The key technology toward the self-driving car

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Abstract
Purpose – The successful and commercial use of self-driving/driverless/unmanned/automated car will make human life easier. The paper aims to discuss this issue.
Design/methodology/approach – This paper reviews the key technology of a self-driving car. In this paper, the four key technologies in self-driving car, namely, car navigation system, path planning, environment perception and car control, are addressed and surveyed. The main research institutions and groups in different countries are summarized. Finally, the debates of self-driving car are discussed and the development trend of self-driving car is predicted.
Findings – This paper analyzes the key technology of self-driving car and illuminates the state-of-art of the self-driving car.
Originality/value – The main research contents and key technology have been introduced. The research progress as well as the research institution has been summarized.
Keywords Path planning, Car control, Car navigation, Environment perception, Self-driving car
Paper type General review

1. Introduction
Nowadays, even though vehicle driving assistive technology has been assembled in the premium cars on a large scale, the concept of the self-driving car has constantly appeared in various news and reports (Ross, 2014; Ackerman, 2016a; Harris, 2016; Hassler, 2017; Computerworld, 2012). However, due to few literatures (Van Arem, 2014; Ibanez-Guzman et al., 2012) reviewing the key technology of self-driving car, many problems are ambiguous, i.e., what is the progress of self-driving car? Is the large-scale commercial use of self-driving car helpful to the human society? To address the above problems, this paper investigates the key technology of self-driving car, discusses its implementation obstacles and summarizes the whole picture of the technology progress, which are expected to be helpful for the reader to understand the commercial use of the self-driving car.

Generally, the self-driving car (Berger, 2014; Berger and Dukaczewski, 2014; Walker et al., 2001; Thrun, 2010; Baruch, 2016; Barker et al., 2013; Litman, 2015; Levinson et al., 2011), also termed as the wheeled mobile robot, is a kind of intelligent car, which arrives at a destination based on the information obtained from automotive sensors, including the perception of the path environment, information of the route and car control. The main characteristic of self-driving car is transporting people or objects to a predetermined target without humans driving the car. According to the National...
Highway Traffic Safety Administration, the self-driving car can be classified into four levels, as described in Table I. Due to the maturity of Levels 1 and 2, this paper discusses Levels 3 and 4.

2. The key technology of a self-driving car

The automatic control, architecture, artificial intelligence, computer vision and many other technologies are integrated into the self-driving car, which is a product of the highly developed computer science, pattern recognition and intelligent control technology. From a different viewpoint, the technology of self-driving car represents the level of scientific research and industrial strength of a country. However, few papers have surveyed the technology process of a self-driving car due to its complexity. In view of this problem, this paper proposed a new classification, as shown in Figure 1, for the key technology of self-driving car according to the function implementation, which will make the description easy and clear.

Compared with manual driving, it is the key characteristic of a self-driving car that using automation equipment to replace the human driver. Based on this characteristic and functional requirement on driving and on-board equipment module, the core technology of

<table>
<thead>
<tr>
<th>Level</th>
<th>Judgment standard</th>
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<tbody>
<tr>
<td>No-automation (Level 0)</td>
<td>The driver completely controls the vehicle all the time</td>
</tr>
<tr>
<td>Function-specific automation (Level 1)</td>
<td>Individual vehicle controls are automated, such as electronic stability control or automatic braking</td>
</tr>
<tr>
<td>Combined function automation (Level 2)</td>
<td>At least two controls can be automated in unison, such as adaptive cruise control in combination with lane keeping</td>
</tr>
<tr>
<td>Limited self-driving automation (Level 3)</td>
<td>The driver can fully cede control of all safety-critical functions in certain conditions. The car senses when conditions require the driver to retake control and provides a “sufficiently comfortable transition time” for the driver to do so</td>
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<tr>
<td>Full self-driving automation (Level 4)</td>
<td>The vehicle performs all safety-critical functions for the entire trip, with the driver not expected to control the vehicle at any time. As this vehicle would control all functions from start to stop, including all parking functions, it could include unoccupied cars</td>
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Table I. The classification of vehicle automation by the National Highway Traffic Safety Administration (NHTSA)

![Figure 1.](image_url)
self-driving car is classified into four key parts, which are known as car navigation system, path planning, environment perception and car control. The detailed description is provided in the following sections.

Compared with the classification method according to automotive level, this paper proposes a new classification according to the function realization of the self-driving car. This classification is able to clearly express the technical requirements of a self-driving car, helping the researchers and relevant enterprises to understand the technical implementation of self-driving car; meanwhile, it is able to clearly describe the key technologies of implementing the self-driving car and its latest progress.

From the view of classification, this paper divides the key technology of self-driving car into four parts according to the function of a self-driving car: environment perception, car navigation, path planning, and the car control. Each part is independent with others no overlapping coverage. This classification is inspired by the operation steps of human driving vehicles and is easy for researchers to understand.

2.1 Car navigation system

During self-driving, two issues, which are the current location of the car and how to go from the location to the destination, must be resolved. Certainly, the above two issues can be solved by a human’s own knowledge in human driving. However, in self-driving, the car must be able to automatically and intelligently locate its position and perform the path planning to destination. For this objective, the on-board car navigation system is deployed on the self-driving car.

The structure of car navigation system and its metadata processing model are depicted in Figure 2. In the car navigation system, geographic information system and global positioning system (GPS) are equipped to receive the location information such as longitude and latitude from the satellite. These information, together with the road information generated by location system and digital map database, serve as the source data inputted into the map-matching model, where the intelligent path planning algorithms (i.e. Dijkstra algorithm, Bellman-Ford algorithm) are utilized to enable the path planning calculation. After calculation, the self-driving car can locate itself. With the information of the self-driving car’s location and the destination, the driving route can also be programmed and calculated by the path planning model.

2.2 Location system

The main purpose of the location system is to determine the vehicle location, which generally can be classified into relative location, absolute location and hybrid location. For relative location, the current position of self-driving car is obtained by adding the moving distance and direction to the prior position. For instance, inertial navigation system (INS) (Farrell and Barth, 1999) is a common relative location system. In INS, the vehicle angular velocity and accelerated velocity are obtained by the gyroscope sensor and accelerometer installed in the car. By integrating these data (i.e. angular velocity, accelerated velocity), the

![Figure 2. On-board car navigation system](image-url)
car’s relative course angle and speed can be calculated. Similarly, the car’s direction and mileage can be obtained by integrating the course angle and speed once again. Combining with the prior vehicle location, the current vehicle location can be calculated. However, due to the vehicle vibration during moving, it is inevitable to lead to the deviation between the calculated location and actual location.

The absolute location method is used to locate the vehicle’s position according to the information obtained from positioning system. A common positioning system is the satellite-based system, such as GPS, GLONASS, Galileo, Beidou and so on. However, the satellite signal is prone to the interference from the weather conditions and urban environment, such as building and mountain, which will cause error and noise in the location signal, and thus the measured absolute location is not accurate.

The hybrid location, which combines the characteristics of the above two locating methods, is the most common method used in obtaining the position of a self-driving car. For instance, the self-driving car of Shaihai Jiaotong University involves a typical hybrid location implementation system, which implements the Gmouse UB-353 USB GPS model and Analog Device ADIS16300 INS (Yida, 2013) to obtain information of the location.

GPS/INS can be not only used for navigation, but also for location applications, such as turning. For instance, Zhu et al. (2012) proposed a new vehicle cross-road turning method based on the GPS/INS information. According to this method, the vehicle turning can be achieved by adopting a predefined map, which is generated by the line curve-fitting and predicting method based on the location and road condition given by GPS/INS. Carnegie Mellon University (Urmson and Whittaker, 2017) made use of sparse GPS data combined with the aerial imagery to locate the self-diving car in the road, which was named Boss.

The major GPS/inertial measurement unit (IMU) manufacturers are as follows: NovAtel, Leica, CSI Wireless and Thales Navigation, etc. NovAtel proposed the SPAN technology. SPAN combines the GPS location with absolute accuracy with the IMU gyro and accelerometer measurements stability to provide a solution with 3D position, velocity and attitude. Even when the GPS signal is blocked, it can provide a stable and continuous solution. Based on the SPAN technology, NovAtel has two major GPS/IMU products: SPAN-CPT integrated navigation system and SPAN-FSAS fractional navigation system. SPAN-CPT uses a Novatel professional high-definition GPS board card and the German iMAR company’s fiber optic gyro IMU. Its solution accuracy can be applied to different positioning requirements in different modes, including SBAs, L-band (Omnistar and CDGPS) and RTK difference and so on. This system has the highest course accuracy of 0.05°, and the pitch rolling accuracy is 0.015°. SPAN-FSAS also uses the German IMAR company high-definition (HD) close-loop technology IMU, and the gyro deviation obtained is less than 0.75 degree/hour and the accelerometer deviation is less than 1 mg. By combining it with NovAtel FlexPak6™ or ProPak6™, the combination navigation solution can be achieved. The output speed of the GNSS+INS system is up to 200 Hz while IMU-FSAS sending inertial measurement data to GNSS receiver.

2.3 Electronic map (EM)

EM is used for digital map information storage, which mainly includes geographical characteristics, traffic information, building information, traffic signs, road facilities, etc. Nowadays, most of the EMs which are used in a self-driving car are the EMs designed for humans. It is expected that special EMs for self-driving, such as automatic road sign recognition, car’s driving information interacting among self-driving cars, will be developed in the future.

Now, the EM for self-driving car named HD map has already shown up. Compared with the traditional map, on the one hand, the accuracy of absolute coordinates of an HD map is higher. For example, it is declared that its next generation of drawing applications will be accurate in centimeters and, on the other hand, the road traffic information elements are
richer and more detailed. In particular, the HD map is divided into three layers: the active layer, the dynamic layer and the analytical layer:

1. Active layer, compared to the traditional map, adds HD road-level data (road shape, slope, curvature, laying, direction, etc.), the data of lane attribute (lane type, lane width, etc.) and the elevated objects, guardrail, trees, road edge types, roadside landmarks and other large target data.

2. Dynamic layer will update real-time traffic data from other vehicle sensors and road sensors. The update and supplement is in real time. This is the second phase of HD map, namely, network integration-collaborative perception.

3. Analysis layer helps train self-driving car by analyzing the real-time big data of human driving records. Therefore, the HD map enters the third phase of network integration-coordinated decision-making and control.

At present, the ADAS map has the activity layer information and the accuracy is 1-5 m. For example, BMW Adaptive Speed Recommendation (ASR) will remind users to slow down ahead of 50-300 meters in case of a slowdown area, the concrete meters will adjust depending on the current speed, the braking speed and the time of driver responding time will adjust; at the turn of the road, ASR will consider the road width, the number of lanes, the whole road condition, etc. to calculate the reasonable speed of the car.

Current HD map is of an ADAS level, which can be applied to L2/L3 self-driving. In the future, by incorporating the data processing facilities of internet of car by bringing 5G, taking into account the nature of computer vision, considering 3D modeling technology, the development of cloud computing technology based on the deep-learning environment perception and end-closed loop real-time update, HD map will gradually have highly automated driving level. This paper expects that the HD map will gradually mature with the 5G standard establishment and with the artificial intelligence eruption entering the mature stage, and become one of key technologies to support intelligent driving network.

