Collision Avoidance System for Unmanned Aerial Vehicles Using LiDAR and Optical Flow

Technical Report # CSSE 18-07

Amend, Jack J
Elon University
jamend@elon.edu

Seeger, Mason
DePauw University
masonseeger_2019@depauw.edu

Chapman, Richard
Auburn University
chapmro@auburn.edu

Biaz, Saad
Auburn University
biazsaa@auburn.edu

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Abstract

The need for automated collision avoidance is becoming a necessity with the rise in popularity of unmanned aerial vehicles (**UAV**). Advancements in technology are making light detection and ranging (**LiDAR**) and computer vision based collision detection viable for small UAVs in static and dynamic environments. Methods for collision avoidance have included the use of visual and non-visual sensors. Individual sensors have their strengths and weaknesses. This paper explores the possibility of using a combined system using LiDAR and optical flow.

1 Introduction

Unmanned Aerial Vehicles (**UAV**) have seen a spike in popularity over the last decade. They have been used as research tools by the military and the commercial sector; there has also been an increase in UAVs being used for recreational purposes. With so many UAVs taking to the sky, and many more to follow, the need for automated collision avoidance is becoming an absolute necessity. UAVs and their technology and sensors are also becoming less expensive and more lightweight [Li et al., 2017]. However, there are still many drones that are unable to carry more weight than a couple of cameras and sensors and also have limited computing ability. These limitations result in having to choose between different methods of collision avoidance.

Computer vision and *non-visual sensors* are the two main fields in developing collision avoidance techniques. Computer vision involves using cameras similar to those on phones and laptops. Within computer vision, common techniques used are stereo vision, optical flow, object detection, and machine learning.

Stereo vision uses two cameras set apart at a precise distance. From these positions both cameras document the same terrain. Using different processing techniques and mathematical computations for the images, the distance between the cameras and objects in the picture can be found. Denis Horvat et al. describe how useful stereo vision is in creating 3D maps and accurate point-clouds; an important aspect of some collision avoidance techniques [Horvat et al., 2016]. Stefan Hrabar wrote an evaluation of different stereo vision set-ups and their success in avoiding static objects [Hrabar, 2012]. Hrabar also highlights some of the pros and cons of using stereo vision is his paper.

Optical flow uses a single camera to detect movement of pixels from one frame to another in a video. This allows for movement and relative velocity detection which can help give an idea for where an object is moving in the future. Optical flow can also be used to subtract moving parts of an image against a static background. A paper by Yeong-Kang Lai talked about the difficulties using optical flow when the camera is in motion [Lai et al., 2016], something important to think about when using optical flow on UAVs.

Object detection also uses a single camera, but focuses on edge and feature detection. Cameras and computers have no baseline of knowledge when it comes to images, so detecting objects from an image is difficult. *Machine learning* takes many pictures of an object and trains a network to understand what the object looks like. The network can then pick out whatever it has been trained to detect. This enables rough estimation of distance to each object based on a median size.

These vision based techniques have many flaws. Stereo vision requires an extremely precise distance between cameras, so it is difficult to capture large images using a UAV [Hrabar, 2012]. Optical flow is only useful when the camera is stationary and there is constant flowing motion and object detection is not useful in an environment of unknown objects.

Non-visual techniques include sound and light sensors. *Sound sensors* have been used to track objects and are used in many landing sequences for UAVs, but they are not accurate at long ranges. The most common light sensor, Light Detection and Ranging (**LiDAR**), has been used for range-finding and 3D mapping [He et al., 2010] [Horvat et al., 2016] [Merz and Kendoul, 2011] [Azevedo et al., 2017]. The range finding and 3D mapping described in these papers include collision avoidance in dynamic environments, obstacle detection, and terrain following. LiDAR is accurate at medium to long range distances,but can be inconsistent at extremely close range [Hrabar, 2012].

The paper will continue as follows: The problem and the scope of this research is clearly defined. Then a section on related works is presented and describes what has been done relating to collision avoidance using LiDAR and optical flow. The next section talks the hardware, preparation, and experiments being done to conduct this research. The results will then be given and discussed. The paper ends with giving a summary of what has been accomplished in this project and directions for future work.

