A Heterogeneous Sensor Fusion Framework for Obstacle Detection in Piloted UAVs

A Thesis Submitted for the Degree of Master of Science in Computer Science

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DECLARATION

I hereby declare that the thesis is my original work, and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis. This thesis has also not been submitted for any degree in any university previously.

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This is to certify that this thesis is based on the work of Mr. K. Avenash under my supervision. The thesis has been prepared according to the format stipulated and is of acceptable standard.

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Supervisor Name: Prof. G. D. S. P. Wimalaratne

Signature of the Supervisor & Date 30th November 2021

To my beloved parents.

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ABSTRACT

Teleoperation of Unmanned Aerial Vehicle (UAV) is a demanding task that requires skill and experience. For the most part, commercial-grade UAVs are still manually piloted. Some form of obstacle detection capability is desired in UAVs to minimize the chance of collisions and to ensure safety to human lives and properties. This thesis presents a heterogeneous sensor fusion framework for obstacle detection using complementary sensors, a monocular visual camera, and distance sensors to detect obstacles. The approach focuses on obstacles at low altitude, such as static obstacles with a large surface area and thin obstacles such as cables. The fusion of inputs is performed using fuzzy logic. The warning alerts to the pilots are sent using graphical and auditory signal methods when an obstacle is encountered. The evaluation was conducted using the simulation platform Microsoft AirSim. The approach detects thin obstacles, static large obstacles, and thin obstacles with a static obstacle in the background successfully. A case study was also conducted involving a human subject to obtain qualitative evaluation. Results obtained shows that the proposed approach has a great potential in the UAV obstacle detection. The proposed framework and the evaluation results are the contributions of this work. The thesis discusses the framework's limitations and provides an overview of aspects that should be focused on when the approach is extended and implemented for a real hardware platform.

Keywords: Sensor Fusion, Collision Avoidance, Unmanned Aerial Vehicle, Obstacle Detection

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LIST OF ABBREVIATIONS

ADAS	Advanced Driver Assistance System
ADS-B	Automatic Dependent Surveillance–Broadcast
BVLOS	Beyond Visual Line of Sight
CNN	Convolutional Neural Network
EVLOS	Extended Visual Line of Sight
FIS	Fuzzy Inference System
GCS	Ground Control Station
LiDAR	Light Detection and Ranging
MAV	Micro Aerial Vehicle
MMW	Milli Meter Wave
ODR	Obstacle Detection Region
RPAS	Remotely Piloted Aircraft System
SIFT	Scale Invariant Feature Transform
TCAS	Traffic Collision Avoidance System
ToF	Time of Flight
UAV	Unmanned Aerial Vehicle
VLOS	Visual Line of Sight

CHAPTER 1
INTRODUCTION

1.1 Motivation

Recent years have seen immense growth in the Unmanned Aerial Vehicles (UAV) domain, from both research community and commercial applications. The usage of UAVs has increased significantly with a continuous rise in demand in various application domains. UAVs have the capability to perform tasks in situations where the conditions might be challenging, expensive, or risky when performed using human personnel (Martin *et al.*, 2016; Li *et al.*, 2017).

Most of the commercial-grade UAVs are still manually teleoperated (Wang and Voos, 2019). Hence, it heavily depends on the skill of the pilot (Aguilar, Casaliglla and Pólit, 2017). Piloting a UAV is a skill-intensive task that requires experience in order to successfully complete a mission without collisions (Wang and Voos, 2020). Loss of line of sight, operating in difficult terrains and fatigue are some of the key challenges in piloting UAVs. Fatigue affects pilot performance during teleoperation (Aguilar, Casaliglla and Pólit, 2017; Yasin *et al.*, 2020). Moreover, UAV accidents can happen due to limited situational awareness, operator negligence, equipment malfunction and bad weather. It is important that UAV operations must be conducted safely without causing risk to human lives or properties (Peng, Lin and Dai, 2016; Zhou *et al.*, 2017).

In order to successfully pilot a UAV and to minimize the chance of collisions, some sort of real-time collision avoidance approaches are desired (Lu *et al.*, 2018; Carrio *et al.*, 2020). Collision avoidance approaches range from systems that warn the pilot to complex approaches that autonomously avoid the obstacles (Yasin *et al.*, 2020). The ability to automatically detect obstacles will put a lesser cognitive load on the pilots and reduce stress levels (Gageik, Benz and Montenegro, 2015; Alvarez *et al.*, 2016). Moreover, with the increase in UAV usage and the rapid growth in the applications, more UAVs are expected to be seen in public areas and everyday lives. Yasin et al. (2020) discussed that this creates demand for highly reliable collision avoidance systems from the public safety point of view. Obstacle avoidance in UAVs is currently an active field of research (Lu *et al.*, 2018; Carrio *et al.*, 2020). Most of the existing work focuses on autonomous UAVs and a limited number of works have addressed this in piloted or teleoperated UAVs. The main motivation of this research is to investigate and develop a sensor fusion-based obstacle detection framework for piloted UAVs.

1.2 Statement of the Problem

Collision avoidance approaches can be designed to autonomously avoid obstacles or can be a simple approach that warns the pilot about the potential threat (Yasin *et al.*, 2020). In comparison to autonomous UAVs, a limited focus is given to collision avoidance approaches in piloted UAVs. The state-of-the-art collision avoidance approaches for piloted UAVs use a limited number of sensor options. Expensive sensors like Light Detection and Ranging (LiDAR) sensors are being used commonly. Gauci et al., (2018) mentioned in future work that fusing the inputs from individual sensors can improve the overall performance and robustness. Relying on a particular sensor to extensively cover all types of obstacles can be a risk as some sensors are poor at detecting certain types of obstacles (Zhou *et al.*, 2017). Heterogeneous sensors with different sensors can significantly improve the detection capability, as the approach will not suffer due to a certain limitation of one type of sensor (De Silva, Roche and Kondoz, 2018). Using sensor data from different technologies gives more accurate results (Yu and Marinov, 2020). The literature indicates a little focus on sensor fusion in obstacle detection approaches for manually piloted UAVs.

These collision avoidance approaches are developed based on varied requirements and operating environments. Hence, one approach might not successfully function across different conditions. This affects the overall design of the approach and the choice of sensors. Understanding of the common obstacles and operating environment can help in designing optimal collision avoidance approaches. For example, there is a high chance that UAVs can be operated more closer to the ground and the obstacles can be different from that are found in high altitude. A limited number of researches on collision avoidance focus on the obstacles at low altitude flying such as stationary obstacles like buildings, structures, and thin obstacles. Various existing works have emphasized the aspect of obstacles in low altitude flying (Candamo *et al.*, 2009; Ramasamy *et al.*, 2016; Zhou *et al.*, 2017). This area has not been well explored with manually piloted UAVs.

Monocular visual cameras are a good candidate for being the choice of the sensor in obstacle detection approaches. But several disadvantages are there with this sensor choice such as the inability to sense depth. On the other hand, stereo cameras provide the ability to sense depth. However, it increases the required computational power (Yasin *et al.*, 2020). Monocular visual cameras are complemented using other types of sensors to counterbalance their limitations. Due to the recent advancements in imaging technologies, modern camera sensors have become more compact and are available at a low price. Therefore, a low-priced collision avoidance system is achievable using vision-based sensors (Discant *et al.*, 2007). There are various distance sensing options that can be used to address the obstacle detection problem by fusing with a monocular visual camera.

The purpose of this thesis is to investigate and develop a sensor fusion-based obstacle detection framework in a collision avoidance approach for piloted UAVs that detects and warns the pilots about obstacles.

1.2.1 Research Question

This thesis is concerned with the following research questions:

Q) How to develop an efficient sensor fusion-based obstacle detection framework for piloted UAVs using heterogeneous sensors?

Sub Questions:

(a) What type of sensors can be used in fusion to achieve the real-time sensing capability that is expected by the main research question?
(b) What data processing or fusion methods can be leveraged considering the limited onboard resources to solve real-time obstacle detection and to alert the pilot about the potential collision?

1.3 Aims and Objectives

Integrating a collision avoidance approach in piloted UAVs will be highly effective because there is an associated high probability of human error related accidents. The aim of this research is to develop a heterogeneous sensor fusion-based obstacle detection framework in a collision avoidance approach for piloted UAVs.

The objectives of this research are,

- Conduct critical review about existing work that is done in obstacle detection in piloted UAVs and other related applications including mobile robots, autonomous vehicles, and assistive approaches.
- Investigate and select heterogeneous sensors for obstacle detection framework design.
- Investigate and develop a sensor fusion-based obstacle detection framework for piloted UAVs.
- Evaluate the proposed approach using a simulation platform.

1.4 Scope

The scope of this research is limited to investigating and developing a sensor fusion-based obstacle detection framework in piloted UAVs. The proposed approach performs obstacle detection using onboard sensors deployed in the UAV platform and alerts the operator about the potential collision. This work only focuses on frontal obstacle detection.

Autonomously avoiding the obstacles will not be covered in this research. Moreover, obstacle detection under extreme weather and low lighting will not be covered. Detecting and tracking the dynamic obstacles is out of scope for this research. Usage of cooperative sensors (Lai *et al.*, 2012) will not be evaluated. Flying under inverted controls will not be tested in this research.

The evaluation of the approach will be conducted only using simulations.

1.5 Structure of the Thesis

Chapter 2 discusses on UAV operation types, applications, and a review of sensors. Furthermore, it presents a comprehensive overview of the most recent and relevant work done in the collision avoidance domain particularly focusing on obstacle detection. The chapter enumerates existing collision avoidance approaches that use monocular visual camera sensors on recent collision avoidance approaches in manually operated UAVs as it is the primary interest of this research. Additionally, the section discusses related approaches in the non-aerial vehicle domain. Lastly, the chapter covers the review of sensor fusion methods.

Chapter 3 covers the implementation of the proposed sensor fusion framework for obstacle detection in piloted UAVs. The section details the methodology of the research by adopting the constructive research method. Sensor fusion framework design, obstacle detection, sensor fusion approach and implementation of the control application including the warning interface are discussed in this chapter.

Chapter 4 presents the results and discussion from the evaluation of the proof-of-concept prototype. The results from performance evaluation, profiling, and user study are summarized under the results subsection. The results are discussed based on the research objectives under the discussion subsection.

Finally, a summary of the research and an outlook on the future work are discussed in Chapter 5.

CHAPTER 2
LITERATURE REVIEW

The literature review section begins with an overview of the UAV operation types, applications and a review of sensors. Next, some of the existing works in the domain of collision avoidance were studied particularly focusing on the obstacle detection aspect of the approach, and a brief review of some of the key work is presented. Approaches that use monocular visual cameras and approaches focused on operator assistance in aerial and non-aerial vehicles are the main two categories of work considered in this research. Moreover, the background of sensor fusion approach is reviewed. Finally, the chapter concludes with a summary validating the research questions with the literature.

2.1 UAV Operation Types and Applications

The UAV technology is being adopted in a wide variety of applications that span both military and civilian domains (Sadraey, 2020). The applications include surveillance, forest fire (Mahjri, Dhraief and Belghith, 2015), precision agriculture (Radoglou-Grammatikis *et al.*, 2020), natural disaster, visual inspection, surveying (Darwin, 2017), search and rescue (SAR), and military scenarios where it is challenging for humans to access (Carloni *et al.*, 2013; Aguilar, Casaliglla and Pólit, 2017). UAVs have become a versatile and effective tool during the 2020 Coronavirus pandemic too. Although the regulations around UAV usage are mostly restrictive around the world, many countries utilized the technology in applications like contact-free delivery, surveillance, enforcement, and hygiene applications. In Sri Lanka, on several occasions, drones were utilized in enforcement and lockdown monitoring operations (Zulfick Farzan, 2020). Harrison (2020) discussed that the golden age for drones is coming as he goes on to highlight that the world has now started to see the utility of UAVs outweigh the potential threat. In the same post, the author mentioned new aerial technologies are set to play a key role in the economy, which focuses on innovative ways to cater to the demands from the COVID-19 crisis. This clearly indicates that there will be significant growth in UAV technology adoption as an integrated part of many businesses in the future. Recent research by Alvarado (2021) states that the investments gone into the drone industry have reached record levels during the year 2020 despite the challenging conditions posed by the Coronavirus pandemic. The growing trend strongly indicates that the adoption of the technology is expected to grow during the year 2021 and beyond (Sartori, 2021). Currently, the International Civil Aviation Authority expects that considering the limited number of UAVs in the airspace and lack of regulations, with suitable enabling technologies, UAVs can be accommodated in the airspace. The integration is expected in the near future where there will be more mature technologies in this domain (ICAO, 2017).

UAVs are operated remotely by a pilot at a Ground Control Station (GCS) or autonomously controlled based on a pre-programmed flight plan (Sadraey, 2020; *STARS Project*, no date). Depending on the operation type UAVs are mainly categorized as teleoperated (manually piloted UAVs and autonomous UAVs accordingly. UAVs can operate in diverse environments where various types of obstacles can be found e.g., static, or dynamic obstacles, buildings, humans, trees, thin objects like cables. Designing an effective obstacle detection approach that works well in all scenarios can be a real challenge. Although there are many existing approaches for collision avoidance in UAVs, each approach suffers from different drawbacks (Al-Kaff *et al.*, 2017). Obstacle detection approaches can provide improved durability in long-range missions such as Beyond Visual Line of Sight (BVLOS) operations and operations in new terrains. One of the aspects that were given less emphasis in the literature about collision avoidance approaches for piloted UAVs is the operating environment and common obstacles that can be encountered. By focusing on the target obstacles, the collision avoidance system can be optimized in terms of cost and performance. LiDAR is a popular choice in collision avoidance systems of UAVs and is preferred in low-flight applications because of the low angular resolution (Sabatini, Gardi and Richardson, 2014). LiDARs are typically expensive which increases the cost of the hardware.

According to the current regulation by the Federal Aviation Administration (FAA), 400 feet is the maximum limit at which drones must be operated without additional approvals (*Unmanned Aircraft Systems (UAS)*, no date). Thin cables like obstacles are missed by the pilots in the presence of heavily cluttered backgrounds (Candamo *et al.*, 2009). As UAVs being more agile flying equipment, there is a high possibility for collisions in cases where the UAV is operated close to the ground (Hrabar, 2011). Small-to-medium-sized UAVs are prone to this risk. Most of the static obstacles that the UAV encounters are buildings, structures, poles, trees, bridges, power cables, etc. (Parappat *et al.*, 2014; Kong, Xu and Zhang, 2021). Sensors have limitations on which type of obstacle it can detect better. For example, thin subjects can be challenging to detect for active sensors like sonar, LiDAR and even with stereo cameras (Zhou *et al.*, 2017). When designing a system for real-world usage the understanding of the common obstacles that the UAV will encounter in its operating region is advantageous.

The UAV operations (Figure 1) can be divided into mainly three categories: VLOS (Visual Line of Sight), EVLOS (Extended Visual Line of Sight) and BVLOS (Beyond Visual Line of

Sight) (The SOARIZON Team, 2020). In VLOS, the operator must maintain unaided visual contact with the UAV and in EVLOS, it is allowed flight Beyond Visual Line of Sight using “Trained Observers”. There will be one or more observers who observe the flight path and communicate flight safety information with the pilot to maintain a safe flight. BVLOS flights are flown beyond the pilot’s visual range, and it enables a UAV to cover far greater distances. Moreover, BVLOS operations allow in performing tasks in fewer deployments which reduces the overall cost (Choudhary, 2019). With the increasing demand in UAV applications, the motivation towards enabling UAVs for BVLOS operations is also growing (ICAO, 2017; Davies *et al.*, 2018).

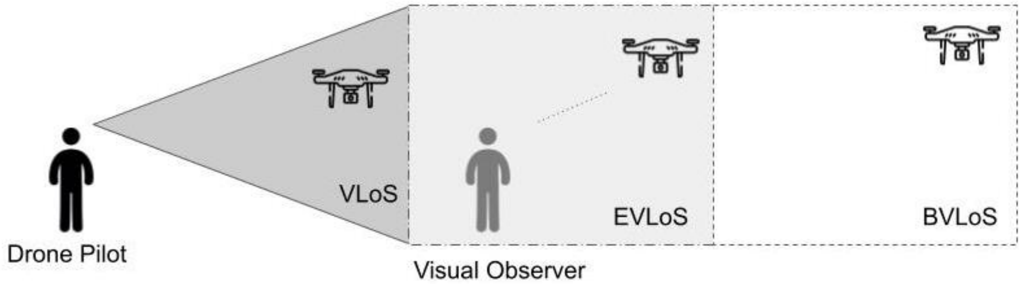


Figure 1: Types of UAV Operations

2.2 Sensors

The ability to perceive the environment is a key factor in obstacle avoidance methods. Various types of sensors such as range-based sensors (e.g., laser) and vision-based sensors (e.g., camera) are currently available, which can enable UAVs to perceive the environment (Alvarez *et al.*, 2016; Yasin *et al.*, 2020). This perceived information can be then used to provide better situational awareness to pilots as well as in enabling autonomous decision-making capabilities in UAVs. All the sensors have some limitations and strengths over the others e.g., a range-based sensor like LiDAR can detect the distance from the obstacle accurately but it does not realize the visual characteristic information of the obstacles. Whereas a vision-based sensor like a typical visual camera can be used to detect the shape or visual features of an obstacle but is not useful to recognize the distance from the obstacle because it lacks depth sensing. Yasin et al. (2020) mentioned that not one type of sensor can comprehensively cover the problem of collision avoidance. A single type of sensor cannot fulfill the requirement of obstacle detection due to the limitations in range, technology, signal features, and environmental conditions. Therefore, this has motivated researchers to develop alternative solutions using multi–sensor fusion-based methodology. Silva and Wimalaratne (2017, 2020) further acknowledged this by discussing that a single sensor cannot provide sufficient information on its environment. Typically to design an effective collision avoidance system, multi-sensor methods are considered as an option. Yasin also mentioned that more than one sensor can be used to cover large areas to eliminate blind spots or data from multiple sensors can be fused together to counterbalance the weaknesses between sensors.

This section discusses the common sensors that are used to build obstacle detection systems in UAVs. Sensors can be classified based on their perception mode (Figure *2*): Active Sensors and Passive Sensors (Yasin *et al.*, 2020). Sensors enable perception capability to the UAVs as well as other autonomous entities.

