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LiDAR-based Obstacle Detection and Avoidance for Autonomous Vehicles using Raspberry Pi 3B

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Abstract— **Autonomous vehicles are redefining the transport industry – obstacle detection and avoidance are key to their operation. A number of sensor technologies have been developed and trialled. This paper presents the implementation of a Hokuyo URG-04LX Light Detection And Ranging (LiDAR) sensor on an autonomous vehicle developed with a Raspberry Pi 3B microcontroller and demonstrates its effectiveness for object detection and avoidance in varying conditions. The LiDAR sensor was integrated with the Raspberry Pi 3B using Python on LUbuntu (lightweight version of Ubuntu) and Robot Operating System (ROS). Various scenarios with low light conditions, reflective surfaces at multiple angles, simple stopping tests and different motion paths at varying speeds were tested. All tests were run at 3.2 and 4mph speed. It was found that the LiDAR sensor performed well for basic object detection but did not respond well to reflective or dark surfaces. We further compared the LiDAR's performance with ultrasonic sensors and found that it outperformed ultrasonic sensors for stopping distances. Overall, the LiDAR acts as an effective sensor for the autonomous vehicle, showing its viability in detecting objects and acting as a small scale representation of autonomous technology.**

Keywords—LiDAR, obstacle avoidance, autonomous vehicle, Raspberry Pi 3B

I. INTRODUCTION

Autonomous vehicles have seen a rapid development over the past decade and as technology continues to improve, the more prevalent they become. Companies such as Tesla and Waymo (a subsidiary of Google) have a range of vehicles out on the road today that are somewhat autonomous. Autonomous vehicles make use of a large number of sensors such as cameras, global positioning systems (GPS), Light Detection And Ranging (LiDAR) sensors and many other sensors to achieve a real-time perception of the environment.

LiDAR sensors can now be seen in many other application areas such as building restoration, meteorology, gaming and geology. LiDARs uses point cloud data to build up a 3D image of the environment through echo location via laser, similar to how a bat identifies its surroundings.

According to statistics from the World Health Organisation (WHO), around 1.35 million road traffic deaths occur every year [1] with 72% of crashes in Europe being down to road user errors [2]. The widespread use of autonomous vehicles could rapidly reduce that number however, statistics such as 71% of people being concerned about loss of driving skills due to self-driving cars and more than 60% being concerned about job losses implicates a hesitance by the general populous [3]. The integration of a small scale computer like the Raspberry Pi with LiDAR technology should demonstrate the effectiveness and accessibility of this technology, aiding the understanding and public perception of autonomous vehicles as they become more prevalent in everyday life.

The main contribution of this paper is twofold: Firstly, to implement a Hokuyo URG-04LX LiDAR sensor onto a Raspberry Pi model 3B for object detection and avoidance. Secondly, to compare the obstacle detection and avoidance results from the LiDAR with ultrasonic sensors. The LiDAR is connected to a Raspberry Pi 3B microcontroller of an autonomous vehicle repurposed from a mobility scooter [4] and subjected to a pre-determined route using the programming language Python on LUbuntu and ROS installed on the Pi.

The rest of the paper is organized as follows. Section II presents the literature review. The autonomous vehicle is described in Section III, whereas, Section IV presents the experiments, results and discussion. The paper is concluded in Section V.

II. LITERATURE REVIEW

With the advancements in technology, autonomy is becoming more prevalent within many industries. For full autonomy, the vehicle should be able to navigate in a dynamic changing environment. Companies such as Tesla and Waymo are leading the push towards an autonomous vehicle future. Tesla cars use a system known as 'Tesla Vision' to sense the world around them and it consists of 8 cameras around the car coupled with 12 ultrasonic sensors and radar for a 360° coverage with range up to 250m [5]. Whereas, Waymo cars use 3 LiDAR's, high resolution cameras and radar to perceive the world around the vehicle.

