on InMoov initiated by Langevin (2014), a French sculptor in 2012. The whole structure, as well as other necessary backgrounds, have been illustrated in the previous work (Gong et al., 2017). 22 out of 29 DOF are controlled during motion imitation, including 5 DOF for each hand, 2 for each arm, 3 for each shoulder and 2 for the neck, as shown in Figure 4. As for control, the slave controller is composed of 4 small Arduino Nano control core boards, each of which can drive 6 servos with corresponding angles through PWM, and an Arduino Mega 2560 master board which communicates with the aforementioned nano nodes via 485 Hub based on the Modbus RTU control.

### 4. Real-time imitation of human motion

The whole structure of the proposed method is shown in Figure 5. First, the publish-subscribe messaging mechanism and the designed communication protocol ensures the security of data transfer. Second, the fast mapping algorithm converts BVH data into corresponding joint angles. Next, visualization terminals enable users to make comparisons between different but simultaneous motion systems.

#### 4.1 Data transmission

During data transmission, communication protocols and quantization are necessary to prevent undesirable communication delays and packet dropouts (Liu et al., 2016). Herein the publish-subscribe messaging mechanism and a specific protocol are designed to realize the reliable data transmission. To be more
specific, the publish-subscribe messaging mechanism allows nodes, which are executables after compilation, to publish messages or subscribe to a topic (Wang et al., 2016). Topics are asynchronous and highly efficient. The whole data stream is mainly enabled through such a messaging mechanism, as shown in Figure 6, where ellipses stand for nodes and squares represent topics:

- **Socket_node** connects with the win32 console through TCP/IP and then advertises the topic, PN_node/data.
- **Mapping_node** subscribes to the previous topic and then converts BVH data to joint angles, which are then published to another topic called Joint_angle.
- **Joint_state_publisher** achieves the real-time simulation of the robot model using the calculated joint angles.
- **Serial_node** realizes the serial communication between the master and slave computers.

While topics have been successfully implemented in the data transfer process, reliable communication between the master and slave computers is still necessary to control the robot. Before transmission, all these data including a time stamp and joint angles are quantized to integers. The communication protocol contains 2 bits of time stamp data, 22 bits of position data corresponding to each joint, and 2 bits of CRC16 check code which are generated according to prior 27 bits to ensure the safety of data transfer, as shown in Figure 7.

### 4.2 Mapping algorithm

Several methods have been adopted to achieve motion imitation. Riley et al. (2003) computes joint angles through a fast full-body inverse kinematics (IK) method. The full-body IK problem is divided into many sub-problems to realize real-time imitation on a Sarcos humanoid robot with 30 DOF. Koenemann et al. (2014) realizes complex whole-body motion imitation on a Nao humanoid based on the positions of end-effectors and center of mass. By actively balancing the center of mass over the support polygon, the proposed approach enables the robot to stand on one foot as the demonstrator does. Durdu et al. (2014) classified the collected data with the assistance of ANN to perform movements on the robot. Herein, a fastest mapping algorithm is employed to realize the transformation.

To make the robot imitate human motion, the key point is how to compute the corresponding joint angles from BVH data. BVH has provided us with three euler angles for each node, enabling us to ascertain the rotation matrix between child and parent links. Denote euler angles with a rotation order of ZYX as $\varphi, \theta, \psi$, the rotation matrix of child frame with respect to parent frame is:

$$
\mathbf{R}_{\text{child}}^{\text{parent}} = 
\begin{pmatrix}
\cos \varphi & -\sin \varphi & 0 \\
\sin \varphi & \cos \varphi & 0 \\
0 & 0 & 1
\end{pmatrix} 
\begin{pmatrix}
\cos \theta & 0 & \sin \theta \\
0 & 1 & 0 \\
-\sin \theta & 0 & \cos \theta
\end{pmatrix} 
\begin{pmatrix}
1 & 0 & 0 \\
0 & \cos \gamma & -\sin \gamma \\
0 & \sin \gamma & \cos \gamma
\end{pmatrix}
$$

(1)

To describe the motion quantitatively, here we consider human motion as a sequence of rotation matrices. $f_i$ is the rotation matrix at BVH frame $i$:

$$
f_i = \begin{cases}
\mathbf{R}_{\text{LHand}}^{\text{Body}} & \mathbf{R}_{\text{LArm}}^{\text{Body}} & \mathbf{R}_{\text{LForearm}}^{\text{LArm}} & \mathbf{R}_{\text{LHand}}^{\text{LArm}} \\
\mathbf{R}_{\text{RHand}}^{\text{Body}} & \mathbf{R}_{\text{RArm}}^{\text{Body}} & \mathbf{R}_{\text{RForearm}}^{\text{RArm}} & \mathbf{R}_{\text{RHand}}^{\text{RArm}} 
\end{cases}
$$

(2)

Thus, each posture is defined as a sequence of rotation matrices at frame i, i.e. $\mathbf{R}_{\text{LJoint}}^{\text{LJoint2}}$ stands for the rotation matrix between left hand and left forearm. Similarly, we can also define robot motion as another sequence. The goal is to eliminate the difference between each corresponding rotation matrix of human and robot as much as possible. Figure 8 states the mapping problem. On one hand, human, with physiological constraints, cannot have 3 rotational DOF at each joint and some of them are not completely independent. On the other hand, due to mechanical constraints, many joints of the humanoid are also unable to rotate in three independent directions. Hence, each joint requires respective discussion for the mapping algorithm.

Thanks to the structural symmetry, the algorithms for $\mathbf{R}_{\text{LJoint}}^{\text{LJoint2}}$ and $\mathbf{R}_{\text{RJoint}}^{\text{RJoint2}}$ share the same principle.

#### 4.2.1 Shoulder joint

The first case is the mapping between shoulders, which entails conversion from 3 human DOF to 3 robot DOF. Three rotational joints are installed on each shoulder part of InMoov and their axes of rotation can be approximately treated as perpendicular to each other. Denote the joint angles of 3 shoulder parts as respectively $\alpha, \beta, \gamma$ and the rotation matrix of the arm link with respect to the body can be similarly expressed as:

$$
\mathbf{R}_{\text{Arm}}^{\text{Body}} = 
\begin{pmatrix}
\cos \alpha & -\sin \alpha & 0 \\
\sin \alpha & \cos \alpha & 0 \\
0 & 0 & 1
\end{pmatrix} 
\begin{pmatrix}
\cos \beta & 0 & \sin \beta \\
0 & 1 & 0 \\
-\sin \beta & 0 & \cos \beta
\end{pmatrix} 
\begin{pmatrix}
1 & 0 & 0 \\
0 & \cos \gamma & -\sin \gamma \\
0 & \sin \gamma & \cos \gamma
\end{pmatrix}
$$

(3)

With equations (1) and (3), we can derive a one-to-one correlation:

$$
\alpha = \varphi, \beta = \theta, \gamma = \psi
$$

(4)
4.2.2 Elbow joint
The mapping between elbow joints entails the conversion from 2 human DOF to 1 robot DOF. Human elbows are able to bend and rotate while those of the robot can only bend. Then we need to compute the joint angle for bending, which is shown in Figure 9. With the assumption that sensors are fixed with respect to the human body and the x-direction is along the forearm link, we can derive the following equations:

$$\mathbf{x}_2^1 = R_2^1 \mathbf{x}_2^2 = (\cos \varphi \cos \theta, \cos \varphi \sin \theta, -\sin \theta)^T$$

$$\mathbf{a}_2 = \cos \varphi \cos \theta$$

$$\mathbf{b}_2 = \cos \varphi \sin \theta$$

$$\mathbf{c}_2 = -\sin \theta$$

$$\mathbf{R}^1_2$$ stands for the rotation matrix of frame $x_{2}y_{2}z_{2}$ with respect to $x_{1}y_{1}z_{1}$. $\mathbf{x}_2^1$ is a unit vector of $x_2$ in frame $x_1y_1z_1$.

4.2.3 Neck joint
Mapping between neck joints requires the conversion from 3 human DOF ($\psi, \theta, \phi$) to 2 robot DOF ($\alpha, \beta$). Due to the mechanical constraints, only rotations in two directions can be retained. The solution to this case resembles that for the shoulder joint and should be written as

$$\alpha = \varphi, \beta = \theta$$

4.3 Visualization terminals
On one hand, in the display of human motion collected from the motion sensor, ANP can visualize the aforementioned skeletal model, where each joint possesses three DOF despite human’s physiological constraints. On the other hand, to visualize motion on the humanoid and to make the simulation more convenient, another visualization scheme is provided with the assistance of robot operating system (ROS). A 3D visualization model is created in URDF (Unified Robot Description Format), a language based on XML and designed to describe the robot simulation model universally in ROS system, including the shape, size, and color, kinematic and dynamic characteristics of the model. Wang et al. (2016) has introduced the basic grammars. However, the highly repetitive mechanical structure of InMoov makes it arduous to write a URDF manually. Hence we resort to a powerful tool called Xacro (XML Macros). Xacro is adopted to reuse the same structure for two different parts, i.e. left arms and right arms and to auto-generate a URDF file. Fundamental grammars are shown in Table I. After importing STL files with scale adjustments, the robot model can operate with the computed joint angles in RVIZ, a 3D visualization tool in ROS. These two visualization terminals are shown in Figure 10.

5. Experiment
This section designs several experiments to demonstrate the accuracy, repeatability, and dexterity of the proposed natural teaching paradigm and discusses the experimental results.

5.1 Accuracy
First, the accuracy of the control method is verified with several motion imitation experiments. Snapshots of postures are taken, including various positions of two arms, face orientations and movements of fingers. The results can be examined in Figure 11 and Figure 12. For these complicated gestures, the high degree of similarity between the demonstrator and the humanoid robot has proven that the robot can successfully follow the upper limb motion of the demonstrator, thus reflecting the feasibility and accuracy of our proposed method. Moreover, the synchronous
latency of fewer than 0.5 seconds validates the real-time performance.

To further illustrate accuracy, the second experiment is carried out to measure the angle errors for individual motions. Figure 13 shows the rotation directions and initial gestures. The angle errors for three motions are measured and plotted in Figure 14 and it follows

$$ \text{Error} = |\text{Angle}_{\text{Robot}} - \text{Angle}_{\text{Human}}|$$

The generally small errors are acceptable for natural teaching and further prove that the motion imitation system possess high accuracy.

However, there are still some limitations. The first one is the difference between the structures of human and robot. Each of our arms has 7 DOF but the robot has only 5 and the rotational axes of the wrists are not the same. Besides, for some joints, the range of movement is limited due to its mechanical constraints. The second one is the mismatch between the skeletal model visualized through BVH data and the demonstrator’s real motion. Revolution of each joint is achieved through skeletons in the human body, while the wearable sensors can only remain fixed to the skin or clothes. The angular displacements between our skin and skeletons cause the measurement error. Other factors include the accumulated drift errors and different positions of wearable sensors relative to human bodies. Nevertheless, there are still some possible solutions to these limitations. For example, sensors can be bound tightly to limbs in case of relative displacement. Human motion can be confined to a certain range to achieve a higher accuracy. Reasonable compensations for angular error can also be designed to render the motion retargeting more reliable.

5.2 Repeatability

After the demonstration is completed, the robot is expected to repeat the same motion, which means high repeatability is desired. To verify the repeatability of the proposed natural teaching paradigm, an experiment is carried out where the robot is expected to approach the same point with its index finger. The distance errors are listed in Table II. The average distance error is 6.8mm, which is relatively small compared to its size. Aging of actuators, frictions in transmission mechanisms and instability of power supply may contribute to these gross distance errors.

To further illustrate the repeatability, another more complicated teaching experiment is carried out. Industrial robots are often required to repeat precise operations. Hence,
in the experiment, the demonstrator first teaches the robot to approach the left and right holes of 3 flanges in sequence and then the robot is requested to approach 6 holes continuously and automatically in the following experiments without demonstration. The diameter of these holes is close to that of the fingertip. Figure 15 shows the teaching process and Table III shows the success rates. The experiment is carried out 5 times and failure mainly happens when the finger collides with the flange due to accumulated translational errors. The high success rate can validate the high repeatability and reliability of the proposed natural teaching paradigm. Once the demonstration is completed and the desired position of the end-effector is also reached, the robot can repeat the same motion using the recorded joint angles during the whole process.

5.3 Dexterity

With the proposed natural teaching paradigm, the humanoid robot is capable of accomplishing complicated movements. Two experiments are conducted to demonstrate the dexterity of natural teaching. First, an eye-body synergic experiment is performed via scene-motion cross-modal perception. In the experiment, the robot is confronted with a complicated situation where flanges and other things heap up together on the table. As is the same with the aforementioned teaching experiment, the robot is expected to approach the inner circle of each flange with its index finger. The experimental results are shown in Figures 16-18.

The second one is the classical experiment of obstacle avoidance. As shown in Figure 19, the end-effector needs to cross the obstacle first before it reaches the desired position and orientation. The trajectory is generated by means of natural teaching. In such a complicated mission scene, motion planning always consumes a great amount of computation and time, while natural teaching can fully utilize human’s perception and decision-making ability, making it more convenient and less time-consuming. The scene-motion cross-modal perception enables human to perceive the surroundings
Hence, complicated missions can usually be accomplished with natural teaching at a minimum cost.

6. Conclusions

This paper presents a novel natural teaching paradigm for a humanoid robot. A perception system composed of a vision sensor and a motion capture system realizes the cross-modal combination of scene and motion information. Through multiple visualization terminals for different motion systems, a fast mapping algorithm and reliable data transfer methods, real-time motion imitation is accomplished. Several experiments are designed to validate the accuracy, repeatability, and dexterity of the proposed natural teaching paradigm. Through natural teaching from FPV, human intelligence builds connections between scene information and movement policy, thus making it possible for robots to make autonomous decisions based on around the robot and the robot to reproduce human’s motions.

### Table III Results of repeating process

<table>
<thead>
<tr>
<th>Experiment no.</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
</tr>
<tr>
<td>2</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
</tr>
<tr>
<td>3</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>F</td>
<td>S</td>
</tr>
<tr>
<td>4</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>F</td>
<td>S</td>
<td>S</td>
</tr>
<tr>
<td>5</td>
<td>S</td>
<td>S</td>
<td>F</td>
<td>S</td>
<td>S</td>
<td>S</td>
</tr>
<tr>
<td>Success rate (%)</td>
<td>100</td>
<td>100</td>
<td>80</td>
<td>80</td>
<td>100</td>
<td>80</td>
</tr>
</tbody>
</table>

**Notes:** a, b, c, d, e and f represent each hole in Figure 15. F stands for failure and S stands for success.
cross-modal perception. Future work will lay more emphasis on the development of the perception system to improve the user experience as well as the accuracy of motion imitation. Encouraged by Tri-Co Robot initiative (Ding et al., 2017), we hope this work will further contribute to the enhancement of industrial robot intelligence.

References


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Model-based deep reinforcement learning with heuristic search for satellite attitude control

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Abstract
Purpose – Recently, deep reinforcement learning is developing rapidly and shows its power to solve difficult problems such as robotics and game of GO. Meanwhile, satellite attitude control systems are still using classical control techniques such as proportional – integral – derivative and slide mode control as major solutions, facing problems with adaptability and automation.

Design/methodology/approach – In this paper, an approach based on deep reinforcement learning is proposed to increase adaptability and autonomy of satellite control system. It is a model-based algorithm which could find solutions with fewer episodes of learning than model-free algorithms.

Findings – Simulation experiment shows that when classical control crashed, this approach could find solution and reach the target with hundreds times of explorations and learning.

Originality/value – This approach is a non-gradient method using heuristic search to optimize policy to avoid local optima. Compared with classical control techniques, this approach does not need prior knowledge of satellite or its orbit, has the ability to adapt different kinds of situations with data learning and has the ability to adapt different kinds of satellite and different tasks through transfer learning.

Keywords Control, Artificial Intelligence, Deep reinforcement learning, Satellite attitude

Paper type Research paper

1. Introduction

With the rapid development of small satellite, satellite attitude control is facing problems with autonomous and adaptivity. Owing to the lower cost and faster design of small satellite, hundreds of satellites are launched each year, and the number is increasing year by year. It is harder to design control system for each small satellite with their different space tasks, different physical parameters, actors and sensors, different orbits and so on. The limited ground measuring and control system cannot meet the needs of them at the same time. The unstable space environment (Williams et al., 2016) and satellite component errors (Hu et al., 2015; Mazmzanyan and Ayoubi, 2014) also influence control precision and stability. Therefore, an intelligence control system that can adapt different kinds of situations and work autonomously is urgently needed to be developed.

Meanwhile, deep reinforcement learning has recently been used to solve challenging problems successfully, from autonomous racing (Williams et al., 2017) to robotics (Levine et al., 2016). Alpha-zero (Silver et al., 2017) is an impressive application of deep reinforcement learning, which could solve different kinds of board games without offline data and human knowledge. Guided policy search (GPS) (Levine et al., 2016) is a kind of successful model-based solution for different kinds of robot tasks which could be repeated learnt with the help of guided policy. Deep deterministic policy gradient (DDPG) (Lillicrap et al., 2015) gives a model-free greedy solution for general control problems that described in Open-AI gym (Brockman et al., 2016). These results show that deep reinforcement learning is a promising solution for intelligence satellite attitude control system.

Unfortunately, deep reinforcement learning needs too much computing and storage resource for an on-board computer, which leads to most satellite attitude control systems are still using traditional control algorithm such as proportional – integral – derivative (PID) (Gross et al., 2015; Akella et al., 2014) or fuzzy control (Walker et al., 2015; Ghadiri et al., 2015). PID is still the most commonly used method in satellite attitude control, for its implementation simplicity and stability. The problem of PID is adaptability and robustness, where many adaptive approaches are used to improve that. Slide mode considers non-linear systems, and similar to PID, the main problem is adaptability. Current intelligent approaches such as fuzzy control bring adaptability to control system. The main problem of fuzzy control is that it needs expert knowledge to build control system. Besides these approaches, few of them use machine learning as a support method (Wu et al., 2015). To solve this problem, a new kind of satellite called phonesat (Shimmin et al., 2014) is proposed, which uses smartphone as a new kind of on-board computer, to upgrade computing and storage ability for satellites. Many deep learning tools such as...
tensorflow (Abadi et al., 2016) and caffe (Jia et al., 2014) also support Android OS and make it more convenient to develop deep reinforcement learning applications on smartphones.

In this paper, a model-based deep reinforcement learning algorithm is proposed to learn from data that generated by satellite attitude control system, optimizes control system online and makes it more adaptive to space environment and hardware changes of satellite itself. There are three main parts of the algorithm: a model network that predicts the next state according to current state and action, a policy network that outputs control policy and a heuristic search part that optimizes control policy. The model network could be trained initially offline by ground simulation, and then trained online by actual attitude data. The main error of the whole system is generated by model predict error, so a feedback compensation is given to make up the error. Neural network gives non-linear dynamics in general; however, two predict state neighbours in time dimension may have errors in detail, and they always close in space dimensions, which make the predict error more linear, that is to say a linear feedback compensation could work fine. The policy network could also be trained initially offline by existing control policy such as PID or slide mode control, and then trained online by optimized policy generated by heuristic search. Paper (Sugimura et al., 2012) shows the ground test of a satellite attitude simulation system which could be used as pre-trained environment. The heuristic search algorithm searches better policy around initial actions given by policy network output; if the optimized policy works better in model network, then the system will use it as real output to control attitude, and if the policy also works better in the real environment, the policy network use it as training data. Simulation result shows this algorithm has the ability to find a better policy to reach the control target.

