4-25-2023

Optimization of a Simultaneous Localization and Mapping (SLAM) System for an Autonomous Vehicle Using a 2-Dimensional Light Detection and Ranging Sensor (LiDAR) by Sensor Fusion

Shaen Mehrzed
Georgia Southern University

Optimization of a Simultaneous Localization and Mapping (SLAM) System for an Autonomous Vehicle Using a 2-Dimensional Light Detection and Ranging Sensor (LiDAR) by Sensor Fusion

An Honors Thesis Update submitted in partial fulfillment of the requirements for Honors in *Mechanical Engineering*

By:

Shaen Mehrzed

Under the mentorship of Dr. Valentin Soloiu

Thesis Mentor: _____

Dr. Valentin Soloiu

Honors Director: _____

Dr. Steven Engel

Abstract

Fully autonomous vehicles must accurately estimate the extent of their environment as well as their relative location in their environment. A popular approach to organizing such information is creating a map of a given physical environment and defining a point in this map representing the vehicle's location. Simultaneous Mapping and Localization (SLAM) is a computing algorithm that takes inputs from a Light Detection and Ranging (LiDAR) sensor to construct a map of the vehicle's physical environment and determine its respective location in this map based on feature recognition simultaneously. Two fundamental requirements allow an accurate SLAM method: one being accurate distance measurements and the second being an accurate assessment of location. Researched are methods in which a 2D LiDAR sensor system with laser range finders, ultrasonic sensors and stereo camera vision is optimized for distance measurement accuracy, particularly a method using recurrent neural networks. Sensor fusion techniques with infrared, camera and ultrasonic sensors are implemented to investigate their effects on distance measurement accuracy. It was found that the use of a recurrent neural network for fusing data from a 2D LiDAR with laser range finders and ultrasonic sensors outperforms raw sensor data in accuracy (46.6% error reduced to 3.0% error) and precision (0.62m std. deviation reduced to 0.0015m std. deviation). These results demonstrate the effectiveness of machine learning based fusion algorithms for noise reduction, measurement accuracy improvement, and outlier measurement removal which would provide SLAM vehicles more robust performance.

Outline

Acknowledgements

I would like to thank my research mentor Dr. Valentin Soloiu for his guidance and motivation while writing this thesis. I would also like to thank my colleagues David Obando, Kody Pierce, Aidan Rowell, Brad Willis, Timothy Sutton, Luke Kroeger, Nathan Holley, Chipper Smith, Amanda Weaver, and James O' Hara for their support and friendship during my undergraduate research.

I want to thank the honors college and department of mechanical engineering for the opportunity and support to write this thesis and in the process learn more about conducting research in the areas of my interest.

Most importantly, I would like to thank my family for their never-ending support in pursuing my goals.

Hypothesis

The integration of recurrent LSTM neural network-based sensor fusion algorithms for 2D LiDAR, ultrasonic, and 1D infrared ranging sensors can significantly improve the accuracy of distance measurements while mitigating the impact of high noise levels, allowing enhanced SLAM performance in autonomous vehicle applications.

Introduction

Simultaneous Localization and Mapping Algorithm

Localization is the act of an autonomous vehicle using sensors and computing algorithms to estimate its location relative to a given environment. Mapping is the act of using the same tools to create a map of its surroundings. By nature, fully autonomous vehicles need to know their surroundings as well as an accurate estimate of where they stand relative to their surroundings before they can use algorithms to make acting decisions. Simultaneous Localization and Mapping (SLAM) involves a computing algorithm that uses sensor data of moving vehicles to create a map of the unknown environment they are in and find their location within this map [1]. Visualization of such a map which also displays the vehicle's trajectory, known as an occupancy grid map, can be seen in **Fig. 1**.

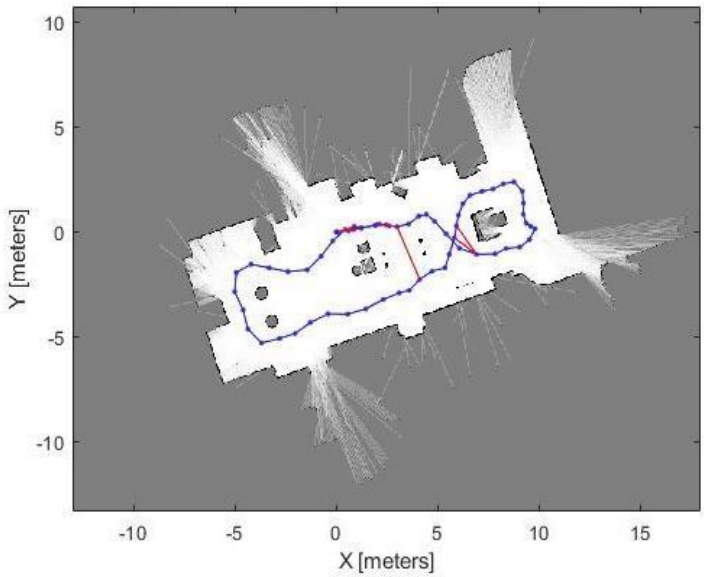

Figure 1. Occupancy Grid Map using LiDAR SLAM [1]

The blue lines represent the vehicle's trajectory while blue dots show where data was taken. The grey area represents the unscanned surroundings, whereas the white area displays the surroundings deemed free of obstacles. **Figure 1** represents an ideal result

from SLAM which can be used by another algorithm to determine an ideal path. SLAM involves an iterative process with multiple steps where sensor data is acquired then processed to build a map of the vehicle's environment.

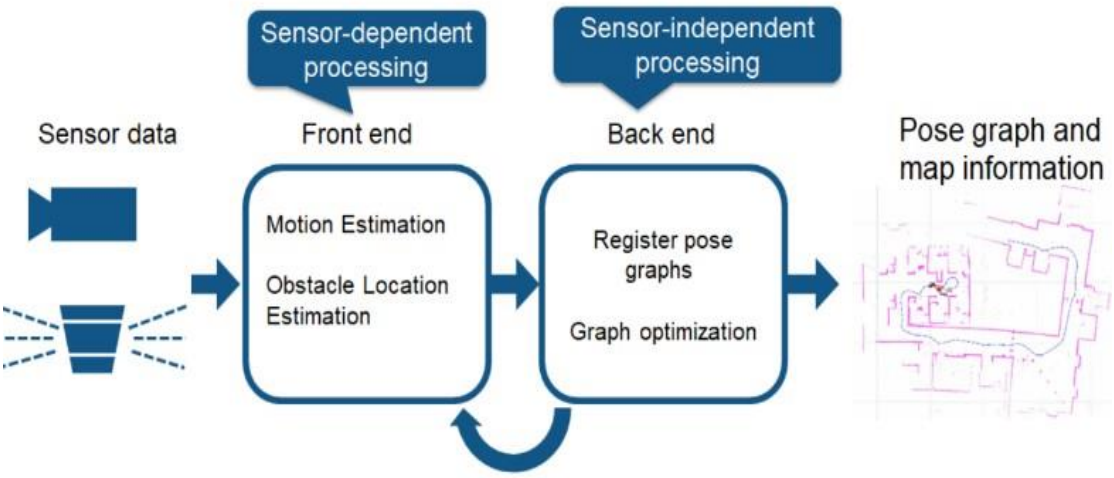

Figure 2. SLAM Process Flowchart [1]

SLAM consists of front- and back-end computer processing. The front-end processing involves the signals received by the vehicle's sensor, whereas the back-end processing involves a pose-graph optimization using the sensor data. Sensor data may include more sensors than LiDAR, though due to the 360-degree horizontal measurement, LiDAR can be the sole sensor used. Typically, inertial measurement units (IMU) are used to estimate the position of the SLAM vehicle.

After receiving data from the LiDAR sensor at a specific location, the SLAM algorithm processes an estimate of its current location relative to the last point at which the LiDAR sensor took a measurement. It does this by recognizing previous features of the environment measured at other locations and times of measurement. Once the vehicle has received sensor data that is similar enough to data of a previous point past a threshold, it has determined that the vehicle has completed a path loop. With path loops, SLAM can

optimize the map it is building as there exist substantial errors in the estimation of the vehicle's location relative to objects throughout data points when solely using LiDAR data.

Distance Measurement Sensor Principles

Sensors are devices capable of measuring quantifiable changes in a physical environment. There are various methods allowing a sensor to measure, as well as various parameters to measure. Sensors can be either active or passive, depending on their method of measurement. Active sensors, such as time of flight (ToF) sensors, must first emit energy to its surroundings to measure its input. Passive sensors such as cameras do not emit energy to capture pictures, rather only receive and record from their environments.