2 Problem Description

Much of the work done in the field of collision avoidance uses a combination of different techniques. Many of the common sensors and cameras used for collision avoidance for ground vehicles are heavy and expensive. The scope of this research is to look for way to implement collision avoidance for UAVs using equipment suited to small aircrafts. However, this brings up multiple logistical problems that need to be noted and addressed.

One of the most outstanding obstacles for a collision avoidance system in a UAV is the space it operates. In comparison to ground vehicles, UAV movements are much more complicated. While a standard ground vehicle operates on a relatively flat plane, drones bring in an additional third axis of movement and operate in a 3D space; they have the ability to turn left or right or increase or decrease their elevation. Since they have freedom to move about the 3D space, that means they have more area to be aware of than a ground vehicle.

The easiest way to account for the expanded area of interest would be to use more advanced sensors, but small UAVs have tiny payload capacity, and inadequate power sources to power such sensors. The rise of autonomous vehicles has paved way for large sensors that are extremely accurate and robust, but are heavy and unrealistic for use on small UAVs. Ground vehicles do not have the same types of restraints for payload that drones have; UAVs have to fly against the force of gravity and the addition of extra weight makes staying in the air more power costly and can offset the center of gravity of the UAV. Alternatives are needed in order to have a functional autonomous UAV with adequate sensors.

Additionally, the micro-controllers that are used in these vehicles have little computing power. This limits what types of calculations can be performed; large computations may be too much for these controllers to handle and could potentially drain more battery from the already limited amount. Additional hardware can be added to help handle the more complex computations, but that adds to the payload on the vehicle. There are many trade-offs that are needed to be made when designing an autonomous flight system.

The scope of this paper is looking for ways to implement realistic and reliable collision avoidance for UAVs while combating these many obstacles. While looking for reasonable solutions, two promising methods of collision avoidance were found: LiDAR and optical flow.

LiDAR is highly advantageous for use in collision avoidance. Previous research, mainly in ground vehicles and robots, has found great success for it in experiments [He et al., 2010]. Unfortunately, LiDAR does face the problem of being electrically expensive and the device itself can be heavy. Furthermore, on ground vehicles LiDAR is operating on an essentially 2D plane while UAVs operate in the 3D plane; ground vehicles do not have to worry about the same space as drones.

When using LiDAR on a UAVs, multiple problems occur. First, many LiDAR sensors are heavy, and can only be lifted by large and expensive drones. This makes them less desirable for smaller and more affordable aircrafts. Second, when the LiDAR reads in data, the position of the drone will affect what values are read in and what part of the environment it gathers measurements from; extra calculations are needed to be able to correctly analyze and translate the data being read in from the LiDAR based on the pitch and roll of the aircraft. Lastly, there are many different types of LiDAR, like rangefinders and 360 degree scanners. Rangefinders find the distance of an object that is directly in front of the LiDAR while 360 degree scanners give input of an entire area compressed to a 2D view, similar to the output of a radar.

To combat the limitations of small drones and the problems presented above, a small LiDAR range finder will be used in this research for quick and accurate distance measurement. This deals with the payload, power usage, and much of the calculation correction. Consequently, it introduces the new problem that rangefinders have a small area of detection. The best cost and computationally efficient solution to this is to supplement the information with computer vision, specifically optical flow.

Advancements in computer vision make it an appealing tool. Computer vision provides information about the surrounding environment with a large frame of view while simultaneously being a lightweight and compact option; many UAVs come already equipped with built-in cameras. There are many functions that computer vision can implement such as using feature detection and tracking algorithms. Optical flow is implemented by determining the relative movement of a group of pixels from one frame to the next in order to provide the relative path of an object. On the other hand, it has problems determining the distance of objects within the camera's field of view. Without a reference object of a known size, it is difficult to determine sizes and distance of potential obstacles. It may also inaccurately determine the boundaries of objects which can provide issues when objects are recorded smaller than they actually are.

The success of individual LiDAR and optical flow based systems has been evaluated independently with each having varying degrees of success. Using the two methods together, a lightweight and computationally efficient system can be made for static and dynamic collision avoidance with the intent to increase reliability and reduce computational costs while also making these systems more obtainable to a larger consumer base.