2.4 Map matching
Map matching, which is the foundation of the path planning, calculates out the car’s location by using the geographical information from GPS/INS and the map information from EM. During the calculation, the advanced fusing technique is employed to fuse the longitude and attitude or other coordinates information into the EM. From the practical viewpoint, the output of car location should be accurate and time efficient. In this regard, it is an important issue to find a good method to fuse the information from GPS and INS. In fact, sometimes the satellite signal in GPS or the INS could be lost, therefore, a good data fusion method that can integrate the information from the existing location and route scenario will greatly enhance the accuracy, robustness and reliability.

Therefore, it is the research hotspot to make use of vehicle running characteristics in map matching, for example, those literatures proposed a novel method to solve map matching (Liu et al., 2017; Rohani et al., 2016; Zeng et al., 2016). Besides, hidden Markov model (HMM) and heuristic algorithms are some competitive algorithms in those methods, for example, the literature (Mohamed et al., 2017) presents a new method named SnapNet, which provides accurate real-time map matching for a cellular-based trajectory trace and employs a novel incremental HMM algorithm to solve the problem. In the paper of Jagadeesh and Srikanthan (2017), a novel map-matching solution is proposed which combines the widely used approach based on a HMM with the concept of drivers’ route choice. The similar articles using HMM include: Atia et al. (2017), Zhou et al. (2017) and Wang and Zimmermann (2014) and so on. We argue that there will be more and more heuristic algorithms for map matching, for example, the literature (Gong et al., 2017) develops a novel map-matching algorithm.
model that considers local geometric/topological information and a global similarity measure simultaneously and adopts the ant colony algorithm to accomplish the optimization goal in this complex model.

2.5 Global Path Planning
Global Path Planning is used to determine the optimal driving path between the start point and end point. Generally, the typical path planning algorithms, such as Dijkstra algorithm, Bellman-Ford algorithm, Floyd algorithm and heuristic algorithm (Seshan and Maitra, 2014) are employed to fuse the EM information and calculate the optimal path. Due to the global path planning is at mature stage and already implemented commercially on a large scale, so this paper will not cover this topic.

2.6 The next step of navigation system
In path planning, the module of location is required to integrate the information from EM. Even though the key technology of location (i.e. location system and the EM) in self-driving car has been matured and implemented at the commercial level, there are still many challenges that we have to face in the future:

(1) The tradeoff between the cost and the accuracy: the current location system in a self-driving car depends mainly on the satellite location system; however, to achieve the stable and accuracy of satellite signal, high-accuracy location information extraction is required, and then high cost is required to spend on the additional equipment. Therefore, it is necessary to reduce the cost in the future large-scale commercial use, while at the same time maintaining the accuracy of location.

(2) The tradeoff between the location accuracy and speed: It is necessary to accurately locate the self-driving car even in high-speed moving scenario; however, higher speed leads to fast update of the location information, and more information is required to be integrated. However, due to the limited computation ability and processing speed (i.e. CPU) of the equipment, the in-time calculation of location information cannot be achieved, and thus it leads to the inaccuracy of location. Therefore, obtaining high-accuracy location under high-speed condition is a future research direction.

(3) The special EM for self-driving car: in recent times, the general EM is utilized in self-driving, while it is necessary to develop a special EM for a self-driving car to consider the human identity, i.e. hobby of human, profession of human, which can reduce the response time of EM.

2.7 Environment perception
Environment perception is the second module of a self-driving car. To provide necessary information for a car’s control decision, the car is required to independently perceive surrounding environment. The major methods of environment perception include laser navigation, visual navigation and radar navigation.

During environment perception, multi-sensors (i.e. laser sensor, radar sensor) are deployed to sense the comprehensive information from the environment, which are then fused to perceive the environment. Among the sensors, the laser sensor is utilized for bridging between the real world and data world, radar sensor is used for distance perception and visual sensor is for traffic sign recognition. A typical recognition scheme is shown in Figure 3, the self-driving car fuses data from laser sensors, radar sensors and visual sensors, and generates the surrounding environment perception, such as road edge stone, obstacles, road marking and so on.
2.8 Laser perception

Strictly speaking, laser perception system is a kind of radar system. In laser perception, a continuous laser or laser pulse is launched to the target, and a reflected signal is received at the transmitter. By measuring the reflection time, reflection signal strength and the shift of the operation frequency, the cloud data of target point can be generated, then the testing object information, such as location (distance and angle), shape (size) and state (velocity and attitude) can be calculated out.

Laser sensor is the main sensor in environment perception (Ackerman, 2016b). According to the dimension of sensed information, laser sensor can be classified into single-line laser radar, multi-line laser radar and three-dimensional omnidirectional laser radar (Fei, 2012). These lasers usually work in complicated outdoor environment. Different kinds of laser radar have their defects. For instance, false detection usually occurs in a single-line laser radar due to less information sensed by the single-line radar; owing to the asymmetry information from different line in multiple-line laser radar, the accuracy of output is limited and insufficient, and the vision range is smaller due to the smaller inter-section region among the lines; due to the large amount of data generated in a three-dimensional omnidirectional laser radar, it is difficult for the algorithm to generate the real-time output. Therefore, in the complex outdoor environment, especially the moving of the cars and human, it is challenging to reasonably configure different kinds of sensors to achieve the location of a moving obstacle, and improve the output performance in terms of vision, accuracy and real time.

To speed up the process of implementing self-driving car into the market, many other issues, such as accuracy, cost, are required to be considered. Since laser sensor is the main sensor of self-driving car in the environment perception, the accuracy and reliability of laser radar is important, and it represents the degree of maturity of a self-driving car. In addition, the cost is also an important factor in deploying the laser sensors. For instance, the 3D omnidirectional laser radar HDL-64E provided by Velodyne company installed on the Google self-driving car can achieve high accuracy and reliability, however, it cost up to $80,000. Therefore, how to reduce the price of laser sensor in a self-driving car is another important research topic.

In the field of LiDAR, the major manufacturers are Velodyne LiDAR, Inc., Ibeo Automotive Systems GmbH, Quanergy Systems, Inc. etc. Velodyne does not provide algorithm products, but the laser radar raw data to the automakers. It has three LiDAR productions: HDL-64E (64 lines), HDL-32E (32 lines), VLP-16 (line 16). Unlike Velodyne, Ibeo’s products offer a complete solution including the hardware and software. For the current Ibeo self-driving car, miniLUX and LUX are the common two products used in the multiple point layout combination. Quanergy is a new venture company in the field of LiDAR. In 2016 CES, Quanergy showed the new product S3, its size is close to the business card box.
2.9 Radar perception

Radar perception is generally used for distance detection, which is achieved by calculating the return time of millimeter wave transmitted by the radar sensor. As the radar detecting distance has been relatively matured, this paper will not cover this topic, but will only introduce some productions.

The major global suppliers of automotive millimeter wave radar are traditional enterprises with advantage of automotive electronic, such as Bosch, Continental, Hella, Fujitsu Ten, DENSO, TRW, Delphi, Autoliv and Valeo and so on. Among them, the core product of Bosch is a long-range millimeter wave radar, which is mainly used in the ACC system. The latest product LRR4 can detect vehicles 250 meters away, as currently it is the only wave radar with farthest detection range of millimeter and has the highest market share. However, the customers of Bosch mainly concentrate on Audi and Volkswagen. Continental has a wide range of customers and a complete product line. The main products are 24 GHz millimeter wave radar, which has a high market share in the field of Stop & Go ACC. Hella has the widest range of customers in the 24GHz-ISM field. Ten million 4 GHz millimeter wave radar has been off the assembly line, 6.5 million have been shipped; therefore, the market share of Hella is first in the world. The fourth-generation 24 GHz radar sensor will be ready for global production in 2017. Fujitsu and Denso dominate the Japanese market, where Fujitsu has a slightly better market share. Fujitsu, Panasonic and Denso will be strong competitors in the 79 GHz radar market in the future.

2.10 Visual perception

Visual perception is necessary for a self-driving car, i.e. it is necessary to identify the traffic signals. Nowadays, most traffic signals are designed for the human vision; therefore, it is necessary to recognize the traffic signal. Besides, the machine vision is also used for location, navigation, to judge the motion and so on. However, it is complex that environment perception use vision due to the large amount of information and inefficient algorithms. Specifically, the most complex visual perception is how to ensure the reliability and robustness of the algorithm (Ben-Afia et al., 2014).

There are two main development directions in visual-perception-based intelligent vehicle navigation. One is primarily visual Simultaneous Localization And Mapping (SLAM) based on the map. Another is visual understanding based on the understanding of captured image, which use the machine vision and machine learning to process the image, the self-driving car then reconstructs the 3D scene for navigating and recognizing the traffic lights, traffic signs and stop line (Gim Hee Lee and Pollefeys, 2013; Hane et al., 2015). On account of the intense research for machine visual, this paper skips introducing this part, the literature (Ben-Afia et al., 2014) can be used as a reference, which details the visual navigation. This paper mainly introduces the SLAM.

SLAM problem can be described as the robot performs moving within an unknown location in an unknown environment. During the moving, the robot locates itself according to the position estimation and sensor data, and at the same time builds the incremental map. The schematic diagram of SLAM including the localization and mapping is shown in Figure 4. In the figure, $S_k$ are the data gathered from the sensors, $M_{k-1}$ is the local map at previous time $k-1$, $R_k$ is the self-driving car position at time $k$. When the robot starts moving from an unknown location in an unknown environment, the robot locates itself and builds the incremental map during the moving based on the position estimation information $R_k$ and sensed data $S_k$.

Four issues are required to be solved in SLAM. They are: how to express the environment, namely environment map expression method; how to get the environment information, i.e. robot roams in the environment and records the perception data from
sensors, which are related to the robot location and environment feature extraction; how to express the obtained environment information and refresh the map according to the environment information, which require to find a suitable way to describe and handle the uncertain situation; and develop a stable and reliable SLAM.

In view of calculating the complexity problem for Scale Invariant Feature Transform (SIFT), a new method called Iterative SIFT Monte Carlo Localization SLAM was proposed in the literature (Dongbo, 2012). The SLAM solution based on vision of the indoor robot in the literature (Dongbo, 2012) is also helpful for a self-driving car. The environment perception function is prone to the influence from the vehicle condition, vibration, performance degradation, roads emergency, weather conditions, accident shade, and so on. So it is a great challenge for a self-driving car to improve the reliability and robustness of laser radar and visual sensors. However, to make the self-driving car marketization, the challenges on reliability and robustness of laser radar and visual sensors are required to be solved. Therefore, the above issues are the key problems for self-driving car’s widespread application.

2.1.1 Vehicle control
Vehicle control mainly includes vehicle speed and direction control. Generally, the functionalities of vehicle control are the vehicle’s status perception and the development of vehicle’s control method. The position of vehicle control in a self-driving framework is shown in Figure 5. To achieve vehicle speed and direction calculation, the EM information including environment perception, vehicle status, driving target, traffic regulations and driving knowledge are fed as input into the perception module, then the vehicle control algorithm performs the calculation of the control target, which is then passed into the vehicle control system. Finally, the vehicle control system executes those instructions to control the vehicle’s direction, speed, light, horn and so on.