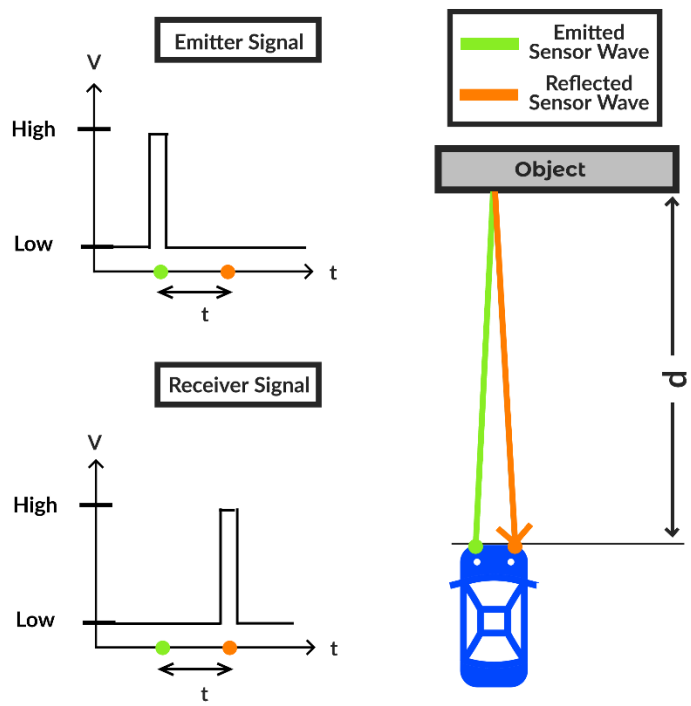

Figure 3. Simplification of ToF Sensor Function

The ToF principle can be seen in **Fig. 3** where a given wave is emitted from the sensor toward an object, reflected from the object back to the sensor and the time elapsed

from emitting to receiving the wave is measured. Knowing the speed at which the sensor's wave travels, the relative distance between the sensor and the object can be found using **Eqn. 1** below.

$$d = \frac{ct}{2} \tag{1}$$

Sensors use various types of waves to measure distance, including the use of electromagnetic waves. Except for ultrasonic sensors, which use sound waves, most sensors such as LiDAR and Radar sensors use electromagnetic waves for ranging. Different types of electromagnetic waves are discerned by their wavelengths and frequencies. Different types of electromagnetic waves result in varying characteristics, which make them suitable for different types of sensing and measurement. A notable aspect of electromagnetic waves for distance measurements is the wavelength. The wavelength is the maximum limit of resolution for an array of measurements using the electromagnetic wave.

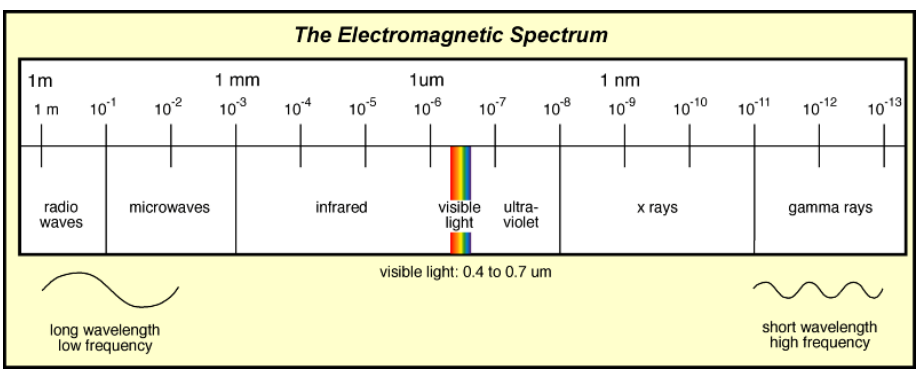

Figure 4. Electromagnetic Wave Spectrum [2]

Radio waves are electromagnetic waves with frequencies ranging from about 3 kHz to 300 GHz. Radar sensors use radio waves with wavelengths, typically in the range of 1-10 centimeters, which can penetrate through certain materials such as water

droplets, making them less affected by weather conditions. Radar sensors are widely used in automotive safety systems and have a long history of use in other aerospace, maritime and communication applications.

Laser beams, which are used in LiDAR sensors, are electromagnetic waves with much higher frequencies and smaller wavelengths than radio waves, with frequencies typically in the range of hundreds of terahertz to petahertz and wavelengths in the range of 700-1000 nanometers, enabling the possibility of highly detailed maps and precise distance measurements.

Visible light waves are electromagnetic waves with wavelengths typically in the range of 400-700 nanometers. Cameras use visible light to capture 2D images defined by an RGB matrix of pixels where each pixel's color is defined by the red, green, and blue intensities to define any color.

Sensor Fusion

The development of individual sensors involves maximizing measurable ranges and minimizing noise or other constraints. Despite this, sensors will inherently have ideal measurement ranges and physical restrictions. For example, ultrasonic sensors have a shorter measurement range than LiDAR sensors, as the dissipation of ultrasonic sound waves occurs over large distances, whereas infrared light waves used in LiDAR do not dissipate over large distances. On the other hand, an ultrasonic sensor typically outperforms LiDAR sensors while measuring very short distances.

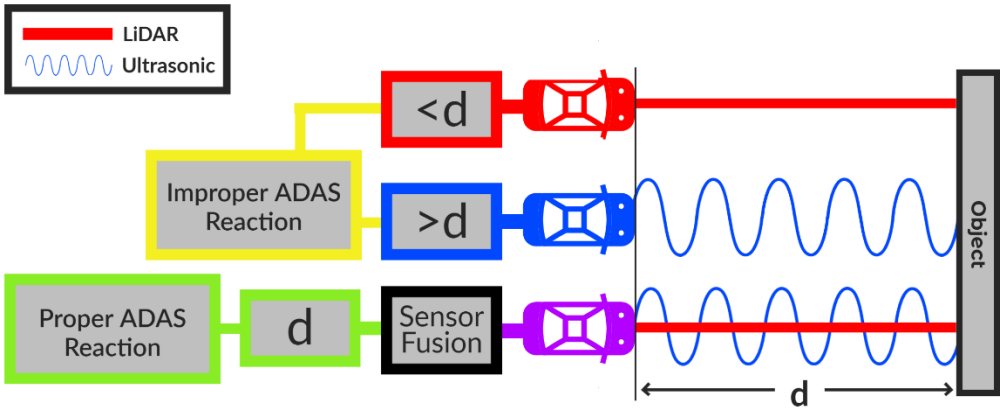

Figure 4. Sensor Fusion Functioning Principle

Sensor fusion techniques play a crucial role in improving the accuracy and reliability of distance measurements by integrating data from multiple sensors. These methods help overcome the limitations of individual sensors and provide a more comprehensive understanding of the environment.

Kalman Filtering

Kalman filtering is a widely used recursive estimation algorithm for fusing data from multiple sensors. It provides a real-time update of the state estimate based on the observation and prediction of system models. Kalman filtering is commonly applied in distance measurement fusion involving sensors such as LIDAR, RADAR, and ultrasonic sensors. [3]

Kalman filtering is a recursive estimation algorithm that operates in two primary steps: prediction and update. In the prediction step, the algorithm estimates the state of a system by propagating its previous state through a dynamic model, which incorporates the system's uncertainty. In the update step, the algorithm combines the predicted state with the new measurement data from sensors, considering the observation model and the measurement uncertainty. By performing these steps in real-time, the Kalman filter

provides an optimal estimation of the system state under the assumptions of linear Gaussian models for both the dynamic and observation models. To achieve distance measurement fusion, the state typically represents the position or distance, and the Kalman filter integrates the data from multiple sensors to improve the accuracy and reduce the estimation uncertainty.

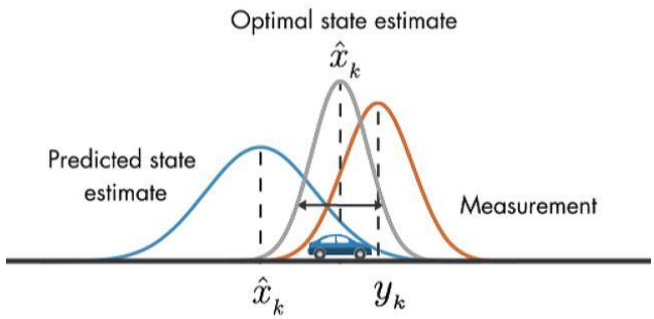

Figure 5. Kalman Filtering Concept [4]

In real-world applications, many systems exhibit nonlinear behavior, which cannot be accurately modeled by linear functions such as the traditional Kalman Filter. UKF (Unscented Kalman Filter) is a type of Kalman Filter that can deal with nonlinear systems more effectively. Instead of linearizing the nonlinear functions, as done in the Extended Kalman Filter (EKF), the UKF uses a deterministic sampling technique called the unscented transformation which selects a set of weighted sample points, called sigma points, which capture the mean and covariance of the underlying Gaussian distribution. The sigma points are propagated through the nonlinear functions, and the resulting transformed points are used to estimate the new mean and covariance of the state. [3]