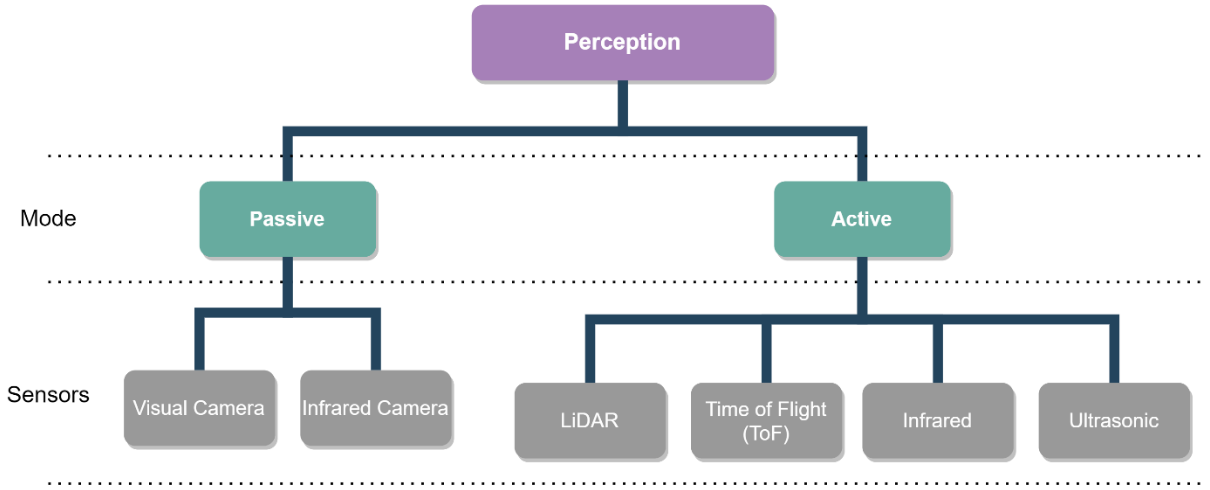


Figure 2: Sensor Categories

UAVs can be equipped with cooperative and non-cooperative sensors (Gauci *et al.*, 2018). Investigating on utilizing cooperative sensors will be out of scope for this research.

2.2.1 Active Sensors

Distance sensors are a type of active sensor that is used to measure the distance to objects without physical contact. Distance sensors are categorized based on their technology.

The different distance sensor types:

- Ultrasonic/Sonar
- Infrared
- LiDAR
- Time of Flight

Ultrasonic/Sonar

Ultrasonic or Sound Navigation and Ranging (Sonar) sensor functions based on emitting ultrasonic sound waves to the environment and listening to its reflection back to estimate the distance to any obstacle that may exist. This type of sensor offers a limited sensing range and a low sampling rate. Ultrasonic sensors are not suitable when measuring distance to fast-moving obstacles, have complex surfaces or extreme textures.

Infrared

Infrared-based distance sensors are compact in size and can be suitable for both daytime and night-time usages. Unlike other types of distance sensors, infrared sensors are much cheaper and are readily available (Yasin *et al.*, 2020).

The principle of triangulation is the theory behind the functioning of infrared-based distance sensors. The distance to the object is measured based on the angle of the reflected beam. The infrared light is emitted from the LED emitter. The emitted light beam hits the object in the environment, and it reflects off a certain angle. This reflected light beam then reaches the position-sensitive device where the position/distance of the reflective object is determined. This category of the sensor has a limited range too.

LiDAR

LiDAR sensor is a popular choice of a sensor in obstacle detection approaches. This is an attractive option because of the low angular resolution and is preferred in low-flight applications (Sabatini, Gardi and Richardson, 2014). LiDARs are available in 1D, 2D and 3D configurations. LIDAR typically uses laser and operates based on the time-of-flight concept. LiDAR systems have become much smaller, lighter and affordable in recent years (Yasin *et al.*, 2020). The inability to detect transparent objects such as glass is a weakness of LiDAR.

Time of Flight

The functioning of Time of Flight (ToF) is like LiDAR. The transmitter on the ToF sensor emits an infrared LED light to the environment. The pulse of the transmitted LED is picked up by the obstacles in the environment and reflected. The distance to an object is estimated by using the relationship between the time between the sending and receiving of the signal and the constant speed of light in the air (Shawn, 2020).

One of the important benefits of using infrared LED technology is its eye safety. Moreover, sensors of this class provide field-of-view (FOV) rather than point measurement which in turn provides a more stable data stream in many use cases ('Sensor Modules from Terabee: TOF, Lidar & More', 2019). For example, the Terabee TeraRanger Evo 60m sensor's FOV is illustrated in Figure *3*.

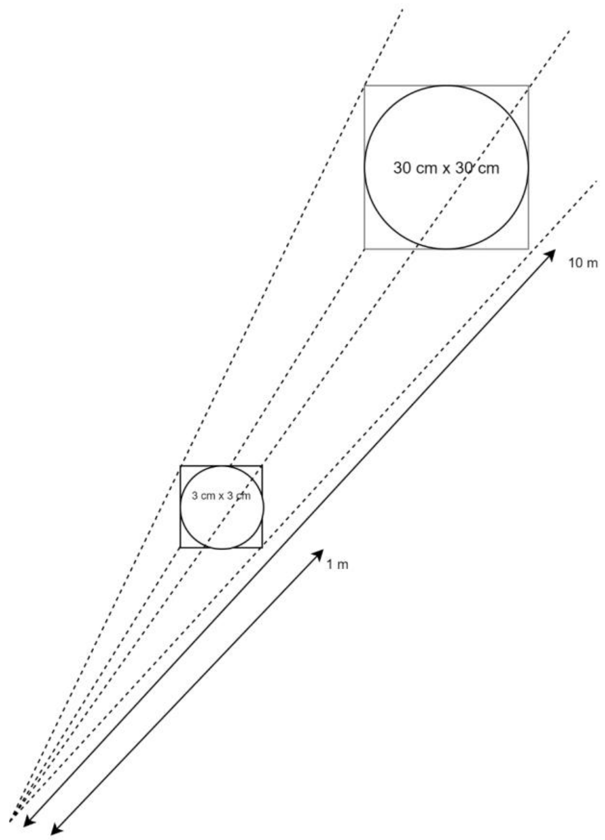


Figure 3: Resolution of Terabee Evo 60m at Different Distance Points

The diameter of the FOV is measured as 3cm at 1m and 30cm at 10m (Laughlin *et al.*, 2020). Low power consumption, small form factor and high refresh rate are some other advantages too. LED ToF offers excellent sensing capability at a moderate cost. Terabee Evo 60m sensor is available at the price of 99$ and weighs 12 grams. Figure *4* has some examples for ToF sensors.

Figure 4: ToF Sensors – Terabee Evo 60m and TF Mini LiDAR

Table 1 provides a comparison of distance sensors in terms of several key selection criteria for collision avoidance systems.

Table 1: Comparison of Distance Sensor Characteristics:

	Ultrasonic or Sonar	**Infrared**	**Time of Flight**	**LiDAR**
Range	Low	Low	High	Very High
Sampling Rate	Low	Low	High	High
Cost of the sensor	Low	Low	Low	High
Ability to detect complex objects	No	Yes	Yes	Yes
Sensitive to external environmental conditions	Yes	No	No	No

2.2.2 Passive Sensors

Passive sensors work based on detecting the natural energy emitted by the objects in the environment. Visual Cameras, Thermal or Infrared (IR) cameras and spectrometers are some examples of passive sensors.

Visual Camera

Visual cameras can be used to capture the environment and the image can be used to extract useful information through processing. Visual cameras can be monocular, stereo and event based. Nowadays, most UAVs are equipped with a camera (Nous *et al.*, 2016). Therefore, it is advantageous to utilize the same hardware as part of any obstacle detection system without additional hardware. Moreover, modern camera hardware has become more compact in size and low cost, so it is preferred over other sensors. Visual cameras can be of types: monocular or stereo. These cameras function in the visible light spectrum. Range finders are not suitable for complex environments because of the limited FOV, opposed to visual cameras which can capture an abundance of information (Lu *et al.*, 2018). On the other hand, this requires high processing to filter important characteristics.

Infrared Camera

Infrared or thermal cameras are sensors that work in the infrared band of the light spectrum. These types of cameras are particularly preferred in low-light situations. All objects in the environment emit infrared energy. These IR cameras can detect and measure the infrared energy of objects. Compared to RGB camera output, the results from IR cameras are lower resolution, distorted and blurry at times. IR cameras are typically used in combination with RGB cameras.

Table 2 provides an overview on the sensors that are discussed in this section.

Table 2: Comparison of Sensor Characteristics:

Sensor	Mode	Range	Accuracy	Weather Dependency	Sensor Size	Processing Requirement	Power Requirement	Price (USD)
Sonar	Active	Low	Medium	Partial	Small	Low	Medium	<100
Infrared	Active	Low	Medium	Partial	Small	Low	Low	<100
ToF	Active	Medium	Medium	Partial	Small	Low	Low	<200
LiDAR	Active	High	High	Low	Medium-Large	Low	Medium	>1000
Camera	Passive	Low	Medium	High	Small	High	Low	<100
IR or Thermal Camera	Passive	Medium	Medium	High	Small	High	Low	>1000

2.3 Collision Avoidance Approaches using Visual Cameras

Using visual cameras as an obstacle detection sensor can bring notable advantages as they can bring the overall cost of the system low by using lightweight modern cameras (Peng, Lin and Dai, 2016). Although LiDAR-like sensors can provide better accuracy and precision, they can be too large to carry for small scale UAVs. In such situations, imaging-related approaches can provide benefits. Peng et al. (2016) proposed a totally imaging-based obstacle avoidance approach using the optical flow method to sense the environment. The drawback here is that the approach performs well under single obstacle circumstances and fails to perform better otherwise. Zhou et al. (2017) attempted to propose an obstacle detection method for mobile robots using a monocular camera, stereo, and an ultrasonic sensor. It is evaluated that the system performs well in static object conditions. This approach was focused on detecting thin obstacles such as a wire in indoor environments. This approach was also tested by deploying in a UAV.

Chakravarty et al. (2017) proposed a collision avoidance method and navigation of a quadrotor using a single camera with a trained Convolutional Neural Network (CNN) using depth image information. The depth estimation approach failed in some conditions due to not much contextual information being extracted from the scene. An approach of using a single monocular camera in combination with Scale Invariant Feature Transform (SIFT) feature point detection was also explored (Aguilar, Casaliglla and Pólit, 2017). Here, a database is stored with the obstacle images. The obstacle images are compared with real-time images captured using the onboard camera. The comparison is done based on the feature points to detect the obstacle and perform any avoidance manoeuvre. Depth sensing is another characteristic explored in obstacle detection. Carrio *et al.* (2020) proposed an approach in detecting other drones that are moving in mid-air using a model that is trained using depth images. Karlsson's (2020) work on collision avoidance in Micro Aerial Vehicles (MAV) used YOLO (You Only Look Once) object detection to avoid pedestrians in the path. Hatch, Mern and Kochenderfer (2021) used a hybrid neural network to avoid collisions in UAVs. These works are categorized under the trained or data-based approaches. Deep learning or trained methods do not perform well in new environments. Yu *et al.* (2020) further validated that saying deep learning approaches are good at detecting road obstacles that are predictable in nature e.g., pedestrian detection in autonomous vehicles. This approach can be challenging in the context of UAVs where the obstacles are mostly unknown in a large outdoor space.

With a monocular camera, Al-Kaff et al.'s (2017) work on detecting approaching obstacles by analysing consecutive frames using SIFT feature points worked well in most situations. The drawback observed is that the camera-based systems are sensitive and prone to fail when confronted with high-intensity lighting conditions, such as sunlight. This may lead to UAV sensing a lack of information which can potentially cause collisions. Kim and Do (2012) in their work in obstacle detection for mobile robots using a single camera proposed a block-based motion estimation technique. This method failed in tough imaging situations with respect to distance to the obstacle, object colour, and lighting. Although imaging-based approaches can give better perception ability it is not a good approach for realizing distance to obstacles.

A multi-sensor approach proposed by Anis et al. (2018) used heterogeneous sensors such as a visual camera and ultrasonic sensor. The approach resulted in a high success rate (85%) in detecting obstacles. Here an observed disadvantage is that the camera's resolution played a vital role in detecting obstacles and reduced effectiveness. This is due to the loss of information on the obstacles which are farther away from the drone. Furthermore, the effective range of ultrasonic sensors is low. A sensor fusion of ultrasonic sensor and camera was proposed by Yu *et al.* (2017) to detect frontal obstacles for mobile robots. Yu *et al.* used information fusion to detect and measure the obstacles. The complementary characteristics of the sensors are utilized. Yu *et al.* (2020) proposed a sensor fusion-based collision avoidance approach using radar and a monocular camera in UAVs. The radar is used to detect the distance to the obstacle while the image is used to determine the regions precisely for avoidance path planning. The approach was tested to be feasible to operate in outdoor environments and in detecting different kinds of obstacles while only using very little onboard power.

Using limited FOV sensing is another category of obstacle avoidance methods under visual-based approaches (Lopez and How, 2017). Limited FOV sensing will capture less information per frame and enables reduced computation time to perform obstacle detection and avoidance. Figure *5* summarizes the discussed past work into categories.

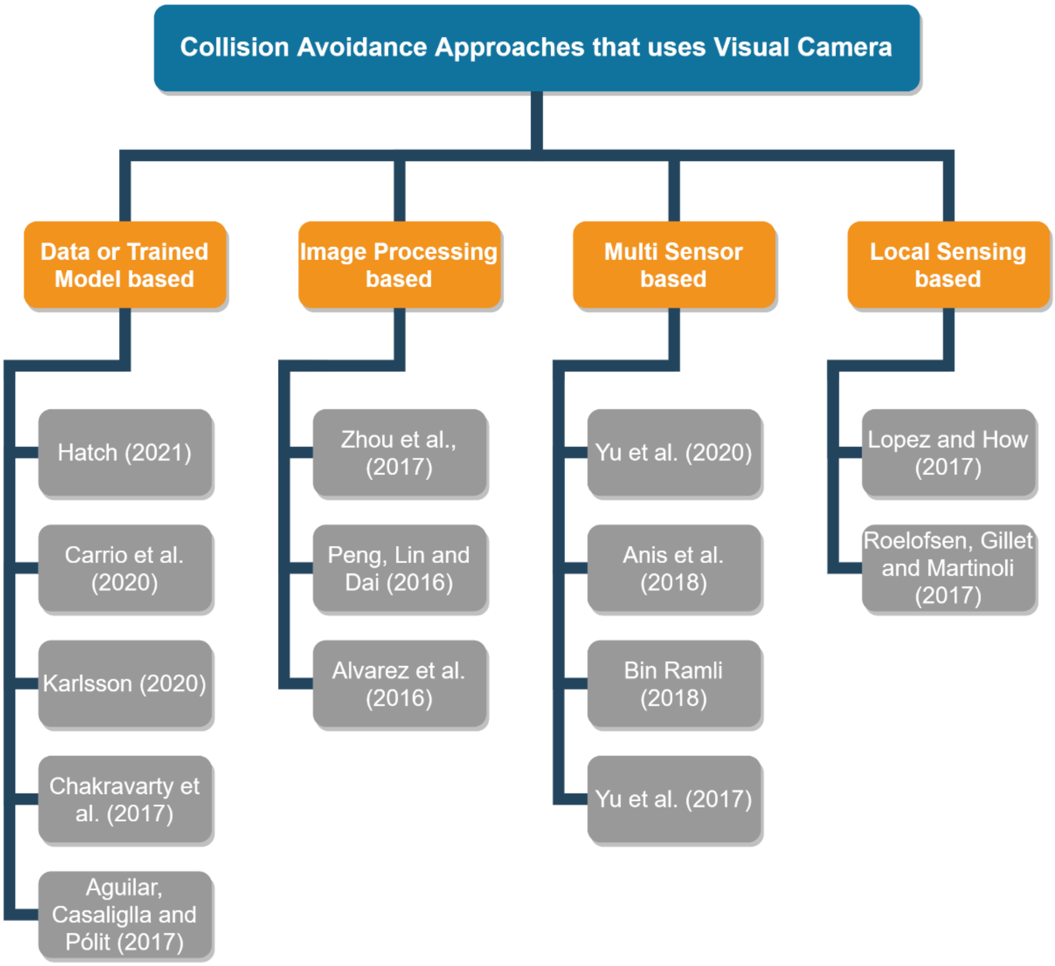


Figure 5: Taxonomy of Collision Avoidance Approaches that use Visual Camera

Stereo vision is another type of vision-based obstacle detection method. Instead of using one camera, two cameras are used together (Nous *et al.*, 2016). The major advantage here is that it is possible to measure the distance from the obstacle using properties like pixel displacement, focal length, and the distance between cameras. García Carrillo et al.'s (2012) work on fusing data from sensors experimented with quadrotors. As monocular camera related work is the primary focus of this thesis, this area was not further explored.

For UAVs, to safely integrate into the non-segregated airspace, a robust collision avoidance system is required. Using sensors that are cooperative and non-cooperative can bring advantages in terms of robustness. Ramasamy et al. (2014) proposed a data fusion approach that uses inputs from varied types of cooperative (TCAS, ADS-B, Transponder) and noncooperative (Visual Camera, Thermal Camera, LIDAR, MMW Radar and Acoustic) sensors in combination to determine the obstacles in UAVs path. This approach was tested to detect obstacles at the accuracy of 500m and allows flexibility (choosing suitable sensor combination) in implementation depending on the use cases (Ramasamy, Sabatini and Gardi, 2014). These work highlights the considerations that go into designing a sensor fusion approach.

2.4 Collision Avoidance Approaches in Manually Teleoperated UAVs and Driver Assistance Systems in Non-Aerial Vehicles

This subsection provides an outlook on some of the selected work on collision avoidance targeting manually teleoperated UAVs and Driver Assistive Systems for non-aerial vehicles. The approaches in these two domains are based on the principle of assisting the operators and enabling safe operation. Hence, both contexts have common requirements.