The control platform is the core component of the self-driving car and controls the various systems of the vehicle, which includes the car anti-lock braking system, the car drive anti-slip system, the car electronic stability program, the automobile Sensotronic Brake Control, electronic brake force distribution, auxiliary brake system, supplementary restraint system and car radar anti-collision system, electronically controlled automatic transmission, continuously variable transmission, cruise control system, electronic control suspension, electric power steering system and so on. The control platform mainly
includes two parts, i.e., electronic control unit (ECU) and communication bus. ECU mainly implements the control algorithm, whereas the communication bus realizes the communication function between ECU and mechanical parts.

2.12 The perception of vehicle speed and direction
The perception of vehicle self-status mainly includes vehicle speed and direction perception. Photoelectric code is usually used in speed perception, while both photoelectric angle code and potentiometer are employed in the direction perception. Photoelectric angle code disc is a widely utilized encoding digital sensor, which converts the measured angular displacement into digital signal output. There are two types of photoelectric angle code disc sensors, which are known as absolute photoelectric code disc and incremental photoelectric code disc. For an absolute photoelectric code disc, the vehicle angle is obtained by measuring the rotating object absolute position, while for the incremental photoelectric code disc, the vehicle angle is calculated out by measuring the accumulative angular displacement during the turning of the rotating object, and by integrating a period of accumulative angle (Yongfeng, 2007).

On the other hand, the vehicle can use GPS/INS or attitude and heading reference system (AHRS) to perceive self-status. AHRS is a high-performance three-dimensional motion measurement system based on micro-electromechanical systems. It consists of a three-axis gyroscope, three-axis inertial measurement unit (IMU), three-axis electronic compass and other auxiliary three-axis motion sensors. AHRS can timely provide 360-degree posture information in both static and dynamic environments; therefore, it is widely used in many automatic control system or test system.

2.13 Vehicle control method
PID algorithm or improved PID algorithm is usually adopted by vehicle control methods. PID control algorithm is the most common control algorithm in the current industrial production process. The principle of PID algorithm is shown in Figure 6. In the figure, \( r(t) \) is the input expired signal, \( e(t) \) is the feedback error signal, \( u(t) \) is the control signal calculated by PID control algorithm, and \( c(t) \) is the current actual output signal by the controlled object. From the figure, the PID algorithm employs three parameters and math operations, including proportion, integration and differentiation, to control the target. The difference between the control target and reality value is employed as the input of feedback loop to adjust the position of the target.
It is noticed that classic PID algorithm has the problems such as complex parameter adjustment, low adaptability and so on. Especially when the transmission system is highly nonlinear and the longitudinal interference is too complex, the control accuracy is too low. The improved PID algorithms employed by the most recent self-driving car can overcome the drawbacks of classic PID algorithm. For instance, a vehicle direction control method including longitudinal and lateral control was proposed in the literature (Pan, 2012). The longitudinal control was achieved by the expert control method formulated by the expert rules established from the driving experience. It was found that the control accuracy was highly improved by using the longitudinal control even when the system is nonlinear and longitudinal interference is complex. Moreover, a new autonomous vehicle’s lateral control algorithm based on a composite of the Cerebellar Model Articulation Controller and PID control was proposed in the literature. Combined with the longitudinal control, the system can compensate automatically even when the model and input signal change quickly and unpredictably, and thus the self-driving car can drive steadily and accurately in any kind of urban environments.

3. The main research institutions of self-driving car
The idea of self-driving car is same as of the vehicle invention. Until recent years, the self-driving car achieved the laboratory applications level with the development of sensor technology, computing technology and mobile internet. The self-driving cars that appear in the self-driving car trial represent the top level of this industry. The main research institutions can be found out by introducing several competitions.

The first challenge is the DARPA Grand Challenge, which was held in (DARPA, 2007) 2004, 2005 and 2007. In 2004, 15 teams joint the first challenge that was held in the Mojave Desert region of the USA. The goal of the challenge was passing through 240-km desert; however, no team could complete the task. Until 2005, five teams completed the task smoothly with the champion completion time of 6 hours and 54 minutes. Different from the previous two challenges, the third DARPA Challenge held in 2007 was an urban challenge, in which the test environment was an urban road. Six teams completed the competition requirements. The Stanford Racing team won the second good result. The teams from Virginia Tech, Blacksburg, Virginia and MIT, Cambridge, Massachusetts came in the third and fourth, respectively (Table II).

The second trail is The European Land-Robot trial (ELROB) (Trial, 2017); the first ELROB took place in the infantry training area near Hammelburg on May 15-18, 2006. Unlike the DARPA, European Robotics bridges the gap between industry and research in the field of ground robotics. The robotics’ competition also held in a game form, which includes the military and civilian form, and these two forms held in turn every year since
2007. The unmanned game was held in the odd-numbered years since 2007. The last four games scene (Scenarios) are named as reconnaissance and surveillance, autonomous navigation, camp security and transport mule, respectively, and the Transport Mule is a typical scene for a self-driving car.

The third trail was named “China Smart Car Future Challenge” and held since 2009. A major research plan “visual auditory information cognitive computing” (study period: 2008-2015) was launched by the National Natural Science Foundation of China (NNSFC) in August 2008. As an important component of NNSFC major research plan, the purpose of “China Smart Car Future Challenge” are fourfold: first is to exchange experience in a real physical environment; the second is to test the research progress of “visual auditory information cognitive computing;” the third is to explore the efficient calculation model and improve the computer’s ability to understand complex perception information and processing efficiency of huge amounts of heterogeneous information; and the fourth is to promote the major research plan to achieve better progress, and thus improve the original innovation of the major research. The first challenge, which includes comprehensive road test (about 15 kilometers highway and suburb road) and a special way test (urban road), was held in a closed environment in 2014. The self-driving car 4 S performance, namely, safety, smartness, smoothness and speed, is the emphasis of this challenge.

From the above trails, we can know a lot of famous self-driving car institutes, which are summarized in Tables III and IV.

Moreover, the development process of a self-driving car can be represented by some typical events, the details of which are described as follows:

In September 2011, a free self-driving car trail named “Made in Germany” was held in the University of Berlin. The self-driving car set off from the Brandenburg gate in Berlin, passed through Berlin International Conference Center and finally returned to the starting point safely. During this journey, the self-driving car traveled nearly 20 kilometers, which includes 46 traffic lights and two island rings.

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<tr>
<th>Year</th>
<th>Vehicle</th>
<th>Team name</th>
<th>Team home</th>
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<tr>
<td>2007</td>
<td>Sandstorm</td>
<td>Red Team</td>
<td>Carnegie Mellon University, Pittsburgh, Pennsylvania</td>
</tr>
<tr>
<td>2007</td>
<td>Stanley</td>
<td>Stanford Racing Team</td>
<td>Stanford University, Palo Alto, California</td>
</tr>
<tr>
<td>2007</td>
<td>Boss</td>
<td>Tartan Racing</td>
<td>Carnegie Mellon University, Pittsburgh, Pennsylvania</td>
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Table II. The DARPA Grand Challenge Champions

<table>
<thead>
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<th>Year</th>
<th>Project</th>
<th>Team/source</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>Urban scenario: situation awareness in urban environment</td>
<td>University of Würzburg</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Telerob</td>
</tr>
<tr>
<td></td>
<td></td>
<td>University of Hannover</td>
</tr>
<tr>
<td>2009</td>
<td>Transport – Mule (non-urban)</td>
<td>University of Hannover</td>
</tr>
<tr>
<td></td>
<td></td>
<td>University of Kaiserslautern</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Robotics Inventions</td>
</tr>
<tr>
<td>2011</td>
<td>Transport – Mule</td>
<td>Fraunhofer FKIE</td>
</tr>
<tr>
<td></td>
<td></td>
<td>University of Hannover</td>
</tr>
<tr>
<td>2013</td>
<td>Autonomous navigation using GPS, GLONASS and Galileo</td>
<td>MuCAR/University of the Bundeswehr Munich</td>
</tr>
<tr>
<td></td>
<td></td>
<td>RIS/LAAS/CNRS</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NAMT/Nizhny Novgorod Automotive Technical School (NAMT)</td>
</tr>
</tbody>
</table>
In July 2013, a self-driving car developed by the Artificial Vision and Intelligent Systems Laboratory (VisLab) of the Parma University, Italy drove around the old section of Parma city without any human participation. The self-driving car passed successfully the single two-lane and roundabout, recognized the traffic lights, pedestrians crossing the road, man-made raised pavement conditions and so on.

Other events in VisLab include:

- In 2010, a driverless van has completed the longest-ever trip of around 13,000 kilometers (8,077 miles) that began from Italy and ended in China within three months (Kent, 2010).
- In 2013, a driverless car testing program named PROUD-Car Test was held by Vislab. It can be seen that a car with nobody on the driver seat can move successfully on a mixed traffic route (rural, freeway and urban) open to public traffic.
- In 2014, a new driverless vehicle named Deeva was designed with an appearance similar to normal vehicle (VisLAB, 2016).

Nonetheless, Google is the most famous agency in area of self-driving car. Google’s self-driving car is developed by a team headed by Sebastian Thrun, who is the Director of Artificial Intelligence Laboratory, Stanford University. The accumulation of Google’s self-driving car technology began in 2005, the first driving license was issued to Google’s self-driving car in Nevada, USA in May 2012. By the end of 2014, the project with eight self-driving cars has been tested on more than 700,000 kilometers; even if the driving road covered urban, highway, mountainous road and various roads, no proactive accident happened. Before the Christmas Eve of 2014, Google announced the “first real build” of their self-driving vehicle.

4. The trend and discussion of self-driving car

From the previous sections, we know that the experimental prototypes of the self-driving car have been developed, some typical self-driving cars have been tested on more than one million kilometers, and the test for driving license for a self-driving car has been issued by some states in USA. However, we should know that the realization of self-driving car is not only influenced by the self-driving car technology, but also by the vehicle cost, social habits, human psychology, law and so on; therefore, there will be a long way to go for the entire commercialization of self-driving car.

At present, self-driving car configures many sensors that are non-existent in a traditional car. For instance, the lasers and vision sensors used for environment perception are the typical key sensors. These sensors are expensive and have high requirement on using condition. Moreover, the service lifetime of these sensors will be greatly reduced when they are installed in the moving car. Meanwhile, the reliability is also worrying.

<table>
<thead>
<tr>
<th>Year</th>
<th>Team</th>
<th>From</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009</td>
<td>Self-driving car</td>
<td>Hunan University</td>
</tr>
<tr>
<td>2010</td>
<td>Intelligente Pioneer</td>
<td>Institute of Advanced Manufacturing Technology, Hefei Institutes of Physical Science Chinese Academy of Science and Chery Central Research Institute</td>
</tr>
<tr>
<td>2011</td>
<td>Explore Lion</td>
<td>National University of Defense Technology</td>
</tr>
<tr>
<td>2012</td>
<td>Brave Lion 3</td>
<td>Military Transportation University</td>
</tr>
<tr>
<td>2013</td>
<td>Smart 2</td>
<td>Beijing Institute of Technology and BYD Corporation</td>
</tr>
<tr>
<td>2014</td>
<td>Junjiao Lion</td>
<td>Military Transportation University</td>
</tr>
</tbody>
</table>

Table IV. The best player in future challenge over the year
In addition, it needs time for the social habit of humans to accept the self-driving car, for instance, the share of self-driving car among the people, the development of automatic supporting facilities for self-driving car energy compensation, the human psychological acceptance degree for self-driving car, and the development of law to deal with the traffic accident on self-driving car. Therefore, there are some obstacles in the way toward the self-driving car, especially, there are four parts.