Julier et al presented the unscented Kalman filter (UKF) as an extension of the standard Kalman filter for nonlinear estimation problems. They demonstrated the application of the UKF in several scenarios, including target tracking and distance

measurement fusion showing its effectiveness in handling nonlinear system dynamics and observation models. [5]

Particle Filtering

Particle filtering is a non-parametric, recursive Bayesian filtering technique that represents the posterior distribution of the system state using a set of particles or samples. Each particle carries a weight, which indicates the likelihood of the particle representing the true state. The algorithm involves three main steps: prediction, update, and resampling. In the prediction step, particles are propagated through the system's dynamic model, incorporating process noise. In the update step, the particle weights are updated based on the likelihood of the current sensor measurements given the particle states. In the resampling step, particles with low weights are replaced by replicating particles with high weights, maintaining the same number of particles while focusing on the most likely regions of the state space. Particle filtering is particularly useful for fusing distance measurements when dealing with non-linear and non-Gaussian system models. [6]

Bayesian Inference

Bayesian inference is a statistical framework for updating the probability distribution of a system state based on new observations while incorporating prior knowledge. For distance measurement fusion, Bayesian inference combines the likelihood functions of different sensors to obtain a joint likelihood function. The joint likelihood is then combined with the prior distribution of the system state, such as distance, to derive the posterior distribution. This process allows for the fusion of sensor data while accounting for the uncertainty and noise associated with each sensor. In the case of linear Gaussian models, Bayesian inference reduces the Kalman filter, unlike

non-linear and non-Gaussian models, more advanced techniques such as particle filtering.

Fox et al applied Bayesian filtering to location estimation in pervasive computing environments. They fused data from various sensors, such as Wi-Fi signal strength, infrared beacons, and ultrasonic sensors, to accurately estimate the location of users and devices in indoor environments. [7]

Fuzzy Logic

Fuzzy logic is a mathematical approach for modeling and reasoning with imprecise and uncertain information. In distance measurement fusion, fuzzy logic represents the uncertainty in sensor measurements using fuzzy sets and membership functions. The fusion process involves defining fuzzy rules that determine how to combine the fuzzy sets corresponding to the individual sensor measurements. The combined fuzzy set is then defuzzied to obtain a distance estimate. Fuzzy logic fusion techniques are particularly suitable for handling situations where sensor measurements are subject to varying environmental conditions or noise, as they can effectively model and manage the imprecision and uncertainty in the data.

Neural Networks

Neural networks are computational models inspired by the function of biological neural systems. They consist of interconnected layers of nodes that process and transform input data through nonlinear activation functions. In distance measurement fusion, neural networks learn to combine sensor data by extracting features and modeling complex relationships among the inputs. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are commonly used for fusing data from distance

measurement sensors. CNNs are particularly suitable for processing spatially structured data, while RNNs are effective in handling time-related dependencies in the data. By training the neural networks on a large dataset of sensor measurements, they can learn to effectively fuse the data and provide accurate distance estimates. Soloiu et al developed a neural network based data in-data out fusion algorithm for the increase in accuracy of ADAS safety envelope distance measurements. [8]

Methodology

Tested in this research are the performance effects of fusing additional sensors with a 2D LiDAR sensor when measuring the distance of a wall. The platform used to conduct this research was a vehicle equipped with an A3M1 2D LiDAR sensor, two ultrasonic sensors, a 1D LiDAR sensor and two camera sensors. Data from these sensors were received, processed, and fused using MATLAB.

A range of distance measurements were done from 0.05m to 0.50m with increments of 0.05m. This results in 10 different distances measured by the sensors. Data at each distance was taken for 5 hours for the sake of providing sufficient data for machine learning models. The data was randomly shuffled then split in half for training and testing. Multiple iterations of training and testing could be completed in an hour, which was done iteratively until the fusion was performing as good as possible.

A MATLAB algorithm was developed which can let the 2D LiDAR sensor, infrared ranging sensor and ultrasonic sensor simultaneously take data at 10Hz, record this data, and fuse in various ways. 5 hours of 10 different distances were measured ranging from 0.05m to 0.50m, and each sensor’s accuracy has been evaluated.

The 2D LiDAR measures 360 degrees of its plane environment, whereas the ultrasonic, and infrared distance sensor measure effectively at a single point. To fuse data from the 2D LiDAR sensor with the single-point infrared and ultrasonic sensors, it is essential to define a region of interest (ROI) for the LiDAR sensor. For this testing, the ROI of the LiDAR sensor was defined as -5 and 5 degrees, the 10 degrees centered at the frontal direction of the sensor as seen in **Fig. 13**.

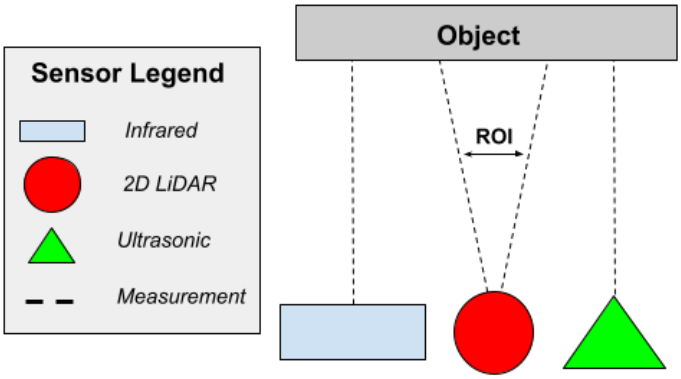

Figure 10. ROI Visualization

To receive critical distance data, a testing environment was built where a flat obstacle was placed at a distance between 0 and 0.5m from the ultrasonic, 2D LiDAR and laser ranging sensor. This setup was used extensively to evaluate the data returned from the different sensors at the short distance.

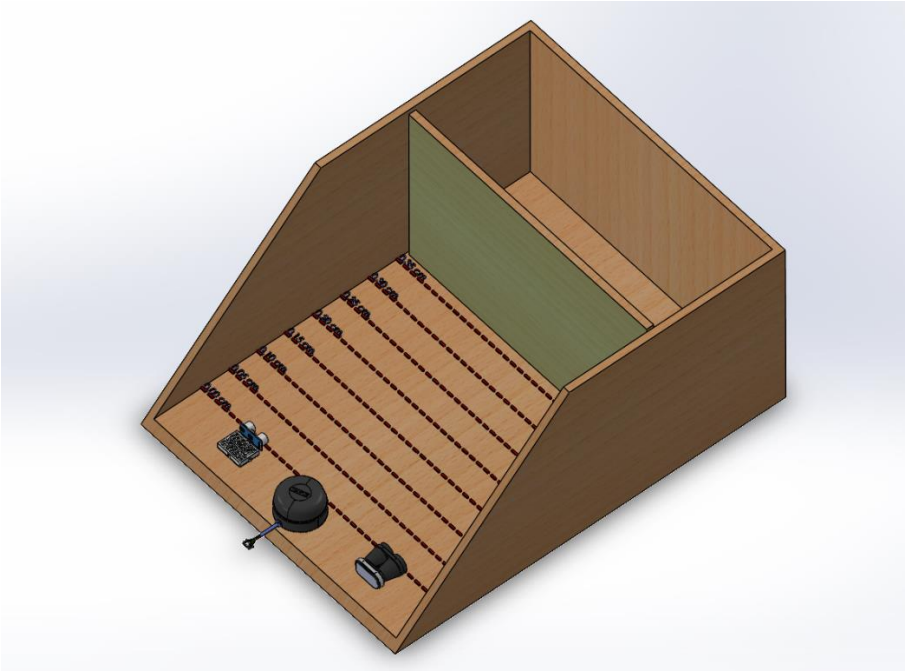

Figure 11. Testing Bench for Varying Distance Data for Fusion

LiDAR Sensor

For this application, the primary front-end sensor is an A3M1 2D RPLiDAR sensor as shown in **Fig. 6**.

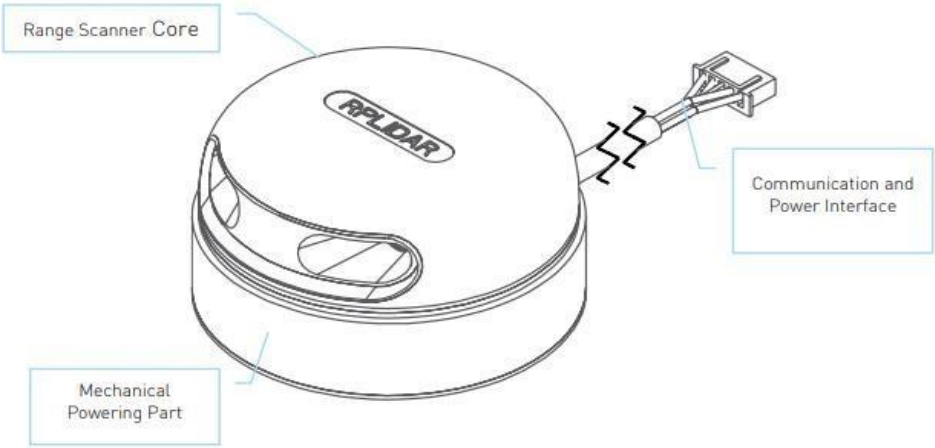

Figure 6. A3M1 2D RPLiDAR Sensor [9]

Its ability to measure distances to surrounding objects is possible the ToF principle. The top half of this a LiDAR sensor rotates while sending and receiving 16000 signals a second to estimate distance at 360°.

