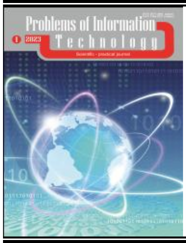

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Analysis of various techniques for ensuring autonomous navigation of unmanned aerial vehicles

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ABSTRACT

Unmanned Aerial Vehicles (UAVs) have many advantages compared to other vehicle systems. UAVs are faster, cheaper, and more flexible. However, like many other systems UAVs also need navigation. But, it's not safe to use only one navigation system for various reasons. The recent increase in the number of cyberattacks is one of these reasons. Failure of the navigation system can cause the UAV to lose control. This, in turn, can lead to serious accidents. Therefore, this work analyzes various techniques to ensure the autonomous navigation of UAVs. Also, the advantages and disadvantages of each technique are discussed. Finally, the implementation of these techniques with Kalman filters (KF), deep learning, and machine learning is demonstrated and the results of various studies on this subject are also highlighted.

1. Introduction

It is obvious that autonomous control is very essential for UAVs. With the help of autonomous UAVs, any given task can be performed more efficiently and quickly. To make UAVs autonomous, it's necessary to implement navigation systems. Thus, by using navigation systems, UAVs can position themselves, determine their velocity and altitude.

Any problem with the navigation system can cause serious incidents including injuries and even deaths. In 2012, Global Positioning System (GPS) jamming attack was performed against a rotor-based UAV, S-100 Camcopter (Krishna & Murphy, 2017). As a result, the UAV crashed into the ground control station (GCS), killing one person and injuring two more. In 2011, American UAV, Lockheed Martin RQ-170 Sentinel was targeted by Iranian forces. According to the reports, GPS spoofing and jamming attacks were performed to capture the UAV (Krishna & Murphy, 2017). After capturing the UAV, reverse engineering was carried out on it and a similar version was created.

Given the above, it's very important to provide safe autonomous navigation for UAVs. In most cases, UAVs use only one navigation system. Unfortunately, this approach is not safe for several reasons. These reasons can be described as below:

- **Cyberattacks.** Attacks such as Global Navigation Satellite System (GNSS) jamming and spoofing may bring down any UAV.
- **Sensor failures.** One or more sensors used by the navigation system may fail in midair.
- **Environmental dependencies.** Some navigation systems depend on the environment in which they are being

used. For example, GNSS can be used outdoors but not indoors.

- **Low accuracy factors.** Depending on different circumstances, the accuracy of the navigation system may decrease.

There are many techniques used in UAV navigation. In this work, the most used techniques for UAV navigation are investigated. These techniques include GNSS, inertial measurement unit (IMU), visual odometry (VO), visual SLAM (Simultaneous Localization and Mapping), Sonar (Sound navigation and ranging), and LiDAR (light detection and ranging). Each technique is analyzed separately, advantages and disadvantages of them are given. Finally, to use multiple sensors together, fusing methods are analyzed.

2. Global Navigation Satellite Systems

GNSS consists of multiple satellites to provide navigation. It's the most widely used navigation system. Not only UAVs, cars, ships, smartphones, and other systems use GNSS to navigate. There are several GNSSs including GPS, Galileo, GLONASS (Global Navigation Satellite System), and BDS (BeiDou Navigation Satellite System). Each satellite sends signals which carry important information. When devices receive such information, they conduct special calculations to provide navigation (Figure 1). Each satellite system broadcasts signals at different frequencies.

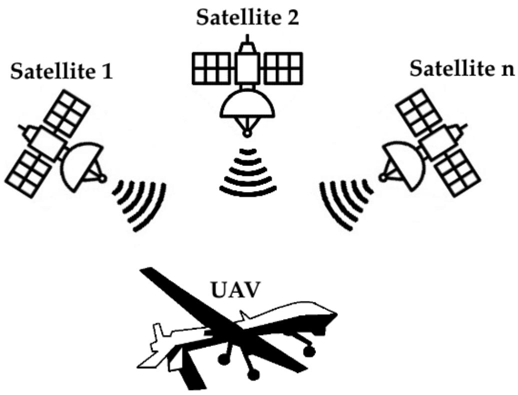


Figure 1. GNSS and UAV

GNSS receivers are cheap and easy to implement. But systems which use this technology are vulnerable to cyberattacks such as GNSS spoofing and jamming. During GNSS spoofing, the attacker transmits counterfeit signals to deceive the navigation system. While in a jamming attack, the attacker disrupts radio signals to prevent them from reaching the receiver. Another disadvantage of this techniques is that it can't be used indoors. Because GNSS signals are not strong enough to pass through some obstacles.