4.1 Contention between camera and LiDAR
There are two key sensors for the self-driving car perceiving environment: LIDAR and Vision, and each has its own advantages and disadvantages. The advantage of LIDAR is able to perceive more clearly the surrounding environment of vehicle, less interfered by external factors, especially the light. The three-dimensional imaging laser radar is currently the most efficient sensor, but also the most accurate sensor obtaining a wide range of three-dimensional scene image. The drawback is that the current LIDAR production process is complex and expensive, taking Velodyne HDL-64 as an example, the current price is up to $80,000. Contrasting with the LiDAR, the Vision is low price, but the ability to perceive the environment is less than the laser, and is influenced by the quality of the algorithm and the environment, especially the light. The debate of environment perception is caused by both the pros and cons. For the implementation technology of a self-driving car, Google as a representative mainly uses LiDAR, and Tesla uses Vision. Some literature (Harris, 2015) argues that the cameras will replace LiDAR in the future, we believe that the production technology of LiDAR will have a new breakthrough along with the strong demand; therefore, the cost of the LiDAR will decrease significantly (Shchetko, 2014). Laser will be the main sensor of environmental perception under the full self-driving mode; however, Vision will also be used to assist self-driving to perceive the environment. In future, a LIDAR-based, vision-assisted mixed environment perception model will be required.

4.2 Social habit
Social habit is a very important issue in sociological research. As the level of self-driving matures, it will have a great impact on people’s transportation. First of all, the taxi and the truck will be replaced, it is difficult to effectively reduce the impact on various industries brought by the technological progress. The second one is the impact on public transport. The self-driving car may be more convenient for the people to travel, on the other hand, it is possible to collapse the existing social transport model, leading to less bus services and more congested urban traffic. Finally, the self-driving cars may bring different perceptions of wealth. Today, sharing economy is growing in the world, in the future, the self-driving car must promote the development of sharing economic in the field of road traffic, then human beings will be more willing to share in the future. Some typical literatures, such as Richards and Stedmon (2016), Banks and Stanton (2016), Banks et al. (2014), Brooks (2017), Conejero et al. (2016), Yang and Coughlin (2014), Surden and Williams (2016), etc. discuss these issues.

4.3 Human psychology
The problem stems from two aspects, one is the human demand for security, and the other is the social and ethical issues. For more than one century, people have been accustomed to the control of vehicles. Different from other new things, the self-driving car is more likely to cause passangers injuries or even death. It has a great impact on the human psychology. Many people are not willing to use self-driving car in order to achieve more psychological
security, while few people do not use self-driving because of their love for driving. Therefore, for a long time, it will be the era of co-existence of both self-driving car and human driving car. In terms of social ethics, how to choose between passenger safety and pedestrian safety when they are in danger? When the danger occurs, how to choose a young child and an old man? How to make an emergency safe haven is always a human psychological problem. This issue has also aroused the attention of scholars (Kirkpatrick, 2015; Baruch, 2016; Diels and Bos, 2016; Li et al., 2016; Lee et al., 2015).

4.4 Law problem
The current legal system already cannot meet the self-driving car. There are four problems: first is the license problem. At present, many countries do not make the rules for the self-driving cars. There are no countries or regions that give self-driving car license, only California and some American states issued a test permit and with the progress of the self-driving car, whether it is legal that the existing vehicles be equipped with self-driving control system? Second is driving regulations. Whether the driving regulations of self-driving cars are determined according to the requirements of human driving, it is also an issue in the current legal profession. Third is the definition of responsibility. How to define the responsibility? Whether there should be someone sitting in the driver’s seat, whether the passengers sitting in the driving position should have the driving skills, whether the passengers should bear the corresponding responsibility, all those are the legal problems of self-driving. Fourth is the information security. Whether the self-driving car has the right to record the path of passage? Is the mapping of self-driving car related to information security in a country or region?

In any case, law problem is going forward with dispute (Greenblatt, 2016). The Vienna Convention for Road Traffic, which is on the road traffic management, was amended in the United Nations on March 23, 2016. It removes the obstacle for applying a self-driving car in the transportation. The 1958 Agreement, developed by the United Nations Coordination Forum on World Vehicle Regulations, proposes to remove the speed limit for the active steering function application, which is expected to be discussed in 2017. The USA is doing its best in the self-driving car legal framework, not only some states have enacted relevant test bills and developed rules, but also the federal formulates the related rules and laws; Federal Automated Vehicles Policy (USDO Transportation, 2016), Safely Ensuring Lives Future Deployment and Research in Vehicle Evolution Act (US Congress, 2017). The other countries are only enacting some testing allowable terms and are considering the relevant legislation.

Nowadays, more and more driving assistance technologies originated from the self-driving car have been utilized in the traditional car. It can be predicted that the realization of self-driving car will gradually develop from the assistance driving to the self-driving in special environment (such as highway), and finally to the total self-driving. In recent times, many driving assistance technologies such as lane keeping assist, adaptive cruise control and so on, have been commercialized. In the near future, the commercial self-driving car under supervision in some special sections will be developed, such as the car will self-drive in a highway, which will be the milestone of self-driving. In the future, full self-driving car will be accepted as a common driving pattern.

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UAV attitude estimation based on the dual filtering methods

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Abstract

Purpose – A toy UAV performs tumbling, rolling, racing and other complex activities. It is based on low-cost hardware and hence requires a better algorithm to estimate the attitudes more accurately with low power consumption. The proposed technique based on optimized Madgwick filter and moving average filter (MAF) ensures improved convergence speed in estimating the attitude, achieves higher accuracy and provides robustness and stability of the toy UAV. The paper aims to discuss this issue.

Design/methodology/approach – Traditional methods are prone to problems such as slow convergence speed and errors in calculation of the attitude angles. These errors cause the vehicle to drift and tremble, thus affecting the overall stability of the vehicle. The proposed method combines the features of optimized Madgwick filter and MAF to provide better accuracy, achieved through the fusion of gyroscope and accelerometer data, and zero correction to eliminate the random drift error of the gyroscope and removal of high-frequency interference by MAF of the accelerometer data. The experimental results on actual flight data showed that the method was better than the conventional Madgwick and Mahony complementary filters.

Findings – The performance of the proposed method was analyzed by estimating the pitch and roll angles under the static and dynamic condition of the toy UAV. The results were compared with two traditional methods: Madgwick and Mahony complement filter. In the static condition, the variance and average error while estimating the attitudes was comparatively lower than the traditional method. For the dynamic conditions, the convergence time to achieve a prescribed swing angle was again lower than the traditional method. From these two experiments, it can be seen that the proposed method provides better attitude estimation at lower computation time.

Originality/value – The proposed method combines the optimized Madgwick filter and MAF to accuracy estimate the attitude of toy UAV. The algorithm mainly suits the toy UAVs which are based on low-cost hardware and require better control systems to ensure stability of the vehicle. The experimental results on real flight data illustrate that the method not only improves the convergence speed in estimating the attitude angle for large maneuvers of the toy UAV, but also achieves higher accuracy in the attitude estimation, thus ensuring the robustness and stability of the UAV.

Keywords Attitude estimation, Moving average filter, Optimized Madgwick filter, Quad-rotor unmanned aerial vehicle

1. Introduction

MICRO-UAV is a miniature unmanned aerial vehicle with no pilot on board and is controlled by radio remote control and program control units. According to the flight model, the MICRO-UAV can be classified into: fixed-wing (Paull et al., 2014; Skulstad et al., 2015; Hakan et al., 2017), flapping wing (Roll et al., 2015; Paranjape et al., 2013; Hoang et al., 2015) and rotor type (Driessens and Pounds, 2015; Miao and Li, 2015; Deepak and Pritpal, 2016). A quad-rotor aircraft is a kind of low-cost rotor-type miniature UAV with a simple mechanical structure but requires automatic controllers and navigation systems to

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provide complete stability while flying and performing maneuvers. Since 1990s, with the development of the Micro-Electro-Mechanical System technology, a control algorithm has been gradually matured, and the navigation system, with the weight of only a few grams (He et al., 2015), has been developed rapidly. Nowadays, the research and application of multi-rotor UAV has become the focus.

The quad-rotor aircraft can be classified into professional and consumer type. The former is more expensive and focuses mainly on stability and reliability in order to meet the requirements of aerial photography and other functions. While the latter, especially the toy types, whose cost is very low, pays more attention to meet the requirements of users' manipulating experience. The vehicle focuses on flight stability, but also can perform complex actions such as tumbling, drifting, rotating and so on. However, a four-axis rotor toy-type aircraft is easily affected by the sensor output deviations, the accuracy in calculating the attitudes and the drift of the axial error; thus, it cannot perform the prescribed actions accurately (Zhang et al., 2014; Ahmed and Tahir, 2017). Consequently, a better attitude calculation system is needed.

Extended Kalman filter (Kang et al., 2016; Wenjing et al., 2017) is a technique that is commonly used in aircrafts attitude calculation systems. It requires high-speed DSP processors to perform the complex matrix operations and thus not suited for the toy-type MICRO-UAVs which employ low power processors. As for toy-type MICRO-UAV, Mahony complementary filtering algorithm (Mahony et al., 2008) is a better choice which requires less calculations and hence low power requirements. Nevertheless, there also exist some problems. For example, the slow convergence of estimating the attitude angle results in the poor real-time performance, thus causing the MICRO-UAV to drift. So far, the Madgwick filter algorithm (Madgwick, 2010), which employs the gradient descent method, is good in improving the convergence rate of the attitude calculation system but may result in an output angle of low precision and large error, since less attention is paid to the gyroscope data. Subsequently, an optimized Madgwick filter algorithm was proposed (Sarbishei, 2016) which solves the above problems, but we still find some room for improvement like eliminating random zero error and high-frequency interference (Yongyuan, 2014) in the calculation of the UAV attitude. The paper presents a new method for calculating the attitude of a small four-axis rotor toy-type UAV, by combining an optimized Madgwick filter algorithm and moving average filter (MFA).

The proposed method, in addition to effectively reducing the tremor and drift of the targeted UAV, also improves its stability and robustness while satisfying the real-time constraints.

The paper is organized as follows. Section 2 presents a description of UAV's attitude calculation, and Section 3 introduces attitude calculation of MFA filtering combined with optimal Madgwick filter. Section 4 presents the experimental results of attitude estimation of a toy UAV, where the proposed filter is compared with two commonly used filters, Madgwick and Mahony complementary filters, and Section 5 presents the summary of the paper.

2. Description of UAV attitude calculation

We have employed the coordinate system to describe the attitude information like pitch, roll, yaw. This enables us to mathematically express the flight attitude and trajectory as space vector transformation. Therefore, two space coordinate systems were defined, respectively, geodetic coordinate (R-XYZ) system, and UAV coordinate system (r-xyz), as shown in Figure 1.