2. Model-based deep reinforcement learning with heuristic search

In the game of Gø, state transition is explicit, so there is no need to propose a model network, but the Q-value need to be built. In model-based deep reinforcement learning with heuristic (MDRLH) search, once a model network is built, the Q-value could be decided by model output, so there is no need to propose a Q-value network. In DDPG, there are four networks, two of them output Q-value, and the other two output policy, whereas in MDRLH, there are two networks, one outputs state prediction, and the other outputs policy. In addition, DDPG uses gradient descent to optimize policy, whereas MDRLH uses heuristic search to optimize policy. Figure 1 shows MDRLH workflow.

The algorithm works as follows:

- Random initialize networks or initialize networks from ground simulation.
- Calculate policy predict output in state through model network as well as its Q-value to initialize heuristic search.
- Use heuristic search to find better policy model to get lower Q-value than initial policy.
- Execute optimized policy, get real output and its Q-value, calculate model predict error.
- If the result is better than initial policy, use it as policy training data.

### 2.1 Model network

Some works have been used machine learning technics to build satellite attitude dynamics model (Straub et al., 2013). In this paper, a neural network-based dynamic model is used as a part of MDRLH algorithm. The model network \(s_{t+1} = f_{w}(s_t, a_t)\) uses previous state–action pair as input, and predicted state as output. \(\theta\) are parameters of network. They could be random initialized or pre-trained with ground simulation or data from other satellites, and then apply it to model network using fine-tune or transfer learning (need references). Pre-trained process will accelerate network’s convergence and improve online performance of the whole algorithm.

Network uses leaky-ReLU (Xu et al., 2015) as activate function, instead of ReLU. There are some results that show the limitation of ReLU networks (Punjani and Abeel, 2015), and they use initial parameter settings to avoid gradient missing problem, whereas a leaky-ReLU network has no need to worry about this kind of problem.

Loss function of model network is \(L = ||s' - e||^2\), which is mean square error (MSE) between network output and next state from data. This loss function minimizes error between predicted state and real state after actions. Although model network is able to fetch the majority of system’s non-linearity, minor error still remains because of leak of data and limitations of network itself, and this error causes main error of the whole algorithm. So, an estimation of this error is necessary while using model network to predict state. Model network could be seen as a feedforward part of algorithm and error estimation as a feedback part of algorithm: \(e_{t+1} = (s'_{t} - s_t) \cdot w_p + e_\theta w_i + (e_t - e_{t-1}) \cdot w_fh\) the initial error \(e_0\) could be set as 0, this function is actually PID control algorithm, where \(s'_{t} - s_t\) is proportional part, \(e_\theta\) is integral part and \(e_t - e_{t-1}\) is differential part. When algorithm uses model network to predict state, error estimation is added:
\[ s_{t+1} = f^o(s_t, a_t) + \epsilon, \] whereas update \( \theta^o \) does not need this error.

A model-based algorithm makes control system perform better every episode, but a model-free algorithm will wander longer and can hardly perform better until it reaches the target state, and the model network can learn the dynamics online as long as the satellite attitude control system is working, even if the system uses other control algorithms, which makes algorithm more adaptable.

2.2 Policy network
The policy network \( a_t = g^\theta(s_t) \) uses current state as input and current policy as output. \( \theta^\alpha \) is the parameter of network. They could be random initialized or pre-trained with guided policies such as PID control. Pre-trained process will reduce the probability of reaching beyond the safe zone and improve the performance of the whole algorithm.

Network uses similar structure as model network for the same reason mentioned before.

Loss function of policy network is \( L(\theta^\alpha) = ||a_t - a^*_t||^2 = ||a_t - g^\theta(s_t)||^2 \), which is MSE between network output, \( a_t = g^\theta(s_t) \), and policy from data \( a^*_t \) in same state. This loss function minimizes error between output policy and guided policy from data. Unlike the error in model network, there is no “correct policy” for control system. There is difference between output of policy network and guided policy from data, but there is also no idea of whether output of policy network is better. Also during learning episodes, output of policy network is an initial input of heuristic search and not directly control output. So, there is no need to model the error between them.

This network is able to find a global solution of control system, which is different from the GPS, and the solution follows a certain routine. If necessary, policy network can imitate other policies to adapt new tasks quickly.

2.3 Heuristic search
There are several algorithms that could be used as a heuristic search, such as simulated annealing (Kirkpatrick et al., 1987), particle swarm optimization (Kennedy and Eberhart, 2002) and normal evolution strategy (OpenAI, 2017). It uses output of policy network as its input and outputs an optimized policy where \( Q \)-value is higher. \( Q \)-value is defined as follows:

\[ Q(s_t, a_t) = ||s_{t+1} - s_T||^2 \cdot w_t. \]  

In equation (1), \( s_t \) is the result state after action taken at time \( t \), and it could be model prediction or real output of environment. \( s_T \) is a target state which is decided by space missions such as target tracking and taking photos. \( w_t \) is a weight parameter, which is also decided by missions. \( Q \)-value measures MSE between next state and target state, which is different from temporal difference. As it known in reinforcement learning, different \( Q \)-value definitions lead to different agent behaviours when algorithm converges. In satellite attitude control, for example, a state contains quaternion of satellite and angular velocity, and if weight of quaternion is bigger, then the satellite prefers to move fast, and the attitude will be less stable because big angular velocity affects little to \( Q \)-value. On the other hand, if the weight of velocity is bigger, then the satellite prefers to stay still, which will take a longer time to get target. So, a proper \( w_t \) should be set to get an acceptable performance; for instance, weight of quaternion should be set bigger when satellite learns a fast attitude manoeuvre task, and weight of angular velocity should be set bigger when satellite needs to take a high definition photo.

Simulated annealing is used to optimize policy. This algorithm is a kind of Markov chain Monte Carlo algorithm, where initial input is deterministic and makes a random change to it and decides whether it is better than the original one. It is rather general, so it needs modification to fit certain situation:

\[ a'_t = a_t \cdot (1 + SR) \quad (2) \]

\[ \Delta = Q(s, a'_t) - Q(s, a_t) \quad (3) \]

\[ p = \begin{cases} \exp \left( \frac{-\Delta}{k \cdot T_0} \right) & \text{if } \Delta > 0 \cr 1 & \text{if } \Delta \leq 0 \end{cases} \quad (4) \]

Equation (2) shows the random search change of input in each episode, where \( SR \in (-\delta, \delta) \) is a uniform random variable with same dimension of \( a_t \) and \( 0 < \delta \ll 1 \), which means policy will move slowly to improve stability of learning, similar in DDPG. \( a_t \) also has constrains and depends on satellite actor output abilities, reaction wheels and magnetic torque, for example. The initial input from policy network is \( a_0 \), and 1 will be added to \( i \) when a new action is accepted by algorithm.

Equation (3) shows the difference of \( Q \)-values between input action \( a_t \) and its random change \( a'_t \) and \( s \) is a current state. \( Q(s, a) \) is calculated by the model network and equation (1). If \( \Delta < 0 \), it means new action is better than initial action; otherwise, it means it is worse than initial action.

Equation (4) shows the accept probability of \( a'_t \) and if \( \Delta \) is bigger than 0, it means \( a'_t \) is better than original \( a_t \) so it will be accepted. If \( \Delta \) is smaller than 0, although \( a'_t \) is worse than \( a_t \), it still has chance to be accepted by the probability of \( p \), which ensures that algorithm will not stuck in local optima. \( 0 < k < 1 \) is a decay rate of acceptance function and makes the function harder to accept policy where \( \Delta < 0 \), here \( k = 0.99 \). \( T_0 \) is initial temperature of simulated annealing, \( \Delta \) is calculated by \( Q \)-value difference, \( T_0 \) is multiplied by \( Q(s_t, a_{t-1}) \) to make initial temperature more reasonable.

In Algorithm 1, first, while loop is less than 4,096 episodes, algorithm will stop if it still cannot find the solution. Second, while loop is less than 1,024 episodes, heuristic search will output current optimize action after searching:

**Algorithm 1. Model-based Deep Reinforcement Learning with Heuristic Search**

1. Randomly initialize \( Q^o \) and \( Q^p \) or initialized by transfer learning
2. while Not find solution yet do
3. Generate initial policy: \( a_{in} \leftarrow g^\theta(s_t) \), optimum action \( a_{opt} \)
4. while in heuristic search do
5. Generate explore policy: \( a_{out} \leftarrow a_{in} \cdot (1 + SR) \)
6. Predict state: \( s_{t+1} \leftarrow f^o(s_t, a_{out}) \)
7: \( Q(s_t, a_{out}) \leftarrow \|s_{t+1} - y_t\|^2 \cdot w_t \)
8: if \( Q(s_t, a_{out}) \) is accepted by heuristic search then
9: \( a_{in} = a_{out} \)
10: if \( Q(s_t, a_{out}) > Q(s_t, a_{opt}) \) then
11: \( a_{opt} = a_{out} \)
12: end if
13: end if
14: end while
15: Execute \( a_{opt} \) and get data. Update \( \theta^a \) by data.
16: if data \( a_{opt} \) actually better than \( a_{in} \) then
17: Update \( \theta^a \) by data.
18: end if
19: end while

3. Experimental results

The experiment uses satellite attitude simulation system to show when classical control algorithm perform worse and cannot reach the control target, and MDRLH could learn from data and find its way to reach control target without prior knowledge of satellites that classical control algorithm demands: inertia of satellite, orbit of satellite and functions of quaternion. It only needs to know the dimension of quaternion, angular velocity and actors.

Figure 2 shows PID performance with random initial angular velocity and quaternion. It converges around \( 10^{-5} \) of MSE less than 200 episodes. At first 20 episodes, angular velocity increases to reach the target quaternion faster, so total MSE does not decrease.

Figure 3 shows that for some reason classical control cannot reach the target but not diverge. Assume that a guided policy performs like this and satellite attitude determination system works fine and then apply MDRLH to see if it could help satellite reach the target. The guided policy is set to give random output when \( \omega^s < 0.5 \), otherwise use PID control.

Figure 4 shows MDRLH performance with guided policy. In this experiment, MDRLH is initial with random parameters and control output may diverge after some episodes, so guided policy is used to prevent MDRLH diverging. In the outer space, control system cannot just be set to initial state, so a guided policy is needed when learning algorithm explores too much. Figure 4(a) shows best case of learning process. In this case, algorithm could find solutions with small episodes of guidance. Figure 4(b) shows the normal case of learning process, in this case, algorithm could find solutions after 1,000 episodes with several trials. Figure 4(c) shows the worst case, in this case, algorithm could find solutions after tens of trials, and sometimes it is close to convergence, but loses it again. The experiment is limited to 4,096 episodes as mentioned in Algorithm 1, and sometimes it cannot find solutions after 4,096 episodes; however, these figures indicate that it still has a chance to converge after these episodes. The differences between these cases may because of the random initialization of model network and policy network parameters. So, if the network could be pre-trained with ground simulation, the episodes of learning process may be reduced significantly.

An interesting property of quaternion is \( ||q|| = 1 \). However, the model network does not know this property. In Figure 5, \( y \)-axis is the quaternion prediction of model network. During the learning process, the result shows that the model network is able to learn this property from training data. This is an important feature to measure the quality of satellite attitude dynamics model.

4. Conclusion

MDRLH uses deep learning to learn dynamics model and optimum policy from data generated by control system and uses heuristic search to find better policy under dynamics model. This is more like a framework, and many deep learning technics and heuristic search technics could be implemented to this framework. This work uses fully connected leaky-ReLU network to build models and uses simulated annealing to implement heuristic search. The experiment shows that the algorithm could reach the target without prior knowledge of satellite and orbit parameters when guided policy could not work well, which makes the control system much more adaptive to the environment.

MDRLH is a general algorithm that could be suitable for many other control systems, not only for satellite attitude control system. There are several advantages of the algorithm: first, deep learning makes it do not need prior knowledge of
satellite and orbit of it, which make the algorithm easy to be transformed to different types of satellites and wanders in different orbits without design the control system for each of them. Second, it is a model-based algorithm, which could learn faster than model-free algorithm such as DDPG. Third, heuristic search is a kind of non-gradient method, which can avoid local optima.

However, MDRLH is a greedy algorithm, which is not suitable for programming tasks. Online learning tasks also need large amount of computation resources, which may influence other satellite tasks. From view of control theory, this algorithm cannot make sure stability of control system, which makes expensive satellite in danger of lost control.

So in the future, the algorithm should be improved to use less computing resources to adapt online tasks. The algorithm also needs to add dynamic programming ability to fulfil harder tasks. A plan of experiment on phonesat is also needed to test stability and robustness of the algorithm.

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Learning and planning of stair ascent for lower-limb exoskeleton systems

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Abstract

Purpose – Lower-limb exoskeleton systems enable people with spinal cord injury to regain some degree of locomotion ability, as the expected motion curve needs to adapt with changing scenarios, i.e. stair heights, distance to the stairs. The authors’ approach enables exoskeleton systems to adapt to different scenarios in stair ascent task safely.

Design/methodology/approach – In this paper, the authors learn the locomotion from predefined trajectories and walk upstairs by re-planning the trajectories according to external forces posed on exoskeleton systems. Moreover, instead of using complex sensors as inputs for re-planning in real-time, the approach can obtain forces acting on exoskeleton through dynamic model of human-exoskeleton system learned by an online machine learning approach without accurate parameters.

Findings – The proposed approach is validated in both simulation environment and a real walking assistance exoskeleton system. Experimental results prove that the proposed approach achieves better performance than the traditional predefined gait approach.

Originality/value – First, the approach obtain the external forces by a learned dynamic model of human-exoskeleton system, which reduces the cost of exoskeletons and avoids the heavy task of translating sensor input into actuator output. Second, the approach enables exoskeleton accomplish stair ascent task safely in different scenarios.

Keywords Sensors, Exoskeletons, Man machine interface (MMI), Stair ascent, Imitation learning, Paraplegics

Paper type Research paper

1. Introduction

Spinal cord injury (SCI) is temporary or permanent damage to the spinal cord that changes its function and might cause loss of muscle function, sensation or autonomic function in parts of the body served by the spinal cord below the level of the lesion. According to the survey of world health organization, around the world, between 250,000 and 500,000 people are suffering from SCI every year (WHO, 2017). People with a SCI are two to five times more likely to die prematurely than those without a SCI, with worse survival rates in low and middle-income countries. Therefore, lower-limb exoskeletons are designed to provide movement assistance for people suffering SCI and have attracted increasing interests from both academic researchers and industrial entrepreneurs.

While much efforts are made on investigating the development of lower exoskeletons (Yan et al., 2015) (Huo et al., 2016), (Li et al., 2017), (Bogue, 2009, 2015), most of them use predefined trajectories method and are restricted to only normal scenarios, such as level walking and sitting down/standing up. Among these exoskeletons, ReWalk, HAL, eLEGS and MindWalker are most famous exoskeletons for patients with gait-disorder or weakness. Hybrid Assistive Limb (HAL) (Hassan et al., 2012; Tsukahara et al., 2009; Kasaoka and Sankai, 2001) is an exoskeleton designed for helping people to execute and move their daily-life activities. Electromyography (EMG) signals are needed for motion intention estimation of patients (Suzuki et al., 2005) and calculation of joint torques (Hayashi et al., 2005; Kawamoto and Sankai, 2009). However, it is difficult to detect for SCI patient. ReWalk is an exoskeleton designed to assist patients who suffer thoracic-level complete SCI to walk again independently. It executes standing, walking, sitting and stair climbing motion following the commands of pilots with a wrist-pad controller (Talaty et al., 2013). Staircase tasks can be completed with the new version of ReWalk by following a predefined trajectory. eLEGS (Strausser and Kazerooni, 2011) exoskeleton is developed to help patients who have difficulties in
lower-limb functions such as sitting, walking and standing. A finite state machine is used to model the movements eLEGS, and each movement is predefined according to different patients. MindWalker (Wang et al., 2013) is a powered exoskeleton designed for paraplegics to regain locomotion capability. In the sagittal plane, during swing phase, predefined trajectories recording form a healthy person walking with MindWalker in zero-assistance mode are used as reference of hip and knee joints. Thus, in these famous exoskeletons, motion tasks are manually planned and off-line. Moreover, stair ascent is an essential basic task for people’s daily life, helping disabled people walk upstairs has seldom been done by the existing exoskeletons. This paper focuses on proposing an approach helping disabled people regain the stair ascent ability.

Designing controllers for lower limb exoskeletons is a challenging especially for stair ascent task. Due to uncertainty of environment, both environment perception and motion planning need to be considered. For environment perception, visual systems like radars and 3D cameras are commonly used in other robots. However, interacting with the environment, these kinds of sensors are easily shielded and broken. Instead of directly detecting the contact with multi-dimensional force sensor (which is expensive and difficult to be equipped), calculating the forces through a known the dynamic model of human-exoskeleton system seems to be feasible. However, because of the uncertainty of different human (pilots’) body parameters, modeling the dynamics of human-exoskeleton system is quite difficult. For motion planning, predefined trajectories approach is commonly used for many kinds of exoskeleton (robot) systems. The trajectories are executed by exoskeleton following the commands of a pilot. Both the uncertainty of environment and mis-operation would lead the human-exoskeleton falling (to fall) to complete the task. Moreover, the contact force between the exoskeleton and environment would make the human-exoskeleton unstable which is unsafe and unacceptable.

In this paper, we present an approach tackling both of the two aforementioned challenges. First, our approach obtains the external forces based on a dynamic model learned by locally weighted projection regression (LWPR) without complex sensors (e.g. cameras, force sensors and distance sensors). On the other hand, we model trajectories of swing foot to adapt with different situations with dynamic movement primitives (DMP) and re-plan them according to the external forces. Hence, our contributions are two folded: First, our approach obtains the external forces by a learned dynamic model of human-exoskeleton system, which reduces the cost of exoskeletons and avoids the heavy task of translating sensor input into actuator output. Second, our approach enables exoskeleton accomplish stair ascent task safely in different scenarios. The proposed approach is validated in both simulation environment as well as a real walking assistance exoskeleton system. Experimental results prove that the proposed approach achieves better performance than the traditional predefined trajectory approach.

This paper is organized as follows: we present our approach in Section 2, followed by simulation and experimental results in Section 3 and Section 4. This paper ends with conclusion and future work in Section 5.

2. Learning and planning for stair ascent

2.1 The locally weighted projection regression - dynamic movement primitives framework

In this section, we will lay down the proposed approach for lower-limb exoskeleton stair ascent task. We will first introduce the framework of our approach, followed by the approach of learning external force by LWPR, and in the last subsection, we will use DMP to re-plan the trajectory with the known external force learned before. Thus, our approach is named as LWPR-DMP.