Ultrasonic Sensor

Ultrasonic sensors work similarly to LiDAR sensors in the determination of obstacle distances: time of flight (ToF). Much different from LiDAR sensors, ultrasonic sensors rely on the time of flight of ultrasound waves which are emitted and reflected by an obstacle. One attractive advantage of ultrasonic sensors is their cost: the HC-SR04 sensor, seen below in **Fig. 7** is used in this work and only costs a few dollars.

Figure 7. HC-SR04 Ultrasonic Sensor

Ultrasonic sensors in general are mostly used at distances less than 5 m and specifically this one has a maximum range of 4m. Sound waves are larger than light waves, making this sensor inherently lack in sensing precision in comparison to light-based sensors. Not only is the precision affected using a larger wave, but so is the measuring angle: the sound waves of ultrasonic sensors become wider as they travel away from the

sound emitter, limiting this sensor's measuring angle to 15 degrees. Light on the other hand does not spread relative to this application.

Infrared Ranging Sensor

Infrared ranging sensors are also ToF sensors and can be considered a1D LiDAR sensor which does not rotate and measure multiple angles. These infrared sensors also rely on the time of flight of infrared lasers which are emitted and reflected by an obstacle. One attractive advantage of infrared sensors is their range: the SF11/C, seen below in **Fig. 8** is used in this work has a range of 100m and costs less than the 2D LiDAR: $289.

Figure 8. SF11/C Laser Infrared Ranging Sensor

Laser ranging sensors have been developed and used long before rotating LiDAR sensors became popular for mapping and navigation applications. In its essence, these are the same as LiDAR sensors, except that they measure the distance of a single point rather than a range of directions.

Camera Sensor

Camera sensors are highly optimized passive sensors able to recreate closely the human eye's photoreceptive ability. They are generally categorized by their pixel counts and a lens which defines the field of view. Attractive advantages of camera sensors include their versatility and similarity to human navigational ability. Unfortunately, camera sensors do not have built-in depth perception, as they only record the colors of incoming light. A method can be used to receive depth from camera sensors which is called stereo vision. Stereo vision is the basis of human depth perception as well as often depth perception of intelligent vehicles. It functions by knowing the distance between two cameras facing the same direction as well as information on their field of view. From this, an estimation can be made of the distance of an object, seen by both cameras. The stereo vision camera set used in this research is the GoPro Hero 10 camera seen in **Figure 9**.

Figure 9. GoPro Hero 10 Camera

Cameras are often at a disadvantage in low-light, snowy, dusty, and rainy conditions. Reliance on the stereo vision assumes ideal conditions for both sensors without

any obstacle, meaning it is more likely to fail in adverse conditions. They are useful in object recognition, as many machine learning databases exist that can allow recognition of humans, traffic signs, road markings, traffic lights and more.

Machine Learning Training and Testing Method

The machine learning based fusion method was set to be a recurrent neural network (RNN), specifically a Long-Short-Term-Memory (LSTM) RNN. Given the low-level fusion: data in (m) - data out (m), the network was built to perform a regression rather than a classification. This means that the output of the neural network is a number rather than a title given in classification. The reason which this type of neural network was chosen was mainly due to these network's ability to consider time-related dependencies in sequence data. The nature of distance measurements over time involves time-related issues such as noise and measurement drift, which are intended to be minimized using the developed machine learning platform. The layer structure of the LSTM neural network optimized in this work can be seen below in **Figure 10**.

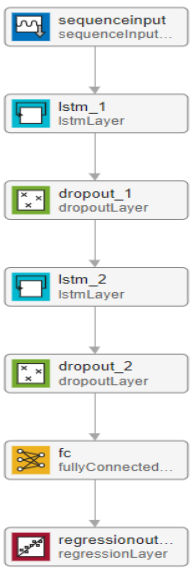

Figure 10. LSTM Sensor Fusion Regression Layer Structure

Various aspects of the network's parameters were changed until the optimal fusion was found during testing. The training process of the final network able to perform fusion with any given distance between the 0.50m and 0.05m constraints can be seen below in **Figure 11**.

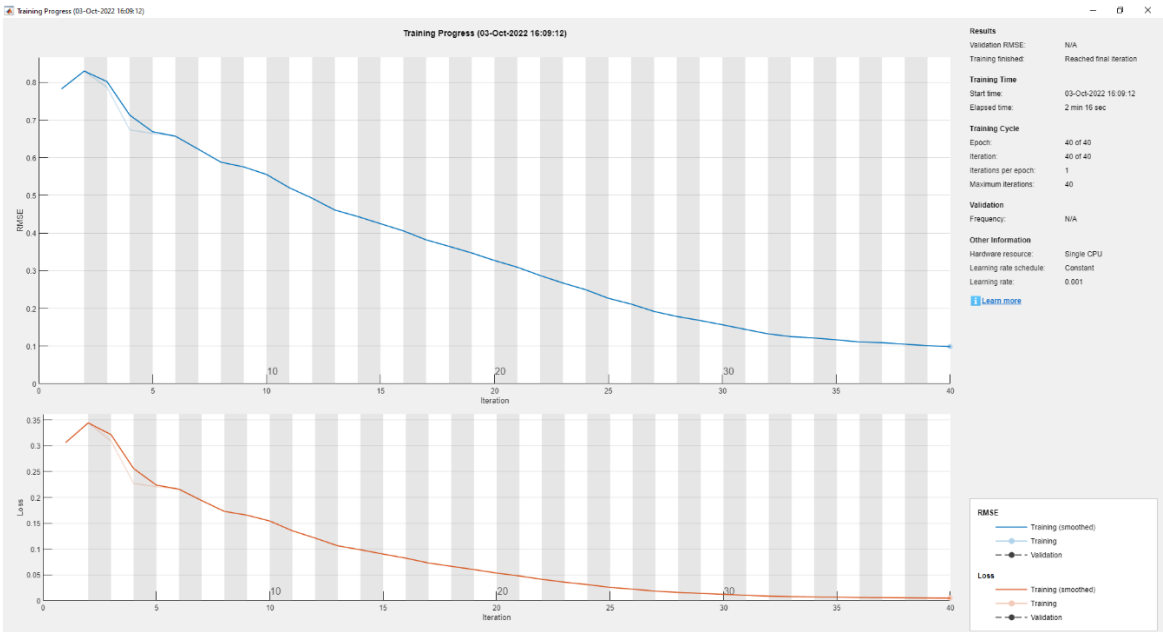

Figure 11. Training Progress Final LSTM

This training progress represents the network's learning progression during the training process. This training took 2min and 16s using a single CPU and a learning rate of 0.001.

Results

All sensors were interfaced with a MATLAB-windows environment, where in a loop structure data was taken at 10Hz from each sensor in a forced manner. This meant that a request was sent 10 times a second to each sensor to receive distance data. Sample data from all three sensors measuring a wall placed at the 0.5m distance ground truth can be seen in **Figure 12**. The upper and lower limits of the y-axis for each sensor are

determined by the min and max value measured in this time frame. In other words, the limits are defined automatically depending on the range of distances measured. Immediately one can notice the high distance noise which the 2D LiDAR has, providing occasional measurements as high as almost 20m. The ultrasonic sensor and the 1D microlidar did not have this high distance noise problem, where all measurements are within 0.1m of the ground truth (GT).