In Figure 1, where R is the center of rotation of toy UAV, r is the centroid of the UAV and the angles of rotation about z-axis, y-axis and x-axis are defined as ψ, θ and φ, respectively. Here, the Euler angle representation is adopted to describe the rotation of the UAV.
coordinate system relative to the geodetic coordinate system. Thus, the attitude matrix is given by (Magnussen et al., 2013):

\[
\mathbf{C}_R = \begin{bmatrix}
    c_{xx} & c_{xy} & c_{xz} \\
    c_{yx} & c_{yy} & c_{yz} \\
    c_{zx} & c_{zy} & c_{zz}
\end{bmatrix}
\]

\[
= \begin{bmatrix}
    \cos \theta \cos \psi & \cos \theta \sin \psi & -\sin \theta \\
    \sin \phi \sin \theta \cos \psi - \cos \phi \sin \psi & \sin \phi \sin \theta \sin \psi + \cos \phi \cos \psi & \sin \phi \cos \theta \\
    \cos \phi \sin \theta \cos \psi + \sin \phi \sin \psi & \cos \phi \sin \theta \sin \psi - \sin \phi \cos \psi & \cos \phi \cos \theta
\end{bmatrix}
\]

(1)

Accordingly, the Euler angle is presented as:

\[
\begin{bmatrix}
    \phi \\
    \theta \\
    \psi
\end{bmatrix} = \begin{bmatrix}
    \arctan2(C_{yz}, C_{xz}) \\
    \arcsin(C_{xx}) \\
    \arctan2(C_{xy}, C_{xx})
\end{bmatrix}
\]

(2)

Therefore, attitude matrix \( \mathbf{C}_R \) can also be written as (Yongyuan, 2014):

\[
\mathbf{C}_R = \begin{bmatrix}
    1 - 2y^2 - 2z^2 & 2xy + 2wz & 2xz - 2wyz \\
    2xy - 2wz & 1 - 2x^2 - 2z^2 & 2yz + 2wz \\
    2xz + 2wz & 2yz - 2wz & 1 - 2x^2 - 2y^2
\end{bmatrix}
\]

(3)

where \( w, x, y, z \) are four vectors of quaternion. Then, substituting Equation (3) by Equation (2), the Euler angle of the attitude angle of UAV described by quaternion is given by (Magnussen et al., 2013):

\[
\begin{bmatrix}
    \phi \\
    \theta \\
    \psi
\end{bmatrix} = \begin{bmatrix}
    \arctan2(2yz + 2wz, 1 - 2x^2 - 2y^2) \\
    \arcsin(2xz - 2wz) \\
    \arctan2(2xy + 2wz, 1 - 2y^2 - 2z^2)
\end{bmatrix}
\]

(4)

It is generally known that the gyroscope has good dynamic performance, but over a time period, the errors get accumulated and thus suffer from a poor steady-state performance.
On the other hand, the accelerometer presents a good steady-state performance and poor dynamic performance; therefore, a more accurate attitude calculate of the UAV can be obtained by integrating a weighted sum of the inputs from both gyroscope and accelerometer data.

3. Attitude calculation of MFA filtering combined with optimal Madgwick filter

For computational convenience, quaternion is used to represent the attitude data. The attitude of gyroscope can be determined by using the rate of change of quaternion, which is described by the following differential equation:

\[
\dot{\mathbf{Q}_g} = \frac{1}{2} \mathbf{Q}_g \otimes \mathbf{w}_R
\]  

(5)

where \( \dot{\mathbf{Q}_g} \) denotes the time-varying quaternion, \( \mathbf{w}_R \) denotes a certain angular velocity of the clockwise rotation of rigid body about axis, while \( \otimes \) denotes quaternion multiplication (Yongyuan, 2014). Then, the expansion of Equation (5) based on the rigid body coordinate system is given by:

\[
\dot{\mathbf{Q}_g} = \begin{bmatrix}
\dot{w} \\
\dot{x} \\
\dot{y} \\
\dot{z}
\end{bmatrix} = \frac{1}{2} \begin{bmatrix}
w & -x & -y & -z \\
x & w & -z & y \\
y & z & w & -x \\
z & -y & x & w
\end{bmatrix}
\begin{bmatrix}
0 \\
w_x \\
w_y \\
w_z
\end{bmatrix}
\]  

(6)

where \([\dot{w} \ \dot{x} \ \dot{y} \ \dot{z}]\) denotes a four-dimensional vector, and \(w_x, w_y\) and \(w_z\) define the tri-axis angular velocity of gyroscope outputs, respectively.

To find the rate of change of quaternion, the gradient descent method is employed wherein the local minima of the function is found iteratively by the correction steps that are proportional to the negative of the gradient of the function at the current point.

Now, the accelerometer error function of the UAV is represented as a quaternion and is given by (Madgwick, 2010):

\[
F\left(\mathbf{Q}_k, \mathbf{\hat{a}}_t\right) = \begin{bmatrix}
2xz - 2wy - ax \\
2yz + 2wx - ay \\
1 - 2x^2 - 2y^2 - az
\end{bmatrix}
\]  

(7)

where \(\mathbf{Q}_k\) denotes the position after \(k\) iterations, \(a_x, a_y, a_z\) denote the tri-axis acceleration of accelerometer, while \(\mathbf{\hat{a}}_t = [0 \ a_x \ a_y \ a_z]\) indicates a four-dimensional vector.

The derivative of \(F(\mathbf{Q}_k, \mathbf{\hat{a}}_t)\), represented as a Jacobian matrix, is given by the following equation:

\[
J(\mathbf{Q}_k) = \frac{dF(\mathbf{Q}_k, \mathbf{\hat{a}}_t)}{d\mathbf{Q}_k}
\]  

(8)

Now, the descent of function (7) is represented as the product of (7) and (8), and is described as:

\[
\nabla F\left(\mathbf{Q}_k, \mathbf{\hat{a}}_t\right) = J^T(\mathbf{Q}_k) \otimes F\left(\mathbf{Q}_k, \mathbf{\hat{a}}_t\right)
\]  

(9)
The gradient is normalized as the inverse unit vector, and the rate of change of quaternion for the accelerometer is given by:

\[
\dot{Q}_a = -\beta \frac{\nabla F(\hat{Q}_{est,t-1}, \hat{a}_t)}{\|\nabla F(\hat{Q}_{est,t-1}, \hat{a}_t)\|}
\] (10)

where \(-\beta\) is the correction step value and has a negative sign to represent that the corrections steps are proportional to the negative of the gradient of the function.

Finally, the current attitude is obtained by combining Equations (6) and (10), i.e. the fusion the past attitude with the change in attitude of the gyroscope and the weighted change of the accelerometer attitude:

\[
\hat{Q}_{est,t} = \hat{Q}_{est,t-1} + \Delta t \hat{Q}_g - (\Delta t \beta) \frac{\nabla F(\hat{Q}_{est,t-1}, \hat{a}_t)}{\|\nabla F(\hat{Q}_{est,t-1}, \hat{a}_t)\|}
\] (11)

where \(\hat{Q}_{est,t}\) denotes the quaternion calculated at time \(t\), \(\hat{Q}_{est,t-1}\) denotes the quaternion at time \(t-1\), \(\Delta t\) denotes the sampling time and the simplified representation of Equation (10) is given as (Sarbishei, 2016):

\[
\hat{Q}_{est,t} = \hat{Q}_{est,t-1} + \Delta t \hat{Q}_g - (\Delta t \beta) \nabla F(\hat{Q}_{est,t-1}, \hat{a}_t)
\] (12)

However, calculating the attitude directly from Equation (12) results in poor accuracy, since the toy-type MICRO-UAV, due to its small size and light weight, is greatly affected by vibrations when compared to a large-size UAV. Also, determining the quaternion \(\hat{Q}_{est,t-1}\) directly results in a large gradient error with more steps requiring to determine rate of change of the accelerometer. From our experimental analysis, we found that the gyroscope data of the UAV moving at high speed are more reliable and thus can be used to modify the input quaternion \(w, x, y, z\). Thus, the modified quaternion \(w', x', y', z'\) is obtained by the addition of gyroscope data at time internals \(\Delta t\). Therefore, the quaternion \(w', x', y', z'\) after calibration is described in the following equation:

\[
\begin{bmatrix}
w' \\
x' \\
y' \\
z'
\end{bmatrix} =
\begin{bmatrix}
w + \Delta t \dot{w} \\
x + \Delta t \dot{x} \\
y + \Delta t \dot{y} \\
z + \Delta t \dot{z}
\end{bmatrix}
\] (13)

Substituting Equation (13) in Equation (7) yields Equation (14), which gives the quaternion vector error function with an improved accuracy:

\[
F(\hat{Q}_d, \hat{Q}_g, \hat{a}_t) =
\begin{bmatrix}
2x'z'' - 2w'y' - a_x \\
2y'z'' + 2w'x' - a_y \\
1 - 2x'^2 - 2y'^2 - a_z
\end{bmatrix}
\] (14)

Thus, the optimized Madgwick filter (Equation (15)) is achieved by substituting Equation (14) by Equation (12), where, \(F(\hat{Q}_d, \hat{Q}_g, \hat{a}_t)\) supersedes the quaternion vector error function
where \( w \) denotes the window length of MAF, and \( a_s(t), a_l(t) \) and \( a_f(t) \) denote the three-dimensional inputs to MAF. The gyro data are also filtered by the MAF. Let \( f \) be the time taken for zero calibration of gyroscope. The gyro data also filtered by the MAF. Let \( f \) be the time taken for zero calibration of gyroscope. The gyro tri-axis data \( w_s(f), w_l(f), w_f(f) \) are given as inputs to MAF and \( w_s^0(f), w_l^0(f), w_f^0(f) \) represent MAF-filtered outputs. The filtering process is described in the following equation:

\[
\begin{bmatrix}
    w_s^0(t) \\
    w_l^0(t) \\
    w_f^0(t)
\end{bmatrix}
= \begin{bmatrix}
    \frac{1}{L} \int_{t-L}^{t} w_s(k)dk \\
    \frac{1}{L} \int_{t-L}^{t} w_l(k)dk \\
    \frac{1}{L} \int_{t-L}^{t} w_f(k)dk
\end{bmatrix}
\]

where \( L \) denotes the window length of MAF, and \( a_s(t), a_l(t) \) and \( a_f(t) \) denote the three-dimensional inputs to MAF. The gyro data are also filtered by the MAF. Let \( f \) be the time taken for zero calibration of gyroscope. The gyro tri-axis data \( w_s(f), w_l(f), w_f(f) \) are given as inputs to MAF and \( w_s^0(f), w_l^0(f), w_f^0(f) \) represent MAF-filtered outputs. The filtering process is described in the following equation:

\[
\begin{bmatrix}
    w_s^0(t) \\
    w_l^0(t) \\
    w_f^0(t)
\end{bmatrix}
= \begin{bmatrix}
    \frac{1}{L} \int_{t-L}^{t} w_s(k)dk \\
    \frac{1}{L} \int_{t-L}^{t} w_l(k)dk \\
    \frac{1}{L} \int_{t-L}^{t} w_f(k)dk
\end{bmatrix}
\]

Since it is hard to place the IMU horizontally, there is always a small tilt angle generated when starting the UVA. In order to remove this offset, we subtract the output data of the gyroscope at time \( t \) with the MAF filter output obtained after time \( f \). Thus, the gyro tri-axis data \( w_s(t), w_l(t), w_f(t) \) after zero calibration is given by the following equation:

\[
\begin{bmatrix}
    w_s(t) \\
    w_l(t) \\
    w_f(t)
\end{bmatrix}
= \begin{bmatrix}
    w_s(t) - w_s^0(t) \\
    w_l(t) - w_l^0(t) \\
    w_f(t) - w_f^0(t)
\end{bmatrix}
\]

Figure 2 shows a block diagram representation of attitude estimation of toy UAVs based on optimized Madgwick filter combined with MAF.