As shown in Figure 2, stair ascent task consists of three subtasks:
1. putting the foot of swing leg on the stair;
2. translating the weight of body to this leg and control the angles of hip joints and knee joints to stand position; and

![Figure 1](image.png)

**Figure 1** The framework of our approach consists of two parts: trajectories re-planning and learning external force with LWPR.

**Notes:** Sub-system 1: Trajectories Modeled by DMPs: DMPs describing the trajectories in; input1: external forces; output1: trajectories in Cartesian space. Sub-system 2: inverse kinematic: convert trajectories in Catesian space to joint space; input2: trajectories in Cartesian space; output2: trajectories in joint space. Sub-system 3: PID controllers in joint space: servo the trajectories in joint space; input3: trajectories in joint space; output3: joint torques. Sub-system 4: exoskeleton system; input4: joint torques; output4: joint motion. Sub-system 5: Dynamic model learned by LWPR; input5: joint motion and actuating torques; output5: estimation of total joint torques. Sub-system 6: inverse of the transpose of exoskeleton’s Jacobin matrix; input6: difference of actuating torque and estimation of total torque; output6: estimation of external forces.
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3 moving another foot to the same position in the sagittal plane.

Since (2) and (3) can be completed easily, our research focus on the first sub-task. To complete the first step, predefined trajectory approach is commonly employed for many exoskeletons. Human-exoskeleton system is able to complete the first sub-task by following predefined trajectories with an appropriate (d, h). However, with a short d or a high h, the foot of swing leg would be obstructed by the edge of stairs. As most of exoskeletons use PID joint controller, once obstructed by stairs, the contact forces would increase rapidly. The increasing contact forces would lead human-exoskeleton system to fall down. This situation is unsafe and unacceptable.

Considering the task of stair ascent, both the perception and motion planning should be covered. Thus, framework of our approach consists of two parts as shown in Figure 1:

1 obtaining the external forces: we calculate the external forces posed on swing foot by motion state and dynamic model which is learned by LWPR on-line; and
2 re-planning the trajectories of swing foot: we utilize DMPs to model trajectories of foot in Cartesian space.

After training DMPs with predicted trajectories we re-generate these trajectories with the known external forces obtained before.

Two cases are considered in the implement of our approach. When the (d, h) is appropriate, the foot can step on the surface of stairs with little contact force following the trajectories generated by our approach. With a long distance or a high height, as the goal position exceeds motion range, we let the foot of human-exoskeleton system move back to the ground. It makes it easier for human-exoskeleton system to take a next step.

2.2 Online model learning with locally weighted projection regression
Models are essential kits such as kinematics and dynamics models of the robots body and controllable external objects for the control of exoskeleton robots. However, classical robotics usually depend on manually generated models that are based on human insights into physics, cognitive robots need to automatically generate models that are based on information which is extracted from the data streams accessible to the robot. Many approaches have been used to learn the model of exoskeleton systems. For BLEEX, system identification with least squares has been used to get parameters of dynamics (Ghan and Kazerooni, 2006).

Global regression approaches such as gaussian process regression (GPR) (Seeger, 2008) and support vector regression (SVR) (Chang and Lin, 2002) are commonly used to learn the model. SVR is a continuous-valued function to data in a way that shares many of the advantages of support vector machine (SVM) classification. GPR is an approach inferring of continuous values with a Gaussian process prior. It provides a principled, practical and probabilistic approach to learning in kernel machines. This gives advantages with respect to the interpretation of model predictions and provides a well-founded framework for learning and model selection. As all these global function approximators were developed primarily for batch data analysis they are not efficiently adjusted for incrementally arriving data. Therefore, bringing in a new sample data point in SVR or GPR is rather computationally expensive. In contrast, LWPR is a non-parametric regression algorithm which consists of many locally linear models with a small number of univariate regressions in selected directions in input space in the spirit of partial least squares regression (Vijayakumar and Schaal, 2000; Vijayakumar et al., 2005). With redundant and irrelevant input dimensions, it can approximate nonlinear function incrementally in high dimensional spaces and achieves good performance in high dimensions system learning with both computation efficiency and numerical robustness. Thus, LWPR is widely used in robotics (e.g. learning inverse kinematics (D’Souza et al., 2001) and inverse dynamics model (Nguyen-Tuong et al., 2008)). In this subsection, we learn the model LWPR and calculate the external force with learned model.

As shown in Figure 2(a) for first sub-task of stair ascent, the pilot holds the bar to keep balance and his/her swing leg move to the top of stair. As the pilot holds the bar, we suppose that the back link of exoskeleton is fixed to the bar. Thus, in this process, we model human-exoskeleton with a 3-DOFs (hip, knee, ankle) mechanism in the sagittal plane with a base coordinate fixed on its back. The dynamic model of human-exoskeleton system can be written in the general form as follows:

\[ M(q)\ddot{q} + C(q, \dot{q}) + G(q) = \tau - \mathbf{j}^T f_{\text{ext}} \]  

(1)

where \( q \) is a \( 3 \times 1 \) vector which refers to the angles of hip, knee and ankle joints in the sagittal plane. \( \dot{q} \) and \( \ddot{q} \) are \( 3 \times 1 \) vectors referring to the angular velocity and acceleration of these joints. \( M(q) \) is a \( 3 \times 3 \) inertia matrix and a function of \( q \). \( C(q, \dot{q}) \) is a \( 3 \times 3 \) Coriolis matrix and a function of \( q \) and \( \dot{q} \). Meanwhile, \( G(q) \) is a \( 3 \times 1 \) vector of gravitational torques. \( \tau \) is joint torques powered by the exoskeleton. \( \mathbf{j} \) is Jacobin matrix of exoskeleton. \( f_{\text{ext}} \) is external force posed on exoskeleton. The \( f_{\text{ext}} \) can be calculated by a measured motion states and actuating torque of joints with (1). As both dynamic model and external forces are unknown, we cannot calculate \( f_{\text{ext}} \) directly. Thus, as shown in Figure 2(b), we make the foot follow the trajectory with upright segment in the beginning. In the upright segment, we suppose that the swing foot moves vertically without contacting with stairs. Thus, \( f_{\text{ext}} \) is 0 in this segment and the dynamic equation can be re-written as follows:

\[ M(q)\ddot{q} + C(q, \dot{q}) + G(q) = \tau \]  

(2)

Sample data in this segment can be used to learn the map from \( (q, \dot{q}, \ddot{q}) \) to \( \tau \) with LWPR. The LWPR regression function is constructed by blending local linear models \( \tau_i \) in the form:

**Figure 2** Description of stair ascent task

- **Notes:** (a) Stair ascent task with exoskeleton; (b) stair ascent task with distance \( d \) and height of stair \( h \)
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where $\hat{\tau}$ is the prediction torques of system. Where $w_k$ is a local kernel that defines the area of validity of the local model. We can model it by a Gaussian:

$$w_k = \exp\left(-\frac{1}{2}(x - c_k)^2D_k(x - c_k)\right)$$

where $x$ is training sample, $c_k$ is the center of the $K$th linear model and $D_k$ is its distance metric. For learning the local linear models, LWPR uses an online formulation of weighted partial least squares (PLS) regression (Vijayakumar et al., 2005) for dimensional reduction. Gradient descent is used to update the distance metric $D_k$. If the average predicted error of LWPR $Ep$ is less than a threshold $E_t$, the model is learned successfully and can be used to predict external force $f_{ext}$. When $f_{ext} < \hat{f}$, it is considered that the swing foot of human-exoskeleton system doesn’t touch the edge of stair. Therefore, sample data can also be used to retrain the model even the motion of foot is out of upright segment.

2.3 Trajectory planning with dynamic movement primitives
Predefined gait trajectory approaches are used for most of exoskeleton systems designed for SCI patients. In this approach, the desired joint trajectories are recorded from a healthy person, or extracted from a gait analysis data and then reproduce on an exoskeleton. To improve usability and flexibility of the controller, the desired trajectories are usually encoded according to different postures. Various approaches have been used to model trajectories, ranging from memorizing the entire trajectory at the sampling rate of the control servo, using spline-based methods, optimization criteria, employing lookup tables and neural networks or using DMP. In this section, we first introduce the dynamic movement primitive framework following by discussion of movement generalization to new goals. Then, we present our modified DMP equations, and its extension to stair ascent task.

After learning process, we generate new trajectories with start point $x_0$ and end point $g$.

**DMP** DMP is a framework by which a unit of action can be formalized as stable nonlinear attractor system. In the framework of DMP, any recorded movement can be represented with a set of differential equations (Ijspeert et al., 2002a, 2002b; Gams et al., 2014) As representing a movement with a differential equation, a perturbation can be corrected automatically by the dynamics of the system (robustness against perturbation). Moreover, these equations are formulated in a way in which adaptation to a new goal is achieved by simply changing a goal parameter [26]. Thus, motion trajectories can be imitated and adapted with different aims with DMP. As shown in Figure 3, dynamic movement primitives can be used to imitation learning, learning a trajectory and generating a new one. It learns from a known trajectory and re-generate new trajectories with similar forms and different goal positions. In learning process, for encoding a trajectory, $x(t)$ is supposed to be the output of amass-damper-spring system perturbed by an external forcing term:

$$\tau = K(g - x) - Dv + (g - x_0)f$$

$$\tau x = \nu$$

where $x$ and $v$ indicate the position and velocity of the system, and $x_0$ and $g$ are the start and goal position. $\tau$ is a temporal scaling factor. $K$ and $D$ are the spring and damping factors of the system. $f$ is a non-linear function expressing denoting external force term which can be learned and drive the generation of complex trajectories. This equation is referred to as a transformation system which drives the output of system with an external force term $f$. Thus, this input of system $f$ can be obtained with a known output $x(t)$ with inverse of system:

$$f_{\text{target}}(s) = \frac{K(g - x) + Dv + \tau t}{g - x_0}$$

While, the $f$ does not depend on time $t$ directly; instead, it depends on a phase variable $s$. For the convergence of system, this variable $s$ can be obtained from the equation as follows:

$$\tau s = \alpha s$$

where $\alpha$ is a pre-defined constant parameter. This equation is referred to as canonical system. Then, we can fit the external force with variable $s$ and parameters $\delta$ as follows:

$$f(s) = \sum_{i=1}^{N} \delta_i \psi_i(s)$$

where $\psi = \exp(-h_i(s - c_i)^2)$ are Gaussian basis functions, with center $c_i$ and with $h_i$ and $w_i$ are adjustable weights. To learn a trajectory from demonstration, first, a movement $x(t)$ is recorded and the derivatives $v(t)$ and $\dot{z}(t)$ are calculated for each time sample time $t = 0, \ldots, T$. Second, integrated with canonical system, $s(t)$ is calculated for an appropriately adjusted temporal scaling $\tau$. Then, computing the weights $\delta_i$ in that minimize the error criterion $f = \sum (f_{\text{target}}(s) - f(s))^2$, which is a linear regression problem that can be solved efficiently.

**Figure 3** The framework of a one-dimensional DMP with two process: learning from a recorded trajectories and re-generating a new trajectory with special parameters

**Notes:** In learning process, we get the input of system $f(t)$ by the output of system $x(t)$ and the equation of system and using. Then, using variable $s$ and $w$ to describe $f(t)$
In re-generation process, a trajectory plan is generated by learned weight and target parameters. With learned weights $w_{i}$, $f(t)$ can be obtained the target function. Then, integrating the canonical system, we can get $s(t)$, and with and specifying a desired start $x_{0}$ and goal $g$, setting $s = 1$, $f(t)$ can be obtained. The non-linear function $f(t)$ drives the linear mass-damper spring system to compute the desired attractor landscape.

Re-plan trajectories online for stair ascent: In stair ascent task, trajectories of swing foot $x(t)$, $z(t)$ shown in Figure 2(b) can be modeled as two DMPs in the sagittal plane separately. For Integrating LWPR and DMP, first, we trained DMPs with known trajectories sampled from healthy people during normal walking. Then, special coupled terms are designed according to external forces motioned before for re-planning. To re-plan the trajectories online, we rewrite transformation system of DMP with coupling terms $Q_{x}$ in $x$ and $z$ as follows:

$$\tau \dot{v}_{x} = K(g - p_{x}) - Dv + Kf_{x}(s) + Q_{x}, \quad (10)$$

$$\tau \dot{v}_{z} = K(g - p_{z}) - Dv + Kf_{z}(s) + Q_{z}, \quad (11)$$

where $p_{x}$, $p_{z}$ is the position of foot in sagittal plane (XoZ). $Q_{x}$, $Q_{z}$ are coupling terms of trajectories $x(t)$, $z(t)$. $f_{x}(s)$, $(s)$ are nonlinear functions learned by (7).

Impedance model is used to build the coupling term $Q_{s}$ in $x$ direction for reducing contact force in $x$ direction which is written as follows:

$$F_{x}(t) = M_{s}\ddot{Q}_{x} + D_{x}\dot{Q}_{x} + K_{x}Q_{x}, \quad (12)$$

$$Q_{s}(s) = \frac{F_{s}(S)}{M_{s}S^{2} + D_{s}S + K_{s}}, \quad (13)$$

where $F_{s}$ refers to the external force posed on the foot in $x$ dimension. $Q_{s}(s)$ is the form of $Q_{s}$ after Laplace transform. $Q_{s}$ makes the trajectory in $x$ direction move back along the direction of external force. In another word, a spring-damper system is equipped in front of the foot of human-exoskeleton system. Thus, the human-exoskeleton system would move back along the direction of external force rather than be stuck beside the edge of the stair.

For the DMP in $z$ direction, coupling term $Q_{z}$ is decided by motion direction of trajectory $z(t)$ when human-exoskeleton system touches the stair. As shown in Figure 4 (B-2), when direction of force in $z$ direction is downward while moving upward, we set $Q_{z}$ to be positive and proportional to the magnitude of $F_{z}$. This positive $Q_{z}$ would let the swing foot move upward along the edge of stairs to step over the corner of stair. As shown in Figure 4 (B-4), the swing foot touches the stair when it is descending. In this situation, target position is unreachable. Therefore, $Q_{z}$ is set to 0 to let the swing foot move back to the ground for taking next step. Thus, the coupling term in $z$ direction designed as follows:

$$Q_{z} = \begin{cases} -K_{z}F_{z}(1 - e(p_{z} - H)), & \text{if } F_{z} < 0 \text{ and } \dot{p}_{z} > 0 \\ 0, & \text{otherwise} \end{cases} \quad (14)$$

where $F_{z}$ is the contact force in $z$ direction. $K_{z}$ is the amplification coefficient. Unit step function $e(t)$ and motion limitation $H$ in $z$ direction is utilized to let $Q_{z}$ to be 0 when $p_{z} > H$. Thus, the swing foot would move back to the ground if height of stair is higher than $H$ as shown in Figure 4 (B-3). At the end of stair ascent task, if $F_{z} > F_{s}$, it is considered that the foot has already touched the surface of stage as shown in Figure 4 (B-2). Thus, according to the value of $F_{z}$, the goal state of DMP is set as follows:

$$g = \begin{cases} p_{current} & \text{if } F_{z} < \bar{F}_{z} \\ g_{init} & \text{if } F_{z} \geq \bar{F}_{z} \end{cases}, \quad (15)$$

where $p_{current}$ is current position of swing foot and $g_{init}$ is the goal state which is set initially.

2.4 Algorithm flow chart

Two flow charts are presented in this section. The following flow chart describes the flow of obtaining external force with LWPR online, while the second flow chart describes the form of LWPR algorithm.

```
Initialize the LWPR model and Set parameters $e, f$.
for Each sample time during stair ascent task:
    Set external force $f_{ext}$ to be 0.
    Calculate position of foot with forward kinematic.
    if Height of foot is larger than 0 $a$
        and The movement of swing leg in $x$ direction from start point $\delta < 1$ cm:
            Calculate the predict error $E_{p}$ of LWPR.
            Training LWPR with sample data.
    end
    if $E_{p} < E$:
        Calculate external force $f_{ext}$ with LWPR.
        Update familiar factor $C_{a}(d)$.
        Get the closest local data set $S_{i}$.
        if $S_{i}$, $\text{dis}(p, c_{i}) < d$
            $c_{i} = c_{i} + p$
        end
    else
        Create a new data set.
    end
    if $f_{ext} < \hat{f}$:
        Re-train LWPR with sample data.
    end
end
return external force
```
3. Simulation and experiments

3.1 Performance metrics definition
Before going into details, we first lay down what we need to evaluate. For online LWPR regression, we care about the accuracy and regression speed. For system-wise integrated performance, we will evaluate the ability to accomplish stair ascent task with different parameters \((d, h)\) and evaluate the contact forces during the process of stair ascent task.

3.2 Simulator introduction
A simulator in a desktop computing platform with CPU: i7 4790k and 8G RAM with Gazebo robotics simulation software. As the pilot holds the handrail during stair ascent task, we suppose the standing leg and back of human-exoskeleton system to be fixed on the ground. The swing leg is modeled as a serial-link robot which has total 3-DOFs (hip (flexion/extension), knee (flexion/extension) and ankle (flexion/extension)) with a based coordination fixed on the back. In this simulator, a PID controller with 1000 Hz sample frequency is used in each joint with limitation of output torque 200 NM. At each joint of human-exoskeleton system, a joint encoder is embedded to obtain motion state of a joint. Environment parameters \((d, h)\) can be set manually in the simulator.

3.3 Locally weighted projection regression evaluation
- Comparison of nMSE with different online learning algorithms for learning 1-dof system.
- Comparison of time consumption with different online algorithms for training a sample data

To adapt with different pilots quickly, online learning algorithms are necessary and different kinds of algorithm have been tested to learn the dynamic model of human-exoskeleton system. In this case, LWPR, online SVR and Sparse Online GPR with 10,000 increasing examples were trained for learning a 1-DOF dynamic system with a 3-dimensional inputs \((q, \dot{q}, \ddot{q})\) and a 1-dimensional output \(r\). As shown in Figure 5(a), LWPR does not achieve the best performance in aspect of accuracy prediction. However, Figure 5(b) shows that for online SVR and online spares GPR, the average time of training one sample data online rises very fast with increasing size of training data set. Comparing to the other two algorithms, LWPR achieved the best performance in terms of time consumption. Thus, for embedded computation platform in exoskeleton, choosing LWPR to learn the MIMO dynamic system online is reasonable.

3.4 Integrated evaluation
Integrated performance lays down the ability to accomplish stair ascent task with different parameters \((d, h)\) and the magnitude of contact forces during the process. We evaluate LWPR-DMP with \((d=0.30 \ m, \ h=0.30 \ m)\) and \((d=0.24 \ m, \ h=0.24 \ m)\).

Figure 6(a) shows the process of simulation with LWPR-DMP during stair ascent task with \((d=0.30 \ m, \ h=0.30 \ m)\). As the distance target position is out of motion range, neither predefined trajectory approach nor LWPR-DMP can move the foot of human-exoskeleton system to the surface the stair. As trajectories are overlaid with the stair in the sagittal plane, human-exoskeleton system touches the stair when it moves downward. Figure 6(b) shows that following predefined trajectories, the swing foot is blocked at \((d=0.20 \ m, \ h=0.11 \ m)\). The pilot haves to order the exoskeleton to move back to the initial position manually. On the contrary, as shown in Figure 6(c), trajectories generated by LWPR-DMP lead the foot move down until touching the ground. Human-exoskeleton system takes a small step closer to the stair for more convenient for the system to take a next step. Figure 6(d) indicates that comparing to predefined trajectory approach, LWPR-DMP reduces the external forces significantly.