Recently, researchers have been investigating the application of LiDARs in obstacle detection and avoidance. Xie et al have developed a clustering algorithm based on point-cloud data collected from a 3D LiDAR [6]. They then propose a multi-frame fusion method based on the clustering results to locate the moving obstacles. Wang et al [7] present pedestrian recognition algorithm based on support vector machine classification of data obtained from a Velodyne 64 LiDAR. Work presented in [8] also proposes a clustering technique from a 2D LiDAR implementation on Raspberry Pi. A similar work is presented in [9] where a LiDAR is implemented on a Raspberry Pi microcontroller to demonstrate obstacle avoidance and detection. Object classification in an autonomous vehicle has been presented in [10] based on point cloud results from LiDAR data obtained using convolution neural networks. Further, work presented in [11]-[13] also demonstrate obstacle avoidance and detection from 2D and 3D LiDAR data respectively.

Research presented in [14] highlight the benefits of both sensor technologies. Camera based technology provides good geometric and object detail information and when combined with radar, provides accurate information in poor weather conditions much like LiDAR however, camera/radar based systems still suffer from light reflections and diverse edges. LiDAR provides accurate geometric data, functions well in low light and poor weather conditions and has a lower risk of false positives from reflections/light etc. however LiDAR sensors are still costly compared to camera/radar sensors and are largely obtrusive to a vehicles profile.

Research has been conducted looking at the combination of ultrasonic and infrared sensors for simultaneous object detection and collision avoidance when implemented on a UAV [15]. Tests were carried out measuring reliability of distance information measured from both sensors and the ability to respond to a collision course with a dynamic object and adjust flight path accordingly. The conclusions drawn from this experiment proved the effectiveness of low cost sensors and suggested the replacement of the IR/Ultrasonic sensors with a lightweight, cheaper sensor such as the RoboPeak-LiDAR.

Recently, there has been an increasing interest from the research community in the application of LiDARs in obstacle avoidance and detection. Most modern vehicles are now equipped with some form of autonomy, however, confidence level in obstacle avoidance and detection has to increase before full autonomy can be employed. Further, there has been limited research in utilizing the computational ability of Raspberry Pi to prove concepts. The novelty of our work as compared to existing work presented in literature is that we have demonstrated the implementation of obstacle detection and avoidance on Raspberry Pi 3B, and hence testing the suitability from a research point of view. Further, we have done tests to simulate reflective and dark surfaces and hence investigated the suitability of a LiDAR sensor in such environments.

III. AUTONOMOUS VEHICLE USING RASPBERRY PI 3B

The vehicle used for this project is a Capricorn Electric Wheelchair from Better life Healthcare [16] as shown in Fig. 1a. It is a small, four wheeled vehicle with caster type front wheels, two fixed driven rear wheels and powered by two 12V batteries. It is driven by two separate electric motors, which are connected directly to each of the rear wheels. It has a maximum speed of 4mph, a maximum incline of 6° and a turning circle of radius 475mm. The maximum range of the wheelchair is 9.5km. The tyres are solid and have a larger radius than many other models of its type, helping to improve performance on rough or uneven surfaces. This section will present the conversion of the mobility scooter into an autonomous vehicle controlled by Raspberry Pi 3B. It will further describe the connection of the LiDAR sensor.

A. Connecting the Raspberry Pi 3B

The autonomous vehicle was built from a mobility scooter as shown in Fig. 1a. The scooter had an inbuilt microcontroller shown in Fig. 1b which was used as a communicative tool between the Raspberry Pi version 3B and the vehicle's motors units. The vehicle has 5 preset speeds dictated by voltage levels that are manipulated by Digital to Analogue Converters (DAC's). These voltages are sent to the vehicle's micro-controller via the vehicle's joystick connection which are then transmitted to the motors. Each DAC has an InterIntegrated Circuit address (I^2C) which acts as a slave device to the Raspberry Pi and allows component to micro-controller communication via transfer of 8-bit packets.

Fig. 1a. Orginal mobility scooter

Fig. 1b. Autonomous vehicle microcontroller

In order to make space for a platform on which the system can be installed, the chair was removed, as was the housing surrounding the frame of the vehicle. The central column between the chair and the frame was also removed, allowing the new chassis to be placed over the frame. The new chassis is shown in Fig. 2a, whereas, the block diagram is presented in Fig. 2b showing the connections of the Raspberry Pi 3B with the sensors and the vehicle's controller.