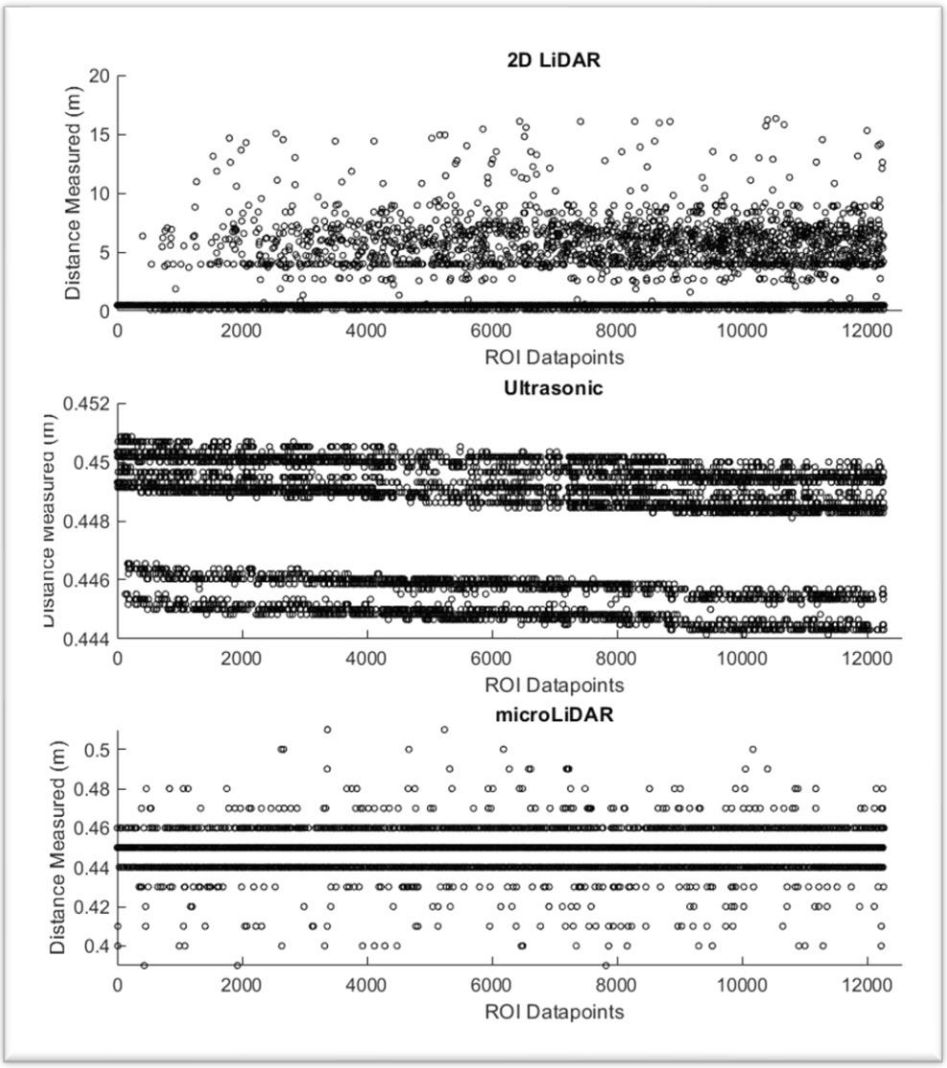

Figure 12. 24Hr Distance Measurement of Obstacle (GT 0.5m)

The 2D LiDAR sensor often did not measure a distance at the defined ROI, returning 0m measurements. This can be seen in **Fig. 13**, where the average ROI response time, defined as the time in between measurements where there was at least a single ROI measurement present, is far above 10Hz: above 1.5s.

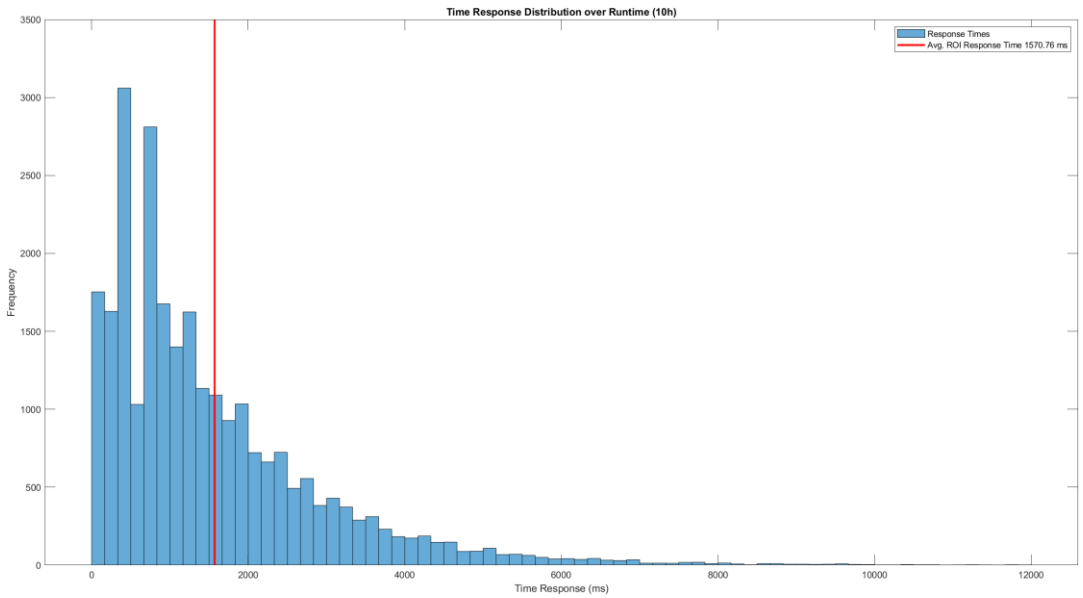

Figure 13. ROI Time Response Distribution

ROI separation was a post-processing data separation, where all measurements that did not have an ROI detection by the 2D LiDAR were discarded. The ultrasonic and infrared ranging sensor had no significant issues reading a distance at 10Hz, as each measurement there existed a provided distance from those sensors.

Not only did the 2D LiDAR have issues in providing timely consistent readings, but it also had significant high distance noise. For a ground truth of 0.59m, the frequency distribution of all measured distances by the 2D LiDAR can be seen in **Figure 14**.

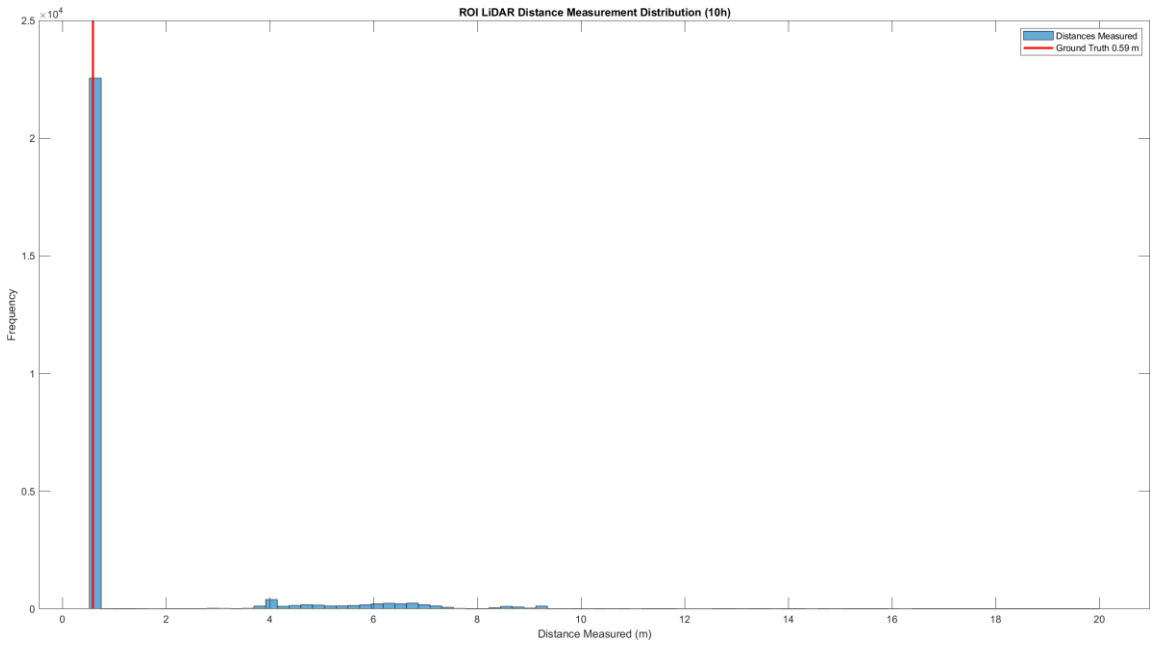

Figure 14. ROI 2D LiDAR Measurement Distribution

It is evident that most distances were measured near the 0.59m ground truth, however, there exist significant numbers of points measured above 2m. A closer look at most of the 2D LiDAR measured points (between 0.6-0.63m) can be seen in **Figure 15**.