Figure 7(a) shows the process of simulation with LWPR-DMP during stair ascent task with \((d=0.24 \ m, \ h=0.24 \ m)\). With a short distance \(d\), human-exoskeleton system touches the stair when it moves upward. As shown in Figure 7(b), human-exoskeleton system is obstructed besides the edge of stair by following predefined trajectories. With PID joint controllers, the contact forces increase rapidly. On the contrary, as shown in Figure 7(c), the human-exoskeleton system fulfills the task by following trajectories generated by LWPR-DMP. It moves across the edge of stair and stop at the surface of stair. Moreover, Figure 7(d) shows that by following trajectories

Figure 5 Comparison of different online learning algorithms

Notes: (a) Comparison of nMSE with different online learning algorithms for learning 1-dof system; (b) comparison of time consumption with different online algorithms for training a sample data
Figure 6 Experimental results with LWPR-DMP and predefined trajectory method in simulation environment (d = 0.3 m, h = 0.30 m)

Notes: (a) The snapshots of simulation of stair ascent with LWPR-DMP (d = 0.3 m and h = 0.30 m); (b) the predefined trajectory of toe with d = 0.3 m and h = 0.3 m; (c) the trajectory of toe generated by LWPRDMP with d = 0.3 m and h = 0.30 m; (d) the comparison of external force by using LWPR-DMP and predefined trajectory method

Figure 7 Experimental results with LWPR-DMP and predefined trajectory approach in simulation environment (d = 0.24 m, h = 0.24 m)

Notes: (a) The snapshot of simulation of stair ascent with LWPR-DMP (d = 0.24 m and h = 0.24 m); (b) the predefined trajectory of toe with d = 0.24 m and h = 0.24 m; (c) the trajectory of toe generated by LWPRDMP with d = 0.24 m and h = 0.24 m; (d) the comparison of external force with d = 0.24 m and h = 0.24 m
generated by LWPR-DMP the contact force is much less than predefined trajectory approach.

4. Experiments on real exoskeleton systems (AIDER)

In this section, experiments are carried out to validate the proposed LWPR-DMP approach on exoskeleton system (AIDER). The experimental performance also lay down the ability to accomplish stair ascent task with different parameters \((d, h)\) and the contact forces which is an important indicator of safety. Experimental setup, results and discussions are demonstrated in the following two subsections Figure 8.

4.1 AIDER description

AIDER system is designed for walking assistance of paraplegic patients with lower extremities, which aims at helping the paraplegia to stand up, walk and climb up and down stairs. The AIDER system has, in total, four active joints in hips and knees, which are activated by DC servo motors. The ankle joints of AIDER system are designed as energy-storage mechanism which can store energy in stance phase and release it in swing phase during normal walking. Besides the joints and rigid links, many compliant connections at waist, thighs, shanks and feet are provided for semi-rigid connecting AIDER to the pilot. A distributed control system with four node controllers and a main controller is built for real-time control applications of the AIDER system. The main controller is set on the backpack, running the control algorithm of the AIDER system. Near each joint, a node controller is utilized to collect sensor data and execute commands from the main controller. AIDER has total four kinds of sensor to measure its current state. Encoders are interpreted in joint actuators to measure the current state of each joint. IMU sensors and pressure sensors on sticks are used to measure orientation of the pilot’s arm and contact forces between the stick and the ground, respectively. The plantar sensors are installed on the shoes of the AIDER system to estimate gait phases.

4.2 Experiment setup and pre-conditions

In the experiments, one pilot with height: 178 cm and weight: 83 kg is chosen to operate the exoskeleton system. The pilot grasps the handrail in the whole process to keep balance. To validate the control performance, distance between the edge of stair and standing leg ranges from 0.21 to 0.40 m.

4.3 Experimental results

As shown in Figure 9(a), the pilot with AIDER gets stuck beside the edge of stair by following the trajectories generated by LWPR-DMP. While, by following trajectories generated by LWPR-DMP, the swing foot moves back to the ground instead of stopping by the edge of the stair which makes the pilot easier to take the next step. The comparison of trajectories during this task is described in Figure 9(b). Moreover, as shown in Figure 9(c), comparing to the results using the predefined trajectories, by using LWPR-DMP external forces posed on the foot of pilot are much less both in \(x\) and \(z\) dimension.

As shown in Figure 9(a) with \((d = 0.23 \text{ m, } h = 0.13 \text{ m})\), using LWPR-DMP the pilot accomplishes the stairs ascend task. As shown in Figure 10(b), trajectories generated by LWPR-DMP turns upward around the corner of the stair and ends on the surface of stair. As shown in Figure 10(c), LWPR-DMP also achieves better performance than predefined trajectory.
approach in terms of reducing external forces posed on AIDER during this process.

5. Conclusions and future works

In this paper, we proposed a novel approach which combines learning and planning techniques to enable exoskeleton to adapt to different situations in stair ascent task. In this approach, LWPR with familiar factor is used to learn the external forces online in real-time. With learned external forces, DMPs are used to present and re-plan the exoskeleton gait trajectories dynamically during the ascent. Experiments on both in simulation and real system with different environment demonstrate the efficiency of this approach.

In the future, we will first extend this approach to different tasks of exoskeleton. For example, during normal walking process foot of exoskeleton will touch ground before arriving the end of trajectory because of the motion of pilot. Thus, these trajectories also need to be re-planned. Then, considering the external force would let the system lose balance during walking process which is unacceptable, special coupling terms of DMPs should be proposed to keep balance of system during.

References


Figure 10 Experimental results with LWPR-DMP and predefined trajectory with d = 0.23 m and h = 0.13 m

Notes: (a) Experiments in Aider by using LWPR-DMP with d = 0.23 m and h = 0.13 m; (b) comparison of trajectories generated by LWPR-DMP and predefined trajectory; (c) comparison of external forces by using LWPR-DMP and predefined trajectory.


**Further reading**


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Dynamic obstacle-surmounting analysis of a bilateral-wheeled cable-climbing robot for cable-stayed bridges

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Abstract
Purpose – Field robots can surmount or avoid some obstacles when operating on rough ground. However, cable-climbing robots can only surmount obstacles because their moving path is completely restricted along the cables. This paper aims to analyse the dynamic obstacle-surmounting models for the driving and driven wheels of the climbing mechanism, and design a mechanical structure for a bilateral-wheeled cable-climbing robot to improve the obstacle crossing capability.

Design/methodology/approach – A mechanical structure of the bilateral-wheeled cable-climbing robot is designed in this paper. Then, the kinematic and dynamic obstacle-surmounting of the driven and driving wheels are investigated through static-dynamic analysis and Lagrangian mechanical analysis, respectively. The climbing and obstacle-surmounting experiments are carried out to improve the obstacle crossing capability. The required motion curve, speed and driving moment of the robot during obstacle-surmounting are generated from the experiments results.

Findings – The presented method offers a solution for dynamic obstacle-surmounting analysis of a bilateral-wheeled cable-climbing robot. The simulation, laboratory testing and field experimental results prove that the climbing capability of the robot is near-constant on cables with diameters between 60 and 205 mm.

Originality/value – The dynamic analysis method presented in this paper is found to be applicable to rod structures with large obstacles and improved the stability of the robot at high altitude. Simulations and experiments are also conducted for performance evaluation.

Keywords Field tests, Cable-climbing robot, Obstacle-surmounting performance, Static and dynamic analysis

Paper type Research paper

1. Introduction

Rod structures are widely applied in modern society; accordingly, much interest has been directed towards the development of corresponding robots to automatically detect and maintain rod structures. In the process, the interservice intervals of these structures can be prolonged. In line with this interest, cable-climbing aerial robots are typically used for long-span cable-stayed bridges. The length of the cables used for long-span cable-stayed bridges are several hundred metres, and the cables need to bear heavy loads and operate in harsh environments (such as high-altitude wind or vibration induced by traffic). If a cable surface is damaged, cable-climbing robots may encounter various obstacles, including the cracking of protective layers, pits, scratches and bumps (Li et al., 2013). Therefore, the obstacle-surmounting performance of round pole- or cable-type climbing robots should be investigated.

Recently, many researchers have proposed similar special robots for cable-like structures. For example, Cho et al. (2013) designed a cable-climbing robot composed of three similar modules for the inspection of long cables. These modules were circumferentially placed 120° apart from one another on a main frame around the cable. Every module featured three functional mechanisms: driving mechanism, adsorption mechanism and safe reclaiming mechanism. They improved the robot system to address the need for fast installation. Luo et al. (2007) presented a cable-painting robot structure, which can carry coating materials for painting cables. It was successfully trialled on cable-stayed bridges in China. Irani et al. (2013) established a new dynamic model for wheeled moving robots on the basis of the traditional wheel-soil modelling for light-weight models to study pull fluctuations. Debenest and Guarnieri (2010) developed an “Expliner” robot to inspect electricity lines. The robot can adjust the position of its own centre of mass by altering its configuration.

This project is supported by the National Natural Science Foundation of China (51775284), Primary Research & Development Plan of Jiangsu Province (BE2018734), Supported by State Key Laboratory of Robotics and System (HIT)(SKLRS-2017-KF-10) and Joint Research Fund for Overseas Chinese, Hong Kong and Macao Young Scholars (61728302).

Received 25 July 2018
Revised 14 November 2018
Accepted 6 December 2018
This design feature enables the robot to move on live transmission lines and inspect conductors without interrupting the power supply so that it could reduce the operators. The Robotics and Artificial Intelligence Laboratory of the University of Tehran developed a pole-climbing robot consisting of a triangular mechanism and six limbs (Mahdavi et al., 2007). These limbs are tipped with ordinary wheels. This robot is mainly used to clean highway lighting-pole systems and is powered by electrical wires that can destabilize the robot when it moves at high altitude. Sadeghi et al. (2012) also proposed a human-climbing-inspired pole-climbing robot that motivated the novel design, static analysis, simulation and realization of a naturally stable climbing robot. Patrick et al. (2011) proposed a miniature magnetic caterpillar climbing robot. With the particular geometry of the caterpillar, it has plane transition ability. Atsushi (2016) presented an in-pipe robot design based on the spring principle for climbing vertically positioned bent pipes. The robot is composed of three parts: a front-rotating unit, a middle-steering unit and a rear-supporting unit. Other researchers (Spenko et al., 2008; Haynes et al., 2009) produced a spine-based, bio-inspired climbing robot called RiSE for scannorial environments using micro-spines that catch onto rough surface asperities and use these as bases. Manufacturers also constructed tree-climbing robots by combining six complex modules as legs. Wei et al. (2014) introduced a snake-like robot consisting of modules with only 1-DOF. The number of modules can be increased or decreased to realize manual reconstruction and adaptation to the cable features. However, these manufactured robots require numerous driving devices. As a result, their mechanical structures are complicated.

The independent pole inspection robots have been established and implemented in some industry applications, such as the 3-DCLIMBER for 3-d pole-like structures (Tavakoli et al., 2011), the climbing robot RiSE V3 (Haynes et al., 2009), a crawling snake robot (Sun et al., 2008), a wheeled robot that climbs over ground obstacles (Yu et al., 2007, 2008) and a hybrid pole-climbing and manipulation robot (Tavakoli et al., 2005). However, these robots are mainly used to inspect certain low-altitude structures. Moreover, the obstacle-surmounting requirements of cable-climbing robots differ significantly from those of round rod-type robots.

Although the round rod-type robots mentioned above can climb rod structures, their efficiency is very low when the length of the cable reaches several hundreds of metres. We concluded that it is difficult for a squirmly or legged-type robot to return to the ground safely during an electrical malfunction (Xu et al., 2014, 2011). The mechanism of a crawler mobile robot is complicated and the cost is high. Tether supports are the most suitable for high-rise building applications. Under the action of high-altitude wind loading, the long towing wire can easily wrap around the cable especially when the slant angle is small. Therefore, in this work, to achieve suitable modes of the movement at high altitudes, the modes of movement of various specialized robots are analysed and a wheel-driven robot with high reliability and the ability to surmount obstacles is designed. This system is more flexible when inspecting high-altitude cabling. Furthermore, the authors select a bilateral-wheeled structure for the sake of easy installation on the robot. The climbing robot possesses the following advantages:

- the robot is lightweight and climbs fast with payloads under 4 kg;
- the climbing mechanism designed is suitable for the cables with several kinds of diameters (ranging from 77.4 to 124.4 mm);
- the recovery mechanism guarantees the robot to decline downward in case of electrical malfunction; and
- remote monitoring and controlling, and data wireless transmission is achieved in the inspecting robot system.

The paper is organized as follows: the mechanical structure of a cable-climbing mechanism is designed in Section 2, the kinematic and dynamic models of the upper driven robot wheels when surmounting certain obstacles are analysed in Section 3. In Section 4, we analyse the dynamic characteristics of the robot’s driving wheel. We conduct a simulation and field experiment analysis on the obstacle-surmounting ability of the cable-climbing robot in Section 5. Conclusions and future works are presented in Section 6.

2. The mechanism of a bilateral-wheeled cable-climbing robot

2.1 Structure of the cable-climbing robot

The cable of a cable-stayed bridge is generally inclined between 20° and 89.7°. Thus, the designed robot is orientated to detect a vertical cable. Resistances should be minimized, and climbing dynamic forces should be maximized to increase the climbing capability of the mechanism. Figure 1(a) shows the mechanical model of the bilateral-wheeled climbing mechanism. The robot can be used for cables with different diameters by adjusting the lengths of the connecting components.

The driving trolley [Figure 1(b)] consists of a sub-driving trolley and a speed-limiting descent mechanism. The driving module forms the power supply for the climbing mechanism. As the driving trolley climbs, the electromagnetic clutch is closed, and the motor directly drives the upper driving wheel of this trolley upwards. The driving wheel is machined through casting a special rubber with cast aluminium used to improve its coefficient of friction against the cable or pole surface. The electromagnetic clutch is separated in the event of an electrical system fault and robot down-sliding. The overall dimensions of the climbing robot are as follows: the height of the robot is 385 mm, and its width is 250 mm. Moreover, the length of the robot can be varied from 145 mm to 295 mm as the diameter of the cable increases from 60 mm to 205 mm.

The driven trolley merely balances the entire robot. The trolley consists of upper and lower swing arms that are connected to a driven wheel. The clamping force is generated by tensioning the upper and lower driven wheels using a tensile spring to install the wheels on the cable. The two swing arms stretch smoothly along the trolley to adapt to the rugged surface of the cable and to maintain contact with the wheels. The driving and driven, moving wheels are machined to a “V-shape” to increase the contact area between the travelling wheel and cable surface (Table I).

2.2 The obstacle-surmounting process of the cable-climbing robot

The obstacles on cable surfaces generally include transverse cracking of the protective layers, pits, scratches, and bumps
Such obstacles generate more factors for consideration compared with ground obstacles to be surmounted because the normal pressure exerted on the travelling wheel of the mechanism is induced through a spring instead of the self-weight of the mechanism. Some obstacles on cables can significantly influence robot motion even though their size is small. Therefore, the obstacle-surmounting process of robots should be analysed from both kinematic and dynamic perspectives. Thus, this study analyses dynamic robot problems using a simplified model (linkage mechanism). The upper and lower travelling wheels are not located in the same horizontal planes to guarantee only one travelling wheel crosses the obstacle at a given time. The obstacle-surmounting process of a robot involves the following two stages:

1. Deviation of the robot body occurred when driving Wheel 1 or driven Wheel 4 climbs over an obstacle. The robot deflects itself and surmounts obstacles according to the coordinated swing of the upper and lower supporting arms, given that driving Wheel 1 and driven Wheel 4 are situated in a dead joint as they cross an obstacle. In this case, the centre of gravity of the robot moves on a plane, as shown in Figure 2(a).

2. Non-deflection obstacle-surmounting of the robot occurred when the driven wheels on the driven trolley climb. In this process, the driving trolley moves in a straight line. The robot body is not deflected when Wheels 2 and 3 cross the obstacle. The driving and driven wheels on one side of the driving trolley remain invariant, whereas the two supporting arms of the driven trolley will swing around the trolley to surmount obstacles, as indicated in Figure 2(b). In this case, the centre of gravity of the robot moves upwards in a straight line and at a constant speed.

To simplify this problem, some appropriate assumptions are supposed as follows:

- The cable surface is rigid. The climbing wheel does not slip on the cable surface (Kang et al., 2013); therefore, we focus only on the motion of the robot on the x–y plane, where y is the direction of motion.
- The climbing robot does not revolve around the cable-axis during obstacle-surmounting. Only one travelling wheel crosses the obstacle at a given time. The edge of the “V”-shaped wheel makes contact with the obstacle at two points.
- The tiny swing angle of the tension spring, and friction among robot components, are ignored in the analysis of the travelling process when the driven wheel surmounts an obstacle.

From the robot structure, the obstacle-negotiating capability of the upper wheels is greater than that of the lower wheels. Therefore, we only describe the object-negotiation analysis with reference to the upper wheels here.

### Table 1: Dimension of the climbing robot

<table>
<thead>
<tr>
<th>Symbol and value</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Height of the robot</td>
<td>H = 385 mm</td>
</tr>
<tr>
<td>Length of the robot</td>
<td>L = (145-295) mm</td>
</tr>
<tr>
<td>Width of the robot</td>
<td>W = 250 mm</td>
</tr>
</tbody>
</table>

### 3. Analysis of obstacle-surmounting for the upper driven wheel of the robot

The obstacle-surmounting model of the robot’s upper driven wheel is composed of the dynamic equilibrium of Wheel 2, the upper swing arm, and the robot body [equations (1) to (3)]. These three parts are mutually
The obstacle-surmounting process of the climbing robot

Figure 2: The obstacle-surmounting process of the climbing robot

Notes: (a) Obstacle-surmounting of the driving wheel; (b) obstacle-surmounting of the driven wheel

influenced by interaction and reaction forces/moments (Figure 3). This model describes the dynamic obstacle-surmounting process of the robot. Moreover, a static-dynamic analysis is conducted by introducing inertial force/momentum (including the inertial forces of the obstacle-surmounting wheel, upper swing arm, driving wheel and Wheel 4).

Considering the Earth as an absolute coordinate system XOY, relative coordinates xo;y are established on the support point of the upper swing arm. This coordinate system is parallel to the absolute coordinates. The transport acceleration of xo;y is presumably ay in the positive y-direction in the fixed coordinate system.