3 Related Works

3.1 LiDAR

[Azevedo et al., 2017] presented an algorithm called *Escape Elliptical Search Point - LiDAR - based Collision Avoidance (E2-SP-LCA)*. This algorithm creates ellipticals around the UAV and potential obstacles. If a potential obstacle is in the safety zone, calculations are made to change the path to the goal to avoid any damages. However, if there are no valid escape points found after a number of increases of the radius of the ellipse, the vehicle moves side to side looking for a safe path. If no path is found, the drone sends a warning message and waits for manual controls. See 1 for an example of how the algorithm works

This algorithm is good for use in real-time obstacle avoidance in unknown environments. It also has a low computational cost. Two tests were performed, one using the robotics simulation software Gazebo and the other in a mixed environment with a physical UAV and simulated obstacles. The future works section includes using LiDAR in combination with monocular vision systems.

In a paper by [Merz and Kendoul, 2011], a LiDAR-based guidance system is proposed for a miniature autonomous helicopter. It is described as a **SMAP**-less (simultaneous mapping and planning) approach for obstacle avoidance by using LiDAR. The goal was to use the **UAS** (unmanned aircraft systems) to perform

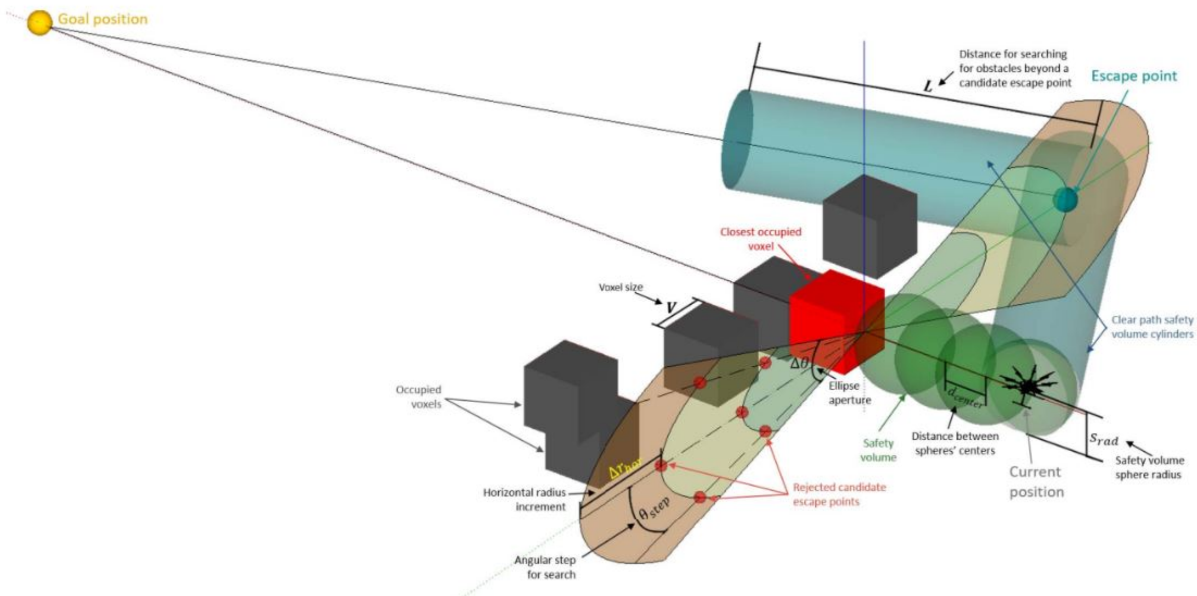

Figure 1: E2-SP-LCA example

two inspection tasks; one of ground objects and the other on vertical structures. Work was done under ideal conditions, including all obstacles being static. When approaching an area of interest, they would lower the altitude and decrease the speed of the helicopter and switch to a LiDAR-based terrain following guidance. When obstacles were detected, a reactive based collision avoidance system with goal-oriented navigation was activated. The speed of the aircraft was limited to keep the values recorded by the LiDAR sensor accurate. This approach is good when traversing known environments via predetermined waypoints.

A paper by [Horvat et al., 2016] compares the data obtained from the standard use of LiDAR and UAV photography in the form of stereo imaging. The data obtained from the drones were much denser, but the LiDAR was able to penetrate vegetation to give more ground data. The use of UAV cameras and stereo imaging has a trade off with some of the additional data given with LiDAR, but was proven to be a reliable and much cheaper option for data collection.