Teleoperation can be defined as the operation of a device or machine at or over a distance where the term "tele" means at or over a distance (Qasim, 2016). Teleoperation of a UAV is a challenging task and even it can be difficult for trained operators when piloted just with live camera-feed from the vehicle particularly in indoor GPS denied environments (Israelsen *et al.*, 2014). To enable successful piloting and to improve situational awareness some form of collision avoidance capability is desired in UAVs in addition to relying on the pilot's ability to see and avoid any obstacles remotely. Modern-day vehicles like cars are no exception to this problem. Vehicles including the autonomous category, nowadays have systems built into them and these systems assist the driver in driving or safely override the operator input if required e.g., Automatic Emergency Braking (*What is AEB and how does it work?*, no date). A collision avoidance system can be simply warning the operator or can autonomously control the vehicle to avoid the collision (Yasin *et al.*, 2020). These kinds of systems can help improve situational awareness as well as allow inexperienced pilots or operators to handle the task without any issues.

Recent works on assistive-based collision avoidance methods for manually teleoperated UAVs used expensive sensors like 2D LiDAR and Motion Capture Camera for obstacle detection (Israelsen *et al.*, 2014; Wang and Voos, 2019, 2020). Work focused on detecting other aircraft from UAVs by integrating sensors like Electro-Optical (EO) and Infrared (IR) cameras and an Automatic Dependent Surveillance-Broadcast (ADS-B) (Gauci *et al.*, 2018). The primary focus is given to the detection of obstacles such as light and commercial aircraft at 2 nautical miles (drone sizes small to medium). As future work, the author proposed fusing the measurements from the individual sensors to improve the overall performance and robustness of the system. Another work that is similar to previously mentioned uses the sensor fusion to detect obstacles (Theuma *et al.*, 2017). This Remotely Piloted Aircraft System (RPAS) is designed for unmanned aircraft of size up to 200kgs. This is a considerably heavy payload for small scale drones.

In addition to what was discussed in the UAV space, the obstacle detection problem is being actively investigated in other domains such as robotics and autonomous driving assistance systems. Although these operate under different environmental conditions than the UAVs, the objective is the same. Sensor fusion of stereo vision and laser was experimented with by Kumar, Gupta and Yadav (2010) focusing on the robotics domain. Here the obstacle avoidance approach could help the robot in navigation by complementing each sensor's different capability (3D sensing of stereo vision and accuracy of laser). A sensor fusion based obstacle detection approach using a monocular camera and radars was proposed by Otto (2013) in an Advanced Driver Assistance System (ADAS). In this work, the visual camera is used to detect pedestrians in the scene and to feed the algorithm. Another work targeting the rail transit field proposed a sensor fusion obstacle detection approach using video recognition and a LiDAR sensor (Yaodong, 2020). Another work proposes sensor integration between LiDAR and camera to perform obstacle detection (Bin Ramli, Shamsudin and Legowo, 2018). The LiDAR and wide angle camera image fusion were explored in research targeting free space detection for autonomous mobile robots (De Silva, Roche and Kondoz, 2018). The author further highlighted that the perception capability can significantly improve using multi-modal sensor fusion.

Table 3 compares the existing approaches on collision avoidance targeting manually teleoperated UAVs and provides a brief overview.

The taxonomy in Figure *6* summarizes the selected works on both aerial and non-aerial vehicles.

Table 3: Comparison of existing Collision Avoidance related work in piloted UAVs:

Literature Work	**Method**	**Sensors**	**Important Contribution**	**Limitations**
Wang and Voos (2020)	Sense-and-avoid	2D LiDAR	Focuses on dynamic obstacles in a complex environment. Assisting unskilled pilots	Expensive sensor.
Wang and Voos (2019)	Sense-and-avoid	2D LiDAR	Focuses on dynamic obstacles in a complex environment. Assisting unskilled pilots	Expensive sensor.
Gauci *et al.* (2018)	Alert the pilot	Electro Optical (EO) camera module, an IR camera module, and an ADS-B receiver	Uses multi-sensor obstacle detection. Detects light and commercial aircrafts.	Limited to detecting light and commercial aircrafts.
Theuma *et al.* (2017)	Alert the pilot	EO camera module, an IR camera module, and an ADS-B receiver	Detecting other aircrafts at 2 nautical miles distance. IR can capture in adverse weather.	Emphasis is on detecting other aircrafts. Designed for RPAS of size of small (up to 50 kg) medium (50-200 kg). < 5000ft.
Qasim (2016)	Sense-and-avoid Override input	Motion Capture System	Overrides the pilot command that are in the direction of the obstacle. Evaluated using simulation and actual hardware in lab environment.	Expensive sensor. Limited real-world testing.
Ramasamy *et al.* (2016)	Alert the pilot Sense-and-avoid	LisDAR	Targets the obstacles at low altitude flying, like wire, structures, and terrain.	Expensive sensor.
Israelsen *et al.* (2014)	Sense-and-avoid	OptiTrack Flex 3 Motion Capture System	Onboard processing and uses force feedback method.	Expensive sensor. Limited real-world testing.

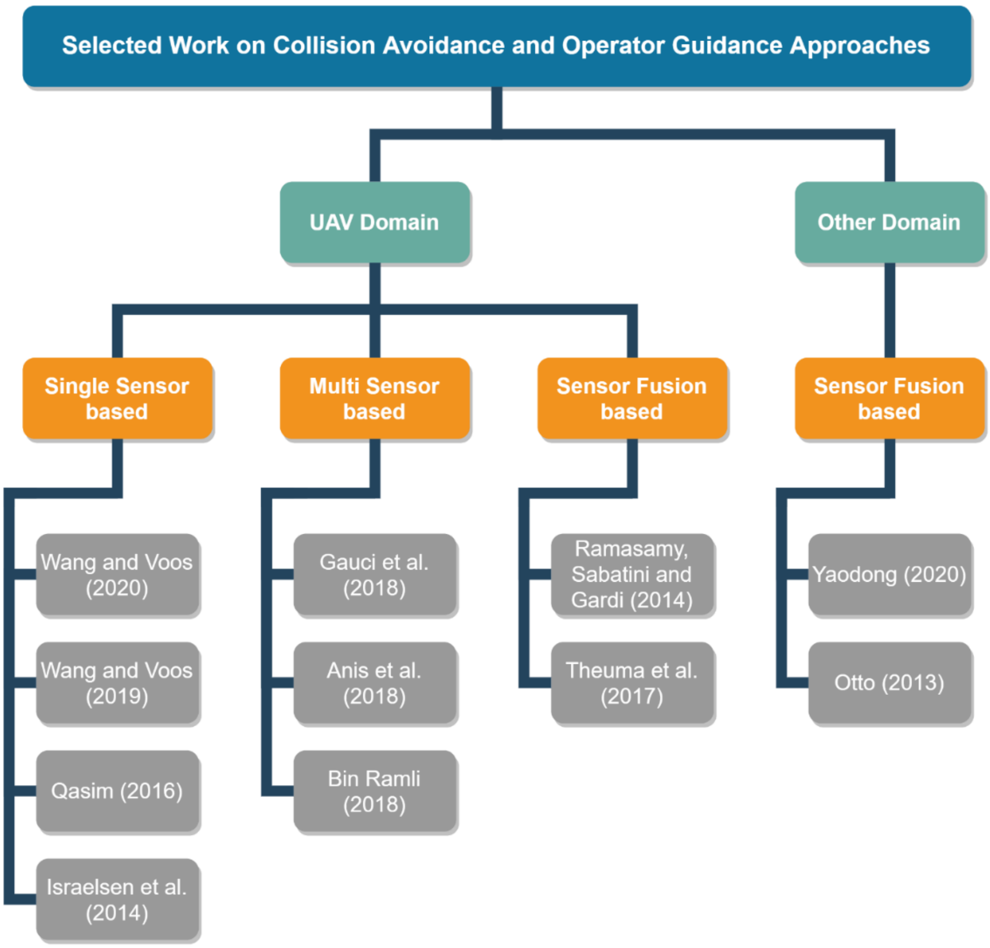


Figure 6: Taxonomy of selected work on Collision Avoidance in UAVs and Non-Aerial Vehicles

2.5 Sensor Fusion

Sensor fusion is an approach to combine data from many sensors or a sensor. The main objective of combining the sensory information is to produce a single representational format of the environment rather than the synergetic use of the sensors also known as sensor integration (Elmenreich, 2002). The data from multiple sensors are processed and results are determined such that the resulting information has less uncertainty than would be possible when these sources were used individually. Human's inference of the surrounding environment is an example of sensor fusion where the inference is based on the fusion of different sensory information such as sight, smell, touch, hearing, and taste.

This approach has gotten rise due to the inherent limitations that resulted when the sensors are used individually (Kumar, Gupta and Yadav, 2010). Sensors can be of any type and can have the capability to sense the environment for different characteristics. The sensor fusion approach provides robustness and reliable output as the result does not rely on a single sensor's input.

Moreover, it allows flexibility in designing a collision avoidance system by allowing the choice of different combinations of sensors. Fusing measurements from individual sensors can improve the overall robustness and performance of the system (Gauci *et al.*, 2018).

Various past researches have discussed advantages in building efficient collision avoidance or obstacle detection approaches using the sensor fusion approach. Silva and Wimalaratne (2017) used different types of sensors to complement the overall performance of the detection process. Sensor fusion helps in designing systems for mission-critical applications where using redundant data can improve reliability and accuracy (Otto, 2013; Ramasamy, Sabatini and Gardi, 2014; Lu *et al.*, 2018). Furthermore, timeliness in response can be achieved using this method (Lu *et al.*, 2018). Sensor fusion is also considered an enabling driver that helps in replacing expensive technology by using similar low-cost alternatives (Gageik, Benz and Montenegro, 2015).

Sensor fusion is not an omnipotent method, and it comes with its own challenges. Based on the existing knowledge on the sensor fusion performance, a slight scepticism is appropriate on the "perfect" or "optimal" sensor fusion approach (Fowler, 1979; Elmenreich, 2002). Optimizing the overall performance of the approach based on individual sensor performance. The performance of a sensor fusion approach relies on the quality of sensor data used. The overall performance of the fusion system might be lower than that of each individual source if a number of sources provide inconsistent data into the algorithm (Abdulhafiz and Khamis, 2013). Therefore, using bad data can degrade the system's performance. Problems often when fusing different types of sensor data, which have varied noise characteristics and poor synchronization (Lu *et al.*, 2018).

The level of sensor fusion is based on the kind of information used in the algorithm. That can be raw sensor feed, extrapolated features or decisions made by using individual sensor nodes (Ruta and Gabrys, 2000). Sensor fusion is alternatively referred to as data fusion in the literature (Castanedo, 2013). Moubayed et al. (2021) referred to data fusion as the process of integrating data and knowledge from multiple sources. Processing of raw sensor data is typically considered as data fusion e.g., fusing of temperature data from multiple sensors. On the other hand, information fusion is a higher level, where it deals with combining various features from data sources into a common feature map which can be later used for detection e.g., the fusion of data from camera and LiDAR (Elmenreich, 2002). Decision fusion or classifier fusion is suitable when it is difficult to combine data from different data sources into a single feature vector representation (Silva and Wimalaratne, 2020). Fusion algorithms can be categorized as direct fusion or indirect fusion. Direct fusion means that the data from heterogeneous or homogeneous sensors are used while indirect fusion uses priori knowledge in addition to sensory data.

Enhanced data authenticity and availability, reduced exchange of redundant data and data transmission energy consumption are some advantages of using the data fusion approach in multi-sensor systems (Khaleghi *et al.*, 2013). It also helps in extending the temporal and spatial coverage using multiple sensors. This advantage comes in handy with developing collision avoidance systems for resource constrained environments like UAVs. Data Fusion methods can be categorized based on their fusion level, fusion model, and architecture (Figure *7*).

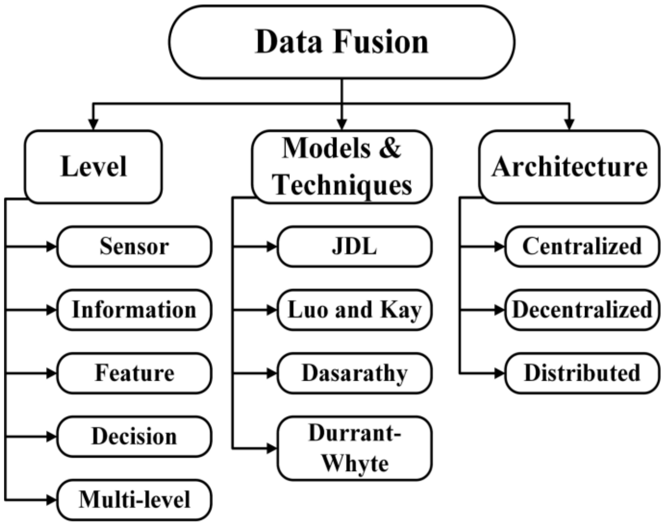


Figure 7: Classification of Data Fusion Methods (Moubayed et al., 2021)

These classifications provide a framework for designing sensor fusion approaches. There are some well-known approaches for data fusion. Probabilistic fusion, Kalman Filter, AI based or soft computing methods such as fuzzy logic, neural networks and genetic algorithms are to name a few (Abdulhafiz and Khamis, 2013; Safari, Shabani and Simon, 2014; Alyannezhadi, Pouyan and Abolghasemi, 2017; Kim and Park, 2020).

Fuzzy logic is a decision fusion method that is based on how humans think. This is an example fusion process for decision fusion (Elmenreich, 2002). Fuzzy inference is performed using a set of defined fuzzy rules based on the inputs determined by the rules. This approach is helpful in modelling decision making like humans where the decisions are not always binary. Kim and Park (2020) have explored fuzzy rules by giving sensors precedence based on their strength. These rules can be further extended to cover more situations. Shitsukane *et al.*, (2018) proposed a fuzzy control approach to autonomously navigate the mobile robot. The author has tried to create rules based on human driving knowledge. A similar approach was tried in the context of navigation where a fusion of GPS and INS is performed (Mayhew, 1999). Mayhew further discussed that, using fuzzy logic, the sensor fusion can be performed in a more structured and easily understood manner.

In summary, the state-of-the-art collision avoidance methods targeting piloted UAVs commonly use expensive sensors like 2D LiDAR and Motion Capture System as outlined in Table 3. There have not been many attempts on exploring low-cost alternatives in this focus area. Heterogeneous sensor fusion-based approaches can bring advantages over methods that rely on a single sensor or technology. In recent literature, sensor fusion-based approaches are explored in dynamic environments like mobile robots, but a limited focus has been given to UAVs. This indicates a research gap for a sensor fusion-based obstacle detection approach in piloted UAVs.

The obstacles to the UAVs are depended on the operating environments. In existing collision avoidance approaches, there is less emphasis on urban low-flight applications. Focusing on the operating environment can help to design optimal collision avoidance approaches. During a flight in an urban environment, UAVs can encounter obstacles such as static obstacles with a large surface area or thin obstacles like cables. A building or a structure is an example of the former. Powerlines and high-tension cables are examples of thin obstacles. A single type of sensor may suffer in detecting both successfully. Therefore, a sensor fusion approach can be a potential candidate in such a situation where the complementary sensing ability of different sensors can be utilized. In existing work, this is not focused well, and the approaches use dedicated sensors to detect different types of obstacles e.g., using a camera to detect the thin obstacles and using ultrasound to detect obstacles with large surfaces (Zhou *et al.*, 2017). Moreover, from the past work, it can be observed that there hasn’t been a significant focus on establishing a sensor fusion framework that can be extended and used depending on the sensor choices and the obstacle to detect. This also indicates a gap in the knowledge in terms of a sensor fusion-based framework for obstacle detection. This is the basis of the main research question.

Based on the taxonomy in Figure 5, visual cameras are a popular choice in collision avoidance approaches. This is due to the recent advancements in the technology, cost, and compactness of the hardware. However, it lacks the ability to sense depth in the scene. Hence, it is mostly paired with some distance sensors to counterbalance the limitation. With regards to distance sensing, there is not much focus given to LED ToF sensors in obstacle detection approaches.

ToF sensor offers a high detection range and high sampling rate at a considerably low cost based on the comparison in Table 1. This positions itself in between the low range ultrasonic sensors and expensive LiDARs or Laser based methods. Furthermore, it makes it a candidate to be considered for obstacle detection approaches. However, this type of sensor is not currently explored in existing collision avoidance approaches for dynamic environments in general. Therefore, the combination of visual camera and distance sensing is investigated in this proposed research, attempting to validate the sub question (a).

In terms of data processing, as this research attempts to address the main research question by using heterogeneous sensors, decision fusion is deemed as a suitable option. Fuzzy logic is utilized in this presented framework considering the advantages it provides and it enables a more structured way of implementing the fusion and it is extendable with improving the rule base. The sub question (b) focuses on this.

CHAPTER 3

METHODOLOGY

In this chapter, the methodology of the proposed research is detailed. The constructive research method was followed (Silva and Wimalaratne, 2020) in this work, and a proof-of-concept prototype was developed as an experimental setup. This is one of the common research approaches in the computing research domain. The approach aims to solve problems faced in real world by producing innovative constructions, and by that means, contributes to the domain in which it is applied (Lukka, 2003). This section is detailed by adopting the constructive research approach.

Figure *8* provides a high-level overview of the Obstacle Detection Framework. The collision avoidance approach is tested on a simulation platform for validity.