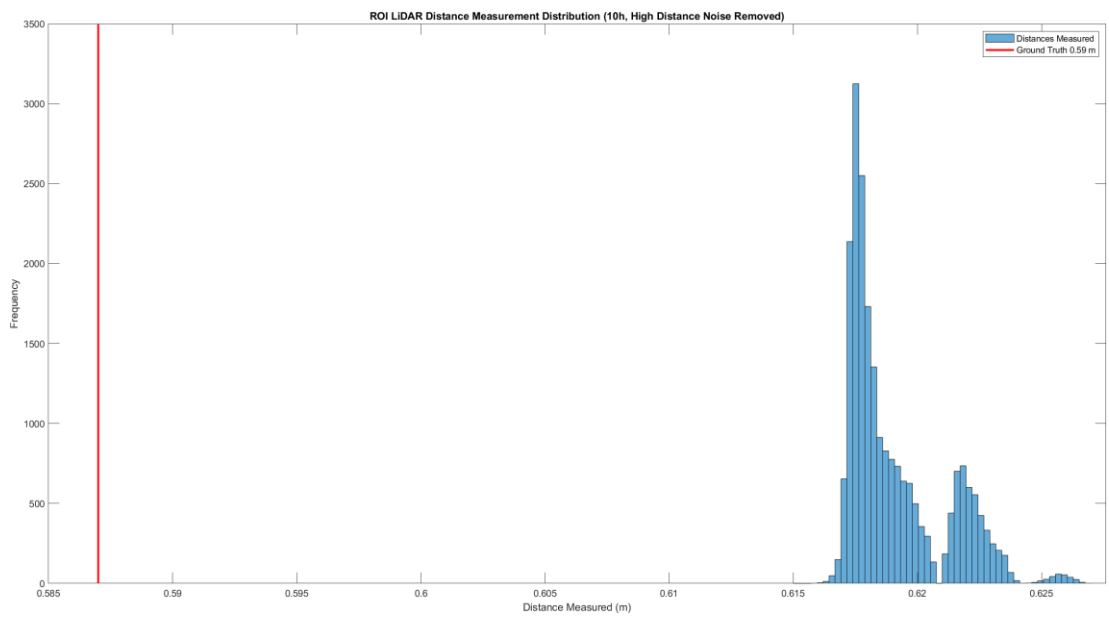

Figure 15. ROI 2D LiDAR Measurement Distribution (High Distance Noise Removed)

There exists a multi-modal normal distribution of the sensor's measurements. They are consistently inaccurate showing the possibility of an effective calibration for this data range. It is evident that the 2D LiDAR has two problems for this ROI: high noise and high response time. These characteristics of this sensor must be considered in the fusion system design with other sensors. Seen below in **Fig. 16-17** are the measurement distributions of the infrared ranging sensor and ultrasonic sensor.

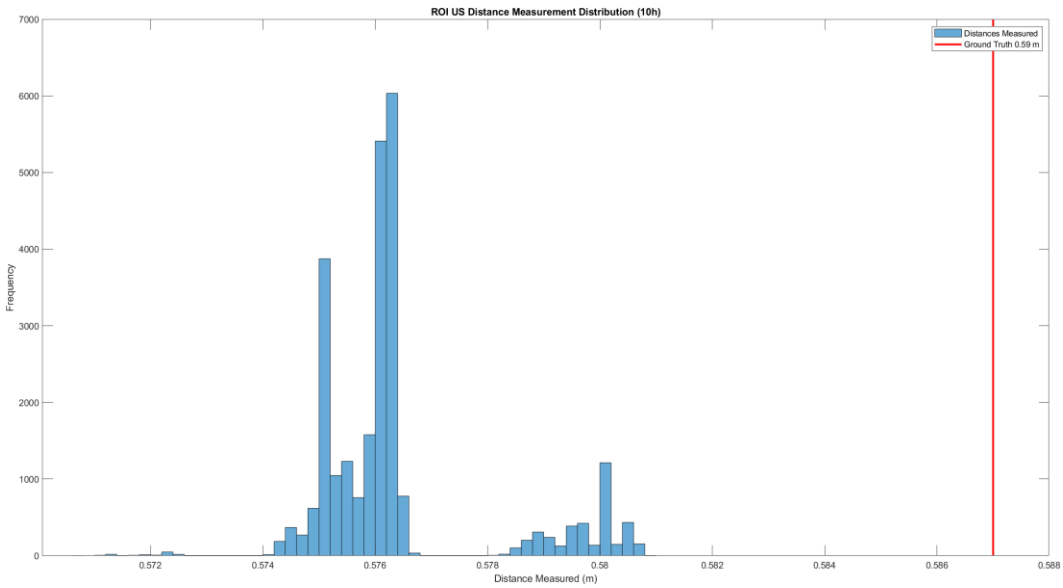

Figure 16. ROI Ultrasonic Measurement Distribution

There exists mainly a single normal distribution of distance measurements, centered around 0.576m. This is far less noisy than the 2D LiDAR sensor and also shows a promising opportunity of calibrating the sensor.

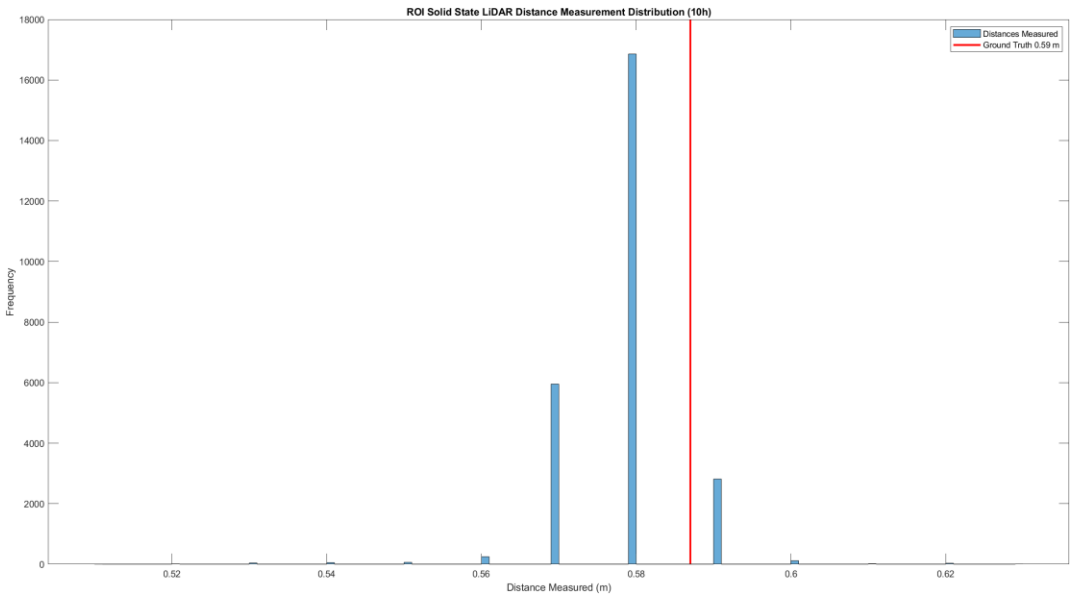

Figure 17. ROI Infrared Ranger Measurement Distribution

The smallest detectible change in distance measured by the 1D microlidar from this plot can be determined to be 0.01m, whereas the resolution found for the 2D LiDAR and ultrasonic sensor are much lower than that. While this sensor lacked to provide data between centimeters, it did perform very well while measuring as closely as possible to the true distance.

Two data-level fusion methods were evaluated: 1. Statistical and 2. Recurrent neural network LSTM. The statistical fusion method is an average of all distances in each measurement. The recurrent LSTM neural network was given 5 hours of training data and tested with the remaining 5 hours. The testing results can be seen below in **Fig. 18**.

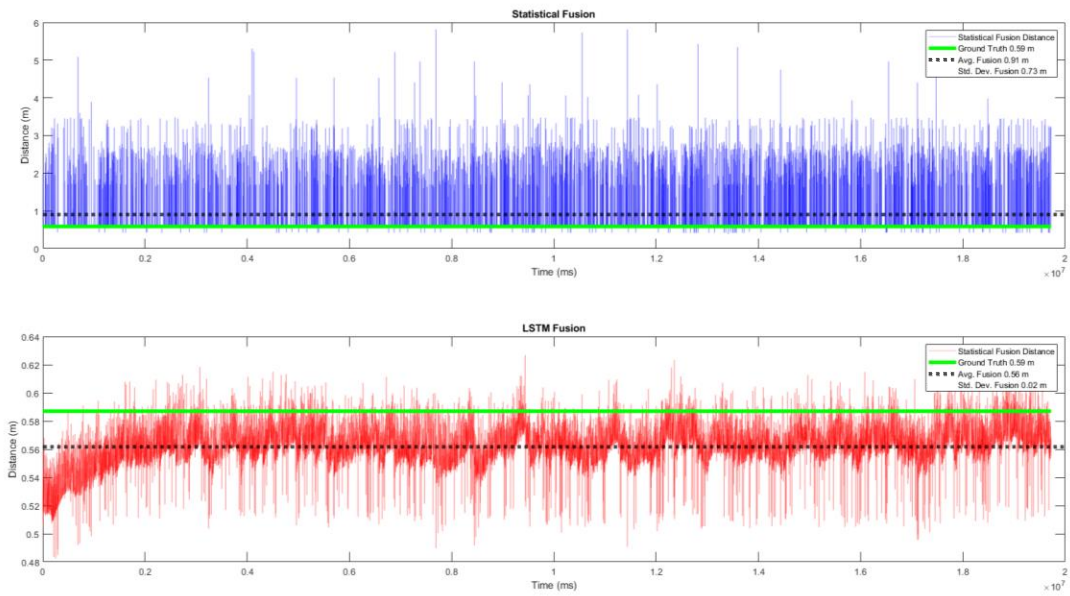

Figure 18. ROI Multi-Sensor Statistical and LSTM Machine Learning Fusion

The standard deviation of the statistical fusion is 0.73m whereas the standard deviation of the LSTM fusion is 0.02m. While the true distance measured was 0.59m, the average statistical fusion was 0.91m and the average LSTM fusion was 0.56m. It is evident that the statistical fusion method is consistently affected by the high distance noise of the 2D LiDAR, whereas the LSTM fusion method filters away the high distance noise. This LSTM fusion algorithm was a preliminary version, trained to only perform fusion at a single ground truth value (in the above cases being 0.59m). This is further regarded as "individual LSTM". As more progress was made, a "compiled LSTM" model was developed, able to fuse distances at any ground truth. The LSTM fusion performance of the compiled and individual model was compared and visualized in **Figure 19**.