There are several methods proposed to detect and mitigate GNSS attacks. These include signal processing-based, signal geometry-based, drift monitoring-based and other methods (Psiaki & Humphreys, 2016). Also, it's possible to detect such attacks using machine and deep learning methods (Abdullayeva & Valikhanli, 2022; Manesh et al., 2019; Shafiee et al., 2017). Each proposed method has advantages and disadvantages. None of them fully guarantee protection against GNSS attacks. Also, it's important to note that an attacker with enough experience and necessary tools can overcome those protections. Thus, it's necessary to implement other navigation techniques as well.

3. Inertial measurement unit

IMU is a special device that measures specific force. IMU consists of several sensors including gyroscope and accelerometer. Some versions of IMU also include magnetometer. Gyroscope is a sensor which measures an angular velocity (Vittorio et al., 2017). Accelerometer is a sensor which measures acceleration force. Magnetometer is a sensor measuring magnetic field. By using these sensor readings, it's possible to obtain position information. An example of IMU is demonstrated in Figure 2.

Figure 2. IMU (courtesy of Racelogic)

Unlike GNSS, IMU calculations are based on internal components only. This aspect of IMU has its advantages, as well as disadvantage. The advantage is that IMU doesn't depend on external sources to work, which makes it durable against cyberattacks. The main drawback of IMU, however, is the accumulated errors. Thus, accumulated errors have a negative impact on the navigation accuracy.

In addition to navigation, there is another important role of IMU. The sensors, which are available in IMU can also be used for the stabilization of UAVs. Thus, those sensor readings are received by the flight controller of the UAV. According to sensor data, the flight controller manages the speed/position of the corresponding motor/actuator. Which in return stabilizes the UAV and prevents it from crashing.

4. Visual odometry and Visual SLAM

The word odometry is derived from two Greek words: odos, which means "route" and metron, which means "measure". The simplest form of odometry is wheel odometry. Thus, it's possible to calculate the distance traveled by counting the number of wheel rotations. Which, in turn, makes it possible to estimate position. For counting wheel rotations, rotary encoders are used.

In UAVs, another odometry type VO is used. VO is the estimation process of the ego-motion of an agent (e.g., vehicle, human, and robot) using images captured from single or multiple cameras attached to it (Scaramuzza & Fraundorfer, 2011). Thus, in VO images are analyzed instead of counting rotations.

VO can be classified based on their camera setup. There are several camera setups, but mostly monocular and stereo are used in UAVs (Figure 3). Both setups have their advantages and disadvantages. The monocular VO uses a single camera as shown in Figure 3 (a). The implementation of monocular VO is easy and cost-effective. The main disadvantage is that with a single camera, only bearing information is available and the lack of recovering absolute scale is a problem (Scaramuzza & Fraundorfer, 2011; Guizilini & Ramos, 2011). The stereo VO uses multiple cameras as shown in Figure 3 (b). Unlike monocular VO, absolute scale is not a problem in stereo VO, but taking into consideration that baseline should be known. According to Scaramuzza & Fraundorfer (2011), if the distance to the scene is larger than the stereo baseline, then using monocular VO will be more effective than stereo VO. Another disadvantage of stereo VO is that it's not a cheap solution compared to monocular VO.

VO can also be classified based on different approaches. These approaches are feature-based, direct-based, and hybrid. In the feature-based approach, features are detected from captured images and then relative motion between frames is computed (Krombach et al., 2017). In the appearance-based approach, entire image pixels or its subregions are used (Scaramuzza & Fraundorfer, 2011). If both described approaches are implemented together, then it's a hybrid method.

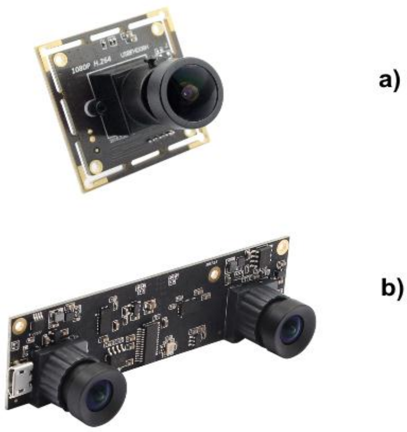


Figure 3. Monocular (a) and stereo (b) camera (courtesy of ELP)

SLAM is a technique in which a robot or a moving rigid body equipped with a specific sensor, estimates its motion and creates a model of the surrounding environment, without any prior information (Gao & Zhang, 2021). If the equipped sensor here is mainly a camera, then it is called Visual SLAM (V-SLAM). Similar to VO, V-SLAM also uses various camera setups such as monocular and stereo. But it's important to note that there is a difference between VO and SLAM. Thus, the main focus of VO is local consistency and it aims to incrementally estimate the path, pose after pose, whereas the goal of SLAM is to obtain a globally consistent estimate of the trajectory and map (Yousif et al., 2015).