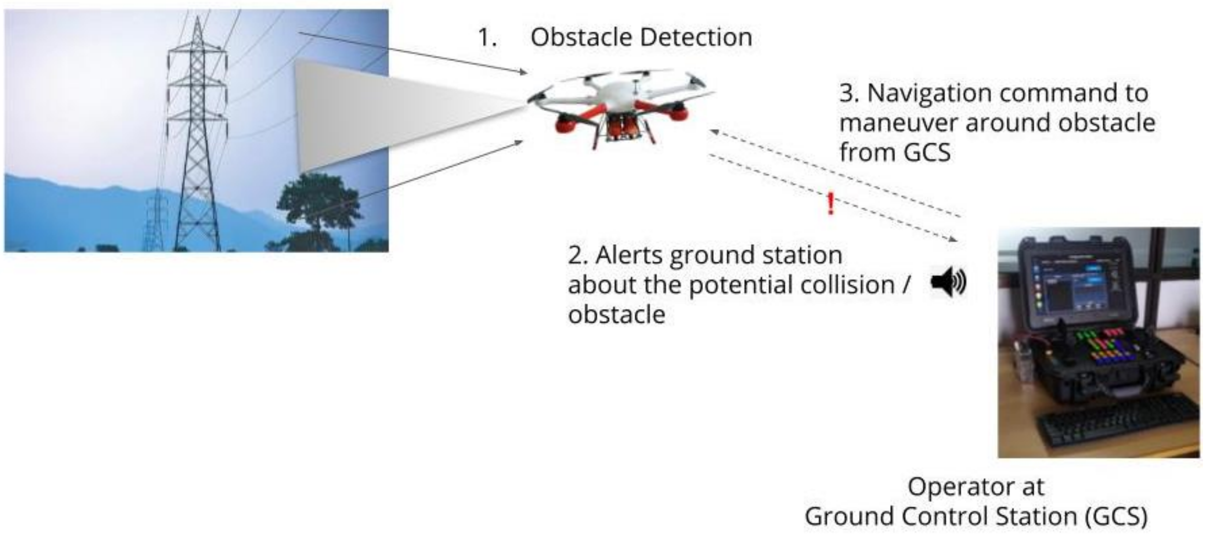


Figure 8: High-Level Overview of the Obstacle Detection Framework

The outcome of this research work is the obstacle detection framework using heterogeneous sensors. As depicted in Figure *8*, obstacle detection is performed on the UAV platform and a warning is given to the pilot when the UAV encounters an obstacle. Then the pilot can manoeuvre the UAV to avoid the obstacle.

3.1 Simulation Platform

The complete development and testing of the approach took place in the simulation environment. The simulation platform of choice for this research is Microsoft AirSim (Shah *et al.*, 2018). AirSim is an open-source simulation platform for drones and cars. It is built on

Unreal Engine; it can provide a high-fidelity simulation experience with rich graphics and physics. This makes it suitable to be used to test image processing algorithms.

This research focuses on the sensor fusion approach between the imaging sensor and distance sensors. AirSim offers simulated sensors such as Camera, LiDAR and Distance Sensors out of the box (Rosique *et al.*, 2019). This makes AirSim an ideal choice for this research work. Although it is a developing platform, it offers necessary APIs through which the simulation can be created and managed easily.

3.2 Obstacle Detection Framework Design

According to the scope of this research, the proposed heterogeneous sensor fusion-based obstacle detection framework is limited to frontal obstacle detection. When selecting sensors for the framework design, the practical aspects of the UAV deployment were considered. Various past works have highlighted the following parameters for sensor selection: payload limitation (Yasin *et al.*, 2020), onboard computational power (Gageik, Benz and Montenegro, 2015), cost of hardware (Yasin *et al.*, 2020), and complexity in integrating the sensors (Carrio *et al.*, 2020). A monocular visual camera and distance sensors are the sensors selected for this development. Figure 9 illustrates the arrangement of the sensors and their coverage.

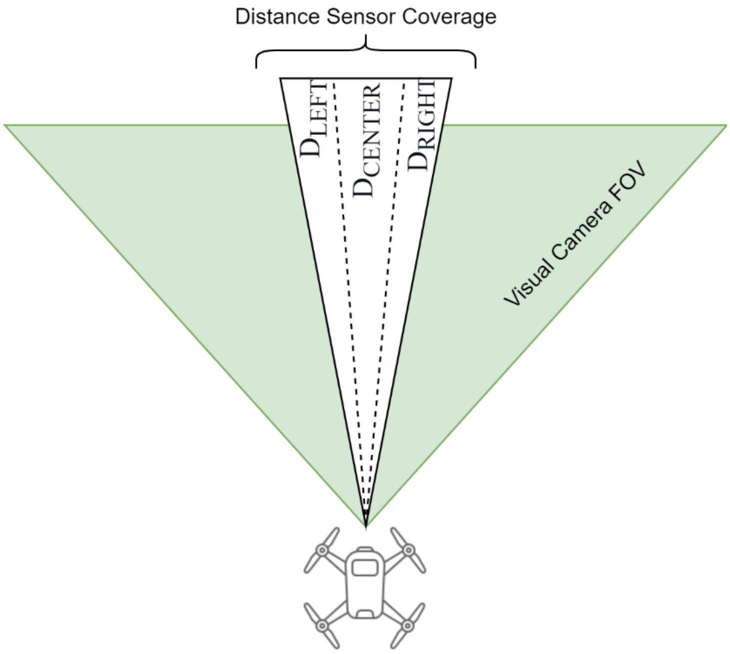


Figure 9: Frontal Sensor Arrangement and Coverage

Albaker and Rahim (2009) outlined the five major design factors related to a collision avoidance system. These are (1) Sensing the environment, (2) Conflict detection and awareness, (3) Selection of escape trajectories, (4) manoeuvre realization and dimensions and (5) Other design factors such as computation complexity and time requirement. On that basis, the proposing approach focuses on areas 1-2 and 5. Since this work is in piloted UAVs, 3 and 4 are not applicable. The framework's performance is expected to be accurate and with a minimal false positive warning about threats.

In a high level, the proposed framework is mainly divided into three components. Individual obstacle detection experts based on imaging and distance sensing, sensor fusion component responsible for fusing inputs from individual sources and the control application that functions as the interface between the obstacle detection approach and pilot. The following sections elaborate on the methodology in detail. The fusion layer uses fuzzy logic to provide output.

3.2.1 Design Assumptions

The prototype is evaluated within a simulated environment. External environmental conditions such as the effect of wind are not considered in the methodology. This research attempts to conceptualize the idea of using a visual camera and distance sensors in sensor fusion. The image processing algorithm is mainly developed to demonstrate the proposed concept. The algorithm does not yield accurate results when the environment has complex objects or is used in a new environment. The environment realism was not focused on the research. Therefore, the simulated environment setup used during the development and evaluation of this research uses primitive obstacles.

3.3 Obstacle Detection using Visual Camera

Typically, UAVs are equipped with one or more visual camera sensors which are used to perceive the environment from the UAV. If a UAV is already equipped with a camera, utilizing it in an obstacle detection approach will be a good idea since it minimizes the additional payload of sensors as part of the obstacle detection system. Unlike other sensors, visual cameras provide an abundance of information in each frame (Yasin *et al.*, 2020). By using various image processing or deep learning approaches, individually or in combination, information can be extracted from the image feed. This can be fed into an algorithm to perform obstacle detection. Candamo et al. (2009) mentioned in their study that vision technology is not considered as a replacement for other sensors but is to enhance the system's reliability.

3.3.1 Sensor Setup and Coverage of Visual Camera

A forward facing camera sensor is placed in the front-centre position of the UAV. The simulated camera captures at 480x240 resolution with 90 degree of FOV. Visual based approaches are known to suffer due to high processing requirements. In the proposed framework, to simplify the detection using visual technology, only the obstacles that intersect the path of the UAV are considered the primary threat to the unit. This approach is inspired from Valavanis' (2019) work on monocular obstacle detection and collision avoidance. Valavanis used bounding boxes to identify obstacles in the environment of the UAV. The bounding boxes that intersect with the centre region are highlighted as immediate threats. Figure *10* illustrates the region of interest for obstacle detection in the proposed work. Focusing only on an enclosed region can reduce the processing load. Therefore, the proposed framework prioritizes obstacle detection in that region. The term "Obstacle Detection Region" (ODR) is used to refer to the region of interest in the following sections of this thesis. The variables w and h are the width and the height of the image frame accordingly.

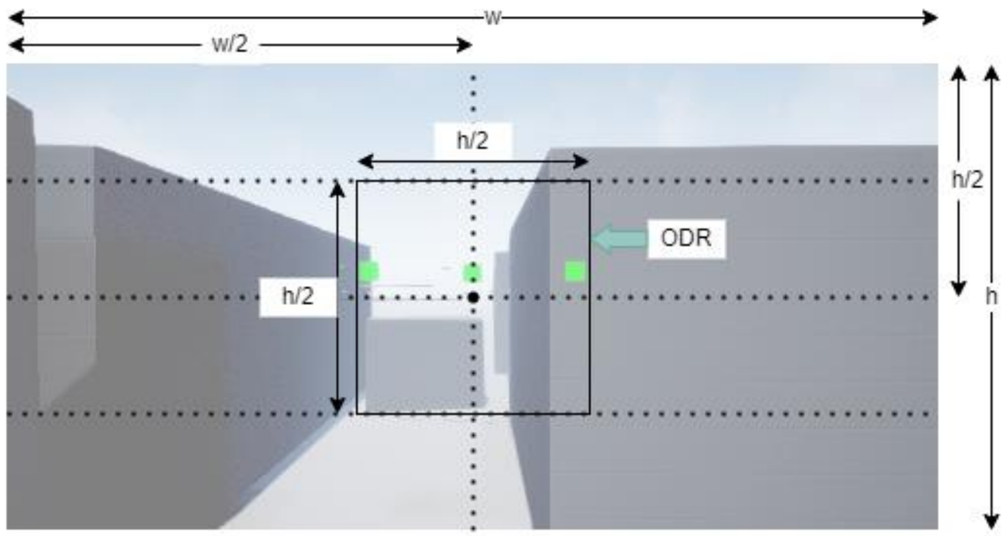


Figure 10: Obstacle Detection Region

3.3.2 Obstacle Detection Algorithm for Visual Camera

Common obstacles that can be found in low flight applications are the primary interest of this research. Thin objects such as cables can be often missed by active sensors, especially in cluttered environments. Visual cameras with a suitable processing algorithm can be effective in such cases in detecting these types of obstacles. Image segmentation and edge detection based approaches are explored in the literature in purely image based obstacle detection situations (Parappat *et al.*, 2014; Zhou *et al.*, 2017).

A simple image processing-based algorithm is developed to estimate the presence of thin obstacles, a category of objects that can be often missed by active sensors when it exists in the environment. The sample result is shown in Figure *11*. As depicted in the flow chart in Figure *12*, this algorithm performs a series of image processing and morphological operations in a feed-forward manner to extract features of interest. This algorithm is primarily developed to demonstrate the working of the proposed framework. This area can be further improved and extended by incorporating various image processing or deep learning algorithms to improve accuracy and robustness.

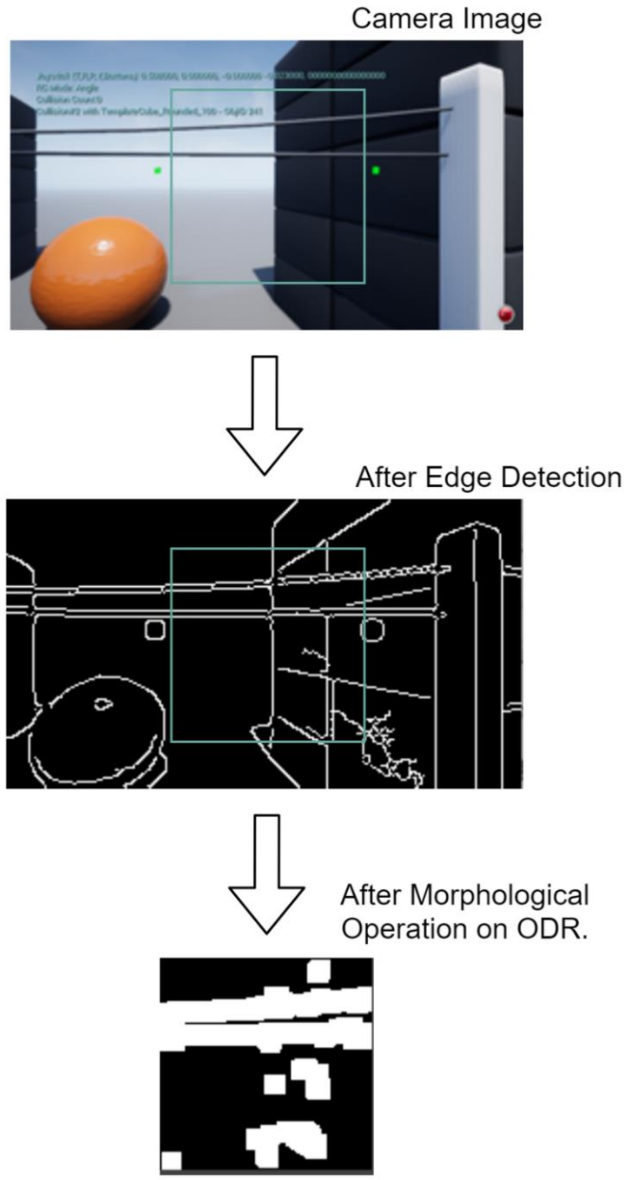


Figure 11: Detection of Simulated Cable using Image Processing

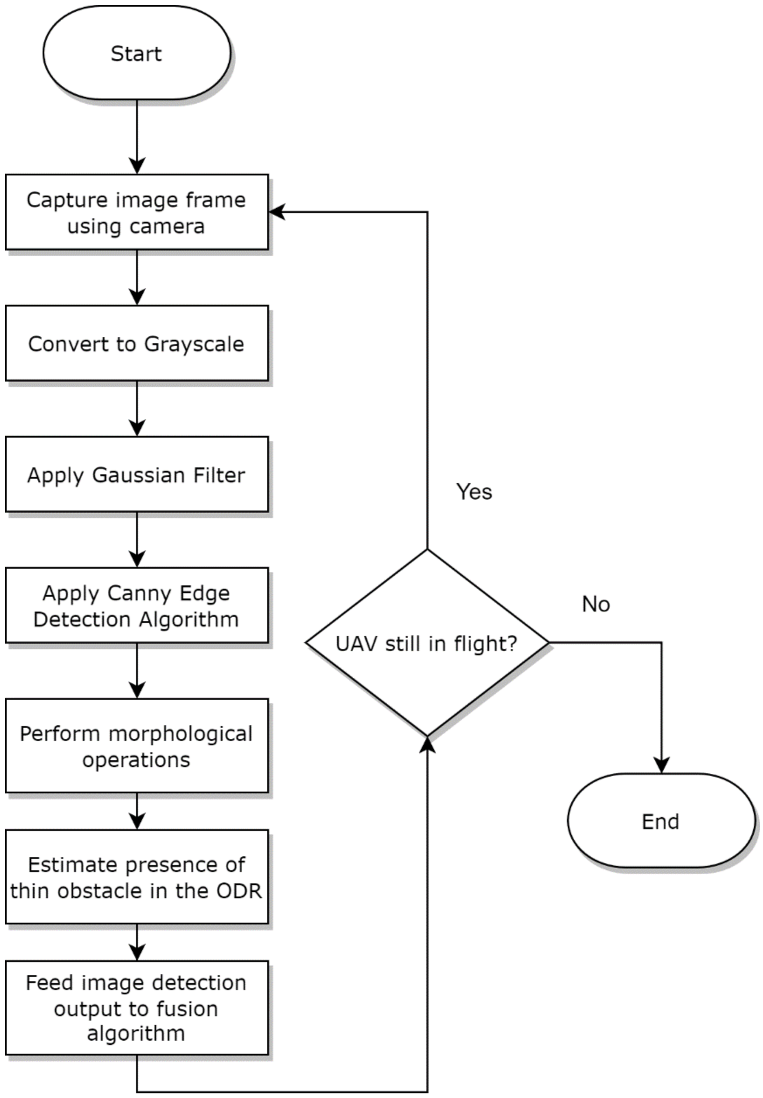


Figure 12: Feed Forward Flow of Image Processing Algorithm for Obstacle Detection

The output of the visual based detection algorithm is given by a value between 0 and 1. The value being closer to 1 shows a high degree of confidence in the presence of obstacles and vice versa. According to this research work, visual based detection focuses on thin obstacles, a category of obstacles that are difficult to detect using active sensors like distance sensors. The approach taken here is to determine the detection value using the occupancy of pixels in the ODR.

An example input frame to the occupancy calculation is shown in Figure *11*. According to the image processing algorithm used (Figure *12*), pixels that are represented by white colour in the binary image are the obstacle or foreground pixels, while the black pixels belong to the background. The certainty of the presence of obstacles is calculated using Equation *1*.

$$Presence\ of obstacle = \frac{Number\ of\ foreground\ pixels}{Total\ number\ of\ pixels\ in\ the\ ODR}$$

Equation 1: Formula for Obstacle Detection in Image Frame

As the monocular image does not realize the depth to the obstacle, it is a challenge to clearly identify how close the threat is to the subject. Hence, the value from Equation *1* is an indication of whether an obstacle is visible from the perspective of the UAV.

Proposing a state-of-the-art thin obstacle detection algorithm is not clearly the focus of this thesis. As stated in the design assumptions, the algorithm used in this proof of concept has limitations and only applicable within the simulation environment conditions used in this research. If the algorithm is used in complex environments or in real-world, it can classify the pixels incorrectly. Therefore, the intent of detecting only the thin obstacle fails. Moreover, the detection is depended on the physical dimensions of the thin obstacle, surface features and shape. The monocular camera sensor's resolution also plays a part in the detection. This is the key area to focus on when adopting this framework for detecting thin obstacles in real world.

3.4 Obstacle Detection using Distance Sensors

Although monocular cameras are good at extracting complex features, it lacks the ability to sense depth (Hatch, Mern and Kochenderfer, 2021). Due to that reason, typically cameras are used with some form of distance sensors in combination to get more meaning out of the perceived information. Unlike cameras, the data from active sensors do not contain unnecessary information that requires filtering. Hence, these data are known as directed data. This eliminates the requirement for complex pre-processing of the data.

The framework proposed in this thesis is limited to forward obstacle detection. Therefore, the preliminary design uses three sensors in combination to cover the horizontal region in the ODR. These distance sensors are used to estimate the distance to obstacles in the proximity of the UAV.

3.4.1 Sensor Placement and Coverage

As shown in Figure *9*, the proposed framework uses three distance sensors (D_{LEFT}, D_{CENTER}, and D_{RIGHT}) which are attached to the UAV in a forward-facing way and positioned to have coverage on horizontally distinct areas of the obstacle detection region. These distance sensors are angled (yaw angle) 1 degree apart and measure the distance to obstacles that intersect the path of the UAV.

IR LED ToF based distance sensor was the sensor of choice for this framework design due to the advantage of supporting FOV as opposed to point measurements in laser-based sensors. This technology was not explored in the existing literature. To simulate this framework in AirSim, the distance sensor was configured based on the range characteristics of the IR LED ToF sensor to mimic that in the simulation environment.