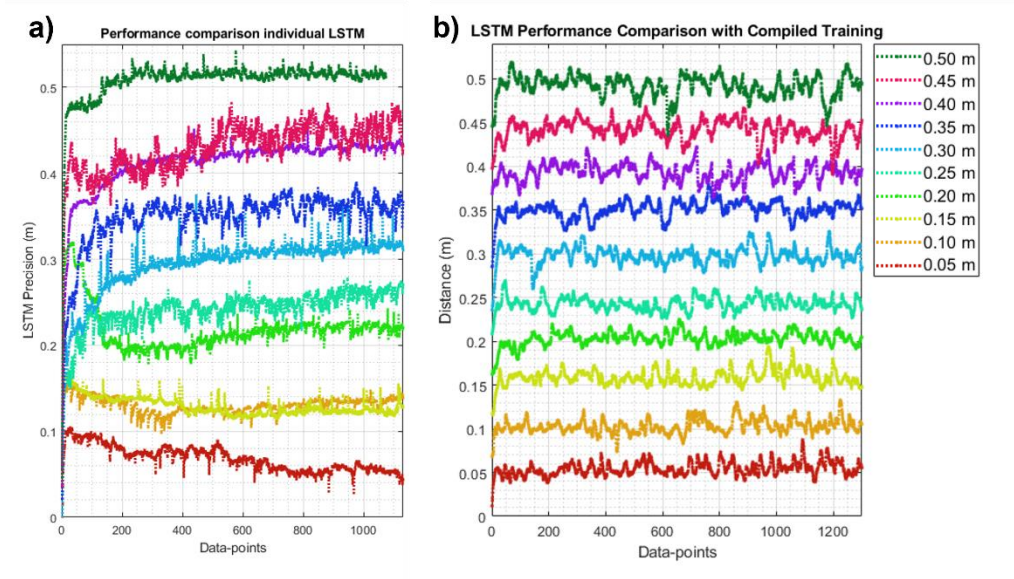

Figure 19. LSTM Machine Learning Fusion Compiled vs Individual Networks

The individual LSTM fusion performances were expected to be better than the compiled performances, as each distance was trained, tested, then optimized for only using one distance rather than multiple. Contrary to the expectation, the compiled training significantly outperformed the individual training.

It is evident that unlike the statistical fusion, which was directly affected by the high-distance noise present from the 2D-LiDAR, both LSTM fusion methods had less noise and was able to properly disregard those high distances by relying on the other sensor measurements when it detected a large measurement spike.

A direct comparison of the percent error and standard deviation of the entire testing data set, comparing raw distance measurements to individual LSTM and compiled LSTM fusion from **Fig. 19**, can be seen in **Figure 20**.

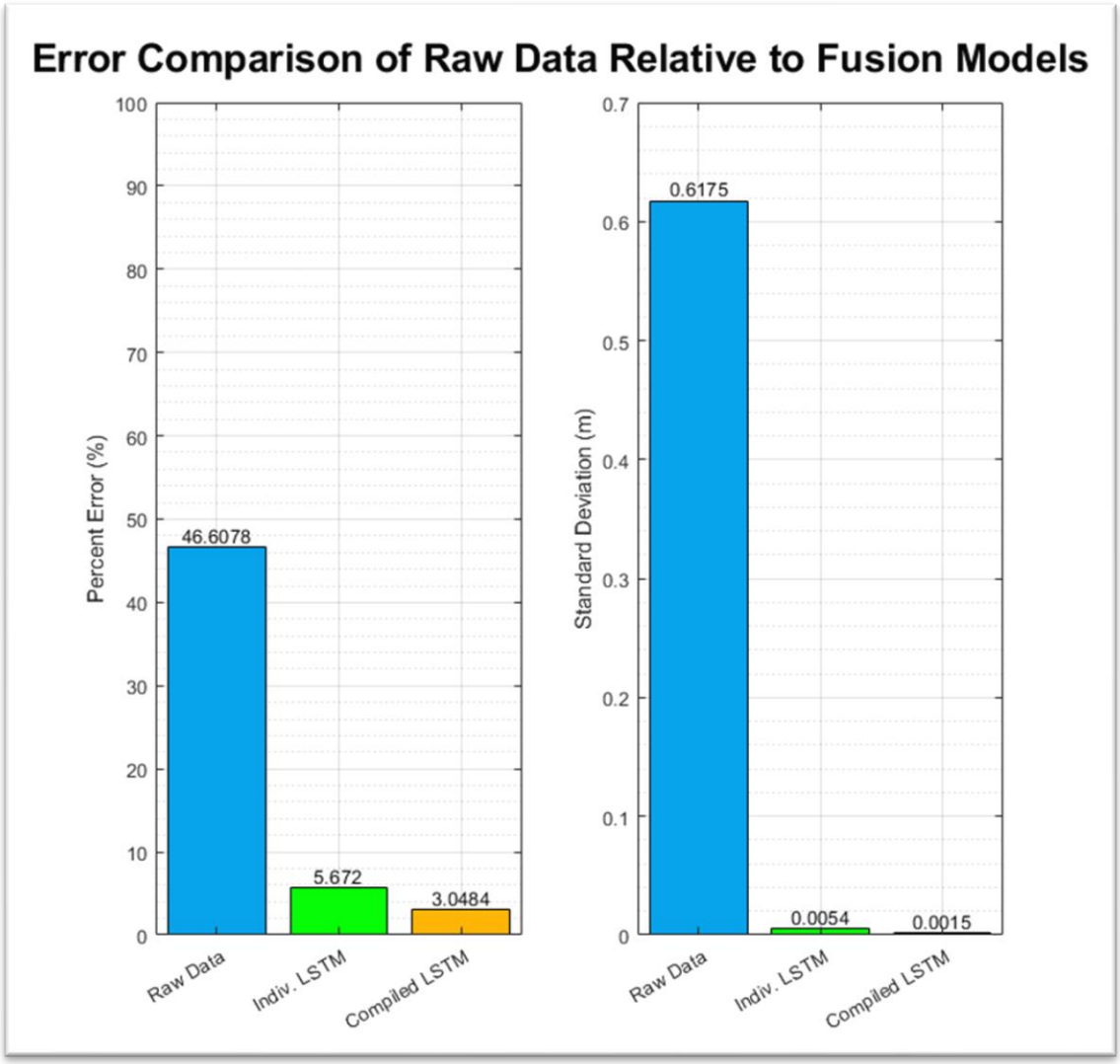

Figure 20. Comparison of Raw Data, Individual LSTM and Compiled LSTM Error

The average error of the raw sensor measurements is 46.61% while the average error of the LSTM fusion data is 5.67% for the individually trained neural networks and 3.05% for the compiled trained LSTM neural network. The average standard deviation of the raw sensor measurements was 0.618m whereas the average standard deviation of the individually trained LSTM is 0.0054m and the average standard deviation of the compiled trained LSTM is 0.0015m, far less than the raw data.

The stereo vision setup with two GoPro Cameras were calibrated in MATLAB with a square checkerboard calibration. The MATLAB function was able to detect the necessary parameters of the cameras to perform disparity recognition.