5. Sonar and LiDAR

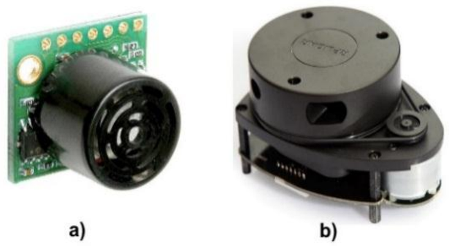
Sonar (a.k.a. ultrasonic) and LiDAR are also preferred types of technology that can be used for navigation. Sonar sensors (Figure 4 - a) transmit sound waves at certain frequencies. When transmitted waves reach an obstacle, they bounce back to the sensor. By this technique, the sensor detects objects. The distance can also be calculated by measuring time-of-flight (TOF). TOF is the total time period in which a signal is sent and received. Thus, if the distance to objects is measured at a certain rate, then it's possible to map the environment and perform navigation. The distance between sonar sensor and object can be calculated as the following formula:

$$d = \frac{v*t}{2} \quad (1)$$

where d is the distance to the object, v is the speed of the sound (depends on the temperature of the environment) and t is the time when a sound wave is sent and received.

Sonar sensors are cheaper compared to LiDAR. Unlike LiDAR, sonar sensors don't depend on lightening conditions, dusty or foggy environments, etc. However, sonar sensors also have drawbacks. The main disadvantage is the electrical and acoustic noises that are created by UAV components which affect sensor performance. Another disadvantage is that some types of materials absorb transmitted ultrasonic waves instead of reflecting them.

Unlike sonar, LiDAR (Figure 4 - b) uses light instead of sound waves for detecting objects. When transmitted light beams reach an obstacle, they bounce back to the sensor.



a) b)

Figure 4. Sonar (a) and LiDAR (b) sensors (courtesy of MaxBotix and Slamtec, respectively)

Using TOF measurements the distance between LiDAR sensor and object can be calculated as the following formula (Mehendale & Neoge, 2020; Christian & Cryan, 2013; Roriz et al., 2022):

$$d = \frac{c*t}{2} \quad (2)$$

where d is the distance to the object, c is the speed of the light, and t is the time when a light beam is sent and received.

LiDAR is very fast compared to sonar. This is because the speed of light is much faster than sound. Another important advantage of LiDAR is its high accuracy. There are disadvantages of LiDAR technology as well. Thus, LiDAR sensors are expensive. Moreover, LiDAR depends on the type of material. Some materials pass light instead of reflecting it. Which makes it difficult for the sensor to detect.

6. Fusing multiple sensors

Each sensor used in UAV navigation has its advantages as well as disadvantages. Table 1 demonstrates a comparison of the various sensors.

As seen from table 1, GNSS has good accuracy but it is often targeted by cyberattacks. Besides, the GNSS receiver can't be used in indoor environments and its performance may be affected by some atmospheric conditions. Compared to a sonar sensor, LiDAR performs better accuracy, however, it is also an expensive solution.

Table 1. Comparison of various sensors

Sensors	Accuracy	Price	Cyber-attacks target	Envir.depend	Material depend
GNSS receiver	Good	Medium	Often	Depends	n/a
Sonar	Fair	Low	Rarely	Depends	Depends
LiDAR	Good	High	Rarely	Depends	Depends
IMU	Poor	Medium/High	Very rarely	Doesn't depend	n/a
Camera (mono-cular)	Fair	Medium	Rarely	Depends	n/a
Camera (stereo)	Good	High	Rarely	Depends	n/a

Both sensors can be targeted by cyberattacks (spoofing, jamming, etc.) but this rarely happens compared to GNSS. Additionally, weather conditions affect the performance of both sensors. Moreover, both sensors depend on the type of material. The materials which absorb sound waves have a negative impact on the performance of the sonar sensors. Also, transparent materials pass light instead of reflecting it, which negatively affects the performance of LiDAR sensors. IMU performs poor accuracy, because, as mentioned earlier, it only uses internal components for pose estimation. The IMU may also be targeted by cyberattacks such as spoofing and acoustic attacks but this happens very rarely. The IMU doesn't depend on the environment where it's being used. Compared to monocular cameras, stereo cameras have good accuracy, but they are an expensive solution. Furthermore, cameras can be targeted by cyberattacks such as blinding attacks where an attacker targets cameras with laser beams. Cameras also depend on the environment. They become unstable in bad weather conditions and dark environments.

Given the above, using only one sensor for the UAV navigation system is not recommended. The implementation of multiple sensors makes UAVs more resilient. To achieve this, it's necessary to fuse multiple sensors together. In Figure 5, demonstrates the fusion of multiple sensors including GNSS receiver, IMU, camera, Sonar, and LiDAR.