Stefan Hrabar evaluated the use of laser-based range sensing for Rotorcraft UAV obstacle avoidance [Hrabar, 2012]. Hrabar explains a difference between the need for see and avoid methods and the close-range obstacle detection necessary for many rotorcraft UAVs. Pros and cons of the LiDAR were detailed in the paper. The tests were limited to a singular LiDAR scanner with a 270 degree view of the horizontal plane. From the LiDAR, a 2D occupancy map was generated by locating hit voxels. These voxels contain a number of points found by the scanner that is over a threshold, marking the voxel as an obstacle. Hrabar also describes how to deal with negative returns, such as a scanner falsely identifying an object. To do this, voxels were not occupied or free, but had a percentage chance that they were occupied. The experiment specified had the UAV traveling from one point to another via waypoints. Objects were detected by the laser scanner, the voxels were updated, boundaries were created around the occupied voxels, and the path was updated so that the UAV could fly to the final waypoint.

Hrabar's research shows great promise for using LiDAR for obstacle avoidance. Out of 19 flights, the laser-based system was successful in 16, with its failures coming from hitting unseen obstacles and false positive readings that prevented movement. Future work included making 3D occupancy maps from rotating the LiDAR.

[He et al., 2010] implemented a system using a robot and LiDAR to actively avoid dynamic obstacles.

The system makes use of the Kalman filter and the Particles Filter for data processing and tracking of objects using LiDAR. Tracking using LiDAR becomes difficult when obstacles and the robot are moving. He *et al.* Describes two methods of addressing this problem. For slower moving robots and obstacles, the motion of the obstacle can be disregarded and motion planning abilities and response of the robot can be increased. Quicker moving obstacles and robots can be dealt with by finding the relative motion of the obstacle to the robot, calculating the anticipated collision time and position, and planning a new path accordingly. The experiment uses the extended Kalman Filter for object tracking to improve accuracy.

There were several scenarios that the robot was put through in order to test the accuracy of its collision avoidance. Each scenario had the robot go from one end of a room to another with different stimuli for scenarios. The first scenario introduced a person walking quickly across the room. This was detected and was not expected to collide with the robot, so the robot simply waited for the obstacle to clear the area. The second scenario had a person walk slowly across the intended path of the robot. The robot calculated that it could speed pass the object, so it accelerated until it was past the obstacle and returned to normal velocity. The last scenario instructed the robot to continue motion. A person then intentionally blocked the robots forward path, and the robot calculated and moved on a path around the person until it could continue to its initial goal. Problems with the LiDAR rangefinder are described in the conclusion. The robot was able to avoid collision when movement was consistent, rigid movements could prove to be difficult to plan for. LiDAR also has no way of determining the size of an object, making the likelihood of hitting the back-end of obstacles high.

A paper by Rongbing Li et al [Li et al., 2014] proposes a *simultaneous localization and mapping* **SLAM** based on LiDAR and *micro electro mechanical systems inertial measurement unit* **MEMS IMU** method for navigation in indoor environments. SLAM is a widely used technique of obstacle avoidance that works by keeping an accurate location of the vehicle whilst mapping the physical environment surrounding it. SLAM can become problematic in large indoor environments where it takes a large amount of processing to accurately locate the vehicle. Li et al. describes the difficulties of using a LiDAR scanner that essentially maps 2D space on a small UAV moves in 3 dimensional space. To fix this, they implemented a transfer matrix to correct planar skew, performed distance based feature and edge detection, and used an *inertial navigation system* (**INS**) and a version of the Kalman filter to correct position, velocity, and angle error. The presented SLAM algorithm effectively improved LiDARs feature extraction accuracy and decreased amount of calculations necessary for filtering. Future works include reducing the uncertainty of the environment and developing a more robust algorithm for the system.

3.2 Optical Flow

[Chang et al., 2017] presents optical flow-based approaches to obstacle avoidance in indoor environments. Two main techniques for obstacle avoidance were researched. The first is using *Time-To-Contact (TTC)*, which is an estimate of the time it will take for objects to collide based on current trajectories, to take some action to avoid a collision. The second technique uses *balance strategy (BS)*, which balances the optical flow on the left and right sides of the vehicle to move in a collision free path. This path is derived by keeping the distance to obstacles on either side of the UAV equal. TTC is used to look for unoccupied areas in the frame and use those areas to plan a collision free path. The robust algorithm accounts for potential incorrect readings by using a threshold and a window-smooth filter, removing any outliers that could result in incorrect outputs. BS relies on the principle that closer obstacles have a faster apparent motion than those that are further away.