From Figure 2, when \( s = 1 \), the toy UAV receives the start signal from the RF control module. Signals \( a_s(t), a_l(t), a_f(t) \) denote the MAF-filtered accelerometer data, and \( w_s(t), w_l(t), w_f(t) \) represent the zero-calibrated gyro data. Both these signals are presented, and the gradient descent algorithm calculates the rate of change of quaternions \( Q_s \) and \( Q_l \) related to gyro and accelerometer, respectively. Finally, the current attitude angle \( \hat{Q}_{est} \) is determined by fusing \( Q_s, Q_l \) with \( \hat{Q}_{est-1} \), the previously estimated attitude quaternion.
4. Experimental result

The complete block diagram of attitude estimation of toy UAV using the optimized Madgwick filter combined with the MAF attitude estimator is shown in Figure 3. The inertial data measured by IMU, represented as quaternion, are filtered by MAF and optimized Madgwick filters. Later, using Equation (4), normalized quaternion is the expressed as Euler angles which are used to control the attitude of flying of the UAV.
As can be seen from Figure 4, the hardware platform of UAV flight control consists of the low-cost and low-power six-axis sensors MPU6050, micro control unit STM32f0, 2.4 GHz module and Barometer module.

The performance of the proposed method is analyzed by considering the static and dynamic performance of the quad-rotor UAV. Further, to have a more realistic comparison, the performance of proposed filter is compared with the Madgwick and Mahony complementary filters.

For the static analysis of the UAV, $\beta$ (the correction step) was set to 0.08, and the static roll and pitch angles are measured. The filters outputs are shown below.

As can be seen from Figure 5, attitude estimation using the Madgwick and Mahony complementary filters is greatly affected by high-frequency vibrations and the periodic noise, which results in poor accuracy in determining the pitch and the roll angles, whereas the proposed method is comparatively stable and thus provides more accurate attitude estimators. Further, from Table I, it can be seen that for the proposed method, the variance and average error of the static roll and pitch of the UAV are much smaller than the other two methods.

For the dynamic performance test of UAV, the UAV is initially allowed to fly on a reference horizontal plane (0°) and later made to swing from −10° to 10°. The pitch and the roll angles, convergence time and overshoot are recorded for all the filters. Figure 6 pictorially illustrates the dynamic performance test. A good 6-second rest time is allowed between each angle change i.e. a swing from 0° to 10° rapidly, 6 seconds rest, then a swing back from 10° to 0° followed by another 6-second rest. A similar pattern is adopted for 0° to −10°, and the cycle repeats again once the UAV reaches the reference horizontal plane. Here, again, the step size is set to 0.08. It can be seen from Figure 7 that for the first two methods, the attitude overshoots largely and it takes more time to converge, whereas the proposed method produces a smaller overshoot with a less convergence time.

From Table II, the roll convergence time of the proposed method are reduced by 165 and 2,622 ms, respectively, when compared with the two traditional methods, while the pitch angle is reduced by 537 and 2,451 ms. Therefore, when compared to the Madgwick filter and the Mahony complementary filter, the proposed filter presents good improvements in convergence time which, in turn, increases the robustness of the system.

5. Conclusion
In summary, the paper presents a method where the attitude angles of toy UAVs can be determined at a higher accuracy. This is achieved by: the fusion of the gyroscope and
Figure 5. Static performance curve of a toy UAV for different filters

Notes: (a) Static roll angle curve; (b) static pitch angle curve

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Proposed method</th>
<th>Madgwick filter</th>
<th>Mahony filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Roll (static)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td>0.00018</td>
<td>0.00281</td>
<td>0.00119</td>
</tr>
<tr>
<td>Average value</td>
<td>0.01073</td>
<td>0.04241</td>
<td>0.02759</td>
</tr>
<tr>
<td>Pitch (static)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td>0.000051</td>
<td>0.001546</td>
<td>0.000052</td>
</tr>
<tr>
<td>Average value</td>
<td>0.00571</td>
<td>0.03145</td>
<td>0.00576</td>
</tr>
</tbody>
</table>

Table I. Static performance table of toy UAV

Figure 6. Dynamic performance test figure
accelerometer data to provide better attitude solution; the zero correction to eliminate the random drift error of the gyroscope which provided better static performance than the traditional method; and the accelerometer data are filtered by the MAF filter to remove the high-frequency interference, thus ensuring that the system has better dynamic performance. Experiments on the actual flight test shows that the method, in addition to estimating the attitude angle accurately, significantly improves the convergence speed, thus ensuring the robustness and stability of the toy UAV. However, the best value of $\beta$ and the best parameters of PID are obtained on the basis of a large number of flight tests, and thus the process is too cumbersome and takes a lot of time. In the follow-up, an optimized genetic algorithm will be used to determine the parameters.

### References


<table>
<thead>
<tr>
<th>Parameter</th>
<th>Proposed method</th>
<th>Madgwick filter</th>
<th>Mahony filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Roll (dynamic)</td>
<td>Convergence time/ms</td>
<td>1,389.0</td>
<td>1,554.0</td>
</tr>
<tr>
<td>Pitch (dynamic)</td>
<td>Convergence time/ms</td>
<td>733.5</td>
<td>1,270.5</td>
</tr>
</tbody>
</table>

Table II. Dynamic performance table of toy UAV


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UAV and obstacle sensing techniques – a perspective

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Abstract

Purpose – The purpose of this paper is to provide an overview of unmanned aerial vehicle (UAV) developments, types, the major functional components of UAV, challenges, and trends of UAVs, and among the various challenges, the authors are concentrating more on obstacle sensing methods. This also highlights the scope of on-board vision-based obstacle sensing for miniature UAVs.

Design/methodology/approach – The paper initially discusses the basic functional elements of UAV, then considers the different challenges faced by UAV designers. The authors have narrowed down the study on obstacle detection and sensing methods for autonomous operation.

Findings – Among the various existing obstacle sensing techniques, on-board vision-based obstacle detection has better scope in the future requirements of miniature UAVs to make it completely autonomous.

Originality/value – The paper gives original review points by doing a thorough literature survey on various obstacle sensing techniques used for UAVs.

Keywords UAV, UAV functional blocks, UAV sensing methods, UAV types, Vision-based sensing

Paper type Literature review

1. Introduction

Unmanned aerial vehicles (UAVs) are aircrafts which fly without a human pilot on board. UAVs have become so popular because of their greatest advantage – no risk of human life! They are playing a predominant role in military services like surveillance, monitoring, tracking enemies, destruction using modern tools and in civil applications like atmospheric research, weather forecasting, firefighting, road traffic monitoring and control, crop, and harvest monitoring. Commercial applications include logistics, aerial photography, film making, etc. Around the world, drones equipped with cameras and sensors are providing companies with clearer, more comprehensive views of their businesses, and the opportunities and threats that surround them.

The further sections are ordered as mentioned. Section 2 presents early developments of UAV, different types and applications. In Section 3, the functional components of UAV are discussed. In Section 4, current and evolving trends and challenges faced by UAVs are discussed. Among the various challenges faced while designing UAVs we have discussed more on the various obstacle sensing mechanisms available in Section 5. Then, Section 6 explores the necessity to incorporate obstacle sensing and processing mechanism on-board UAV. To make this possible, vision-based sensing and avoidance techniques are a better solution compared RADAR, LIDAR, or laser sensors.

2. Overview of UAV development

2.1 Early developments

UAVs date back to 1849 when Austrians attacked Italian city of Venice with unmanned balloons loaded with explosives. There was considerable advancement in the types of UAV
used during early years, the First World War, the Second World War, Korean War, Cold War, Vietnam War, and later in Gulf War (Keane and Carr, 2013). The first UAV was the “Kettering Bug” developed by US Air force during the First World War. It was a self-flying torpedo. When compared to the latest UAVs, it was a simple machine which could be calibrated for precision attacks against fortified enemy defenses up to 75 miles away. Gyroscopes were used to stabilize it. It is more a guided missile than a drone. The German V-1 buzz-bomb, a jet-powered cruise missile, was the World War II’s most used drone. The development of RADAR to replace television as the primary guidance system was a remarkable change in the Second World War operation. OQ2 and OQ3 drones developed had one-hour endurance and a speed of 85 mph. The ideas were good, but the technology was not advanced. In 1960s and 1970s, the USA developed a huge number of UAVs for military purposes. Throughout the twentieth century, there has been a tremendous development in UAV technology. Drones have done remarkable work during anti-terrorist operations performed by the USA. They have done it with little cost, and no risk to armed forces. Even though initially it was used for military purposes, later people started using UAVs for civilian applications. Now, many countries like the USA, UK, France, Iran, China, Israel, India, Pakistan, etc., are using UAVs.

2.2 Types and applications of UAV

The UAVs are of various shapes and sizes depending upon the application. The common types are single rotor (www.ebuav.com/wurenji/chanpinzhongxin/Single_Rotor_UAV/2014/1120/1.html), fixed wing (www.shadowair.com/uavs?lightbox=image23zd), multirotor (http://838inc.com/expertise/unmanned-aerial-vehicles/), and hybrid (http://newatlas.com/carbonix-volanti-vtol-fixed-wing-industrial-uav/48253/#gallery). A comparison in the performance of fixed wing and multirotor UAVs are given in Table I.

With respect to weight, Civil UAVs are classified as micro (less than 2 kg), mini (greater than 2 kg and less than 20 kg), small (greater than 20 kg and less than 150 kg), and large (greater than 150 kg). According to their range/altitude (Gupta et al., 2013), UAV can be classified, as shown in Table II. In Table III, the endurance of some of the UAVs along with examples are given. In Plate 1, images of few UAVs are included (Figure 1).

<table>
<thead>
<tr>
<th>Fixed Wing</th>
<th>Multirotor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficient in fast flying</td>
<td>Efficient in low flying</td>
</tr>
<tr>
<td>High flying</td>
<td>Navigation inside buildings</td>
</tr>
<tr>
<td>More endurance</td>
<td>Vertical take-off capability, hovering</td>
</tr>
<tr>
<td>Good for aerial survey of large areas</td>
<td>Stabilized video return</td>
</tr>
<tr>
<td>Limitation – take-off and landing is difficult.</td>
<td>Limitation – low endurance and mechanical complexity</td>
</tr>
</tbody>
</table>

**Table I.** Comparison of fixed wing and multirotor UAV

<table>
<thead>
<tr>
<th>UAV type</th>
<th>Weight (kg)</th>
<th>Altitude (ft)</th>
<th>Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long range</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HALE</td>
<td>&gt; 600</td>
<td>65,000</td>
<td>Military</td>
</tr>
<tr>
<td>MALE</td>
<td>&gt; 600</td>
<td>45,000</td>
<td>Military</td>
</tr>
<tr>
<td>Medium range</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TUAV</td>
<td>150-600</td>
<td>10,000</td>
<td>Military</td>
</tr>
<tr>
<td>Short range</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Micro UAV</td>
<td>2-20</td>
<td>3,000</td>
<td>Military/Commercial</td>
</tr>
</tbody>
</table>

**Table II.** Classification of UAVs
UAVs can take different forms according to the applications (Accenture, 2016). Depending on their lift capacity and payload specifications, UAVs can also carry multiple sensors to extract a wide range of information, increasing the number of possible applications and the business value of their outcomes.