3.4.2 Obstacle Detection Algorithm for Distance Sensor

The objective of the obstacle detection algorithm is to fuse the data from the coordinated distance sensors D_{LEFT}, D_{CENTER}, and D_{RIGHT} and estimate the distance to the obstacle in the path of the UAV. The arithmetic averaging method is used to fuse these measurements to obtain a single value. Let M_{LEFT}, M_{CENTER}, M_{RIGHT} and are distance measurements from the individual sensors. Then the average or mean distance is calculated using Equation *2*. A similar approach was used by Shitsukane (2018).

$$Mean\ or\ \overline{X} = \frac{M_{LEFT} + M_{CENTER} + M_{RIGHT}}{3}$$

Equation 2: Average Distance Measurement

The averaged distance measurement is mapped to a value sandwiched between 0 and 1 to simplify the handling in the fusion process. The range is divided into three equal sub ranges to calculate the fitting detection level indicating the correct level of threat in the common scheme. The pseudocode of the algorithm used to obtain the corresponding mapped value to the distance measurement is given in Figure *13*. The function accepts the averaged distance as a parameter.

```
MAX_DISTANCE ← 15 // maximum range of the sensor
H_MAX_DISTANCE ← MAX_DISTANCE / 2.0

Function mapped_value_distance(distance_)
If distance_ >= MAX_DISTANCE: //FAR
   value_for_fuzzy = 0
Else If:
   If H_MAX_DISTANCE <= distance_ < MAX_DISTANCE: //THRESH
      dist_to_check_ ← distance_ - H_MAX_DISTANCE
      value_for_fuzzy ← (1 / 3.0) + (1 / 3.0) * (1 - (dist_to_check_ / H_MAX_DISTANCE))
   Else If 0.0 <= distance_ < H_MAX_DISTANCE: //NEAR
      value_for_fuzzy ← (2 / 3.0) + (1 / 3.0) * (1 - (distance_ / H_MAX_DISTANCE))
Return value_for_fuzzy
End Function
```

Figure 13: Pseudocode for Fuzzification of Crisp Distance Value

The pilot must be warned about the obstacles that are located closer relative to the UAV compared to the obstacles that are far away. Based on that notion, a safe boundary distance within the sensor's range is selected as the upper bound. Any measurements from the obstacles beyond the upper bound are suppressed. Detections below the upper bound are calculated and classified accordingly.

These variables can be tweaked depending on used sensor options and required precision. The output of the mapped value is then fused at the fusion layer together with the estimate from the image detection value to get a better estimation of the obstacle.

3.5 Sensor Fusion

3.5.1 Choice of Fusion Method

As discussed in section 2.5, Sensor Fusion is considered as an effective approach when using data from heterogeneous sensor sources. The sensor fusion layer of this proposed framework works by fusing outputs from the individual imaging and distance sensor modules and provides a more robust result that would not be possible if the sensors were used individually.

Figure *14* illustrates the framework in a high-level diagrammatic form with inputs and outputs.

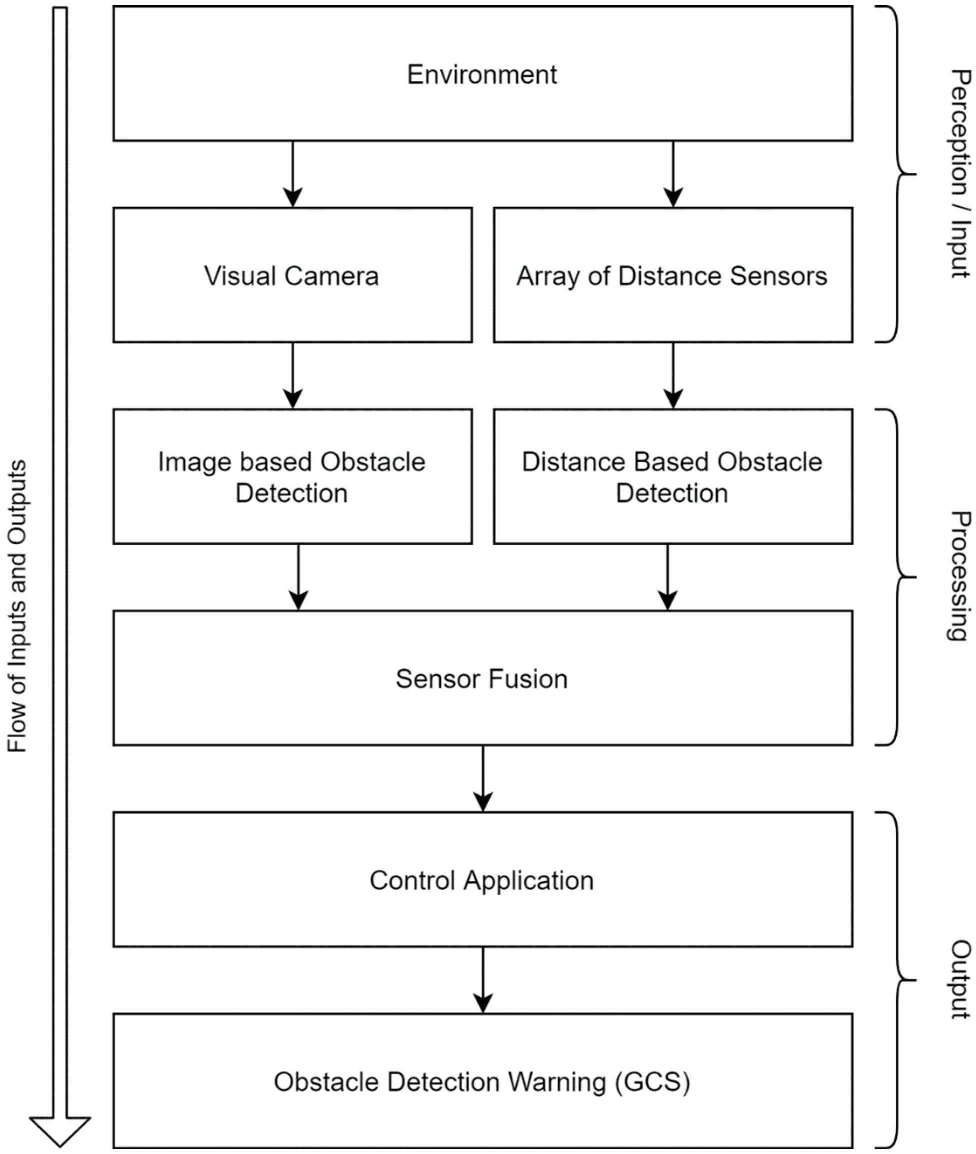


Figure 14: Block Diagram of the Proposed Framework's Architecture

Data level fusion requires compatible types of sensors. This method is not applicable for the proposed framework as the image features and distance measurements are of incompatible types. Feature level fusion also possesses a similar challenge with mapping the features from heterogeneous data to a feature map. Decision fusion is considered more robust over fusion at data or feature levels (Dasarathy, 1991). Moreover, decision fusion is suitable when dealing with data heterogeneous sensors when the data cannot be combined in the same feature vector. Decision level fusion or high-level fusion is considered practical for this proposed obstacle detection framework. One of the main advantages that are seen with the level of fusion is that it can be easily extended to incorporate more components that can further enhance this framework's performance.

3.5.2 Fuzzy Logic and Estimating Alert Level

Fuzzy logic is adopted as the core decision making method of this proposed sensor fusion framework. Figure *15***Error! Not a valid bookmark self-reference.** illustrates the functional blocks of the Fuzzy Inference System (FIS).

The type of FIS used in the proposed sensor fusion-based obstacle detection framework is Mamdani type. This method was originally created as a control system by combining a set of linguistic rules obtained from experienced human operators (Mamdani and Assilian, 1975).

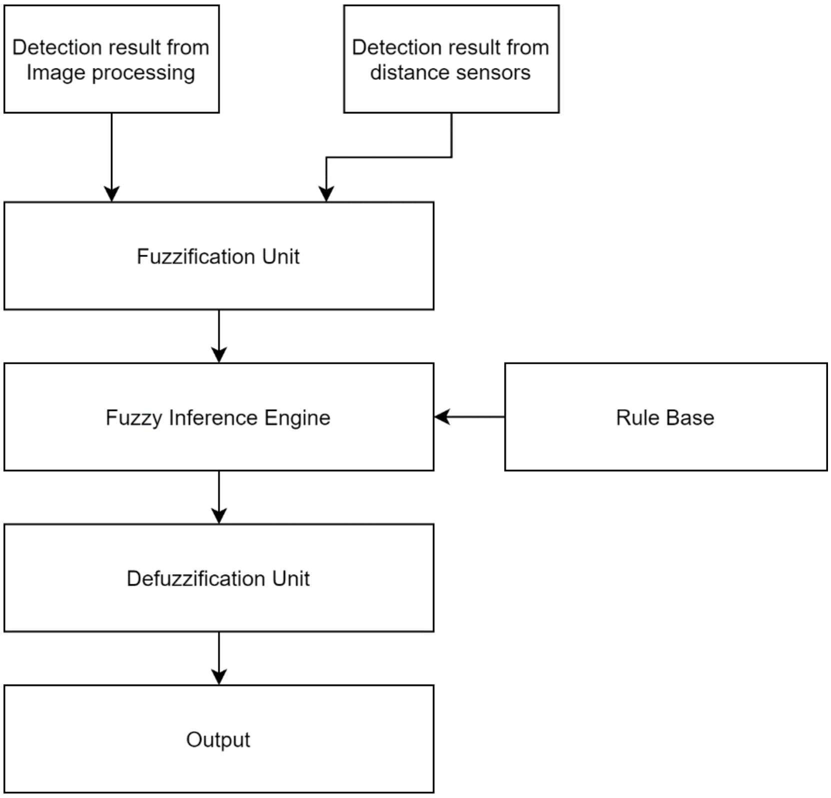


Figure 15: Fuzzy Inference at Sensor Fusion Layer

3.5.3 Fuzzification of Inputs

The inputs to the FIS are the individual outputs from the experts, visual based detection module and distance sensor-based detection module. These crisp values go through the fuzzification to be mapped to their corresponding input fuzzy set. The mapping between crisp values and the input fuzzy set values is detailed in this subsection.

Fuzzification of Visual based Detection Output

As previously described, the visual based obstacle detection module outputs a value between 0 and 1 based on the certainty of the presence of an obstacle. Due to the inability in determining the depth using the monocular image-based approach, it is a challenge to detect how close or far the obstacle is to the subject. Furthermore, the output from the image processing showed inaccuracies due to the noisy pixels. Due to these reasons' threshold was performed on the crisp output value as mentioned in Table 4. During the initial evaluations, the value for the variable threshold = 0.2 gave acceptable results for the proposed obstacle detection framework. The value is obtained by testing the algorithm under the presence of multiple thin objects (two or more) in a single frame to minimize erroneous results.

The fuzzy set label NODET denotes that there is no obstacle in the ODR, while DET denotes the presence of an obstacle.

Table 4: Fuzzification of Image-based Detection Value:

Fuzzy set label	**NODET (no detection)**	**DET (detection)**
Crisp output	Value < Threshold	Value >= Threshold

Fuzzification of Distance Sensor Detection Output

The output from the distance sensor-based detection module is a value given the range between 0 and 1 based on the confidence of obstacles present in the ODR. The range is divided into three equal sub ranges namely as mentioned in Table 5. Each sub range is labelled after a corresponding fuzzy set value. The calculated crisp value from the algorithm in Figure *13* seamlessly fits the fuzzification scheme and can be classified without any additional modification.

Table 5: Mapping of Distance Measurements to Common Scale:

Fuzzy set label	**FAR (far)**	**THRESH (threshold)**	**NEAR (near)**
Distance Range	Greater than 10 meter	Between 5 – 10 meter	Less than 5 meter
Mapped range	0	~0.3 – 0.67	~0.67 – 1

3.5.4 Rule Base and Inference

The rule base is the key functional component of the FIS. Fuzzy rules are a collection of linguistic statements that describe how the system should decide about controlling an output. The rule base for this sensor fusion framework is created according to the obstacle avoidance information provided by the inputs. The Mamdani-type inference system expects the output membership function to be a fuzzy set. The output fuzzy set here is created for alert level, which indicates the level of warning that must be raised to the pilot based on the obstacles in the proximity. The linguistic values of the output fuzzy set are HIGH, MEDIUM, and LOW. Once the inputs are received, the individual rule strength is determined by combining the fuzzified inputs based on the fuzzy rules. Next, the consequent of the rule is estimated by combining the individual rule strength and the output membership function. The output distribution is obtained by combining all the consequents. Finally, the crisp output value for the combined detection also called the alert level is obtained.

Given the input fuzzy variables $INPUT_{IMAGE}$ and $INPUT_{DISTANCE}$ and output fuzzy variable $OUTPUT_{ALERT}$, all the rules used in the proposed framework are shown here,

- IF ($INPUT_{IMAGE}$ = DET) THEN ($OUTPUT_{ALERT}$ = HIGH)
- IF ($INPUT_{IMAGE}$ = NODET) and ($INPUT_{DISTANCE}$ = FAR) THEN ($OUTPUT_{ALERT}$ = LOW)
- IF ($INPUT_{IMAGE}$ = NODET) and ($INPUT_{DISTANCE}$ = THRESH) THEN ($OUTPUT_{ALERT}$ = MEDIUM)
- IF ($INPUT_{IMAGE}$ = NODET) and ($INPUT_{DISTANCE}$ = LOW) THEN ($OUTPUT_{ALERT}$ = HIGH)

The implementation of the FIS of the proposed sensor fusion framework is done using Simpful, a Python library for fuzzy logic reasoning (Spolaor *et al.*, 2020).

The plots of membership functions of each linguistic variable contained in the fuzzy system are shown in Figure *16*.

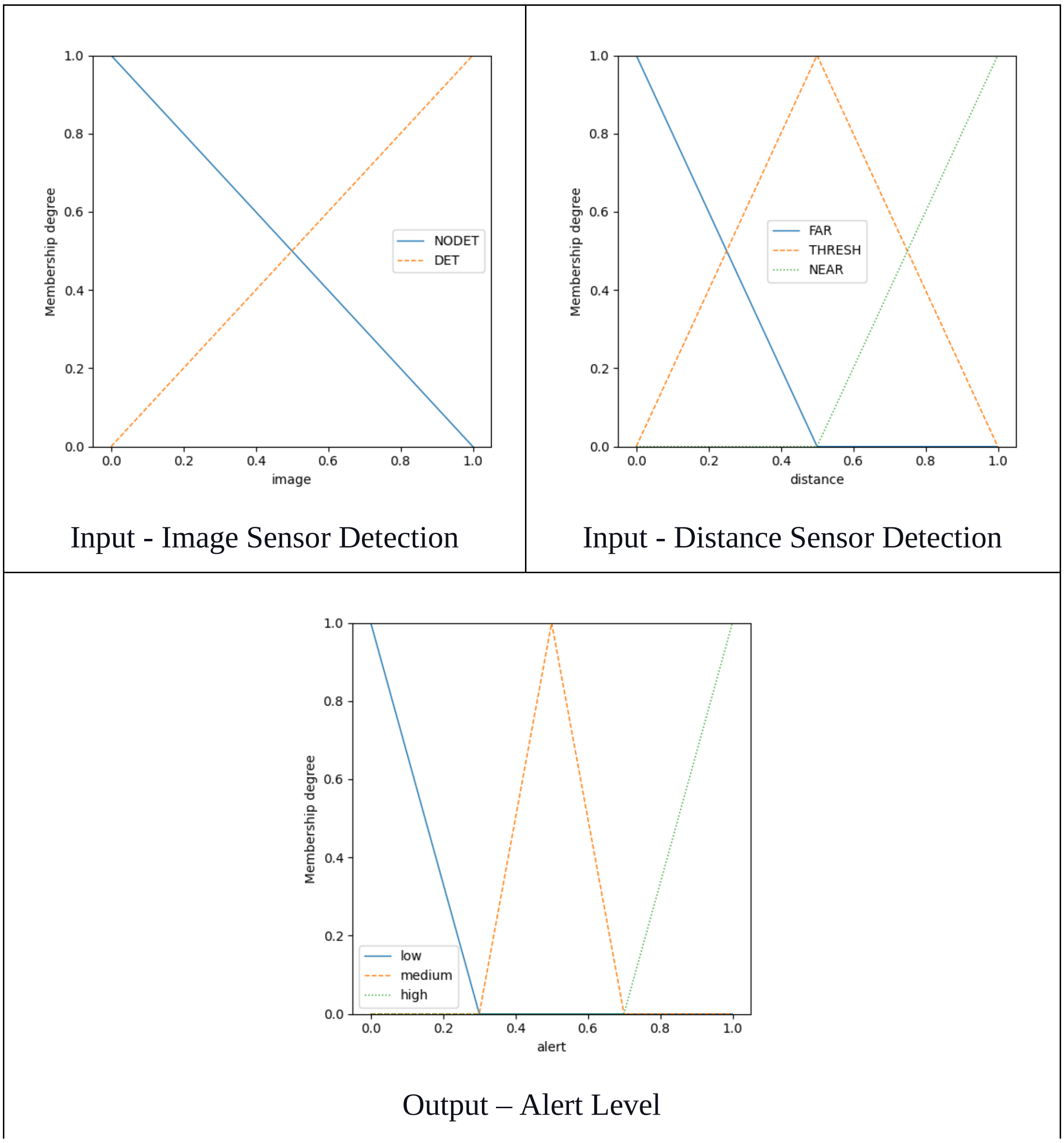


Figure 16: Membership Functions of the Linguistic Variables contained in the Fuzzy System

3.6 Control Application

The control application is the interface between the pilot and the core obstacle detection approach. The control application handles the sensor inputs and implements the warning interface. It is responsible for providing alerts to the pilot about the obstacles based on the fused detection value resulting from the obstacle detection approach.