Chang presents many good ideas on how to utilize optical flow for collision avoidance in UAVs. The algorithm described was not tested in the real world, only in a simulated environment. A cheap LiDAR rangefinder could be used to give accurate distances to objects. Precise distance along with the algorithm described in the paper gives potential for a quick and accurate system for assessing potential collisions.

The utilization of optical flow for object detection was used in [Lai et al., 2016]. Complications for object detection arise when the camera is in motion, such as when mounted to a car or UAV, as opposed to a stationary camera with a static background. They break up the process into three steps. The first is to compute the coordinate conversion of point P to P and create a threshold to compare against other points. The next step checks to see if other points have a larger change than the set threshold; if they do, they are marked as moving objects. The last step takes the points that have been separated as non-moving and use it for the ego-motion, the movement of the camera, computation. This study used stereo cameras to record the image sequence. From the image sequence a depth estimation on objects was made. There is the potential to adjust to a monocular camera and a LiDAR to get similar information about distance of an object.

There are many advantages and disadvantages for using LiDAR and optical flow separately for navigational purposes. In hopes of trying to balance out the disadvantages, a combined system using both LiDAR and optical flow is explored.

4 Experiment

4.1 Equipment

The equipment used in these experiment consists of four parts: the drone, controller, sensors, software. The AR Parrot 2.0 was chosen as our drone because it is the easiest drone available to interface with and it has many pre-existing packages made for it as well. The drone is able to carry about 200 grams of added weight and has a flight time of 6-7 minutes. A Raspberry Pi 3 B was used as the controller for the flight. It collected all of the inputs from the sensors, processed the information, and gave the UAV proper protocol for obstacle avoidance.

Two sensors were used to give input to the drone. The first is the Raspberry Pi Camera Rev 1.3. This was chosen instead of the camera on the AR Parrot 2.0 because it is able to directly connect to the Raspberry Pi, cutting down on processing time for taking in video. Additionally, the quality of the camera is greater than that of the onboard camera. The LiDAR sensor used for this research is the Garmin LiDAR-Lite-V3 Laser Rangefinder. The LiDAR sensor uses I2C connection to send information to the Raspberry Pi.

All coding was written in Python3. The Lidar-Lite package created by Github User Sanderi44 was used to correctly take input from the LiDAR sensor and convert it to distance measurements. The OpenCV module [Bradski, 2000] and NumPy Python libraries were also heavily relied on for image processing and calculations.

4.2 Methods

The AR Parrot was fitted with the Raspberry Pi and the sensors as shown in 2. The goal of the experiment is to fly the UAV and have it detect dynamic objects in the environment and move out of the way of the obstacle. During the experiment, the UAV was able to fly and carry the weight of the sensors.

To find points to track, the Shi Tomasi "Good Features to Track" algorithm is used [Shi and Tomasi, 1994]. This algorithm is implemented through a function in the OpenCV library [Bradski, 2000]. The max number of points detected per frame is 50. The list of points is compiled by taking the quality measure of the best point and setting a minimum quality value level as half of the best point.

The optical flow algorithm performed on the frames is the Lucas-Kanade method [Lucas and Kanade, 1981] through another function in OpenCV. The function takes the points previously found and tracks their movement for five frames. From the list of tracks for each point, the first and last point is added to a list of points of interest.

During the experiment, the frame of view of the camera is divided into 64 smaller frames as seen in 3 and 4. Three zones are calculated by taking the left 37.5% of the frame, the 25% of the middle of the frame and the remaining 37.5% of the right. From the points of interest, points are detected and recorded to then see what section each every point lies in. When a point is added to the frame, it is labeled as occupied and a point is added to the score of that frame. After accounting for all detected points, a final scores for each frames is produced and then a zone score is calculated by taking the total number of the points in that zone divided by the number of smaller frames in the zone. The left and right zone scores decide what is considered the safe-area to travel if an object is detected in the center one by the LiDAR.