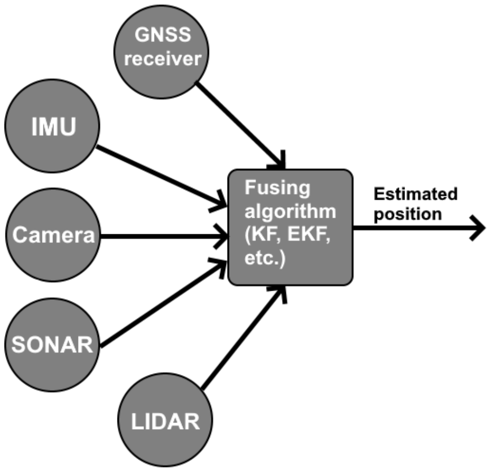


Figure 5. Fusing multiple sensors

For fusing multiple sensors, different methods are used such as Kalman filters, deep and machine learning. One of these commonly used methods is called Kalman filtering (KF). KF was first proposed by scientist Rudolf E. Kálmán in 1960. KF is an algorithm that estimates some unknown variables based on measurements taken over time (Kim & Bang, 2019). It's important to note that, there are several proposed versions of KF. They are extended Kalman filters (EKF), unscented Kalman filters (UKF), adaptive Kalman filters (AKF), and others.

There are many proposed works related to fusing multiple sensors using KF or different versions of KF. In Chambers et al. (2014), a new approach was proposed for Micro Air Vehicles (MAVs) navigation. Multiple sensors including GPS receiver, IMU, barometer, and camera (using VO technique) were used. All sensors were fused with the help of UKF. Several experiments were carried out to test the system. During experiments, the MAV was flown to dark places, buildings, and under bridges. In this way, GPS and camera were deliberately forced to fail. However, even in the absence of GPS and camera, the remaining sensors were able to provide navigation. In Lynen et al. (2014), pressure sensor, IMU, and monocular camera (using the SLAM system) were implemented to provide navigation for MAV. Multi-sensor fusion is implemented using a custom-made framework, MSF-EKF (Multi-Sensor-Fusion Extended Kalman Filter). The biggest advantage of the proposed framework is that it's able to process delayed measurements from different sensors by using buffers. This is an important feature since not all sensors work at the same rates and it has a negative impact on system efficiency. In Driessen et al. (2018), IMU, sonar, and optical-flow sensor (OFS) are used in the process of fusing. EKF is selected for the fusing algorithm. To compare the real and estimated position of the UAV, OptiTrack motion-capture system is used. Results are represented with the help of root-mean-squared error (RMSE) values. According to the results, errors are greatly reduced when all sensors are in use. In Dai et al. (2019), IMU and RGB-D (Red, Green, Blue, and Depth) camera are used. To calculate the location of the UAV using RGB-D images, the RGB-D SLAM system is implemented. Subsequently, EKF is used to fuse sensors. To test the system, UAV flight trajectories with and without fusion are compared. According to the results, the implementation of IMU with SLAM improves the accuracy. In Xu et al. (2021), VO and IMU are implemented for UAV navigation. For the VO, a binocular camera is used. A loosely coupled EKF algorithm is proposed to make fusion possible. Firstly, the Gazebo simulation platform is used to simulate the process, then an experimental multi-sensor fusion platform is built to get more precise results. According to the results, the overall position calculation error was less than 0.1m.

As mentioned earlier, there are other methods for sensor fusion including deep and machine learning. In Liaq & Byun (2019), a method was proposed based on reinforcement learning (Deep Q-Network) for ensuring the autonomous navigation of the UAV. A camera, GPS, IMU, magnetometer, and barometer sensors are used in the proposed work. AirSim tool is used to simulate the process. According to the results, the complete autonomous flight is achieved. In Liu et al. (2022), image, altitude, and angle data are used for UAV autonomous navigation. Convolutional Neural Network (CNN) and long short-term memory (LSTM) are implemented in the proposed work. Overall, the prediction error is within the acceptable range (0.76% - 4.8%). Hodge et al. (2020) proposes a novel recommender system based on collected sensor data and artificial intelligence. The proposed work mostly focuses on environments where UAVs should navigate in hazardous environments. Two deep learning methods, proximal policy optimization (PPO) reinforcement learning, and LSTM are combined. PPO reinforcement learning is implemented to learn navigation using minimal available information and LSTM is used to provide navigation memory to overcome some obstacles. PPO consists of 2 hidden layers with 64 nodes per layer. The length of LSTM is set to 8 and 16. According to the simulation results, LSTM with 8 length is better for not overcrowded environment. But for an overcrowded environment, LSTM with 16 length is better.

7. Conclusion

In this paper, various navigation techniques for UAVs were discussed. Proposed methods based on KFs, deep learning and machine learning for sensor fusion were also analyzed. It's important to note that techniques used for UAV navigation were not limited to those discussed in this work. In the future, other techniques will also be investigated. Thus, implementing more techniques and fusing them can overcome difficulties related to UAV navigation.

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