The balancing relationships between the upper swing arm, the obstacle-negotiating wheel and the robot are determined horizontally, vertically and rotationally, respectively.

\[
\begin{align*}
I_{nhd} - I_{nhu} + Q_{nhn} &= 0 \\
I_{mvd} + I_{mru} - Q_{mru} - G_m &= 0 \\
I_{nhu} b_2 \sin \theta_2 + I_{nhd} a_2 \sin \theta_2 - I_{mru} b_2 \cos \theta_2 &= 0 \\
-I_{mvd} a_2 \cos \theta_2 - P_m &= 0 \\
I_{cu} - N_2 \cos \alpha_2 - m_2 g - F_t - F_a \sin \alpha_2 - Q_{cu} &= 0 \\
I_{hu} + f_a \cos \alpha_2 - F_a \sin \alpha_2 + Q_{hu} &= 0 \\
f_ar2 &= P_a \\
-l_{hd} - N_4 + N_1 + N_3 + Q_{hr} &= 0 \\
F_{f1} + F_t - N_4 \mu - N_3 \mu - G_R - I_{rd} + Q_{cr} &= 0 \\
\tau &= F_{f1}r_1 + r
\end{align*}
\]

where \(m_2g\), \(G_m\) and \(G_R\) are the weights of upper driven Wheel 2, the upper swing arm and robot, respectively; \(F_p\) refers to the friction acting on the \(i^{th}\) traveling wheel; \(N_i\) is the supporting force of the obstacles/cable surface associated with the \(i^{th}\) traveling wheel; and \(I_{hu}\) and \(I_{cu}\) are the horizontal and vertical forces of the upper swing arm as applied to driven Wheel 2, respectively; \(I_{hd}\) and \(I_{rd}\) represent the horizontal and vertical forces on the upper swing arm as applied to the robot, respectively; \(I_{nhud}\) \(I_{nru}\) \(I_{nhu}\) and \(I_{mvd}\) are the corresponding reactive forces; \(\tau\) is the output torque of the driving wheel; \(Q_{hu}\) and \(Q_{cu}\) denote the d’Alembert horizontal and vertical inertial forces on driven Wheel 2, respectively; \(Q_{hd}\) and \(Q_{cr}\) correspond to the d’Alembert horizontal and vertical inertial forces on the upper swing arm, respectively; \(Q_{hr}\) and \(Q_{cr}\) represent the d’Alembert horizontal and vertical inertial forces of the robot, respectively; \(P_{hu}\) \(P_{mu}\) and \(P_r\) are the d’Alembert inertial torques of driven Wheel 2, the upper swing arm and trolley, respectively.

We set the driving wheel to rotate uniformly at a speed of \(\omega\) to optimize robot control during obstacle-surmounting. The ascending speed of the robot is \(v = \omega r_1\).

Given the determined initial state, the pitch angle \(\theta_2\) of the upper swing arm can simply be deduced by the angle \(\alpha_2\) of the obstacle-negotiating wheel during obstacle-surmounting.

According to \(l_1 \cos \theta_{20} - l_2 \cos \theta_2 = r_2 \sin \alpha_2 - r_2 \sin \alpha_{20}\):

\[
\begin{align*}
\alpha_2 &= \arcsin \frac{l_2 \cos \theta_{20} - l_2 \cos \theta_2 + r_2 \sin \alpha_{20}}{r_2} \\
\theta_2 &= \arccos \frac{l_2 \cos \theta_{20} - l_2 \sin \alpha_2 + r_2 \sin \alpha_{20}}{l_2}
\end{align*}
\]

where \(\theta_{20}\) and \(\alpha_{20}\) are the initial values of \(\theta_2\) and \(\alpha_2\), respectively. The projections of the speeds on line \(O_1O_2\) are equal. Therefore, the speed of the centre of driven Wheel 2 is given by:
The motion of the upper swing arm of the robot follows the instantaneous centre law. The vertical line of the motion speed vector of each point passes through the same point I (this point is the instantaneous centre of the upper swing arm at the corresponding time). According to sine and cosine theorems:

$$\frac{l_2}{\sin(90^\circ - \alpha_2)} = \frac{IO_1}{\sin(\alpha_2 + \theta_2 - 90^\circ)} \rightarrow IO_1 = \frac{l_2 \cos(\alpha_2 + \theta_2)}{\cos \alpha_2},$$

(6)

$$IP_{12} = \sqrt{a_z^2 + IO_1^2 + 2a_zIO_1 \cos(\pi - \theta_2)},$$

(7)

where IO_1, IP_{12} and IO_3 denote the rotations around the instantaneous centre I perpendicular to the speed vectors \(\nu_{pl2}\) and \(\nu_{O3}\) respectively. The motions of the points on the upper arm can be treated as uniform rotations around the instantaneous centre I. Thus, the rotational speed \(\omega_m\) is given by:

$$\omega_m = \frac{v}{IO_1}.$$  

(8)

The centre of gravity rate of the upper swing arm is therefore obtained using:

$$v_{pg2} = \omega_m \cdot IP_{12}.$$  

(9)

According to the sine theorem, angle \(\varphi\) in Figure 4 is given by:

$$\frac{a_2}{\sin \varphi} = \frac{P_{21}I}{\sin(\pi - \theta_2)}.$$  

(10)

The velocity \(v\) of point O_1 is parallel to the \(y\)-axis, \(v_{\nu_{pl2}}\) is the velocity direction angle of the centre of the obstacle-negotiating wheel measured from the \(y\)-axis, and \(\varphi\) is the angle between \(v_{pg2}\) (the speed of the centre of gravity of the upper swing arm) and the \(y\)-axis.

The corresponding accelerations can be obtained according to the law governing the motion of the obstacle-negotiating wheel and the robot. The robot moves uniformly, that is to say, the acceleration of point O_1 is 0. The movements of the obstacle-negotiating wheel and the upper swing arm are planar; \(i\) represents the unit vector on the \(x\)-axis; \(j\) represents the unit vector on the \(z\)-axis; and the angular velocity of the obstacle-negotiating wheel is given by:

$$\omega_2 = \frac{v_{O3}}{r_2}.$$  

(11)

According to the sine theorem:

$$\frac{l_2}{\sin(90^\circ - \alpha_2)} = \frac{IO_3}{\sin(\pi - \theta_2)} \rightarrow IO_3 = \frac{l_2 \sin \theta_2}{\cos \alpha_2},$$

(12)

The tangential acceleration of point O_3 is:

$$|a_{O3}^2| = -v^2 r^2 \cos^2 \alpha_2 + \frac{v^2 \sin \theta_2 \sin(\alpha_2 + \theta_2)}{\cos^3(\alpha_2 + \theta_2)}.$$  

The normal acceleration of point O_3 is:

$$|a_{O3}^n| = \frac{v^2 \sin^2 \theta_2}{r_2 \cos^2 \cos(\alpha_2 + \theta_2)}.$$  

\(\omega_m\) is the rotational speed of the obstacle-negotiating wheel measured from the \(y\)-axis, \(v_{\nu_{pl2}}\) is the velocity direction angle of the centre of the obstacle-negotiating wheel measured from the \(y\)-axis, and \(\varphi\) is the angle between \(v_{pg2}\) (the speed of the centre of gravity of the upper swing arm) and the \(y\)-axis.

The velocity \(v\) of point O_1 is parallel to the \(y\)-axis, \(v_{\nu_{pl2}}\) is the velocity direction angle of the centre of the obstacle-negotiating wheel measured from the \(y\)-axis, and \(\varphi\) is the angle between \(v_{pg2}\) (the speed of the centre of gravity of the upper swing arm) and the \(y\)-axis.

Figure 3 Forces on the upper driven wheel

Figure 4 Forces on driven Wheel 2
The acceleration of point $O_3$ is:

\[
a_{O3} = [a_{O3}^x] (-\cos \alpha_2 \cdot i + \sin \alpha_2 \cdot j) + [a_{O3}^y] (\sin \alpha_2 \cdot i + \cos \alpha_2 \cdot j)
\]

\[
= \omega^2 \cdot r_c^2 \cdot \sin^2 \alpha_2 - \omega \cdot r_c \cdot \frac{\sin \theta_2 \cdot \sin (\alpha_2 + \theta_2) + \cos \theta_2 \cdot \cos (\alpha_2 + \theta_2)}{\cos \alpha_2 \cdot \sin \alpha_2} + \frac{\sin \alpha_2 \cdot \omega \cdot r_c \cdot \cos \theta_2}{r_c^2 \cdot \cos^2 (\alpha_2 + \theta_2)} \cdot i + \omega^2 \cdot r_c^2 \cdot \sin \alpha_2 \cdot \cos \alpha_2 \cdot \sin (\alpha_2 + \theta_2) + \frac{\cos \alpha_2 \cdot \sin^2 \theta_2 \cdot \cos (\alpha_2 + \theta_2)}{r_c^2 \cdot \cos^3 (\alpha_2 + \theta_2)} \cdot j
\]

The angular acceleration of the obstacle-negotiating wheel around the instantaneous centre $O_2$ is:

\[
\alpha_{O3} = \frac{\omega}{r_2} \cdot \frac{\cos \alpha_2 + 1}{\cos \alpha_2} \cdot \sin \theta_2 \cdot \sin (\alpha_2 + \theta_2)
\]

Based on the relationships between the acceleration vector points in planar movement, it is found that:

\[
a_{O3} = \bar{a}_{O3} = \bar{a}_{O3}^n + \bar{a}_{O3}^t = \bar{a}_{O3}^n + \bar{a}_{O3}^{nO} + \bar{a}_{O3}^{tO}
\]

(13)

where $\bar{a}_{O3}^n$ and $\bar{a}_{O3}^{tO}$ are the normal and tangential accelerations of points $O_3$ to $O_2$, respectively. By combining the components on axes $x$ and $y$, we can generate the following equation group:

\[
\begin{cases}
\bar{a}_{O3}^n = [\bar{a}_{O3}^n] \cdot \sin \alpha_2 - [\bar{a}_{O3}^n] \cdot \cos \alpha_2 = -[\bar{a}_{O3}^{nO}] \cdot \cos \theta_2 - [\bar{a}_{O3}^{tO}] \cdot \sin \theta_2 \\
[\bar{a}_{O3}^{tO}] \cdot \cos \alpha_2 + [\bar{a}_{O3}^n] \cdot \sin \alpha_2 = -[\bar{a}_{O3}^{nO}] \cdot \sin \theta_2 + [\bar{a}_{O3}^{tO}] \cdot \cos \theta_2
\end{cases}
\]

(14)

Solving this equation group gives:

\[
\bar{a}_{O3} = \frac{[\bar{a}_{O3}^n]}{l_2} \cdot \frac{[\bar{a}_{O3}^{nO}] \cdot \cos (\alpha_2 + \theta_2) - [\bar{a}_{O3}^{tO}] \cdot \sin (\alpha_2 + \theta_2)}{(-\cos \theta_2 \cdot i - \sin \theta_2 \cdot j) + [\bar{a}_{O3}^t] \cdot \cos (\alpha_2 + \theta_2) + [\bar{a}_{O3}^n] \cdot \sin (\alpha_2 + \theta_2)}
\]

(15)

As shown in equation (13), the relationship between $\bar{a}_{O3}$ and $\bar{a}_{P2O}$ is as follows:

\[
\bar{a}_{P2O} = \bar{a}_{O3} + \bar{a}_{P2O} = \bar{a}_{O3} + \bar{a}_{P2O}^n + \bar{a}_{P2O}^t
\]

(17)

According to equations (15) to (17), we can calculate the acceleration vector of the centre of gravity of the upper swing arm as follows:

\[
\bar{a}_{P2} = \frac{[\bar{a}_{O3}^n]}{l_2} \cdot \frac{[\bar{a}_{O3}^{nO}] \cdot \cos (\alpha_2 + \theta_2) - [\bar{a}_{O3}^{tO}] \cdot \sin (\alpha_2 + \theta_2)}{(-\cos \theta_2 \cdot i - \sin \theta_2 \cdot j) + [\bar{a}_{O3}^t] \cdot \cos (\alpha_2 + \theta_2) + [\bar{a}_{O3}^n] \cdot \sin (\alpha_2 + \theta_2)}
\]

(18)

The angular acceleration $\theta_{m2}$ of the centre of gravity of the upper swing arm that rotates around the instantaneous centre $I$ is given by:

\[
\theta_{m2} = \frac{[a_{O3}^n]}{l_2} = \frac{[a_{O3}^{nO}] \cdot \cos (\alpha_2 + \theta_2) - [a_{O3}^{tO}] \cdot \sin (\alpha_2 + \theta_2)}{(-\cos \theta_2 \cdot i - \sin \theta_2 \cdot j) + [a_{O3}^t] \cdot \cos (\alpha_2 + \theta_2) + [a_{O3}^n] \cdot \sin (\alpha_2 + \theta_2)}
\]

(19)

The corresponding inertial forces/torques are determined as follows:

1. The acceleration of the robot: $a_{o1} = 0$; the inertial force of the robot: $Q_{o1} = 0, Q_{o2} = 0$
2. The angular velocity of the robot: $\omega_{o1} = 0$; the inertial torque of the robot: $P_{o1} = 0$
3. The inertial force of the upper obstacle-negotiating wheel:
4. Obstacle-surmounting of the robot’s driving wheel

4.1 Kinematic analysis of obstacle-surmounting by the driving wheel of the robot

We use the second Lagrange equation to analyse the system. To establish the equation, we need the speed of each component. Here, we list the displacement expressions in Cartesian coordinates and their derivatives.

The vertical component of the main active force acts as the driving force of the robot when driving Wheel 1 crosses an obstacle. The obstacle-surmounting method used for Wheel 1 is significant in this study because it is more complicated than that of Wheel 4. The trajectory of the motion of the centre of the obstacle-negotiating wheel is an arc whose contact point is at the centre during obstacle-surmounting. The obstacle-surmounting model is simplified into a 2-d model on plane $x$-$y$ (Figure 5) according to the aforementioned assumptions: $y$ is the movement direction of the climbing mechanism, and $\phi_1$ represents the angle between the $y$-axis and a line that connects the centre of Wheel 1 to the contact point; $\phi_2$ is the angle between the $y$-axis and a line through points A and F (\(\phi_1\) is also defined as the pitch angle of the robot). The other kinematic parameters of the robot can be determined according to the initial phase angle $\phi_{10}$ and the angular velocity $\omega_{OA}$ of the generatrix (OA) on the driving wheel. OA also rotates uniformly with the driving wheel during obstacle-surmounting. Therefore, various kinematic parameters can be derived, including the locus of the centre of the travelling wheel, the centre of gravity of the driven wheel’s supporting arm, and the centre of gravity of the robot.

Considering that the obstacle-surmounting model is a non-free system with only one degree of freedom $\phi_1$, we can find the locus of each component through examination of the value of $\phi_1$.

The coordinates of the centroid of each component can be expressed as:

$$
\begin{aligned}
x_i &= f_{xi}(\phi_1) \\
y_i &= f_{yi}(\phi_1) \\
\phi_i &= f_{\phi i}(\phi_1)
\end{aligned}
$$

Their speeds are given by:

$$
\begin{aligned}
x_i &= df_{xi}(\phi_1)/dt \\
y_i &= df_{yi}(\phi_1)/dt \\
\phi_i &= df_{\phi i}(\phi_1)/dt
\end{aligned}
$$

Their accelerations are given by:

$$
\begin{aligned}
\ddot{x}_i &= d^2f_{xi}(\phi_1)/dt^2 \\
\ddot{y}_i &= d^2f_{yi}(\phi_1)/dt^2 \\
\ddot{\phi}_i &= d^2f_{\phi i}(\phi_1)/dt^2
\end{aligned}
$$

Here, $\phi_1 = \omega \cdot t$, $t$ is time and $\omega$ represents the angular velocity of the driving wheel.
4.2 Dynamic analysis of obstacle-surmounting by the driving wheel of the robot

Given the speed and acceleration in Section 4.1, we need to obtain the generalized force $Q$ and the kinetic energy $T$. We can then establish the equation $\frac{d}{dt} \left( \frac{dT}{d\theta_i} \right) = Q$ and determine the motor torque.

4.2.1 Analysis of spring force

The spring force is the main resistance encountered when the mechanism crosses an obstacle. The work done in altering this spring force can be expressed as:

$$W_i = -K \left( \delta_0^2 - (\delta_0 + \Delta l)^2 \right) / 2$$
(21)

where $\delta_0$ is the initial deflection; $\Delta l$ is the elongation during surmounting; and $K$ is the spring coefficient.

Figure 6 shows the compression variations in the spring when driving Wheel 1 crosses an obstacle. $\Delta l = \Delta l_2 + \Delta l_3 = l_2(\cos \phi_2 - \cos \phi_{20}) + l_3(\cos \phi_3 - \cos \phi_{30})$, where $l_i$ is the length of the swing arm.

4.2.2 Calculation of generalized force $Q$

Unlike static-dynamic analysis, we can ignore the constraint reaction in the Lagrange equation. The rolling friction is negligible because there is no displacement at the contact point, that is to say, it is also a constraint reaction.

The potential energy $V_i$ includes the following:

- The gravitational potential energy $V_i = M_i (y_p - Y_{p0})$ of the robot, where $y_{p0}$ is the initial position of the centre of gravity; and
- The elastic potential energy $V_i = -K \left( \delta_0^2 - (\delta_0 + \Delta l)^2 \right) / 2$.

The active forces $F_i$ include:

- The motor torque $\tau$; and
- The inertial force and moment of each component which act in a direction opposite to that of the acceleration and are expressed as:

$$\tau = \sum F_i \cdot d\phi_i - dW_i - \sum F_{si} \cdot df_{si}(\phi_i) - \sum M_i$$
(23)

$\psi_i$ is the vector of each component.

4.2.3 Calculation of kinetic energy $T$

We calculate the translational energy and rotating kinetic energy because the robot system rotates during obstacle-surmounting. We can obtain the translational energy from:

$$T_1 = \frac{1}{2} m_{ci} v_i^2 = \frac{1}{2} \left( m_{A} v_{A}^2 + m_{B} v_{B}^2 + m_{P} v_{P}^2 + m_{E} v_{E}^2 + m_{P} v_{P}^2 + m_{BC} v_{BC}^2 + m_{DE} v_{DE}^2 \right)$$
(24)

where $v_i$ is the speed of each centroid listed in Section 4.1, $v_i = \sqrt{\dot{\phi}_{i1}^2 + \dot{\phi}_{i2}^2}$. We then measure each moment of inertia $I_i$ and obtain the rotational kinetic energy as follows:

$$T_2 = \frac{1}{2} J_i \omega_i^2 = \sum \frac{1}{2} J_i \phi_i^2 = \frac{1}{2} \left( J_A \phi_A^2 + J_B \phi_B^2 + J_E \phi_E^2 \right.$$

$$+ J_P \phi_P^2 + J_P \phi_P^2 + J_{BC} \phi_{BC}^2 + J_{DE} \phi_{DE}^2 \right)$$
(25)

where $\phi_B$ can be expressed as $\frac{\phi_A}{\tan \alpha}$, and $\phi_E$ and $\phi_F$ can be expressed in the same way.

Through use of equations (24) and (25), the kinetic energy may be obtained from:

$$T = T_1 + T_2$$
(26)
5. Simulation and experiments

5.1 Simulation testing
We simulate the moving tracks of the wheels, the swing arms and torques during obstacle-surmounting on the basis of the robot’s kinematic model. The driving wheel is made of rubber casting on the aluminium wheel hub. The coefficient of friction of the rubber wheel is obtained from the manual, and application of the relevant Chinese National Standard test protocol. We also measured the mass of each component of the robot. Furthermore, based on the 3-d model of the robot, we obtained the angle parameters of the climbing robot. All the parameters for the robot simulation are summarized in Table II.