In a study conducted by Simon (2006) on the learnability of advanced driver assistance systems, it was observed that the drivers who participated in the experiment felt absolutely sure with acoustic and visual alerts in terms of learning the system and when to intervene the control of the vehicle. Simon also highlighted that visual warning, and an acoustic alert is considered effective when the timing is the most important factor. This characteristic aligns with the objective of the proposed framework. Therefore, the warning interface of the proposed framework is developed with a graphical warning display and an auditory warning. Gauci et al. (2018), Theuma et al. (2017) and Ramasamy et al. (2016) have used a graphical display of warnings in their respective approaches targeting teleoperated UAVs. Additionally, Ramasamy et al. have used auditory warning. In recent research by Solovey, Ryan and Cummings (2021) haptic feedback is discussed in the context of alerting the operators.

The fused output crisp value from the obstacle detection algorithm is a numeric value sandwiched between 0 and 1. The interval is equally subdivided into three sub regions, each corresponding to different threat levels defined in the algorithm i.e., low, medium, and high. The acoustic alert switches on when the detection value reaches high. Therefore, the pilot must immediately take action to navigate the UAV without colliding with the obstacle. The signals switch off as the pilot moves the UAV away from the threat. The level to provide auditory alerts can be changed in the algorithm depending on the requirement.

The visual warning display intends to provide the warning in textual form using colour coded labels. Furthermore, the interface algorithm uses individual sensor detections in combination with the fused output to additionally interpret the type of obstacle ahead through visual display. This allows the pilots to make informed manoeuvring to avoid obstacles. An example warning display is shown in Figure 17. Table 6 summarizes the alerts provided by the warning interface.

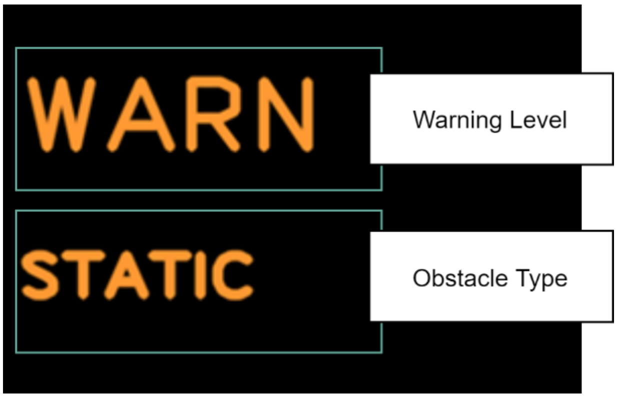


Figure 17: Graphical Warning Display

Table 6: Summary of Alerts Provided by Warning Interface:

Threat Level	**Acoustic Alert**	**Label and Colour Code for Visual Display**	**Example**
LOW	No	CLEAR (Green)	
MEDIUM	No	WARN (Orange)	
HIGH	Yes	ALERT (Red)	

In summary, this chapter summarized the methodology of the proposed sensor fusion-based obstacle detection framework. The approach used complementary sensors, a visual camera and distance sensors to detect obstacles. The fusion of the inputs is performed using fuzzy logic. Through the preliminary testing and modification, the obstacle detection approach yielded positive results. The individual building blocks of the framework have been detailed well so that it allows any users to build or extend the framework to better suit their requirements.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Results

The results section is dedicated to present the evaluation results of the sensor fusion-based obstacle detection framework. The framework is the primary outcome of this research. To validate the framework a proof-of-concept is created, and the performance of the approach is assessed and validated. Due to the restrictions with the COVID-19 pandemic, the real-world testing using actual UAV hardware has been cancelled and the testing was primarily conducted using a simulation platform.

In real-world situations, UAVs can be confronted with various types of obstacles. These obstacles can be in any form or shape and the obstacle detection system of the UAV should be able to detect them and warn the pilot in real-time so that they can effectively perform the avoidance manoeuvre and navigate the UAV to avoid the obstacle. Although it is easier for humans to perceive the environment and sense obstacles, it is a difficult task to automate. Because not all sensors or methods can detect every object type in the real world. This section further elaborates the evaluation strategy and results of this work.

Right now, there are no widely accepted benchmarking methods for evaluating or comparing the performance of UAV collision avoidance approaches. Therefore, existing works have designed their own strategy for evaluation. Nous et al. (2016) discussed that developing a standardized evaluation framework is challenging due to aspects such as a high variety of operating environments and the collision avoidance methods are developed based on different requirements. An attempt to propose a benchmarking framework was done by Montcel *et al.* (2019) which can be used to evaluate the performance of quadrotors and estimate the probability of successful attempts using simulation experiments. Montcel further validated that there is a clear gap for a generic testing framework to evaluate collision avoidance approaches.

Using repeated trials and estimating the capability of the approach in avoiding the obstacle is a method commonly seen in the evaluation of autonomous collision avoidance approaches. This method was considered not suitable in evaluating the proposed sensor fusion framework as this target piloted UAVs. The obstacle detection performance and usability of the framework were identified as the main areas for evaluation.

4.1.1 Simulation Setup and Scenarios

Microsoft AirSim (Shah *et al.*, 2018) was selected as the simulation platform for the evaluation. AirSim offers the ability to virtually test the obstacle detection approach using the multirotor and available sensors. It is capable of providing a high fidelity simulation experience using different environments that are built using Unreal Engine (*Unreal Engine*, no date). Simulation played a vital role in the overall work. Using simulation is beneficial as it is less expensive and enables reproducibility of the tests. All the simulation experiments and calculations were performed on a laptop computer with Intel(R) Core(TM) i5-8250U CPU @ 1.60GHz CPU, 16GB of RAM, and M.2 SSD Storage.

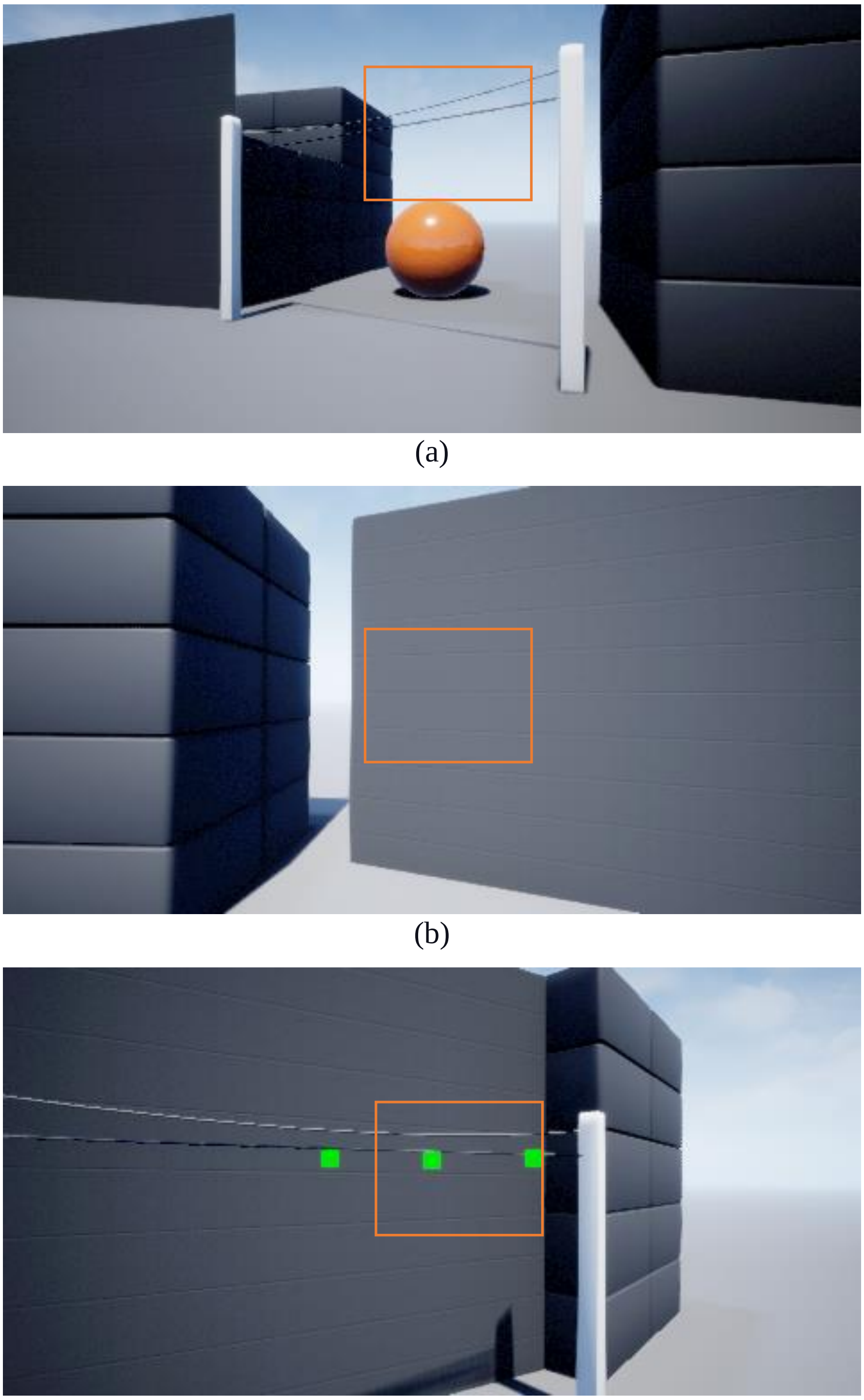
Based on the focus of the proposed obstacle detection framework, obstacles and simulation setups are created to evaluate the performance. Table 7 summarizes the main scenarios that are covered in the evaluation of this research. These scenarios have significance in what obstacles that the proposed framework attempts to detect. The result from this evaluation is considered important when adopting the proposed framework.

The main types of obstacles that are focused on the evaluation are mainly of two categories. The sample simulation setups were created by modifying the blocks environment, packaged with AirSim.

- Type A – Thin Obstacles: Type of obstacles which are often undetected by active sensors like distance sensors e.g., high tension cables and power lines.
    - Created using cable component in Unreal engine. The obstacle width were 7 units in measurement (cm).
- Type B – Large Static Obstacles: Type of obstacles which are detectable using distance sensors and have sufficiently large surface area e.g., buildings.

Table 7: Evaluation Scenarios and Obstacles:

	Scenario 1	**Scenario 2**	**Scenario 3**
Foreground Obstacle Type	A	B	A
Background Obstacle Type	N/A	None	B
Example simulation setup of obstacle	Figure 18 (a)	Figure 18 (b)	Figure 18 (c)



(a) (b) (c)

Figure 18: Simulation Setup of Obstacles

4.1.2 Performance Evaluation of Obstacle Detection Framework

The objective of the performance evaluation is to evaluate the proposed heterogeneous sensor fusion-based obstacle detection framework on how well it can detect obstacles by conducting a series of simulation-based experiments. This section summarizes the results. Using various metrics collected during these experiments, it is attempted to establish a quantitative understanding of the proposed approach.

As elaborated in the methodology the proposed framework detects obstacles by fusing inputs from visual camera and distance sensors. The line graph in Figure *19* illustrates the change in the output detection value when an obstacle is detected using a series of images of ODR using 100 simulated runs. For this example, the algorithm is configured such that 20% or more occupancy of foreground pixels in the ODR is considered as a presence of a Type B obstacle. Hence, the fusion layer produces a stronger detection value (0.9) after 0.2 in the x-axis. Otherwise, a low output value is given. The distance sensor input was maintained constant through these simulated runs.

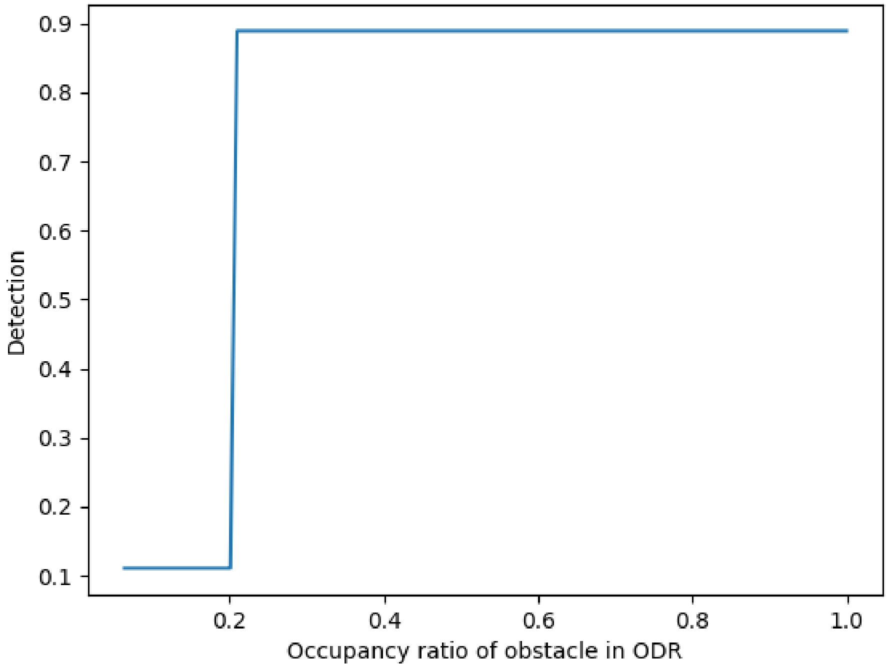


Figure 19: Obstacle Detection with Imaging using Variable Occupancy Values

Similarly, another 100 runs were performed using variable values for distance sensor input. The objective here is to get an understanding of how distance-based detection performs with the change in distance to obstacles in the environment. The image detection was defaulted to 0 to simulate no detection through the image. This result is obtained using a distance sensor configuration that has a maximum range of 10 meter. As illustrated in Figure *20*, a gradual decrease in detection value can be observed as the distance to the obstacle increases from 0 to 10 meter. As the approach does not consider the obstacles that are beyond the maximum range as a threat, a drop in the detection value is seen with the increase in distance.

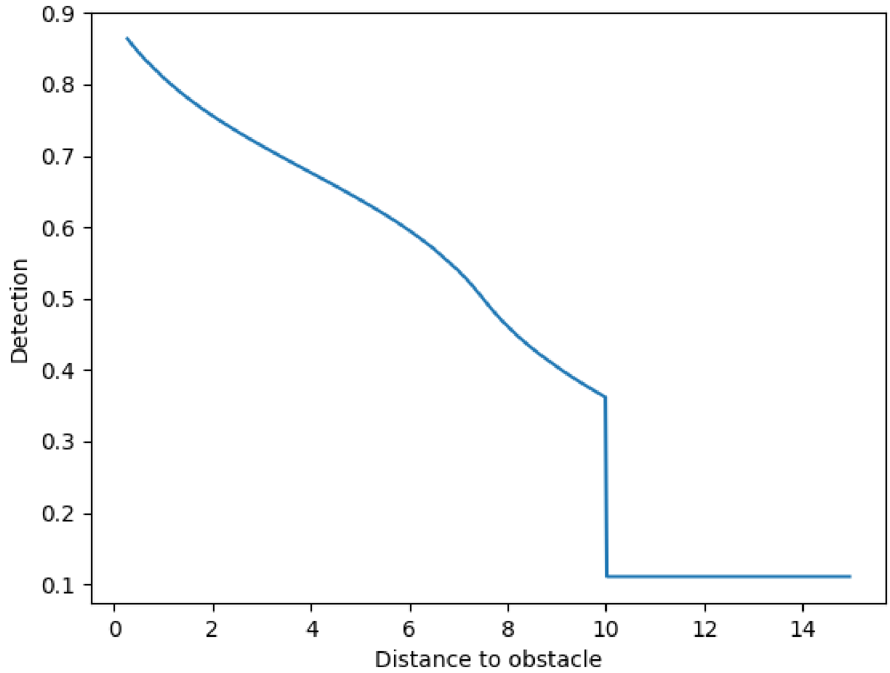


Figure 20: Obstacle Detection with Variable Distance

By comparing the graphs Figure *19* and Figure *20*, it can be observed that the inability to sense the distance to the obstacle in the ODR using image based detection is clearly reflected in the results. The framework gives precedence to the obstacle detected using the image as it has a limitation with realizing the actual distance to the obstacle using imaging.

Simulated flight experiments were conducted on three obstacle scenarios as mentioned in Table 7. The idea here is to autonomously launch and fly the UAV towards the obstacle and observe how well the obstacle is detected using the proposed obstacle detection framework. The simulated flight is started from a point and flown towards the obstacle in a straight path. The flight was set to a constant speed of 5m/s. The UAV was maintained at a fixed altitude and in the forward flight mode. The configurations of the sensors used in this experiment are mentioned in Table 8.

Table 8: Configuration of Sensors used in Simulation:

Sensor	**Configuration**
Visual Camera	Resolution: 480 x 240 FOV: 90°
Distance Sensor	Max Range: 15 meter

The first experiment was to fly the UAV towards the thin obstacle (Scenario 1) the category of obstacles that are detected using image processing in the proposed approach. As this category of obstacle cannot be detected using a distance sensor, the Euclidean distance method was used to obtain the ground truth distance between the UAV and the obstacle for comparison. The fused detection output, actual distance and timestamp were recorded during the simulated flight. The results are plotted in the dual-axis graph shown in Figure *21*. To simplify the labelling the x-axis represents the corresponding frame number in which the metrics were recorded as opposed to timestamp.

A stronger detection response of greater than 0.8 can be seen as the obstacle gets closer to the UAV. The image-based detection is highly sensitive to noise as opposed to distance sensor-based detection. This contributed to the noisy responses during frames 393, 457-463 and 480-492. High detection output has resulted when the actual distance to the obstacle was 16 meter. As the UAV gets closer to the obstacle, the high detection level was maintained until the distance reached approximately 4 meter.