Apart from military operations, UAVs are chosen for:

- atmospheric research;
- geological surveys;
- hurricane evolution and research;

### Table III.

<table>
<thead>
<tr>
<th>UAV type</th>
<th>Examples</th>
<th>Endurance</th>
</tr>
</thead>
<tbody>
<tr>
<td>HALE</td>
<td>Global Hawk</td>
<td>24 hours</td>
</tr>
<tr>
<td></td>
<td>Phantom Eye</td>
<td>80 hours</td>
</tr>
<tr>
<td>MALE</td>
<td>Predator</td>
<td>30-40 hours</td>
</tr>
<tr>
<td></td>
<td>HERON</td>
<td>45 hours</td>
</tr>
<tr>
<td>TUAV</td>
<td>Aerostar</td>
<td>12 hours</td>
</tr>
<tr>
<td>Micro UAV</td>
<td>Zanka III</td>
<td>28 hours</td>
</tr>
<tr>
<td></td>
<td>Netra</td>
<td>30 minutes</td>
</tr>
<tr>
<td></td>
<td>RQ-16 T-Hawk</td>
<td>40 minutes</td>
</tr>
</tbody>
</table>

**Notes:** HALE, High altitude long endurance; MALE, medium altitude long endurance; TUAV, tactile UAV

![Plate 1. Different types of UAV](image)

**Notes:**
(a) Global Hawk (www.nasa.gov/centers/armstrong/news/FactSheets/FS-098-DFRC.html);
(b) Predator (http://defense-update.com/products/p/predator.htm); (c) Aerostar (https://aeronautics-sys.com/home-page/page-systems/page-systems-aerostar-tuas/); (d) Netra (http://aermech.in/drdo-netra-mini-unmanned-aerial-vehicle-uavquadcopter-indian-armed-forces/)
• oceanographic observations;
• volcanoes study and eruption alert;
• weather forecasting;
• cloud study programs;
• ozone layer studies and monitoring;
• disaster operations management;
• firefighting;
• oil slick observations;
• flood watch;
• catastrophic situation assessment;
• search and rescue (looking for survivors from shipwrecks, aircraft accidents, etc.);
• earthquake monitoring; and
• nuclear radiation monitoring
• international border patrol;
• environmental monitoring;
• law enforcement;
• road traffic monitoring and control; and
• crop and harvest monitoring.

In Table IV, the technical details of some of these applications are given.
3. Functional components of UAV

UAV can be remote controlled, or can fly autonomously in a predefined path. The functional categories can be used for:

- military training;
- reconnaissance;
- combat;
- research and development; and
- civil and commercial applications.

Despite the category in which they are used, the main functional units of UAV in general, are the sensors, flight control system, power supply, propulsion system, communication unit and the ground station as depicted in Figure 2. The ground control station (GCS) can be land based or sea based which consists of the facilities for human control of unmanned vehicles. The ground station helps to control and monitor UAV. It will provide information about speed, heading direction, altitude, bank angle, GPS status, battery status, telemetry signal, etc. Endurance and performance of UAV are directly connected with the source of power supplies used for UAVs. The type of energy sources can be fuel based or battery based. The batteries (Meyer et al., 2009; Cwodziński and Adamski, 2014) used are lithium polymer batteries (3.7-4.2 V, six to eight cells), photovoltaic cells, super capacitors, and hydrogen fuel cells. Solar energy collected from photovoltaic cells can also be used as a source of power for UAV. The propulsion system provides the necessary power for the UAV to move forward or hover. The main parts are the brushless motors, propellers, and

---

### Table IV.
Technical details of some of the applications of UAV

<table>
<thead>
<tr>
<th>Area of usage</th>
<th>Technical details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Construction sites</td>
<td>Surveying, mapping, and 3D modelling are done</td>
</tr>
<tr>
<td></td>
<td>UAVs mounted with high definition cameras are used (Accenture, 2016)</td>
</tr>
<tr>
<td></td>
<td>Drones must weigh less than 55 pounds and must fly less than 400 feet height</td>
</tr>
<tr>
<td></td>
<td>above ground level.</td>
</tr>
<tr>
<td></td>
<td>Flown during day time, speed should not exceed 100 mph and should not fly out</td>
</tr>
<tr>
<td></td>
<td>of line of sight (LOS)</td>
</tr>
<tr>
<td>Mining</td>
<td>Vehicles need to travel vertical, horizontal, and hover around to get into tighter</td>
</tr>
<tr>
<td></td>
<td>spots for better imagery</td>
</tr>
<tr>
<td></td>
<td>UAVs can weigh 1-2 kg, with high resolution RGB, infrared cameras, GPS,</td>
</tr>
<tr>
<td></td>
<td>altimeters, and 30-45 minutes endurance</td>
</tr>
<tr>
<td></td>
<td>Use of LIDAR is the latest technology</td>
</tr>
<tr>
<td>Law enforcement, search,</td>
<td>Need to provide full 360° view of the rescue places</td>
</tr>
<tr>
<td>and rescue</td>
<td>Aerial video processing need to be done</td>
</tr>
<tr>
<td></td>
<td>Cover up to 10 miles in an hour</td>
</tr>
<tr>
<td></td>
<td>In military and border control, UAVs equipped with cameras and sensor payloads</td>
</tr>
<tr>
<td></td>
<td>are used</td>
</tr>
<tr>
<td></td>
<td>Providing medical kits to remote areas</td>
</tr>
<tr>
<td>Agriculture</td>
<td>Used in precision farming</td>
</tr>
<tr>
<td></td>
<td>Inbuilt sensors, microcontrollers, and GPS receivers</td>
</tr>
<tr>
<td></td>
<td>Inclusion of plant counting algorithms.</td>
</tr>
<tr>
<td></td>
<td>Spraying of pesticides (Kale et al., 2015)</td>
</tr>
<tr>
<td>Wildlife protection</td>
<td>Use of UAV images in species identification, study of endangered species,</td>
</tr>
<tr>
<td></td>
<td>population count, assessing mortality rate of animals, etc. (Bird, 2014)</td>
</tr>
<tr>
<td></td>
<td>Ultra HD cameras capable of capturing photos at a faster rate</td>
</tr>
<tr>
<td></td>
<td>Equipment of thermal sensors to detect forest fire, provide visual ID on wildlife,</td>
</tr>
<tr>
<td></td>
<td>night surveillance, etc.</td>
</tr>
</tbody>
</table>
There are now many sensors in the market that vary in size, weight, resolution, and cost. Among the sensors, RADARs can detect objects without cooperative communication. They are the most widely used mechanism to detect air to air vehicles. Sunlight, smoke, fog, dust, and other factors do not affect them, and have improved directionality and range characteristics. LIDARs are highly precise and can detect objects of different sizes and shapes by calculating the time taken for light to travel back and forth. They are too large to be incorporated on to small systems.

Optical, ultrasonic sensors are small in size, low cost, and have low-power consumption. Micro electro mechanical system (MEMS) (Kumar et al., 2017) or use of sensor fusion technology is more advanced method of sensing. Camera-based sensing, one of the feasible methods of obstacle detection for small UAVs is discussed in detail in the later sections. Infrared sensors can be used at night. Navigation sensors like inertial navigation sensors and GPS are used to measure position, velocity, attitude, and rotation (pitch, roll, and yaw) of UAV. Sensors are one of the main payloads of an UAV. For long endurance UAV payloads, the processing power has a direct effect on the power consumption. Optical image sensor payloads (Meyer et al., 2009) will be suitable for long endurance UAVs.

A UAV system cannot operate without secure and reliable communication. The communication can be of three ways – communication between UAV and GCS, communication between UAVs, and communication between UAV and satellite. The main parts of the communication module are the transmitter and receiver.

The commonly used UAV control, telemetry, and video frequencies are 900 MHz, 1.2 GHz, and 2.4 GHz and 5.8 MHz. The communication between UAV and GCS provides a data link for transmitting the information captured by UAV in the form of images and videos files. The GCS will be sending the control and guidance commands to UAV.

4. Challenges and trends
UAVs, better known as drones, are one of the technological marvels of our age. Design of an UAV means integrating hardware, software, sensors, actuators, communication systems, and payloads into a single unit for the application involved. It is really a challenging task. The challenges can be technical and managerial. We need to identify the risks associated with UAV system development. The major challenge faced by military UAVs is that they need to
integrate with the existing traffic collision avoidance system (TCAS) done by RADARs. There are various policy challenges (Swaminathan, 2015), related to structure, network of air traffic control, physical and electronic identification of drones, protocols, and communication systems. There are many pre-flight requirements which need to be followed before using UAVs for any commercial application. This includes the registration, pre-flight inspection, use of trained flight operators, air space, height at which UAVs can fly (400 ft), weight (less than 55 pounds), weather visibility, visual line of sight, speed (should be less than 100 mph), time of day, accident reporting, etc. Few more challenges faced by drones are as follows:

- limited flight endurance and payload capacity;
- power;
- limitations in type of sensors used;
- obstacle sensing and avoidance;
- difficulty in launching;
- safety;
- cost; and
- losing control during flight.

Great amount of research works is going on in areas like batteries with longer endurance UAV, stealth technologies for military purpose, smaller, lighter sensors, increased on-board computing power, multifunctional UAVs, etc. Recently Intel engineers set a new world record by flying 500 drones at the same time, all fitted with LED lights. They jointly formed 3D shapes in the air. It was a demonstration of how large number of drones can communicate each other. Tech world is also waiting for EHANG 184, a unique passenger drone which is an aerial version of Uber (http://dronelife.com/2017/01/11/drone-trends-2017/). The latest drone design includes Diodon, an inflatable drone; DJI Spark, which has 3D sensing technology for obstacle avoidance; Cleo drone, of donut design which can be slipped inside our pockets; Mola Ufo, a selfie drone, etc., are a few to list. Technological improvements will make UAVs faster, stronger, and safer. A team of scientists has demonstrated that UAVs were able to build a rope bridge, assemble items to create a structure, or detect and catch an object in the air (Accenture, 2016), as shown in Plate 2.

Addressing all the challenges faced by UAVs is beyond the scope of this paper, so in the further section we are addressing one major challenge faced by UAVs which is sensing and avoiding obstacles.