Driving force torque varies during obstacle-climbing (Figure 7) according to the motion force model of the robot. The result shows that the maximum torque is produced at the beginning of obstacle-negotiation. This curve has reference value in the design of the control system for the robot.

5.2 Laboratory testing
A climbing robot is designed, and some inclined and vertical cables are established to conduct experiments for testing the cable-climbing system. The laboratory testing conditions are as follows:
- Two cables with lengths of 5.3 and 3.7 m and a diameter of 100 mm can be adjusted randomly. These cables are the same as those used on some cable-stayed bridges.
- Two cables with lengths of 2.3 and 3.7 m and a diameter of 139 mm are erected, with the slant angle being 29° to the vertical.
- Some steel pipes with diameters ranging from 40 to 205 mm are used.

Table II Parameters of the climbing robot

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol and value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mass of the robot</td>
<td>( M_1 = 70 \text{N} )</td>
</tr>
<tr>
<td>Mass of the upper and lower arms</td>
<td>( M_{BC} = M_{DE} = 0.2 \text{kg} )</td>
</tr>
<tr>
<td>Mass of the driven wheel</td>
<td>( m_4 = m_5 = m_3 = 0.2 \text{kg} )</td>
</tr>
<tr>
<td>Mass of the driving wheel</td>
<td>( m_1 = 0.7 \text{kg} )</td>
</tr>
<tr>
<td>Overall robot dimensions</td>
<td>( L_{OA} = 25 \text{mm}; L_{AP} = 290 \text{mm}; L_{AC} = 176 \text{mm}; L_{AD} = 310 \text{mm} )</td>
</tr>
<tr>
<td>Initial force on the spring</td>
<td>( T = 321 \text{N} )</td>
</tr>
<tr>
<td>Lengths of the upper and lower arms</td>
<td>( l_2 = l_3 = 50 \text{mm} )</td>
</tr>
<tr>
<td>Radius of the wheel</td>
<td>( r_1 = 25 \text{mm} )</td>
</tr>
<tr>
<td>Stiffness coefficient of the pulling spring</td>
<td>( K_t = 3.61 \text{N/mm} )</td>
</tr>
<tr>
<td>Angle between the limb and the body</td>
<td>( \gamma = 30^\circ )</td>
</tr>
<tr>
<td>Angle of the V-shaped wheels</td>
<td>( \beta = 150^\circ )</td>
</tr>
<tr>
<td>Weight of the passive wheels</td>
<td>( m_{wi} = 0.2 \text{kg} )</td>
</tr>
<tr>
<td>Coefficient of the static friction</td>
<td>( \mu = 0.8 )</td>
</tr>
<tr>
<td>Rolling friction coefficient</td>
<td>( \mu_1 = 0.05 )</td>
</tr>
<tr>
<td>Diameter of the cable</td>
<td>( D = 100 \text{mm} )</td>
</tr>
</tbody>
</table>

Figure 7 Input torque during obstacle-climbing

Notes: (a) Driving moment of obstacle-surmounting by the driving wheel; (b) driving moment of obstacle-surmounting by the upper driven wheel
Some climbing experiments are performed to test the load-carrying capacity of the robot in the laboratory [Figure 8(a)]. The test results demonstrate that the climbing capability of the mechanism almost corresponds to that required for different cables or poles with various diameters. Small velocity fluctuations are mainly caused by different cable diameters.

The climbing capability stands for the load-carrying ability or moving velocity of the robot when traversing a cable. From the experiments it was found that, the climbing velocity was independent of diameter of the cables. This meant that the climbing capability of the robot was also nearly identical to that observed on cables with diameters ranging from 60 to 205 mm. Line 1 in Figure 9(d) shows the nominal velocity of the robot moving on a vertical cable, while carrying almost 3.5 kg of payload. As seen in Lines 2 and 3, the climbing velocity was less than its nominal velocity when the payload exceeded 3.9 kg; these lines represent the climbing velocities with payloads of 3.9 and 4.4 kg, respectively. Lines 1, 2 and 3 show the velocities of the robot when carrying different payloads.

With an increment in payload, the climbing velocity decreased slightly when climbing over an obstacle. The velocity fluctuations were very small when surmounting small obstacles. Curved Lines 4, 5 and 6 represent the reduction in climbing velocities while the robot was climbing over certain obstacles [Figure 8(b)-(c)]. In these circumstances, the driving wheel did not slide; thus, this showed good agreement between the coefficient of friction and the conditions governing movement of the robot. The test results indicated that the payloads were larger than the nominal ability of the robot.

According the methods put forward in this paper, we calculated the climbing performance of the robot when using Wheel 1 or Wheel 3 as the driving wheel, respectively (Table III).

According to Table III, we take Wheel 3 as the power source of the robot because the climbing ability is better.

### 5.3 Field experiment

To verify the feasibility of the detection robot in practical applications, a visual detection system (Figure 9) for surface damages of suspended cables was designed. The robot can carry four cameras to take pictures of the cable surface. Each of the four cameras was responsible for the photography of one fourth of the cable surface. Figure 10 illustrates the visual control interface.

The research team carried out field test on the Hanjiang River Highway Bridge in Yunxian county (Shiyan city, Hubei province, China) (Figure 11). The bridge is one of

**Figure 8** Laboratory cable-climbing experiments

![Cable-climbing experiment](image)

**Figure 9** Structure of the visual detection system for surface damages on the suspended cables

![Visual detection system](image)

**Table III** The obstacle-surmounting performance of the robot (mm)

<table>
<thead>
<tr>
<th></th>
<th>Wheel 1</th>
<th>Wheel 2</th>
<th>Wheel 3</th>
<th>Wheel 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheel 1 as driving wheel</td>
<td>2.78</td>
<td>3.2</td>
<td>3.4</td>
<td>2.87</td>
</tr>
<tr>
<td>Wheel 3 as driving wheel</td>
<td>2.83</td>
<td>3.1</td>
<td>3.0</td>
<td>2.72</td>
</tr>
</tbody>
</table>
the extra-large bridge projects designed and constructed in the 1990s in China and has a main span longer than 400 m. It ranked the second in the world and the first in Asia then as a ground-anchored pre-stressed concrete cable-stayed bridge. The diameter of the suspended cables ranges from 77.4 to 124.4 mm and the length is in the range of 55.369-218.840 m. Due to long-term services, the bridge has serious surface damages of the suspended cables and is under major repair. The appearance detection, as an important part in the detection work before the major repair, lasted for one week, during which about 60 cables (accounting for a quarter of the total suspended cables of the bridge) were detected. The appearance parameters of the robot used in the field work are shown in Table IV.

Generally speaking, the cable is smooth and there is not any obstacles on the surface. All the obstacles are induced by the cable damage. The obstacles can be divided into two main categories including the surface damage (Step, trench and irregular obstacle) and inner steel wire damage (steel corrosion or breakage). In this test, the authors only inspected the surface obstacles using the monitoring system with four cameras. Figure 12 displays the results of the statistic classification of measured damages of the suspended cables. The typical damages measured included surface scratches [Figures 12(a) and (b)], surface bulge [Figure 12(c)-(d)] and surface corrosion [Figure 12(e)-(f)]. From the Figure 12(a)-(b), we can conclude that scratches have less effect because the dimension is no more than 2 mm. The dimension of the surface bulge and bump is not larger than 3 mm and the shape is successive and deformable so that the robot is easy to climb over. For the surface corrosion, it is not the obstacle for the robot. Therefore, the robot successfully completed the test.

The actual application of the visual detection system for suspended cables demonstrated that the robot is able to carry objects weighing 3.5 kg and stably climb upwards along the suspended cables with the diameters of 76~125 mm and the inclination of 30~90° to fulfill the detection. The results verify that the overall scheme of the designed detection robot for suspended cables is feasible.

As the robot climbs upwards, operators can observe the surface roughness of the suspended cables in front of the robot on the PC. However, adaptive control has not been realized in the process. The adaptive control over the motion of the robot is expected to be realized according to the surface damages of suspended cables in future works.

### 6. Conclusion

The obstacle-surmounting process of a cable-climbing robot was analysed along with the obstacle-surmounting mode. The dynamic obstacle-surmounting models of the driving and driven wheels of the climbing mechanism are established for kinematic and dynamic analyses. The required motion curve, speed and driving moment of the robot during obstacle-surmounting are generated from the simulation results. Thus, a favourable theoretical basis for robot control is obtained. This study also investigated the cable-climbing process used by the robot. The simulation, laboratory testing and field experimental results prove that, the climbing capability of the robot is near-constant on cables with diameters ranging from 60 to 205 mm. The proposed dynamic analysis method is found to be applicable to rod structures with large obstacles and improves the stability of the robot at high altitude.

**Table IV Main parameters of the robot**

<table>
<thead>
<tr>
<th></th>
<th>Main body of the robot</th>
<th>One set of video cameras</th>
<th>Two sets of battery packs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deadweight</td>
<td>5.2 kg</td>
<td>1.2 kg</td>
<td>1.3 kg</td>
</tr>
<tr>
<td>Deadweight size</td>
<td>Height = 420 mm</td>
<td>150 mm</td>
<td>170 mm x 110 mm x 22 mm</td>
</tr>
<tr>
<td>Range of cable diameter</td>
<td>(77.4~124.4) mm</td>
<td>(77.4~124.4) mm</td>
<td>(77.4~124.4) mm</td>
</tr>
</tbody>
</table>
Figure 12 Typical damages of the suspended cables

Notes: (a) Surface scratch 1; (b) surface scratch 2; (c) surface bump; (d) corrosion induced bulge; (e) corrosion induced pit; (f) surface corrosion

References

Bilateral-wheeled cable-climbing robot

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Volume 46 · Number 3 · 2019 · 431–443
Research on decision-making of autonomous vehicle following based on reinforcement learning method

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Abstract
Purpose – Over the past decades, there has been significant research effort dedicated to the development of autonomous vehicles. The decision-making system, which is responsible for driving safety, is one of the most important technologies for autonomous vehicles. The purpose of this study is the use of an intensive learning method combined with car-following data by a driving simulator to obtain an explanatory learning following algorithm and establish an anthropomorphic car-following model.

Design/methodology/approach – This paper proposed car-following method based on reinforcement learning for autonomous vehicles decision-making. An approximator is used to approximate the value function by determining state space, action space and state transition relationship. A gradient descent method is used to solve the parameter.

Findings – The effect of car-following on certain driving styles is initially achieved through the simulation of step conditions. The effect of car-following initially proves that the reinforcement learning system is more adaptive to car following and that it has certain explanatory and stability based on the explicit calculation of $R$.

Originality/value – The simulation results show that the car-following method based on reinforcement learning for autonomous vehicle decision-making realizes reliable car-following decision-making and has the advantages of simple sample, small amount of data, simple algorithm and good robustness.

Keywords Decision-making, Reinforcement learning, Autonomous vehicles, Car-following

Paper type Research paper

1. Introduction

Intelligent driving in intelligent vehicles is a technical high point in industrial technology and is studied by various countries and major technological companies. Car following is one of the most significant and common conditions for manual driving, assisted driving, or unmanned driving (Yuan et al., 2015). With the rapid growth of urban traffic scale, car following has become the most primary condition encountered by drivers (Liu et al., 2017b; Gao et al., 2018). Car-following models have been extensively studied since 1950s (Lv et al., 2017), and the research currently focuses on different fields, such as vehicle engineering, traffic safety, big data and artificial intelligence, psychology and cognition. Research on car-following behavior gradually extends from the original operation of acceleration, deceleration, and other specific operations to perception, psychology and physiology. The methodology for studying such behavior has been extended from early mathematic modeling to various fields, such as logistics, planning,

This work was supported by China Postdoctoral Science Foundation Special Funded Projects under Grant No. 2018T110095, Project funded by China Postdoctoral Science Foundation under Grant No. 2017M620765, National Key Research and Development Program of China under Grant No. 2017YFB0102603, the Joint Funds of the National Natural Science Foundation of China under Grant No. U1804161, and Junior Fellowships for Advanced Innovation Think-tank Program of China Association for Science and Technology under Grant No. DXB-ZKQN-2017-035.

Received 29 July 2018
Revised 19 October 2018
Accepted 6 December 2018
transportation, cognitive science, neuroscience, data science, machine learning and artificial intelligence (Wang, 2013; Gao et al., 2016).

In 1950, Reuschel studied the car-following behavior of drivers from an operational research perspective (Zhang, 2015), whereas Pipes proposed the first car-following problem in 1953 (Lv et al., 2018; Xie et al., 2017). Existing car-following models (algorithms) can be divided into two categories. The first category is explanatory car-following model. First, the model predetermines some physical quantities in the car-following process to describe the expression using parameters. Then, the unknown parameters of the expression can be determined based on statistics or experience. This type of car-following model often requires assumptions and explanations of the car-following process. The second category is non-explanatory car-following model. The car-following behavior of drivers is based on a learning algorithm, namely, the fitting or induction of a large number of data.

Explanatory models include linear car-following model, distance inverse model, nonlinear car-following model, memory function model, expected distance model, and physiological–psychological model. In 1958 and 1959, Chandler (Chandler et al., 1958) and Herman (Herman et al., 1959; Liu et al., 2017a), respectively, proposed linear car-following models. In 1959, Gazis et al. presented a range inverse car-following model (Gazis et al., 1959). After two years, Gazis et al. further proposed a nonlinear car-following model (Na and Cole, 2013). In 1967, May and Keller completed the fitting of the nonlinear model with actual vehicle data under highway and tunnel conditions (May and Keller, 1967; Lv et al., 2018). In 1993, Ozaki divided driver motion into four stages: acceleration start, deceleration start, acceleration maximum, and deceleration maximum. When separately fitted, the reaction time is strongly dependent on the stage of driving action. In particular, the reaction times are quite different in the acceleration and deceleration stages. Ozaki suggested that the possible reason for this difference is the use of the taillight of a front car during deceleration stages (Ozaki, 1993). Lee introduced a memory function model in 1966, in which he thought that drivers responded to the integral of the relative speed of the front vehicle rather than the instantaneous value. He then analyzed its stability. In 1972, Darroch and Rothery used spectral analysis methods. The shape of the memory function was estimated based on the experimental data. They found that Dirac delta function can approximate experimental data; in fact, it corresponds to the linear following model (Olson and Rothery, 1972). In 1961, Helly suggested that the driving strategy of drivers not only minimized relative speed but also the difference between real and expected vehicle distances. In 1982, Gabard et al. used Helly’s model in SITRA-B (microscopic traffic flow model) (Gao et al., 2017). In 1974 and 1988, Weidmann and Leutzbach proposed two unreasonable points of the traditional car-following model:

1. In the previous car-following model, even with a large distance to a front vehicle, testing vehicle will also keep following.
2. The previous car-following model assumed that the drivers had the perfect perception and reaction, even if the external incentive was very small; therefore, they introduced a perceptual threshold to define the minimum environmental incentive, which can be reacted to by the drivers.

Evidently, the perceived threshold increased monotonically with the distance to the car. At the same time, they also found that the perception threshold is different during the acceleration and deceleration phases (Leutzbach and Wiedemann, 1986). Explanatory model can generally guarantee the safety of the following process of the car, but accurately describing the highly nonlinear car-following behavior is difficult. Moreover, the model does not have adaptive adjustment ability for different drivers or different conditions (Kim et al., 2003; Gao et al., 2016). With the development of artificial intelligence research, a variety of machine learning methods are the most prominent. These methods have outstanding advantages in dealing with nonlinear problems (Liu et al., 2017b; Zhang, 2015), such as convolutional neural network, reinforcement learning (RL), and inverse reinforcement learning (IRL). A considerable number of researchers have begun to focus on the car-following model based on machine learning methods (Liu et al., 2017b; Zhang, 2015). Richard S. Sutton proposed a temporal-difference learning (TD) method (Sutton and Barto, 2000). Bradtke and Andrew G. Barto established two algorithms which were called least-squares TD (LSTD) and recursive least-squares TD (RLSTD) with the help of the theory of linear least-squares function approximation (Xu and Hu, 2017). Michail G. Lagoudakis and Ronald Parr proposed an approach called least-squares policy iteration (LSPI) by combining value function approximation with linear architectures and approximate policy. Xu et al. (2002) proposed Kernel-based least-squares policy iteration. Xia et al. (2017) proposed a new control strategy of self-driving vehicles using the deep RL model, in which learning with an experience of professional driver and a Q-learning algorithm with filtered experience replay are proposed. Pyeatt and Howe applied RL to learning racing behaviors in Robot Auto Racing Simulator, precursor of the TORCS platform (Xie et al., 2017; Pyeatt and Howe, 1998). Daniele et al. used the tabular Q-learning model to learn the overtaking strategies on TORCS (Loiacono et al., 2010). Riedmiller (2005) proposed a neural RL method, namely neural fitted Q-iteration (NFQ), to generate control strategy for the pole balancing and mountain car task with least interactions. Zheng et al. (2014) established a 14-DOF dynamic model of an autonomous vehicle and use R to build a decision-making system for autonomous driving. By studying the car-following model, analyzing the following behaviors of drivers and proposing the intelligent car-following algorithm have great value and implication in many fields, such as road safety, driving assistance system, and intelligent driving. However, the explanatory model is extremely simple to describe the highly nonlinear car-following behavior accurately. In addition, it does not have the adaptive adjustment capability for different drivers or different conditions. By contrast, the non-explanatory model represented by artificial neural network can fit the complex nonlinear relationships. However, such model is not interpretative because it treats the driver as a “black box.” Theoretically analyzing the stability or
establishing the relationship between driving behavior and neural network structure for further analysis is difficult.

The main contributions of this paper are summarized as follows:

- The RL for autonomous vehicle decision-making is proposed.
- The value function and loss function problem are created and could be solved by the gradient descent method.
- The optimal strategy in RL is obtained through the tradeoff between exploration and exploitation. It is adopted to guarantee both control accuracy and strong robustness.

The remaining part of this paper is organized as follows: The second part is System Architecture of Mengshi Autonomous Vehicle. The third part is Design of RL algorithm. The fourth part is Car-following algorithm based on RL. The fifth part is the experiment and analysis based on the simulation platform and the rest part is conclusion and further work.

2. System architecture of autonomous vehicle

2.1 Hardware and software

The working conditions of vehicle and the road environment must be precisely controlled to study the car-following behavior of drivers under given conditions. Therefore, this work is based on the dynamic driving simulation test bench of Tsinghua University. The dynamic driving simulation test bench is shown in Figure 1, and its system components are shown in Figure 2.

The hardware part of the simulator consists of five parts: simulation cockpit, external visual environment simulation system, vehicle motion simulation system, sound environment simulation system and operation tactile sensation simulation system (Liu et al., 2016). The software part of driving simulator consists of six parts: system control module, environment control and scene creation module, simulation calculation module, input and output module, graphics calculation and rendering module and actuator control module (Li, 2010).

2.2 Environment modeling

This work is about the car-following behavior of drivers under a single lane (no lane change, no overtaking, and no traffic light); therefore, the freeway is selected as a road scene. A two-lane road of 200 km in length is designed. The road includes a fast lane, a slow lane and an emergency lane with widths of 3.75, 3.75 and 2.5 m, respectively. The road model is shown in Figure 3.