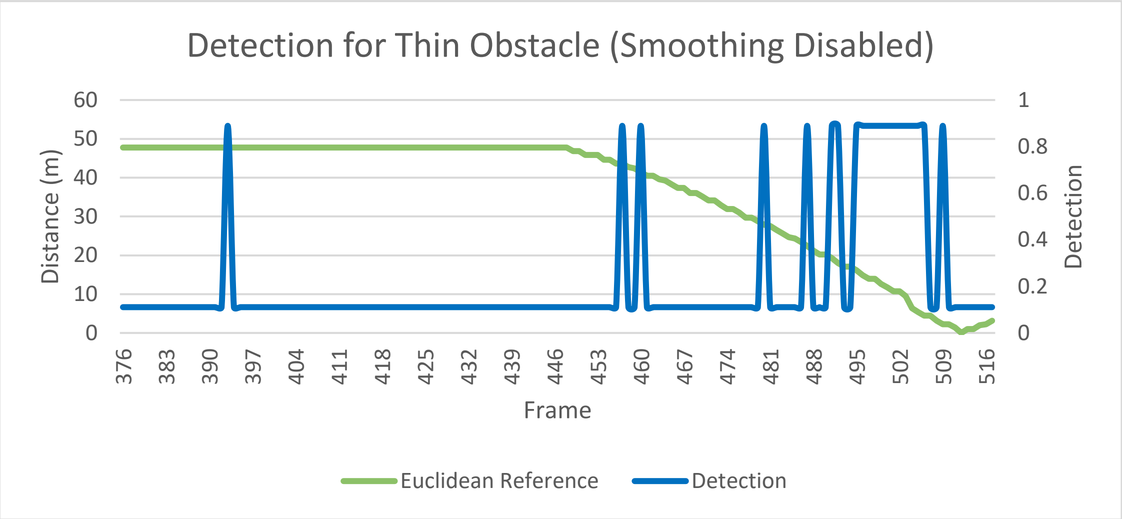


Figure 21: Simulated Flight Experiment for Thin Obstacle (Smoothing Disabled)

Although the approach resulted in the intended detection, the noise in the output can contribute to false alarms. The moving average filtering was performed on the result to minimize the influence of noises in the final output. The smoothing was performed by averaging the last three detections. Moving average is simple and has an easy implementation. This approach is used in reducing the impact of noises (Amposta, 2020; Brett Garberman, 2020). The same experiment was conducted again by enabling smoothing and the result is shown in Figure *22* for the same parameters. Smoothing contributes to minimizing the false detections The smoothed output eliminates the impact due to noisy values and it makes the detection due to the obstacle distinguishable from the noises. The strong obstacle detection can be observed around the same distance to the obstacle as the previous experiment, from 14 meter down to 4 meter. The remaining results mentioned in this chapter are all conducted under smoothing enabled. Under the experimental condition, it was observed that the smoothing did not significantly impact the performance. Furthermore, the imaging-based detection produced erroneous reading when the actual distance is less than 4 meter.

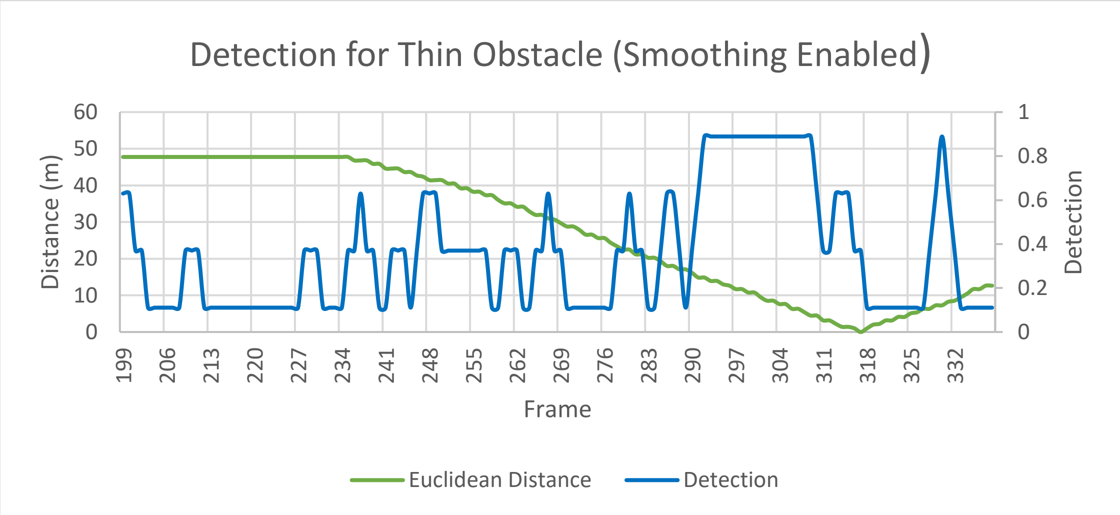


Figure 22: Simulated Flight Experiment for Thin Obstacle (Smoothing Enabled)

The next simulated flight experiment was conducted to evaluate the performance on Scenario 2. There are not any objects in between the large static obstacle and the UAV. A cube object represents an obstacle in this case. Additionally, a distance sensor was attached to the simulated multirotor to measure the actual distance to the obstacle with the objective of providing the ground truth. The static obstacles are intended to be detected by the distance sensors used in the proposed sensor fusion framework. The graph in Figure *23* shows the fused detection of the approach against the actual distance. After the actual distance of 10 meter, the detection gradually increases as the UAV gets closer to the obstacle. The occasional noisy detections were resulted due to false detection of the image processing algorithm. However, the smoothing helped in keeping the false detection low.

The final simulated flight experiment was conducted on the complex scenario where a thin obstacle is in the foreground while a static obstacle is in the background (Scenario 3). The two obstacles were set up within a short distance such that both obstacles fall within the range of distance sensors. Same metrics as in previous experiments were recorded which includes ground measurements from reference distance sensor (static obstacle) and Euclidean method (thin obstacle). The results are shown in Figure *24*.

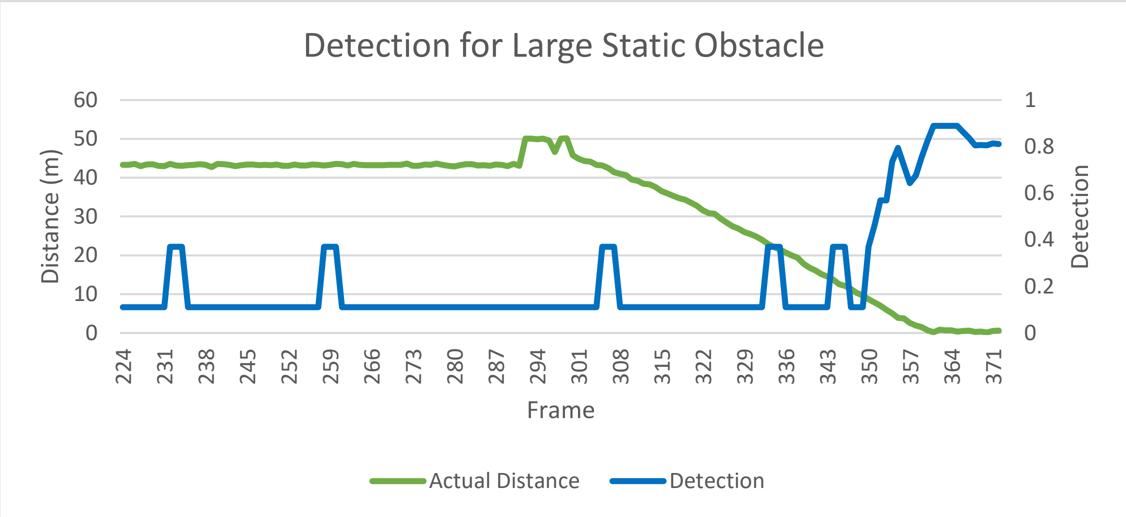


Figure 23: Simulated Flight Experiment for Large Static Obstacle

The “Distance Reference” represents the actual distance to the static obstacle. The “Euclidean Reference” represents the distance to the thin obstacle. The expectation from this experiment is that the image-based detection must be given precedence over the distance sensor-based detection. The reason for this is due to the limitation of image-based detection value not representative of the actual distance to the obstacle. The obstacle is detected at approximately 8 meter distance to the obstacle and a high detection value is obtained. The detection value is maintained at the highest value as the UAV gets closer to the obstacles.

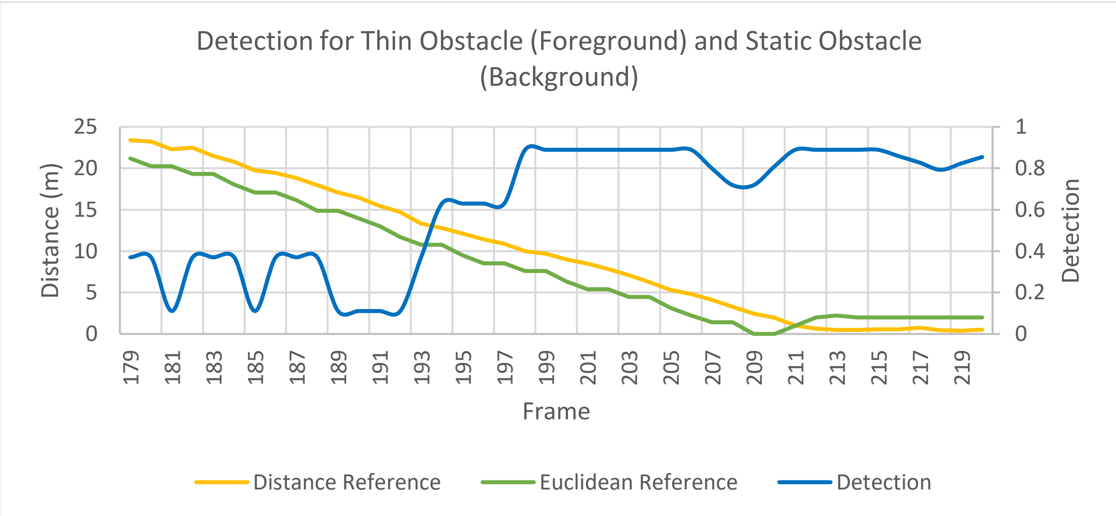


Figure 24: Simulated Flight Experiment for Thin Obstacle and Large Static Obstacle

4.1.3 Profiling Results of Obstacle Detection Algorithm

The algorithm's resource consumption must be evaluated when designing a framework for an environment that is typically resource constrained. UAVs have limitations with onboard power. Furthermore, the obstacle detection application must provide feedback in real time. Hence, the algorithm must have a good time efficiency. The memory consumption and execution timing are the main metrics that were focused on the proposed framework.

The proof-of-concept is developed using Python language. The Python modules memory-profiler and in-built module cProfile are used to profile the algorithm. The profiling was performed on odcontroller.py, the entry point and the main script that implements the obstacle detection algorithm. Furthermore, the functions that are of interest in profiling are summarized with their purpose in Table 9.

Table 9: Python Scripts and Purpose:

Script Name	**Function Name**	**Purpose**
odcontroller	detect()	Main entry point. Implements the detection algorithm.
odimg	detect_cable()	Implements image processing algorithm to detect presence of thin obstacles.
odfuzzy	infer()	Implements fuzzy logic and rules. Performs inference.

The algorithm was executed for 1000 simulated runs to profile. Randomly generated distance values (3) and images recorded from the simulation environment were used. Smoothing was disabled. The profiling results are discussed in the subsections.

Execution Time

The results from the simulated run are visualized using SnakeViz, a browser based graphical viewer for the cProfile output. The execution timing results are shown in Figure *25*.

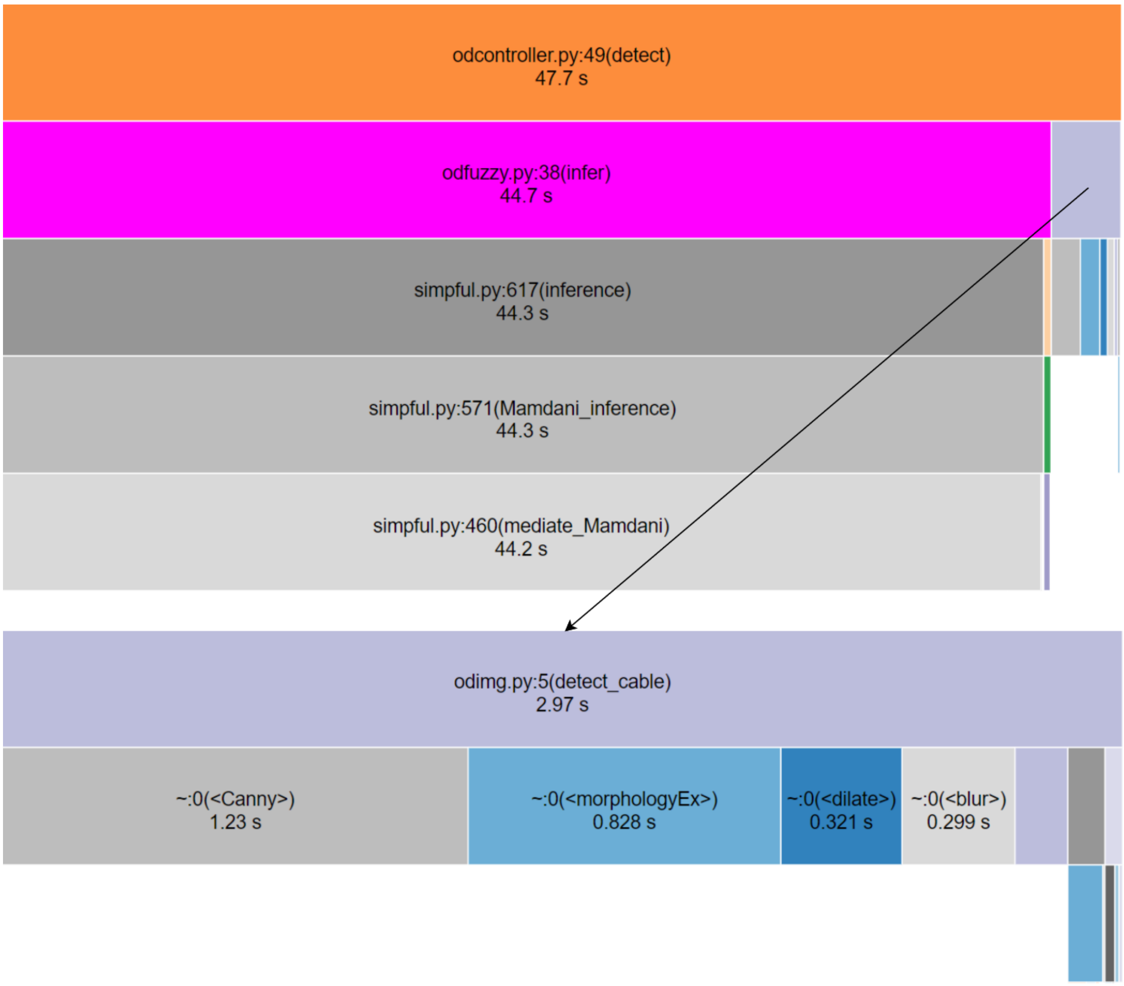


Figure 25: Execution Time Report of the Obstacle Detection Algorithm

Most of the execution time of the root function for detection is taken up by the fuzzy inference and image processing algorithm. Suppose the framework is implemented as per the objective of this proposed research, there will not be a significant change in this execution time due to the chosen library. However, optimizing the fuzzy inference layer and the impact of the growing rule base can be a direction for future work.

The image processing algorithm is another identified hotspot in the proposed framework. During the simulated profiling run the algorithm consumed 2.967s for 1000 calls with an average per call timing of 0.002967s. The image processing algorithm used in the proof-of-concept is developed based on design assumptions and to conceptualize the idea and is not suitable to be directly used in real world situations. Therefore, the algorithm must be replaced using a suitable image processing algorithm or by incorporating deep learning methods. The selection of the approach can cause a considerable impact on the algorithm’s performance due to the required pre-processing of image data.

The fusing of distance sensor inputs is implemented as part of the odcontroller's (detect) internal logic. Additionally, the controller is responsible for constructing and returning the response. The actual time spent on the execution of internal functions is minimal compared to called functions. This indicates that increasing the number of distance sensor inputs will not significantly impact the execution time of the algorithm. This can be applicable when incorporating sensors that provide directed data that does not require much pre-processing. The actual time spent on the internal function during the experiment is as follows,

$$\text{Average actual time spent on internal function} = \frac{\big(47.66 - (44.66 + 2.967)\big)}{1000}$$

$$= 0.000033\ seconds$$

Memory Consumption

When implementing the obstacle detection algorithm on an onboard companion computer memory consumption is an important characteristic to consider. As the algorithm extends, optimizing the memory consumption can speed up the execution to an extent. The proposed framework was profiled using a memory profiler and results are discussed in this section.

The profiling results did not exhibit any significant memory issues. This is due to the algorithm not having any memory intensive operations. The top memory consumed code line was to initialize the fuzzy system (odcontroller). This is a one of initialization that occupies up to < 5MB of memory. Additionally, calling of functions odimg (detect_cable) and odfuzzy (infer) reported memory occupancy of < 1MB per call. Based on the available companion computer options, these memory usages have a considerably lower footprint (Raspberry Pi available in 2GB – 8GB RAM configuration). However, considering that the proposed framework attempts to conceptualize the idea of sensor fusion, there will be opportunities in terms of optimization when implementing.

4.1.4 User Study

A case study evaluation was performed to examine the proposed obstacle detection framework by participating an experienced UAV pilot. The main objective of the study is to obtain a qualitative understanding of the proposed framework in terms of usability. This section presents the details of the case study with the results.

Task

The participant plays the role of the pilot during the study. A simulated course with obstacles is created using AirSim. The layout of the obstacle course is shown in Figure *26*. The obstacles are constructed using cubes and cable objects provided in the Unreal platform.