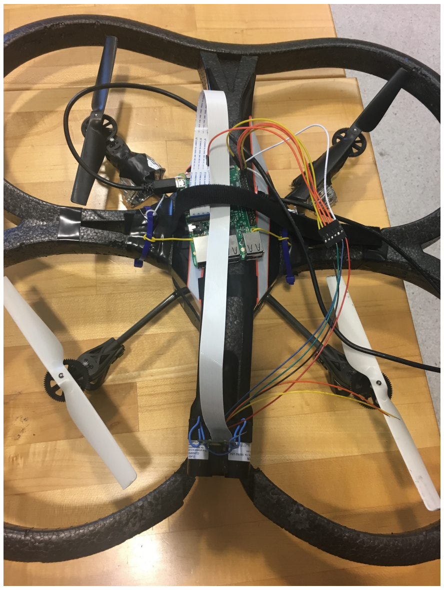

Figure 2: The Parrot AR drone attached with a Raspberry Pi 3B with a PiCamera and a Lidar-Lite V3 attached to the front of the rig.

To simulate objects entering the UAV's safety zone, a bright red cardboard box was used. When the box came within the set threshold distance, the safety travel zone is returned for the drone to have a direction to move towards.

The safe area is calculated by the following mathematical proof. Let r be a positive integer and width, height be equal to the resolution width and height of our image. The set of all points of interest then found on the image can be defined as:

$$P = \{(x_i, y_i) \mid x, y, i \in \mathbb{Z}, 0 \leq x_i < \text{width}, 0 \leq y_i < \text{height}, \text{and } i > 0\}.$$

The index each point falls into is then calculated using P:

$$Q = \{(a_i, b_i) \mid a_i = \lfloor (x_i/\text{width}) \cdot r \rfloor + 1,\ b_i = \lfloor (y_i/height) \cdot r \rfloor + 1\} \quad \text{where } (a_i, b_i) \in P.$$

From this we calculate an $r \times r$ matrix M where:

$$m_{c,d} = |q| \text{ where } q \subset Q \ni \forall\ (a_i, b_i) \in q, a_i = c \text{ and } b_i = d.$$

This research set $r = 8$, $width = 640$, and $height = 480$. From this we get an 8x8 matrix M which is then divided into an 8x3, 8x2, and 8x3 matrices that denote the left, middle, and right sectors respectively. The sum of each of these matrices is calculated and used to find the safe area and the results are shown in 5

5 Results

A combined system using LiDAR and optical flow shows promise for collision avoidance. Based on the zone scores calculated for the left and right, the system gave an accurate output of which way the UAV should travel by returning the zone with the smallest score denoting the safest path. The LiDAR was able to accurately detect when an object was within the safe zone to trigger a move command.

The LiDAR detects the distance to objects, and when an object moves within one meter of the sensor, it alerts the program to begin avoiding the obstacle that is too close to the UAV. The UAV responds by moving in the direction of the safe zone until no object is detected by the LiDAR. Examples of what is seen and calculated by the algorithm are shown by 3 and 4. The red rectangles are a visual to show that the area is occupied with at least one point.

For the image 4, the right zone (zone 2) has the least number of points and is reported as the safe zone. The corresponding third line in 5 reports the individual zone scores with the right having a score of zero meaning that there are no points of interest in that zone. Based on the features detected, the correct safety zone was returned.

All of the computation were performed using a singular Raspberry Pi 3 B. The rig we used seen in 2 weighed 167.7 grams. This was light enough for a the small Parrot AR 2.0 drone to easily fly and maneuver. This fully independent system is light enough to be implemented on small UAVs.

6 Conclusion and Future Works

This paper shows that a small UAV can carry and independently use a system for obstacle avoidance using LiDAR and optical flow. It also shows how a computationally cheap system and hardware can be used for