2.3 Vehicle model

The most common vehicle is chosen as the front car (BMW 3 Series as a template), and the dynamics model of the vehicle was generated by CarSim. In addition, the brake lights turn red when the vehicle is decelerating, which is consistent with the real situation. The road scene of the actual testing process is shown in Figure 4. Three computer screens correspond to three projection screens (middle, left, and right) of the external

---

**Figure 1** Dynamic driving simulation test bench

**Figure 2** System components of the dynamic driving simulation test bench

**Figure 3** Road model

**Figure 4** Road scene of the actual test
virtual environment system. These screens constitute the front view of the drivers.

The reward functions of drivers A and B are visualized to intuitively present the validity and generalization ability of the IRL algorithm. For each driver, the reward functions R are given for two different conditions: The New European Driving Cycle (NEDC) and Japan 10–15. For each condition, two randomly selected tests are performed to verify the reproducibility of the test results.

3. Design of reinforcement learning algorithm

3.1 Reinforcement learning

RL is a vital branch of machine learning, and a typical RL task is usually described by the Markov decision process. The machine (or agent) is in environment $E$, defining a state space $S$, where each state is a description of the environment that the agent can perceive. The actions that an agent can perform constitute action space $A$; $a \in A$ is an action can be taken by an agent. After taking the action, the potential transfer function $P$ enables the environment to be transferred from the current state to another state with certain probability. At the same time, as the state transitions, a reward $r$ is the feedback of the environment to the agent according to the potential reward function $R$ (Na and Cole., 2015). An RL task corresponds to the tetrad $E = \langle S, A, P, R \rangle$; $P \times A \times S \mapsto R$, which represents the probability of state transition; and $R : S \times A \times S \mapsto R$, which represents the reward function. As shown in Figure 5, the agent observes state $s$ and then performs action $a$; $s$ transfers to the next state based on the state transition probability $P_s$ and simultaneously an instant reward $r$ is obtained. In RL, agents continuously interact with the environment and update strategies to learn policy $a = \pi(s)$.

The relative merits of the strategy depend on the cumulative reward of long-term execution, rather than the instant reward for performing an action. Consequently, the RL task maximizes the long-term cumulative reward generated by the policy. Therefore, this work uses the “$\gamma$-discounted cumulative reward” to estimate the long-term cumulative reward, as shown in equation (1):

$$\max_{\pi} \text{E} \left[ \sum_{t=0}^{\infty} \gamma^t r_{t+1} \right]$$

(1)

$\gamma$ is the discount rate, a positive number less than 1, and represents the degree of emphasis that the agent has on future rewards. The greater the value of $\gamma$, the more the attention is paid to the future received rewards. $r_t$ is the instant rewards of the $t$th step, and $E$ is the expression of the expectation of all random variables.

Figure 5 Illustration of RL

3.2 Determining state space design, action space, and state transition relationship

The state space $S$ of RL selects the velocity of the testing vehicle $v$ and the car-following distance $d$ as a two-dimensional variable, i.e. $(v, d)$. The action space $A$ is determined by the actual driving data of drivers. Approximately 99.9 per cent of the acceleration data points is limited in the range $(-3m/s^2, 3m/s^2)$. This range $(-3m/s^2, 3m/s^2)$ is divided into four acceleration intervals, wherein five endpoints are selected to constitute the action space $A = \{a_1 = -3m/s^2, a_2 = -1m/s^2, a_3 = 0m/s^2, a_4 = 1m/s^2, a_5 = 3m/s^2\}$.

According to the law of vehicle movement that determines the state transition relationship, the speed of the testing vehicle, the speed of the front vehicle, and the car-following distance are set to $v_i$. Figure $v_i$, $d_i$ at time $t_i$, respectively, and the action (acceleration) as $a$. A smart car predicts the speed by the following rules: between times $t$ and $t + 1$, (I) the testing car performs uniform acceleration linear motion and (II) the speed of the front car remains the same. Based on the law of motion of particles, the motion law between two adjacent states is obtained, as shown in equation (2):

$$\begin{align*}
v_{t+1} &= v_t + a\Delta t \\
d_{t+1} &= d_t + (v_t - v_i)\Delta t - a(\Delta t)^2/2
\end{align*}$$

(2)

The state transition shown in equation (2) is deterministic and has a probability of 1.

4. Car-following algorithm based on reinforcement learning

4.1 Value function approximation

Each state of an intensive learning task is represented by a number, and a tabular value function is made according to the long-term reward (value function) for each state. The state space $(v, d)$ in this study is continuous (Ozaki, 1993). The value function approximation is implemented by function approximation. Assume that the approximation function can be expressed as a linear function of the state space. The two-dimensional state space can be mapped into a high-dimensional space through an approximation function transformation, and the value function can be expressed as a linear combination of approximation functions, as shown in equation (3):

$$\begin{align*}
K(s, s_i) &= \exp \left(-\frac{||s - s_i||^2}{\alpha^2}\right), 1 \leq i < 15, 1 \leq j \leq 36 \\
V_a(v, d) &= \sum_{i=1}^{15} \sum_{j=1}^{36} w_{ij} V_i(v, d) = \sum_{i=1}^{15} \sum_{j=1}^{36} w_{ij} K(s, s_i)
\end{align*}$$

$$s = (25v/9, d); \quad s_i = (25v_i/9, d_i)$$

(3)

In equation (3), the center point $v$ and $d$ of the approximation function is selected, as shown in equation (4), where the unit of the testing vehicle speed $v$ is km/h, and the car-following distance $d$ is m.

$$\begin{align*}
v_i &= 9(i - 1), 1 \leq i \leq 15 \\
d_i &= 10(j - 1), 1 \leq j \leq 36
\end{align*}$$

(4)
4.2 Loss function solution
By solving $\omega$ using a gradient descent method, the loss function is shown in equation (5).

$$\mathcal{J}(\omega) = \mathbb{E} \left[ (V(v, d) - V_\omega(v, d))^2 \right]$$

(5)

The gradient descent expression is shown in equation (6).

$$\omega_{ij} = \omega_{ij} + \alpha (V(v, d) - V_\omega(v, d)) \cdot \omega_{ij}$$

(6)

where $V(v, d)$ represents the real value of the value function, and $\alpha$ is the learning rate. $V(v, d)$ is estimated according to the definition of value function, as shown in equation (7). The equation (8) could be obtained:

$$V(s) = \mathbb{E} \left( \sum_{t=0}^{\infty} \gamma^t r_{t+1} | s_0 = s \right)$$

(7)

$$V(s) = r_{s, d} + \gamma \cdot \mathbb{E} \left( \sum_{t=0}^{\infty} \gamma^t r_{t+1} | s_0 = s' \right) = r_{s, d} + \gamma \cdot V(s')$$

(8)

According to equation (8), the true value $V(v, d)$ of the cost function is shown in equation (9):

$$V(v, d) = r + \gamma \cdot V_\omega(v', d)$$

(9)

where the combination of state spaces $(v', d')$ reached by the current state when the value function is optimized. Therefore, $\omega$ is solved, as shown in equation (10):

$$\omega_{ij} = \omega_{ij} + \alpha \left( r + \gamma \cdot V_\omega(v', d) - V_\omega(v, d) \right) \cdot \omega_{ij}$$

(10)

After several tests and analyses, the variance of the approximation function is $\sigma^2 = 30$, the discount factor is $\gamma = 0.97$, and the learning rate of the value function is $\alpha = 0.015$.

4.3 $\epsilon$-Greedy and strategy assessment
The optimal strategy in RL is obtained through the tradeoff between exploration and exploitation. This study uses the “$\epsilon$-greedy” algorithm to achieve balance, as shown in equation (11):

$$\pi(s) = \arg\max_{a \in A} \left( R_{s, a} + \gamma V(s') \right)$$

(11)

where $\pi(s)$ randomly select from $A$, random $> \epsilon$

For the selection of the greedy algorithm strategy, the smart car has a $1 - \epsilon$ probability of selecting the current optimal strategy, and $\epsilon$ probability of randomly selecting other strategies. Random is a uniformly distributed random number from 0 to 1; a larger $\epsilon$ denotes greater inclination to “explore.”

This study determines $\epsilon$ as follows: I: The first cycle decreases linearly from 0.6 to 0.3. II: From the beginning of the second cycle, $\epsilon$ reduces to 0.9 times of the previous value for each additional time of cycles.

4.4 Car-following algorithm
The state space, action space, state transition relationship and value function approximation are determined according to the reward function of different drivers. A gradient descent method is utilized, and the strategy assessment uses a greedy algorithm. The car-following algorithm based on RL theory is shown in Algorithm 1.

In the car-following algorithm based on RL theory, convergence is implemented by manifold cycles. When the $i^{th}$ cycle ends and the $(i + 1)^{th}$ cycle is inputted, the output of the previous cycle is used as the input of the next cycle and the greed rate. Moreover, the discount factor and the learning rate are adjusted.

Algorithm 1

Input: Environment $E$; Driver’s reward function $R(s)$; Action space $A$; Initial state $s_0$; Discount factor $\gamma$; learning rate $\alpha$; Greedy rate $\epsilon$;
Output: State sequence $\{s_1, s_2, \ldots, s_N\}$; Action sequence $\{a_1, a_2, \ldots, a_N\}$;

Begin:
\[
\omega = 0; \quad s = s_0
\]
for $t = 1, 2, \ldots, N$ do
\[
r = R(s);
\]
if rand $< \epsilon$ do
\[
\pi(s) = \arg\max_{a \in A} (R_{s, a} + \gamma V_a(s'))
\]
else do
\[
\pi(s) \text{ randomly selected from } A
\]
\[
\omega = \omega + \alpha (r + \gamma \cdot V_\omega(s') - V_\omega(s)) \cdot \omega
\]
\[
s = s'
\]
End for

In Algorithm 1, $\gamma$ represents discount factor, $\alpha$ represents learning rate, $\epsilon$ represents greedy rate, $\omega$ represents the gradient descent expression, $s$ and $s'$ represent state value, $r$ represents driver’s reward value, $R(s)$ represents driver’s reward function, $V_\omega(s)$ and $V_\omega(s')$ represent value function, $\pi(s)$ represents strategy function.

5. Experiment and analysis
5.1 Experiment setup
Two conditions of front vehicle speed curve are adopted in RL simulation, namely, a ramp input condition (Figure 6) and a

Figure 6 Ramp input condition
standard sine condition (Figure 7), to verify the effectiveness of the car-following algorithm based on the RL theory. The following conditions are added to meet the actual situation:

- The maximum speed is set to 130 km/h. Once the speed reaches 130 km/h, the speed will be constant if the driver accelerates again. The minimum speed is set to 0 km/h, and the speed will remain unchanged if it decelerates to 0 km/h.
- The minimum distance is set to 5 m. The cycle will immediately stop if the distance is less than 5 m.

5.2 Experiment result and analysis

The reward functions of drivers A (female) and B (male), which are obtained by the inverse RL algorithm (Gao et al., 2019), are adopted. By using the car-following algorithm based on RL theory, 30 cycles of training are performed under the condition of ramp. The convergence results are shown in Figures 8 and 9. Figure 8(a) shows a speed curve of 30 cycles by using the reward function of driver A (female), Figure 8(b) shows a distance curve of 30 cycles by using the reward function of driver A (female), Figure 9(a) shows a speed curve of 30 cycles by using the reward function of driver B (female), and Figure 9(b) shows a distance curve of 30 cycles by using the reward function of driver B (male).

Figure 7 Standard sine condition

Figure 8 Simulation results using driver A (female) reward function (ramp input condition)

Figure 8(a) shows a speed curve of 30 cycles by using the reward function of driver A (female), Figure 8(b) shows a distance curve of 30 cycles by using the reward function of driver A (female), and Figure 9(b) shows a distance curve of 30 cycles by using the reward function of driver B (male).

Figure 9(a) shows a speed curve of 30 cycles by using the reward function of driver B (male), and Figure 9(b) shows a distance curve of 30 cycles by using the reward function of driver B (male).

More than 30 cycles of training are executed in the standard sine conditions. The convergence results are shown in Figures 10 and 11. Figure 10(a) shows a speed curve by using the reward function of driver A (female) for more than 30 cycles, Figure 10(b) shows a distance curve by using the reward function of driver A (female) for more than 30 cycles, Figure 11(a) shows a speed curve by using the reward function of driver B (male) for more than 30 cycles, and Figure 11(b) shows a distance curve by using the reward function of driver B (male) for more than 30 cycles.

The comparison of Figures 8 and 10, and Figures 9 and 11 show that as follows: (I) After 30 cycles, the value function obtained by the RL algorithm can converge, which can be observed from the simulation result curves (After 30 cycles, these curves do not change). (II) When using the reward function simulation of driver A, the simulation results show that the driving strategy is gentle, the speed variation is small, and the distance with the car is large. When the reward function of driver B is used for simulation, the results show that the speed of driving strategy changes considerably, and the distance with the car is small.

Figure 8(a) shows a driver A's reward function heat map, and Figure 8(b) shows a driver B's reward function heat map. (I) \( R_A \) is closer to the horizontal axis than \( R_B \), which implies that the distance to the vehicle for \( R_A \) is greater. (II) Moreover, the gradient of \( R_A \) is smaller than \( R_B \), which means that \( R_A \) is more sensitive to changes in vehicle distance and vehicle speed.

After simulation, the car-following algorithm based on RL theory can initially realize the algorithm for a certain driving style.

5.3 Conclusion and further work

In this study, the approximation function is used to approximate the value function by determining the state space, action space, and state transition relationship. The gradient descent method is used to solve the parameter. A car-following
Figure 9 Simulation results using driver B (male) reward function (ramp input condition)

Notes: (a) Speed curve for 30 cycles; (b) distance curve for 30 cycles

Figure 10 Simulation results using driver A (female) reward function (standard sine conditions)

Notes: (a) Speed curve for more 30 cycles; (b) distance curve for more than 30 cycles

Figure 11 Simulation results using driver B (male) reward function (standard sine conditions)

Notes: (a) Speed curve for more 30 cycles; (b) distance curve for more than 30 cycles
algorithm is proposed based on RL theory using “ε-greedy” algorithm to achieve the balance between “exploration” and “utilization.” The effect of car-following with certain driving style is initially achieved through the simulation of step conditions. The effect of car-following initially proves that the RL system is adaptive to car following and that it has certain explanatory and stability based on the explicit calculation of R. Car-following algorithm based on RL theory has the advantages of simple sample, small amount of data and simple algorithm. In future works, deep RL methods based on massive real car-following data will be studied, and end-to-end modeling and learning of car-following behavior will be implemented.

The car-following method based on RL for autonomous vehicle has been solved successfully; however, there are still some issues such as lane changing, overtaking, with model establishment and solution problem need to be researched in the future.

References


A welding seam identification method based on cross-modal perception

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Abstract
Purpose – As an automatic welding process may experience some disturbances caused by, for example, splashes and/or welding fumes, misalignments/poor positioning, thermally induced deformations, strong arc lights and diversified welding joints/grooves, precisely identifying the welding seam has a great influence on the welding quality. This paper aims to propose a robust method for identifying this seam based on cross-modal perception.

Design/methodology/approach – First, after a welding image obtained from a structured-light vision sensor (here laser and vision are integrated into a cross-modal perception sensor) is filtered, in a sufficiently small area, the extended Kalman filter is used to prevent possible disturbances to search for its laser stripe. Second, to realize the extraction of the profile of welding seam, the least square method is used to fit a sequence of centroids determined by the scanning result of columns displayed on the tracking window. Third, this profile is then qualitatively described and matched using a proposed character string method.

Findings – It is demonstrated that it maintains real time and is clearly superior in terms of accuracy and robustness, though its real-time performance is not the best.

Originality/value – This paper proposes a robust method for automatically identifying and tracking a welding seam.

Keywords Extended Kalman filter, Structured-light vision, Welding robot, Welding seam identification

Paper type Research paper

1. Introduction

While welding is highly important in modern manufacturing industries, it is very difficult to correctly determine/recognize the welding seam during a robotic welding process. The reason for this is that there are some possible disturbances in a welding image caused by, for example, welding fumes and splashes, thermally induced deformations, diversified welding joints/grooves, strong arc lights and misalignments/poor positioning. There are currently many welding profile monitoring methods developed for various kinds of joint/groove types. As for a V-preparation joint, for example, Li et al. (2006) studied a V preparation groove, direct butt joint without a groove and lap joint in depth, and the main lines and discontinuities points that are determined from the laser stripe are considered as pattern features. Though this method has a greatly improved capability to avoid noise for special joints, it is highly sensitive to joint deformations. Similarly, the laser feature extraction algorithm based on pixels’ intensity distribution and neighborhood search is proposed in Muhammad et al. (2018); however, the method lacks discussion on different types of welding profile. Ding (2017) proposed a neural network model to extract the welding seam features and obtained a well-experimental result, but the drawback of this method is requirement of a

This work was supported in part by the National Natural Science Foundation of China, under Grant 61573097 and 91748106; in part by Key Laboratory of Integrated Automation of Process Industry (PAL-N201704), the Fundamental Research Funds for the Central Universities (3208008401), Qing Lan Project and Six Major Top-talent Plan; and in part by the Priority Academic Program Development of Jiangsu Higher Education Institutions. The authors thank the reviewers and editors for giving valuable comments, which were quite helpful for improving this manuscript.

Received 13 June 2018
Revised 5 September 2018
7 October 2018
Accepted 6 November 2018
great deal of prior knowledge. In Sicard and Levine (1989), to classify various modes of joints that were detected by a laser scanners[1], a character string method was developed. Considering the real-time requirements of the welding system, Lü et al. (2018) used the least square method that was based on the slope analysis to detect the features of the seam image. However, the influence of disturbances on proposed algorithm is lack of discussion. Nevertheless, the above method is not suitable for structured-light vision because of its low precision, as it considers only the filtering of profile points instead of noise disturbances in a welding image. Moreover, as for the fusion filtering problem, different solutions are proposed in Liu et al. (2018) and Yuan et al. (2018), which provide effective methods to the problem of information fusion in multi-modal discrete dynamic systems. To detect welding seam profiles in metal active gas (MAG) arc welding autonomously, He et al. (2016) presented a method that used a novel technique for saliency-based visual attention. In Chen and Feng (2014), the electrical, sound and welding images of a gas tungsten arc weld (GTAW) process are fused together to improve its robustness, but it seems quite high (You et al., 2014). To solve the interference in a high-strength reflection area when using a gantry welding robot, Chen et al. (2015) proposed a multiple peak algorithm that can detect a laser profile for circular pressure vessel welding. A modified Hough Transformation algorithm is proposed in Wu et al. (2015), which is used to acquire the laser’s profile in a gas metal arc welding process, but it appears to be a highly time-wasting method, especially for the line detection.

The main aims of the robust welding seam identification method proposed in this paper are to, first, in sufficiently small areas, track and search a laser stripe’s profile by using the EKF to prevent some disturbances and, second, to enhance the robustness of matching process by using a character string method.