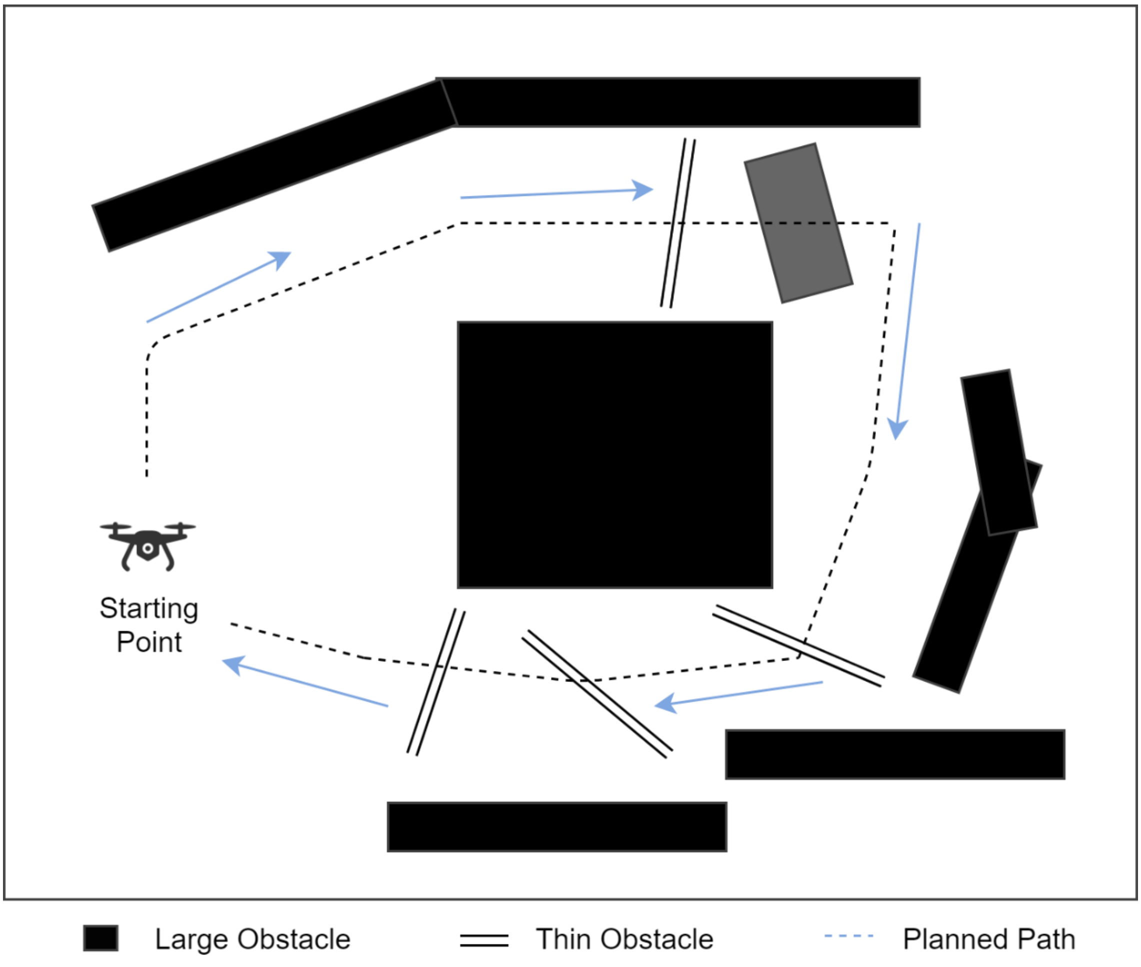


Figure 26: Simulated Obstacle Course for User Study

The pilot is supposed to launch the simulated multirotor UAV from the starting point and navigate the UAV through the course as shown in Figure *26*. The flight must be conducted by using the first-person view mode in the AirSim. When an obstacle is encountered, the pilot must navigate the UAV to avoid making a collision by changing the altitude.

Procedure

The evaluation began with a short briefing about the evaluation plan and the objective using an instruction sheet. Firstly, the pilot will perform an introductory flight in the obstacle course using the remote control. During this step, the pilot is expected to familiarize with the environment. In addition to the path related instruction, the only information provided was on which altitude the UAV must fly. The pilot was provided with a display that shows the current altitude of the UAV measured using a downward-facing distance sensor. The obstacle avoidance is completely manual, and no assistance was given to the pilot.

After the introductory flight, the participant was instructed to enable the obstacle detection and was explained about the functioning of the obstacle detection approach. The participant continues to perform the experimental flight in the obstacle course as the same as the introductory flight. During this step, the pilot uses the Warning Interface as an assistance method.

After the evaluation, the participant was administered the post study questionnaire to reflect on their experience with the obstacle detection framework.

Questionnaire

The post study questionnaire was administered to the participant to get subjective feedback. The questionnaire is the selected evaluation tool for this user study. The questionnaire is used to collect information from the pilot on their experience with the obstacle detection approach. This provides means of subjective evaluation of the proposed framework. The questionnaire used in this research can be found in Appendix A.

The questionnaire has two sections. The first section collected demographic related information. The demographic questions were selected based on several related past works (van Driel and van Arem, 2005; Ažaltovič *et al.*, 2020). A similar approach was adopted by Solovey et al. (2021) too.

Section two of the questionnaire aims to measure the participant’s experience with the obstacle detection framework. This includes questions on understanding of the system, safety in the handling and assessment of the warning interface. The questionnaire used by Simon (2006) in a similar study targeting learnability of an advanced driver assistance system is the foundation of this questionnaire design. The original questionnaire is available in the German language. Hence, it was translated using Google Translate and appropriately modified and adopted into the evaluation of this work. The type of rating scale used for each question was a 7-point Likert-type scale. The digital version of the questionnaire was created using Google Forms and shared with the participant through email.

Participant and Apparatus

The user study was conducted by involving one participant. The recruited participant is 26 years old, male and has UAV piloting experience of 50-60 flight hours. The participant has prior training experience in the simulator and has basic familiarity with using obstacle detection systems in UAVs.

Due to the prevailing situation with the COVID-19, the experiments were administered remotely using the personal computers of the participants at their location. The evaluation was monitored through a screen share session using the Zoom application. The setup used for the study is shown in Figure *27*. The model of the remote controller used in the user study is FlySky i6 (Figure *28*). The computer configuration is intel i5 11th generation, 8GB RAM and Hard Disk Drive.

Figure 27: User Study Setup

Figure 28: FlySky I6 Remote Controller

Data Collection

The data from the simulated environment such as UAV position, sensor readings, and the detection from the obstacle detection approach was collected and logged. The video frames were recorded with the corresponding timestamp through AirSim for post study analysis. The observations and additional comments from the participant during the task were noted as well. The questionnaire answers were obtained through Google Forms.

User Study Results

This subsection presents the observation from the user study and the results from the questionnaire that was administered to the participant.

The pilot performed the introductory flight for 10 minutes. During the flight, the pilot spent most of the time getting familiarized with the course and the navigation instructions provided in an instruction sheet. Initially, it was observed that the pilot ran into sideway collisions at multiple instances when piloting with the forward flight mode. However, the pilot managed to recover and continue the flight in the planned path while paying attention to the altitude display. The pilot did not run into any forward collisions during the flight, except a few times when learning the instructions.

As the second part of the evaluation, the participant was instructed to enable the obstacle detection application and perform the same flight navigation. The participant was briefed about the obstacle detection application before starting the second part of the evaluation. The participant was confident and was able to learn the assistance method quickly. He further stated that he clearly understood the feedback from the system and felt positive about the assistance that the proposed obstacle detection approach was providing.

Although the participant expressed that the warning interface offered meaningful support during the piloting task, he was neutral about the support provided by the graphical warning display. He showed positive agreement with the auditory feedback. During the evaluation, it was clearly observed that the participant was mainly paying attention to the auditory warning cues and correcting the path to avoid collisions. In the post study questionnaire, the participant mentioned that he found the graphical display of warning as a distraction during the task. One of the reasons for this can be that the graphical warning display is a separate window that the participant must pay attention to. Heads up display within the camera view would have improved the experience.

Unexpectedly the detection feedback was not as expected when the UAV was approaching large static obstacles. This was due to the configured sensor range of 15 meter and the speed of the approach. The image-based detection of thin obstacles was consistent throughout the trials and resulted in timely warnings. Another key limitation that was observed during the experimental flight was the distance sensors used in the framework providing point measurement instead of covering a larger FOV. As the multirotor platform becomes more agile the point measurements can be less accurate to depend on. The participant managed to learn the limitation of the framework and expressed this as a comment during the experimental flight.

In terms of collisions with the obstacles in the environment, it was not particularly different from the introductory flight. But the participant perceived the feedback from the warning interface as assistance to modify the path to avoid collisions. The experimental flight lasted for 10 minutes.

The user study provides useful insights on the framework's limitations and areas in which it must be improved. The participant's confidence indicates that the proposed framework could deliver expected results when implemented after addressing the observed limitations. Due to the challenging pandemic conditions, the evaluation was limited to one participant. Hence, the results can be considered less accurate and subject to bias. However, the observation results opened new directions to investigate in terms of improving the approach as part of future work.

4.2 Discussion

The proposed research attempted to investigate and develop a heterogeneous sensor fusion-based obstacle detection framework targeting piloted UAVs. The research on the subject helped in gaining a lot about the domain. The obstacle detection approach by using complementary sensors detected thin obstacles at 14 meter, large static obstacles at 10 meter and thin obstacles with a background at 8 meter of distance. The user study results supported the quantitative outcome. All experiments led to positive results in terms of answering the main research question. The observation from the evaluation clearly showed that the proposed approach can be used to detect obstacles in piloted UAVs. The results give the confidence to extend the approach as part of future work.

The heterogeneous sensors used in the framework were selected as they offer complementary sensing characteristics. The framework has the potential of being used with other types of sensors, as the core of the data fusion method is decision based. The user study results indicate the pilot's approval of the system. Although the user study results can be considered subjective due to the number of participants (one), the positive result enhanced the confidence in the approach. The acceptable real time performance offered by the obstacle detection framework can be considered as a key contributor for this. This supports the sub questions of the research. However, the real time performance is highly subjective due to the chosen algorithms in the implementation of this framework.

The detection results were consistent and predictable throughout the experimental flights despite image processing related noises and known limitations with point measurements from the distance sensors. This can be addressed by using more robust algorithms and replacing them with suitable sensors. In addition, imaging-based detection was observed as producing erroneous results when the UAV gets closer to the obstacle. Unlike distance sensors, image-based detections will not yield accurate results in short range (less than 4 meter). Therefore, it is suitable to ignore any detections within the minimum range. Furthermore, the framework's resource consumption and algorithm's execution timings contributed to satisfactory results. This is indicative of the algorithm's applicability for resource constrained environments. However, an elaborate evaluation using an actual UAV platform with the algorithm running on a companion computer such as Raspberry Pi would be useful to support this conclusion.

The usefulness of the warning interface of the proposed framework is supported by the results from the user study. Based on the results, the auditory warning was preferred by the participant. However, the effectiveness of the warning method was clearly not the focus area of this research. The proposed framework is lenient, and any form of alert mechanism can be adopted and implemented. Although the warnings were considered as a meaningful support tool during the flight task, the observation on forward collisions during the introductory flight and the experimental flight did not exhibit any significant improvements due to the assistive method. This could be due to the layout of the environment. Moreover, the aspect of pilot fatigue or human errors was not reflected in the results.

In summary, the evaluation of the proposed sensor fusion-based obstacle detection framework yielded positive results and it supports the research questions. The user study observation clearly showed several key areas for improvement in terms of accuracy and general usability of the framework. The study also revealed the limitations of the current approach. However, the pilot's confidence and approval of the approach can be a sign of the solution being in line with the expectations. Real-world testing of the framework will provide more confidence.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

This thesis presented a heterogeneous sensor fusion-based obstacle detection framework for piloted UAVs. The purpose of the proposed framework is to detect obstacles from the UAV and alert the pilot so that the pilot can navigate the UAV to avoid collision. The proposed framework uses the complementary sensing capability of the visual camera and distance sensors in detecting obstacles. The framework detects static obstacles with large surface areas and thin cable-like obstacles using sensor fusion. The core sensor fusion layer is implemented using fuzzy logic. The warning interface of the framework uses graphical and auditory cues to alert the pilot about the threat.

A limited number of past works are focused on collision avoidance for manually piloted UAVs while more focus has been given towards fully autonomous UAVs. The state-of-the-art collision avoidance approaches targeting piloted UAVs mainly relied on expensive sensors like LIDARs, and less focus is given to exploring alternative low-cost options. Moreover, sensor fusion-based approaches are not well explored in the context and there is less emphasis on collision avoidance for urban low-flight applications. The idea of detecting static obstacles with a large surface area and thin obstacles using the sensor fusion method is explored in the proposed approach. In real-world terms, a building or a structure is an example for the former while high tension cables and power lines are examples for the latter. The fusion of a visual camera and distance sensors is not considered in the existing collision avoidance approaches for piloted UAVs. Upon completion of this thesis, the sensor fusion-based obstacle detection framework is the main contribution of this research.

The proposed approach is evaluated using the Microsoft Airsim simulation platform. The positive result from this research shows that sensor fusion can be utilized to solve the detection problem in piloted UAVs using heterogeneous sensors. Additionally, by focusing on obstacles in the operating environment an optimal collision avoidance approach can be designed. The evaluation results including the case study result are also considered as a key contribution from this work. The presented sensor fusion framework has the potential of being expanded and adapted to other similar use cases in addition to what this thesis has discussed.

5.2 Future Work

The results from this research are encouraging and show that the proposed approach does work in the context of obstacle detection in piloted UAVs. However, there is more room for improvement. This section discusses on the direction for future research.

Expanding upon this thesis, the first step would be to implement and enhance the image-based detection. Because the current image-based obstacle detection algorithm is implemented based on design assumptions and specifically to demonstrate the sensor fusion algorithm. Hence, the algorithm is expected to give incorrect results with real world applications and complex environments. Replacing the algorithm with a more robust algorithm would allow the framework to be tested under real world conditions or more realistic simulation environments. This will certainly encourage acceptance of this framework.

The distance sensors that are used in this thesis provide point measurements that are representative of one-dimensional laser-based distance sensors. These sensors are good at proximity detection but can result in unstable data with reading. This was experienced in the evaluation of the proposed work. LED ToF distance sensors can be alternatively tested to be used in the framework. This type of sensor offers measurements in a FOV rather than a point measurement. Therefore, a more stable data stream can be expected. This could be verified using simulations by implementing the sensor in a simulation environment or testing the approach using a real UAV platform.

Visual cameras are considered a key candidate in designing obstacle detection approaches due to the recent advancements in technology and the compactness of modern cameras. Many researchers have highlighted that imaging-based approaches can be resource intensive. The same was experienced in this research as well. Therefore, this is an important area to consider when adopting this framework. Moreover, the proposed framework utilizes image-based detection to detect thin obstacles. The data from the same visual sensor can be used to enhance the detection of obstacles not limited to thin subjects, using image processing or deep learning algorithms. Deep learning can be seen as a widely used approach in imaging-based methods in recent years (Figure *5*). The resolution of the camera influences the image-based detection methods. This was not explored well in this research.

The warning interface of the framework uses a graphical display and auditory cues to warn the pilots about the obstacles. Since this area was not the primary focus of this research, it was not well explored. During the evaluation, it was observed that the auditory warning was preferred by the participant at the evaluation. This indicates that the auditory based warning would be an area to improve as part of the direction of future work. However, this being an active field of research, it would be ideal to explore other alternate alert methods that would be superior to auditory based methods (Solovey, Ryan and Cummings, 2021). During the user study evaluation, the participant perceived the graphical display as a distraction. The graphical display being a separate window was one of the reasons for this. The warning interface can be integrated by overlaying the warnings in the video feed itself. Annotating and localizing the obstacles in the pilot view screen would enhance the experience, but the trade-off would be the additional process load that this would require if it ran onboard. Therefore, offloading such non-critical operations to the cloud or a ground computer would be an option.

Another direction for future work from this research would be to extend this work to incorporate obstacle avoidance in the context of piloted UAVs. This would allow the framework to be extended and used in fully autonomous UAVs. The proposed framework's applicability is not limited to UAVs but also can be adopted to other dynamic environments like mobile robotics where a similar requirement exists (Zhou *et al.*, 2017). The flexibility offered by the concept allows the idea to be adopted to situations with varying complexity such as indoor or outdoor situations.

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APPENDICES

6.1 Appendix A. Questionnaire

Demographic Questions

1. Gender: Male/Female

2. Age: ………………

3. Frequency of UAV flying:

    a. >3 times a week

    b. 1-3 times a week

    c. 1-3 times a month

    d. <1 time a month

4. UAV piloting experience in flying hours:

    a. <10

    b. <100

    c. <500

    d. >500

5. Simulator training experience: Yes / No

6. Experience with collision avoidance solutions in UAV:

    a. not familiar with

    b. somewhat familiar with

    c. (very) familiar with

Obstacle Detection (OD) Framework Related Questions

Understanding of the OD System

1. When I used the OD system, I had the feeling that I always understood what the system was doing or what was happening.
   Strongly disagree 1 2 3 4 5 Strongly Agree
2. During the flight, I understood better when I had to perform the avoidance maneuver if an obstacle exists.
   Strongly disagree 1 2 3 4 5 Strongly Agree

Safety in handling the OD System

1. With the warnings from the OD, I had sufficient distance to the obstacle to perform the avoidance maneuver and always experienced safety.
   Strongly disagree 1 2 3 4 5 Strongly Agree
2. I feel confident in using the OD system.
   Strongly disagree 1 2 3 4 5 Strongly Agree

Assessment of the Warning Interface

Support from the Warning Interface

1. The support from the graphical warning display was helpful to me.
   Strongly disagree 1 2 3 4 5 Strongly Agree
2. The support from the auditory signals were helpful to me.
   Strongly disagree 1 2 3 4 5 Strongly Agree
3. The piloting experience was enhanced while piloting with the support of the graphical warning display.
   Strongly disagree 1 2 3 4 5 Strongly Agree
4. The auditory signals offered meaningful support during piloting.
   Strongly disagree 1 2 3 4 5 Strongly Agree

Services provided by the Warning Interface

1. The warning interface helped me by alerting me when there is an obstacle at front.

   Strongly disagree 1 2 3 4 5 Strongly Agree

2. The warning interface helped me get awareness about the type obstacles in front of the UAV.

   Strongly disagree 1 2 3 4 5 Strongly Agree

3. The warning interface helped me in preventing collisions with the obstacles.

   Strongly disagree 1 2 3 4 5 Strongly Agree

Distraction from the Warning Interface

1. I perceived the graphical warning display as a distraction during the piloting task.

   Strongly disagree 1 2 3 4 5 Strongly Agree

2. I perceived the acoustic signal of the OD system as a distraction during the piloting task.

   Strongly disagree 1 2 3 4 5 Strongly Agree

3. The changes in the warning display were clearly distinguishable.

   Strongly disagree 1 2 3 4 5 Strongly Agree

4. Perceiving the information from the graphical warning display is irritating.

   Strongly disagree 1 2 3 4 5 Strongly Agree

5. I found the acoustic signals of the OD display to be irritating.

   Strongly disagree 1 2 3 4 5 Strongly Agree

6. The time at which the auditory signals occurred were,

   Way too early 1 2 3 4 5 Way too late