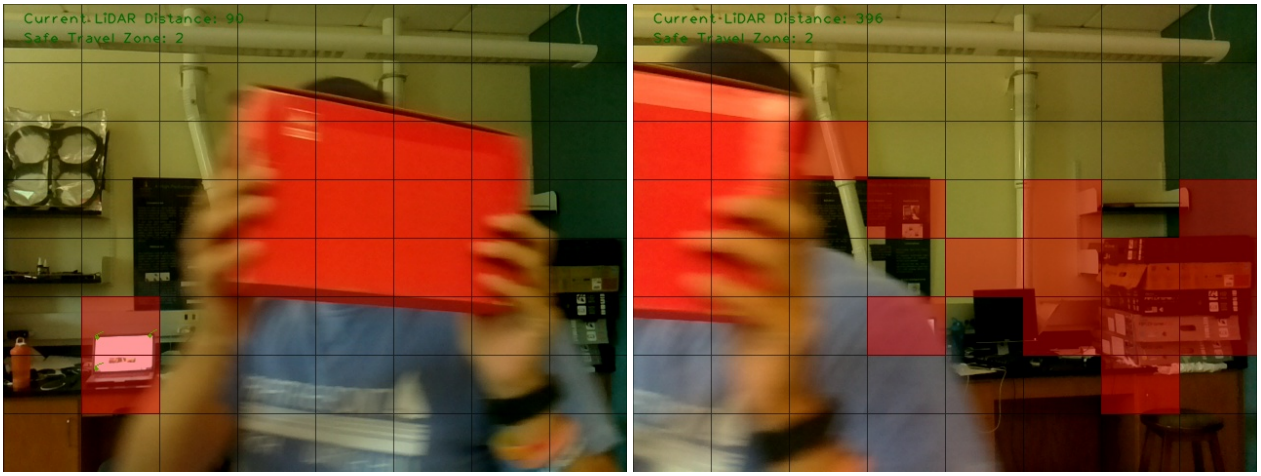

Figure 3: The first image is a screen shot of when the drone first detected there was an object within its safe zone at 22:47:25. Based on the points detected, the safe zone to travel is the left zone. The second image is when the drone no longer detected an object within its safe zone. Images correspond to first two rows in 5

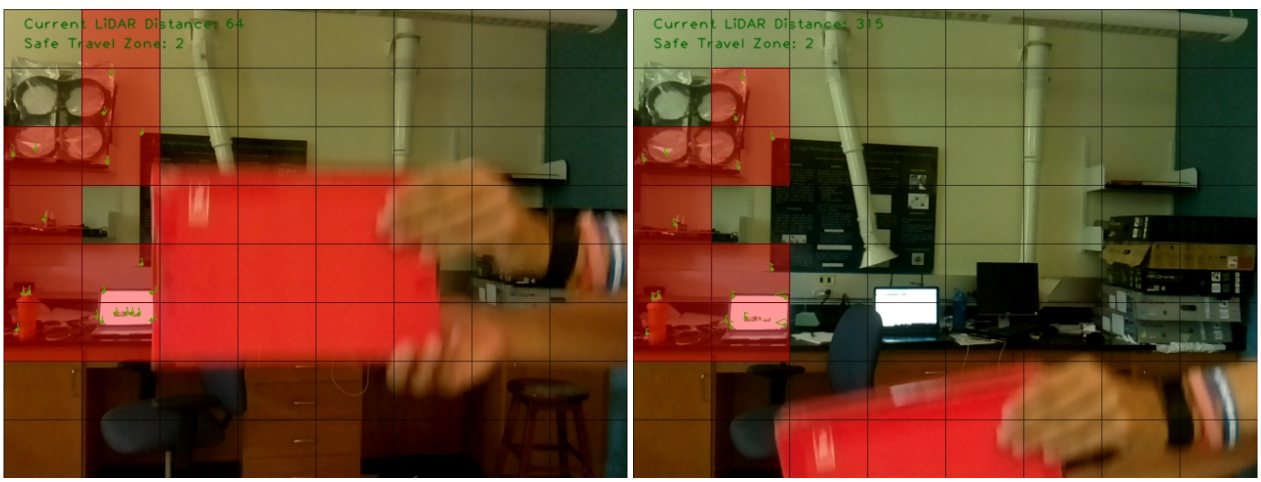

Figure 4: Another example of when the drone's safety state changes. After the box moves out of the path of the LiDAR, the calculated safe travel zone is the right zone. Images correspond to last two rows in 5

Image #	Timestamp	Danger zone?	Lidar distance (cm)	Safe zone	Zone scores
1	22:47:25	in danger zone	90	2	[0.25, 0.375, 0.0]
2	22:47:25	out of danger zone	396	0	[0.1667, 0.0, 0.0]
3	22:48:36	in danger zone	64	2	[1.8333, 0.5, 0.0]
4	22:48:37	out of danger zone	315	2	[1.5, 0.0, 0.0]

Figure 5: This table depicts the data collected when there was a change in the danger state of the drone. The image number corresponds to the image taken at the time of the danger state changed. Safe zone is the least occupied zone in the field of view of the drone; 0 corresponding to the left zone and 2 corresponding to the right.

obstacle avoidance in dynamic environments. The system that was developed is a good stepping stone for further work and research in this field and there are many directions future works could go.