**Plate 2.**
Technical improvements

Source: Accenture (2016)
5. UAV sensing methods

The commercial applications require the small UAVs to fly at lower altitude or operating inside buildings, where they are exposed to many hazards and obstacles. Current UAV technology in automatically sensing, detecting, and avoiding fixed obstacles such as power line, building, tower, tree, and moving obstacles such as birds, and other aircraft is still immature compared to manned aerial vehicle. As UAVs’ market is predicted to provide billions of dollars in economic growth especially in commercial market, researchers around the world are now trying to develop an efficient automatic sense and avoid system to satisfy the demands and requirements of the UAVs. So, there is a great scope of research in embedding Sense-Avoid Detect algorithms on-board UAV. Figure 3 shows how a sense and avoid system works.

Table V gives an account of the merits and demerits of existing UAV sensing techniques. Table VI compares the various types of sensing methods in terms of their range, power, size, and cost.

The obstacle detection and avoidance technology started with sensors detecting objects in front of the drone. TCAS and automatic dependent surveillance-broadcast (ADS-B) technology have already matured for collision avoidance technique in manned aerial vehicle, the system is currently satisfied only for cooperative intruders. Non-cooperative sensors of...
active and passive type can provide better detection for the non-cooperative obstacles especially when problem of data link loss occurs. They are important, particularly for the UAVs that fly inside buildings since the obstacles are mostly wall, machine, office equipment, and humans. Active sensing includes laser ranging, RADAR, and sonar which will transmit signals for detecting obstacles. They usually provide a very good information of the obstacles distance and it is a very essential criterion in tracking operation. On the other hand, passive sensors such as electro optical, infrared, thermal imaging, and motion detector depend on detection of signals emitted from the obstacle.

In Lin and Saripalli (2015), a path planning is done to generate a collision free trajectory for the UAV. They use a cooperative surveillance technology to know the position of intruder aircrafts using ADS-B. In Sahawneh (2016), minimum sensing range to safely avoid a collision is first calculated. They use both deterministic approach and probabilistic approach to estimate the collision risk of an encounter scenario. The implementation is done using various sensors like camera, RADAR, and ADS-B. Using a single fish eye camera of 185° FOV, visual tracking and position estimation of UAVs are performed in Sapkota et al. (2016). Collision avoidance is not incorporated here. A light weight RADAR system which can be used for mini UAVs with complete system design (both hardware and software) is given in Moses et al. (2011). Target detection is done but methods to avoid collision need to be added to it.

A non-cooperative UAV system utilizing a vision-based navigation system, integrated with GNSS system and a MEMS-IMU sensor (Salazar and Sabatini, 2013), performs obstacle detection and tracking. A low-level tracking is done with a Viterbi algorithm and a high-level tracking is done with a Kalman Filter. It tries to avoid both static and dynamic obstacles. Using five cameras (Zarandy et al., 2011), a vision system was developed for calculating the attitude of an UAV and thereby provide collision warning.

Various bottlenecks in the implementation of vision processing on board a small UAV, and their possible solutions are given in Ehsan and McDonald-Maier (2009). There is need of better computer architecture on board that is capable of processing image/video in real time. For increasing the flight time, the power consumption also need to be less. The power constraint will affect the frequency of operation. So, to have vision-based collision avoidance system, we require low-power vision processing on board, low clock frequency, real-time processing, and light weight. One more work which we felt appreciable was the use of four ultrasonic sensors (Bhardwaj et al., 2015), each covering a span of 15°. But since it depends on transmission and reception of echo the range is less (10-15 cm). The angle covered by sensors also needs to be improved.

In Aguilar et al. (2017), a monocular on-board camera is used. It compares the image obtained in real time from UAV with a database of known obstacles. They used feature point detector speeded up robust features (SURF) algorithm. The drawback is that the algorithm works for only the obstacles stored in the database. Scale invariant feature transform (SIFT) techniques (Divya Lakshmi and Vaithiyathan, 2017) can also be used for selecting feature points in the images returned by UAVs. There are two fundamental groups of vision-based obstacle avoidance techniques; those that compute the apparent motion (optical flow), and those that rely on the appearance of individual pixels (basic image processing) for monocular vision-based obstacle avoidance systems. Using optical flow and feature tracking methods, an obstacle avoidance technique is developed for fixed wing UAVs (Dayton et al., 2015). Using Lucas Kanade optical flow technique, the time difference between two frames of video is used to calculate the velocity of the motion. The system works with single moving and stationary target. But they are not considering objects (moving and stationary) from multiple directions. In Omkar et al. (2014), a vision-based obstacle detection method is used for fixed wing UAV. The algorithm works well for dark- and light-colored obstacles in the environment. This method may not be suitable in a
foggy environment and while detecting multiple obstacles in urban areas because of the use of fixed wing. A quadcopter will be suitable for that, since it has hovering capability which is most needed in urban areas. While navigating inside a building, or when a bird comes suddenly in the path, or a person comes in front the method need to be improved. It would be feasible if improved image processing techniques are used to detect obstacles and calculate distance to it. In Agrawal et al. (2014), optical flow-based guidance for UAV is performed. An on-board forward-facing pinhole camera having a field of view 90° and 20 frames/second is used. The various sensors and techniques used in automobiles like car to unmanned air vehicles have been given in Connolly (2007). A collision avoidance scheme is presented using Aerial Quadrotor (drone) (Esrafilian and Taghirad, 2016). Video streams obtained using front camera of drone and navigation data measured by Aerial Quadrotor drone is transmitted to ground placed laptop through wireless network connection. Simultaneously localization and mapping (SLAM) is helpful in navigation and mapping, the navigation data received are processed by oriented FAST and rotated binary robust independent elementary features (BRIEF) (ORB) and SLAM to compute three-dimensional sparse maps and three-dimensional position. The scaling parameter of monocular SLAM is figured out using linear filtering. Kalman Filter is employed for fusing a sensor in monocular camera of Aerial Quadrotor.

From the survey of various UAV sensing and detection methods, we can classify them as given in Figure 4.

For sensing obstacles, small UAVs cannot carry RADAR- or LIDAR-based systems. So, the use of cameras will be a better option. Camera-based sensing can depend on SLAM

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**Figure 4.** UAV sensing and detection methods
techniques, optical flow methods, stereo vision or monocular (single camera) vision-based
techniques. Mono-based methods do not need demonstrating the 3D model of the objects
and are diverse. The various existing monocular vision-based object detection techniques
include estimation of relative size of obstacles (objects coming closer will expand in size),
relative clarity (blurry, foggy or hazy when objects are far away), texture gradient
(front part of the picture has more texturized features), linear perception (parallel lines feel
like converging as they move away from us), interposition (among two objects, one which is
nearer blocks view of the other), and relative motion (motion parallax). Various image
processing algorithms can be used in monocular vision-based techniques. For this, feature
detection and description algorithms are the basic steps for object detection and tracking.
Features can be edges and corners.

Algorithms like Canny, Sobel, or Laplacian edge detectors can be used for edge detection.
For corner and region detection, Harris, ShiTomasi can be used. Feature descriptor
algorithms include SURF, SIFT, and improved ones like BRIEF (Calonder et al., 2010) and
ORB (Rublee et al., 2011). Although SIFT has proven to be very efficient in object recognition
applications, it requires a large computational complexity which is a major drawback
especially for real-time applications. SURF technique, which approximates SIFT, performs
faster than SIFT without reducing the quality of the detected points (Jain et al., 2017). These
two robust feature descriptors are invariant to scale changes, blur, rotation, illumination
changes, and affine transformation.

6. New requirements for UAV sensing and avoidance

In the existing method of collision avoidance to detect the obstacle by using various
sensors like RADAR, LIDAR, ultrasonic sensors, cameras, etc., they transmit the image/
video data to GCS. Maneuvering commands are decided in GCS and sent back to the flight
control system of UAV. Instead of having a wireless transmission to GCS, the
incorporation of an on-board processing unit can reduce the time taken for maneuvering,
as shown in Figure 4. From the previous discussions, what we would like to add is that for
commercial applications, to perform an on-board data processing, vision-based obstacle
avoidance system is the only promising solution because of the constraints of size,
weight, power demand, and cost. We can consider visual sensors rather than RADAR,
because the latter is too bulky and too expensive to fit on a small- or medium-sized UAV.
For micro and small aerial vehicles, the constraint of size, weight, and power makes them
choose digital cameras as the best choice for obstacle detection. Due to this trend,
image processing techniques are emerging as an attractive proposition for UAV
collision avoidance. Advanced photogrammetry software support video/image processing
of UAV captured videos and images. The programming language used to develop
application for UAV depends on the platform you are using to control them. Some of
the platforms are Arduino, Raspberry Pi, and Beagle board. MATLAB/Simulink is a
better choice for video/image processing rapid prototyping and embedded system design.
Using MATLAB, we can perform feature detection, extraction, and matching; object
detection and tracking; motion estimation; and video processing. There are latest tool
boxes like computer vision toolbox, which supports camera calibration, stereo vision,
3D reconstruction, and 3D point cloud processing. We can even design, simulate
estimation, and control algorithms in MATLAB/Simulink and generate Embedded C code
for it (Figure 5).

The on-board camera needs to capture video/images, which must be processed inside
UAV itself. The vision-based processing unit can give its outputs to the flight control
system. The flight control system can take decisions and give maneuvering commands to
UAV. This will drastically reduce the processing time. The plan of action can be
represented, as shown in Figure 6. Use of a camera can make the process easier and simple.
While embedding a single camera, processor, and control system on board, we need to consider the following requirements from a technical point of view for enhanced capabilities in collision avoidance:

1. position, size, speed, and angle of UAV;
2. speed and direction of the moving intruders need to be predicted;
3. size, weight, and electrical power of UAV;
4. payload limitation;
5. path planning algorithm should be efficient, less complex;
6. memory requirement for on-board sensor data processing;
7. processing speed required for on-board data processing;
8. environment, weather conditions, background noise, and clutter;
9. Static/Dynamic intruder;
10. unanticipated maneuvers;
11. the time taken for the obstacle avoidance process;
12. detecting small point like objects;
13. minimum distance between UAV and intruder; and
14. UAV egomotion.

7. Conclusion
An attempt to explore, understand, and compile the different types of UAVs, their major functional components, technological advancements, current, and near future trends in
general along with the studies done to explore the possible problems associated with enhancing the capabilities of UAV while evolving from its current environments of open space to relatively more occupied space with taller or other structures likely to encounter in its flight paths are concluded here. The survey included fundamentals on each of the major functional block with some description of the functional component, elements involved and their working plus the relevant references from literature. Next section explored topics on challenges and trends seen from the perspective of functional blocks. In the following section, a survey on various UAV sensing methods is given. The survey concludes by discussing why and how vision-based sensing techniques emerge as an attractive proposition for UAV collision avoidance in relation to all existing techniques. This concludes highlighting the scope of better understanding of research and its utilization for future.

**Glossary**

- **UAV**: unmanned aerial vehicles
- **GPS**: global positioning system
- **LIDAR**: light detection and ranging
- **RADAR**: radio detection and ranging
- **HD**: high definition
- **MEMS**: micro electro mechanical systems
- **GCS**: ground control system
- **ADS-B**: automatic dependent surveillance-broadcast
- **GNSS**: global navigation satellite system
- **TCAS**: traffic collision avoidance system
- **SIFT**: scale invariant feature transform
- **SURF**: speeded up robust features
- **BRIEF**: binary robust independent elementary features
- **ORB**: oriented FAST and rotated BRIEF
- **SLAM**: simultaneously localization and mapping

**References**


Further reading


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