This paper is organized as follows. Section 2 presents an algorithm based on the EKF for tracking the laser stripe in an object image and attempting to search for it in a sufficiently small area. Section 3 presents the qualitative description method to explain a welding seam’s profile. This method is quite robust in the aspects of recovering a relationship element and integrating segment element. Section 3.5 performs some experiments to test the accuracy, stability and real time of this new method by making a comparison with those obtained from other approaches. The paper is concluded in Section 4.

2. Extended Kalman filter-based tracking algorithm

Though an optical filter and dimmer glass are installed in a structured-light vision sensor, possible disturbances still remaining in an image, for example, welding fumes, reflections and splashes, might seriously affect the extraction of a welding seam’s profile. Therefore, it is necessary to reduce the range of seeking of the laser stripe in real welding images to prevent disturbances. However, because the stripe’s position might change in different frames of an image, the window position must follow it. With the aim of obtaining the window position \((O_{SWk})\) of the \(k\text{th}\) frame of images, we should use the \((k-1)\text{th}\) frame to predict it from the current frame \((O_{SWk-1})\), using the EKF (Einicke and White, 1999).

Kalman filtering provides a good solution to the problem of state estimation of moving targets. However, in the practical welding process, there is a little nonlinear during the motion of welding seam image, e.g. tiny rotation, slight displacement or shape change of laser stripes within two adjacent frame images. Thus, the real position of welding seam cannot be estimated via linear motion method caused by the change of these observed laser. Therefore, it is necessary to consider the nonlinear Kalman filter for eliminating the estimation error caused by system nonlinearity. In addition, complex nonlinear Kalman filters, e.g. unscented Kalman filter and cubature Kalman filters, require a lot of operations in processing data. Thus, EKF is considered in our study for satisfying the real-time requirement.

2.1 Extraction of initial window position

After pre-processing the image[2], because the window position in the current frame may be estimated via the previous one, the accuracy of the initial position looks very important. To adaptively obtain it, we extract the laser stripe’s center line from column scanning by using the center-of-gravity method (Haug and Pritschow, 1998), and center line’s position coordinate can be computed as:

\[
\begin{align*}
q_i(x) &= i \\
q_i(y) &= \frac{\sum_{j=0}^{k} Y_j / C3 - Y_k / C3}{\sum_{j=0}^{k} X_j / C2 - X_k / C2}
\end{align*}
\]

where \(q_i(x)\) and \(q_i(y)\) are the coordinates of point \(q_i\) on its center line, \(\xi\) is the \(y\) coordinates of pixels on stripe line, i.e. \(\xi \in [a, b]\), \(a\) and \(b\) are the stripe’s bottom and top of \(y\) coordinates, and \(g(x_i, y)\) is the gray of pixel \((x_i, y)\) with the center line able to be expressed as \(P = \{q_i\}, i = 1, \ldots, M\).

Because of the stripe position in the viewing field from a structured-light vision sensor may vary with motions of the welding gun, the window size is key, that is, the larger it becomes, the more time the searching will take and, moreover, the more noise there may be in it, whereas the smaller it becomes, the more possible those stripes are outside the window. So the original rectangle window can be defined in (2) as:

\[
\begin{align*}
X_i^{'min} &= \min(q_i(x)), i = 1, \ldots, M \\
X_i^{'max} &= \max(q_i(x)), i = 1, \ldots, M \\
Y_i^{'min} &= \min(q_i(y)) - \beta \times \varphi, i = 1, \ldots, M \\
Y_i^{'max} &= \max(q_i(y)) + \beta \times \varphi, i = 1, \ldots, M
\end{align*}
\]

where \(X_i^{'min}, X_i^{'max}, Y_i^{'min}\) and \(Y_i^{'max}\) are the four vertices of the rectangular search window, \(\varphi\) is the laser stripe’s width and \(\beta\) is the laser stripe’s proportional factor.
2.2 Prediction of window position
According to EKF, to acquire the nonlinear minimum variance estimation \( O_{W_k} \) of current system status \( (O_{W_{k-1}}) \), we have to get the prediction of the most possible position \( O_{W_{k+1}} \) on the k frame of the welding image according to the position \( O_{W_{k-1}} \) of the search window on the \( k-1 \) frame of images and integrate it with information of this motion status as:

\[
O_{W_{k+1}} = A \times O_{W_{k-1}} + \sigma_k
\]  

(3)

where \( A \) is a system’s parameter and \( \sigma_k \) is the system’s random noise generated at the time \( k \). Then, \( (P_{k|k-1}) \) is given as:

\[
P_{k|k-1} = A \times P_{k-1|k-1} A^T + \sigma_k
\]  

(4)

where \( P_{k-1|k-1} \) is the corresponding covariance of position \( O_{W_{k-1}} \); and \( \sigma_k \) is the covariance occurring of the random noise \( \sigma_k \) in the process of movement of this system.

To estimate position \( O_{W_{k+1}} \), the observation sequence \( (Z_k) \) is also necessary. After pre-processing \( k \) frames of the images, a measurement of \( Z_k \) of the window is carried out, with the nonlinear relationship between \( Z_k \) and \( O_{W_k} \):

\[
Z_k = h(O_{W_k}) + \varphi_k
\]  

(5)

where \( h(\cdot) \) is the nonlinear system’s observational function and \( \varphi_k \) is the random noise of an observation at time \( k \). Then, the dynamics is linearized as:

\[
Z_k = h(O_{W_k}) + H_k \times (O_{W_k} - O_{W_{k-1}}) + \varphi_k
\]  

(6)

where:

\[
H_k = \frac{\partial h(O_{W_k})}{\partial O_{W_k}}
\]  

(7)

Therefore, the \( k^{th} \) frame’s filter correction value is obtained as:

\[
V_k = Z_k - h(O_{W_{k-1}})
\]  

(8)

Finally, a search window’s position \( O_{W_{k+1}} \) can be calculated on the basis of the correction value \( V_k \) and prediction value \( O_{W_{k-1}} \) as:

\[
O_{W_{k+1}} = O_{W_{k-1}} + K_k \times V_k
\]  

(9)

where \( K_k \) is the filter gain of the \( k^{th} \) frame of the image derived by:

\[
K_k = \frac{P_{k|k-1} \times H_k^T}{(H_k \times P_{k|k-1} \times H_k^T + \mathbf{R})}
\]  

(10)

where \( \mathbf{R} \) is the covariance of \( \varphi_k \) which can be obtained by statistical analysis of experimental data, or can be selected as a small value according to experience, such as 0.01 in this paper. Then, the covariance \( (P_{k|k}) \) of \( O_{W_{k+1}} \) is updated according to (11) as:

\[
P_{k|k} = (I - K_k \times H_k) \times P_{k|k-1}
\]  

(11)

3. Identification of welding seam

Because a human being can clearly/robustly recognize a welding seam according to its inherent structure, even if it is seriously polluted, it is important for welding robots to be capable of similarly extracting and expressing a welding seam’s profile.

3.1 Qualitative description of welding seam

To make a description of the profile of a welding seam that has no curve qualitatively, its line segment elements \( (L = \{l_i\}, i = 1,\ldots,N) \) and connection relationship \( (R = \{r_{f_i}r_{l_i}\}, f = 1,\ldots,N - 1) \) are used. A line segment element \( (l_i) \) might be defined by both its length \( (length(l_i)) \) and slope \( (slope(l_i)) \), and a junction \( (r_i) \) by its break \( (B = |b_{f_i}b_{l_i}|) \) and connection \( (G = |c_{f_i}c_{l_i}|) \), where \( c_j \) expresses the difference in the slopes of two connected line segments and \( b_j \) can be considered as a different imaginary line segment according to its slope. These line segment and connection relationship elements are defined in Figures 1 and 2, and \( Y = \rho(\cdot) \) is a function for mapping a welding seam’s profile to character strings; such as the V joint could be mapped to \( \rho(\cdot) = hc\Sigmaдвугл. \)

3.2 Extraction of center line of laser stripe

Before using the EKF to figure out laser stripes, their center line should be searched and extracted by scanning the gray area in rectangle window column by column according to (1). However, to reduce the effect of noise disturbances that may result in at least two wave peaks, a proposed similarity measure for distinguishing these peaks is:

\[
S_a = \frac{W_a|f_a - f_{a1}| + W_a|f_a - f_{a2}|}{\text{Max}(|f_a - f_{a1}|, |f_a - f_{a2}|)}
\]  

(12)

Figure 1 Descriptions of line segment elements

<table>
<thead>
<tr>
<th>Qualitative Description</th>
<th>Line Segment Elements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horizontal</td>
<td>( h )</td>
</tr>
<tr>
<td>Vertical</td>
<td>( v )</td>
</tr>
<tr>
<td>Upswept</td>
<td>( u )</td>
</tr>
<tr>
<td>Declivitous</td>
<td>( d )</td>
</tr>
</tbody>
</table>

Figure 2 Descriptions of junction relationship elements

<table>
<thead>
<tr>
<th>Qualitative Description</th>
<th>Junction Relationship Elements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Connection without angle</td>
<td>( c_1 )</td>
</tr>
<tr>
<td>Connection with anti-clockwise angle</td>
<td>( c_2 )</td>
</tr>
<tr>
<td>Connection with clockwise angle</td>
<td>( c_3 )</td>
</tr>
<tr>
<td>Horizontal break</td>
<td>( b_h )</td>
</tr>
<tr>
<td>Vertical break</td>
<td>( b_v )</td>
</tr>
<tr>
<td>Upswept break</td>
<td>( b_u )</td>
</tr>
<tr>
<td>Declivitous break</td>
<td>( b_d )</td>
</tr>
</tbody>
</table>
where \( f_{w}\), \( f_{L}\), and \( f_{w}\) are the maximum values of the widths and gray areas of the standard and detecting laser stripes, respectively, and \( W_{w}\) and \( W_{L}\) are the width’s weight and laser stripe’s gray area, respectively, whereby \( W_{w} + W_{L} = 1 \). Obviously, \( S_{e} \in [0,1] \) is a similarity measurement[3]. The greater the \( S_{e} \) value, the more likely that the relevant peak is of this laser stripe.

After filtering those gray peaks according to (12), the point set of the laser stripe’s center line \( P = \{ P_{i}, i = 1,\cdots, M \} \) can be fitted by the least square method and will be separated into disparate sections (Stigler, 1981).

### 3.3 Model-based matching

A model-based method for recognizing the welding seam could interpret the image data from the bottom layer, based on this model’s information of the top layer, i.e., feature elements. If the object image’s profile \( O_{t} \) is ideal, the character string mapped from \( O_{t} \) will be exactly the same as the model (M) and, therefore, quite simple to match. However, as there are some interference factors, e.g., reflections, arc lights and splashes in the working process, usually, no character string can be obtained directly from \( O_{t} \) or it is repeated or irrelevant, which makes it highly difficult to determine the correspondence relationship when matching.

To interpret the matching between the target image \( O \) and model \( M \) first, the following two definitions are given.

**Definition 1:** If \( \forall \{ r_{i} \}_{O}, \{ l_{i} \}_{O} \in \{ L, R \}_{O} \) and \( \{ r_{i} \}_{M}, \{ l_{i} \}_{M} \in \{ L, R \}_{M} \), if \( \forall \{ r_{i} \}_{O}, \{ r_{i} \}_{M} \in \{ L, R \}_{O} \), then \( \forall \{ r_{i} \}_{O}, \{ r_{i} \}_{M} \in \{ L, R \}_{O} \), the triple group matching (TGM), where \( \forall \{ r_{i} \}_{O}, \{ r_{i} \}_{M} \) are considered fully consistent. When \( \{ r_{i} \}_{O}, \{ r_{i} \}_{M} \) are matched in model \( M \), the triple-matching items \( \{ \{ r_{i} \}_{O}, \{ r_{i} \}_{M} \} \) are consistent. Therefore, Algorithm 1 is applied for search matching to determine the related item \( \{ \{ r_{i} \}_{O}, \{ r_{i} \}_{M} \}_{M-O} \) from target \( O \).

After STGM, target \( O_{t} \) might be matched with model \( M \) because they are both depicted as character strings qualitatively, i.e., \( \{ r_{i} \}_{O}, \{ l_{i} \}_{O} \) are matched with it on the exact position index \( O_{t} \), i.e., \( \forall \{ r_{i} \}_{O}, \{ r_{i} \}_{M} \in \{ L, R \}_{O} \) and, moreover, as the triple-matching items \( \forall \{ r_{i} \}_{O}, \{ r_{i} \}_{M} \) can only be found at index \( j + 1 \), we call this sequence TGM (STGM).

3.4 Integration of segment elements

If there are some corresponding \( n \) continuous segment elements of one segment element in \( S_{M} \), which can be found in target \( O \). They may be broken because of some interference, e.g. splashes and reflections. To solve this, it is necessary for us to calculate their collinear degree:

\[
D_{C} = Dist(g_{1}, g_{2}) / \left( \sum_{i=1}^{n} L(l_{i}) + \sum_{j=1}^{n-1} L(g) \right) \tag{13}
\]

where \( g_{1} \) and \( g_{2} \) are segment element’s original point and end point, respectively, \( Dist(g_{1}, g_{2}) \) is the distance[4] between \( g_{1} \) and \( g_{2} \) and \( L() \) is segment element’s length. When collinear degree \( D_{C} \) is greater than \( T_{C} \), where \( T_{C} \) is a threshold of \( D_{C} \), these elements can be integrated.

### 3.4.1 Recovery of relationship element

Some connection relationships obtained from target \( O_{t} \), i.e., the breaks \( \{ a_{1} \equiv \{ a_{2} \equiv \{ a_{3} \} \} \) and connections \( \{ c_{1} \equiv c_{2} \equiv c_{3} \} \) in Figure 2 may be different and even conflict with those from the initiate model \( (M) \) because of some disturbances. Consequently, the proposed recovery of the relationship element is needed in search-matching process and satisfied conditions as follows:

- \( \forall \{ r_{i} \}_{O}, \{ r_{i} \}_{M} \in \{ L, R \}_{O} \)
- \( \forall \{ r_{i} \}_{O}, \{ r_{i} \}_{M} \in \{ L, R \}_{M} \)
- \( \forall \{ r_{i} \}_{O}, \{ r_{i} \}_{M} \in \{ L, R \}_{O} \), and always \( \{ r_{i} \}_{M} = \{ r_{i} \}_{M} \) when \( \{ r_{i} \}_{O}, \{ r_{i} \}_{M} \in \{ L, R \}_{O} \). The relationship element is considered. Therefore, Algorithm 1 is applied for search matching to determine the related item \( \{ \{ r_{i} \}_{O}, \{ r_{i} \}_{M} \}_{M-O} \) from target \( O \).

**Algorithm 1:**

**Input:** \( \exists \{ l_{j} \}_{O}, \{ r_{j} \}_{j = 1, \cdots} \in \{ L_{O}, R_{O} \} \in \mathfrak{J}_{O} \)

**Output:** \( \{ \{ r_{i} \}_{O}, \{ r_{i} \}_{M} \}_{M-O} \)

1: for \( i = 1 \) to \( j \) do
2: Search the matching item \( \{ l_{j} \}_{O} \) of \( \{ l_{j} \}_{M} \) in object \( O_{t} \) and remember its position \( k \)
3: while \( \{ l_{j} \}_{O} \) not end of \( k \) do
4: Search the matching item \( \{ r_{j} \}_{O} \) of \( \{ r_{j} \}_{M} \) in object \( O_{t} \) and remember its position \( k \)
5: if \( \phi \) of \( \{ l_{j} \}_{O} \) from position \( k + 1 \) then
6: if \( \{ r_{j} \}_{O} \) of \( \{ r_{j} \}_{M} \) in terms of \( \{ r_{j} \}_{O} \) then
7: Recover the relationship element \( \{ r_{j} \}_{O} \) in terms of \( \{ r_{j} \}_{O} \) and \( \{ r_{j} \}_{M} \) in terms of \( \{ r_{j} \}_{M} \) and \( \{ r_{j} \}_{O} \) then
8: return \( \{ r_{i} \} \) from \( \{ r_{i} \}_{O} \) and \( \{ r_{i} \}_{M} \)
3.5 Experiments
These experiments are conducted on an industrial KUKA KR16 robot on which a TBI welding gun [5] is installed, as shown in Figure 3, with an EWM PHOENIX 400 welding machine, which is fit for MIG/MAG/TIG welding and a shielding gas consisting of AR (80 per cent) + CO2 (20 per cent). The structured-light vision sensor installed at the end effector of KR16, as shown in Figure 3, is used to acquire the welding image. In these experiments, our algorithm was tested on different welding seams, which are a V-groove (110 frames) and angle (72 frames) as shown in Figure 4, on a PC [6].

Mean absolute error $E_{\text{mae}}$ and standard deviation $S_{\text{var}}$ are used for assessing this system’s precision and stability/robustness, respectively.

3.6 Effect of size of search window
Two experiments were conducted for V-groove and angle-welding seams, original window sizes of which contain the laser stripe, with the results presented in Figures 5 and 6, respectively. As can be seen in Figure 5, for the x- and y-directions of the V groove, the $S_{\text{var}}$ values always vary similarly, i.e. first, they gradually become smaller, then increase sharply and, finally, remain constant with increases in the window size, whereas, although the $E_{\text{mae}}$ values are different, they always remain constant, with later increases in the window size. Also, all these values appear to be highly similar to those in Figure 6. Based on a comprehensive analysis of these experiment results, it is determined that the search window should be enlarged from its initial size to 3 pixels in both the up and down directions, where it exhibits the best performances in terms of the data accuracy and system stability.

3.7 Contrast with different methods according to accuracy, stability and real time
Comparison has been made between our proposed algorithm ($\Psi_3$) and others (Chen et al., 2015; Wu et al., 2015; Sicard and Levine, 1989; Aviles-Viñas et al., 2015) for determining the system’s accuracy, stability and real time. Additionally, we also tested our method without taking advantage of EKF ($\Psi_1$). For testing our algorithm’s performance, we use 110 and 72 frames of welding images that have V-groove and angle welding seams. The experimental results for the V groove and angle welding seams are given in Tables I and II, respectively. It is clear that the proposed algorithm has the highest data accuracy and stability of other approaches. Comparing with $\Psi_2 \sim \Psi_5$, we can find the shortcomings of these methods, i.e.
the performance of these methods will be greatly worse when disturbances appear because these feature extraction method can only obtain part of the welding seam’s information. Besides, because the search window is only considered in the current frame, the accuracy of the algorithm decreases a little while the relative displacement of welding seam occurs on each frame of the image, but our approach has improved the above shortcomings.

In Tables I and II, time(s) indicates the time taken by the algorithm to process two adjacent frames of image. Nevertheless, its real-time performance is not the best and lies between those of the others. Moreover, we find that the time cost for processing every frame in method $\Psi_2$ and $\Psi_4$ are very close. More specifically, although search window can save search space by using EKF, it will cost some more time to run the EKF.

### Notes

1. This makes differences from a structured light vision sensor which projects/transmits a beam of scanning light through a joint, with the profile of welding seam obtained from recording depth values.
2. The median filter algorithm is used.
3. It satisfies the definition of similarity (Li et al., 2011), i.e. symmetry, consistency and non-negativity.
4. Although we use the Euclidean distance, readers can consider others.
5. Produced by German TBI Industries GmbH.

### References


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