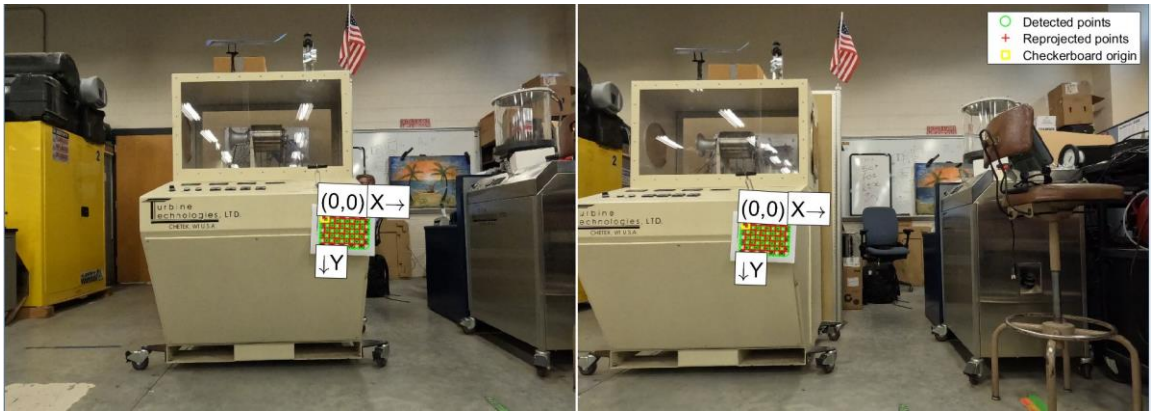

Figure 21a. Checkerboard Calibration (22-millimeter boxes)

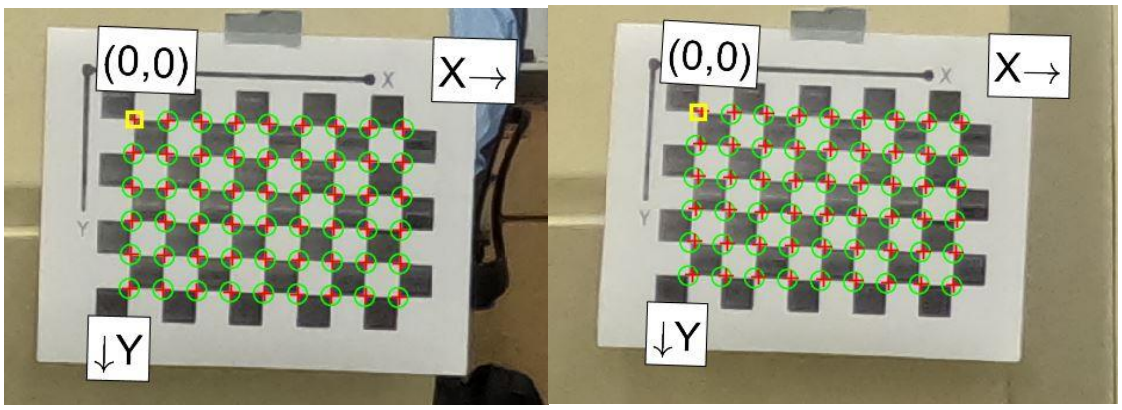

Figure 21b. Checkerboard Calibration (22-millimeter boxes)

From the camera calibration parameters, two images can be provided from each camera and a disparity map representing depth can be generated.

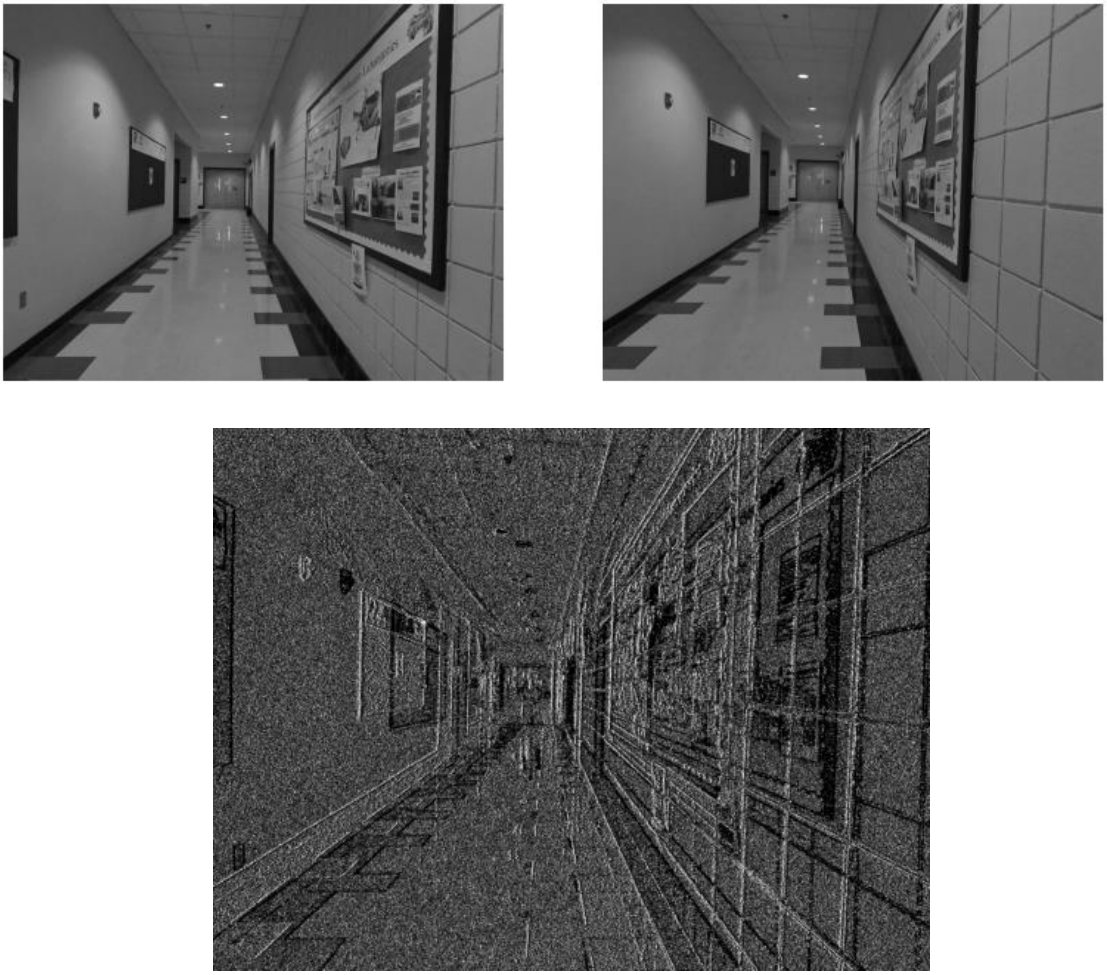

Figure 22. Disparity Map Generation from Simple Stereo Vision Image

Using the generated disparity map, a point cloud in the same format as that returned by the 2D LiDAR will be generated to be used for distance fusion.

Conclusion

Developed was an RNN/LSTM-based sensor fusion algorithm for 2D LiDAR, ultrasonic, and 1D infrared ranging sensors. The evaluation of the sensors showed that the 2D LiDAR had issues with high noise and high response time. The ultrasonic and infrared ranging sensors demonstrated better performance with less noise and more precise measurements.

Two data-level fusion methods were tested: statistical fusion and a recurrent LSTM neural network. The statistical fusion method was significantly affected by the high-distance noise from the 2D LiDAR sensor, while the LSTM fusion method demonstrated better performance with lower noise levels and a more accurate estimate of the true distance. Furthermore, the LSTM fusion had a lower average error rate and standard deviation when compared to raw sensor measurements.

The stereo vision system was calibrated using a checkerboard pattern. The disparity map produced from the stereo vision system provided valuable depth information, which could be combined with the other sensor data for a more accurate and robust distance estimation.

This thesis demonstrates the potential for fusing data from multiple sensors to overcome the limitations of individual sensors, particularly in the case of 2D LiDARs. The use of LSTM fusion methods proved to be an effective way to handle noisy data and improve the accuracy of distance measurements from multiple sensors. This work can serve as a fundamental sensor fusion technique, with potential applications in robotics, autonomous vehicles, and other areas where accurate SLAM is crucial for mobility and safety.

References

[1] “What is SLAM (simultaneous localization and mapping) Available: https://www.mathworks.com/discovery/slam.html.

[2] The electromagnetic spectrum. [Online]. Available: http://www.columbia.edu/~vjd1/electromag_spectrum.htm.

[3] G. Welch, “An introduction to the Kalman filter - university of North Carolina at ...,” University of North Carolina at Chapel Hill, 2006. [Online]. Available: https://www.cs.unc.edu/~welch/media/pdf/kalman_intro.pdf.

[4] “Understanding Kalman filters,” MATLAB. [Online]. Available: https://www.mathworks.com/videos/series/understanding-kalman-filters.html.

[5] S. Julier, “Unscented filtering and nonlinear estimation - IEEE xplore.” [Online]. Available: https://ieeexplore.ieee.org/document/1271397.

[6] F. Gustafsson et al., "Particle filters for positioning, navigation, and tracking," in IEEE Transactions on Signal Processing, vol. 50, no. 2, pp. 425-437, Feb. 2002, doi: 10.1109/78.978396.

[7] V. Fox, J. Hightower, Lin Liao, D. Schulz and G. Borriello, "Bayesian filtering for location estimation," in IEEE Pervasive Computing, vol. 2, no. 3, pp. 24-33, July-Sept. 2003, doi: 10.1109/MPRV.2003.1228524.

[8] V. Soloiu, “Enhancing traffic safety by developing vehicle safety envelope with real time data interface and machine learning based sensor fusion platform,” SAE MOBILUS. [Online]. Available: https://saemobilus.sae.org/content/2023-01-0053. [Accessed: 24-Apr-2023].

[9] Huang, T., “RPLIDAR-A3 Laser Range Scanner_ robot laser range scanner,” SLAMTEC