During testing, issues arose in the hardware of the AR Parrot where it would perform different commands without being prompted. In future work, a UAV that can be reliably controlled would allow for more improvements.

Additionally, work on detecting moving objects with computer vision needs to be made. Currently, points to track are found using the Shi-Tomasi method to determine what features would be best to track. Some issues arise when this method is used in a dynamic environment; the points that are tracked are not always those of moving obstacles. It seems that sudden changes in parts of the screen makes it difficult for the Shi-Tomase method to indicate good features to track. Improvements need to be made so that dynamic objects are detected rather than stationary objects in frame.

Furthermore, using a drone that could handle the payload of a 360 degree LiDAR scanner would be helpful. This would help detect when an object is within a safe distance of the UAVs with minimal need for movement of the drone. Additionally, a 360 degree LiDAR could eliminate search frames by reporting that there are no potential objects there so that the optical flow can focus on closer objects. The current range finder used allows for a single line of sight which means the UAV needs to be pointed directly at the object.

References Cited

[Azevedo et al., 2017] Azevedo, F., Oliveira, A., Dias, A., Almeida, J., Moreira, M., Santos, T., Ferreira, A., Martins, A., and Silva, E. (2017). Collision avoidance for safe structure inspection with multirotor uav. In *Mobile Robots (ECMR), 2017 European Conference on*, pages 1–7. IEEE.

[Bradski, 2000] Bradski, G. (2000). The OpenCV Library. *Dr. Dobb's Journal of Software Tools.*

[Chang et al., 2017] Chang, R., Ding, R., and Lin, M. (2017). Optical flow based obstacle avoidance for multi-rotor aerial vehicles. In *2017 IEEE 29th International Conference on Tools with Artificial Intelligence (ICTAI)*, pages 574–578.

[He et al., 2010] He, F., Du, Z., Liu, X., and Ta, Y. (2010). Laser range finder based moving object tracking and avoidance in dynamic environment. In *Information and Automation (ICIA), 2010 IEEE International Conference on*, pages 2357–2362. IEEE.

[Horvat et al., 2016] Horvat, D., Kobale, D., Zorec, J., Mongus, D., and Žalik, B. (2016). Assessing the usability of lidar processing methods on uav data. In *Computational Science and Computational Intelligence (CSCI), 2016 International Conference on*, pages 665–670. IEEE.

[Hrabar, 2012] Hrabar, S. (2012). An evaluation of stereo and laser-based range sensing for rotorcraft unmanned aerial vehicle obstacle avoidance. *Journal of Field Robotics*, 29(2):215–239.

[Lai et al., 2016] Lai, Y.-K., Huang, Y.-H., and Hwang, C.-M. (2016). Front moving object detection for car collision avoidance applications. In *Consumer Electronics (ICCE), 2016 IEEE International Conference on*, pages 367–368. IEEE.

[Li et al., 2014] Li, R., Liu, J., Zhang, L., and Hang, Y. (2014). Lidar/mems imu integrated navigation (slam) method for a small uav in indoor environments. In *Inertial Sensors and Systems Symposium (ISS), 2014 DGON*, pages 1–15. IEEE.

[Li et al., 2017] Li, X., Li, Z., Fu, B., Wu, B., and Liu, Y. (2017). A mini consumer grade unmanned aerial vehicle (uav) for small scale terrace detection. In *Geoscience and Remote Sensing Symposium (IGARSS), 2017 IEEE International*, pages 3349–3352. IEEE.

[Lucas and Kanade, 1981] Lucas, B. D. and Kanade, T. (1981). An iterative image registration technique with an application to stereo vision. In *Proceedings of the 7th International Joint Conference on Artificial Intelligence - Volume 2*, IJCAI'81, pages 674–679, San Francisco, CA, USA. Morgan Kaufmann Publishers Inc.

[Merz and Kendoul, 2011] Merz, T. and Kendoul, F. (2011). Beyond visual range obstacle avoidance and infrastructure inspection by an autonomous helicopter. In *Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference on*, pages 4953–4960. IEEE.

[Shi and Tomasi, 1994] Shi, J. and Tomasi, C. (1994). Good features to track. In *1994 Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, pages 593–600.