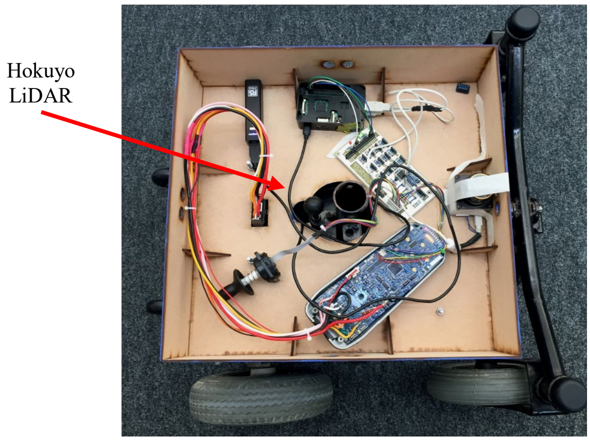

Fig. 2a. The autonomous vehicle modified from the mobility scooter

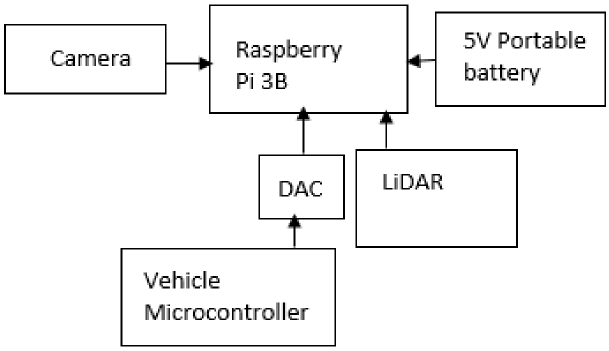

Fig. 2b. Block diagram of the autonomous vehicle

B. *Connecting the LiDAR sensor*

The Hokuyo URG-04LX LiDAR was connected to the Raspberry Pi 3B. The LiDAR had a range of 60-4095mm (240° FoV). For the vehicle to integrate with the LiDAR, Python was used to write the code. Both Lubuntu, a lightweight version of the Ubuntu operating system and Robot Operating System (ROS) Kinetic, a version of the Robot Operating System that allows LiDAR integration, were imaged to the SD card of the Pi as the Hokuyo LiDAR only worked with Linux & Windows based systems. The Rospy package was imported for Python/ROS communication and the Adafruit module allowed Python code to change the DAC voltages. The Y DAC and X DAC allowed for forwards/backwards and left/right movement respectively through using the I^2C bus addresses. The use of separate addresses allowed unrestricted omnidirectional movement.

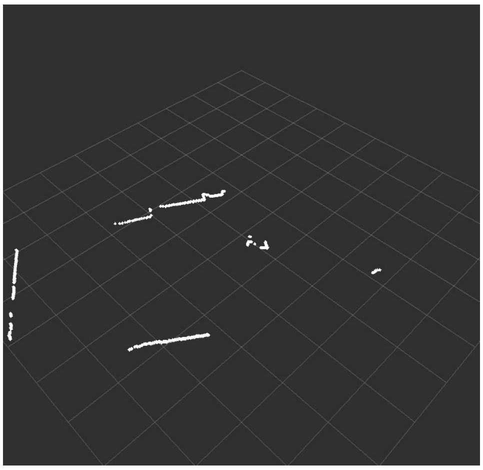

Fig. 3. RViz running on the Raspberry Pi showing point cloud for the test environment

With Lubuntu installed on the Pi several packages had to be installed for the LiDAR to interact with and display range information. The package URG NODE for the Hokuyo URG-04LX LiDAR had to be installed to interact with the device. Ros Visualization (RViz) shown in Fig. 3, shows a visual representation of the range data that the LiDAR sees in a 2D scan as point cloud data at 100ms intervals. The middle value of the range data in a 240° scan from the ROS laserscan topic was used as the reference value within the autonomous script and was acquired through an altered version of the script from [17] and implemented within the simplified block diagram as seen in Fig. 4.

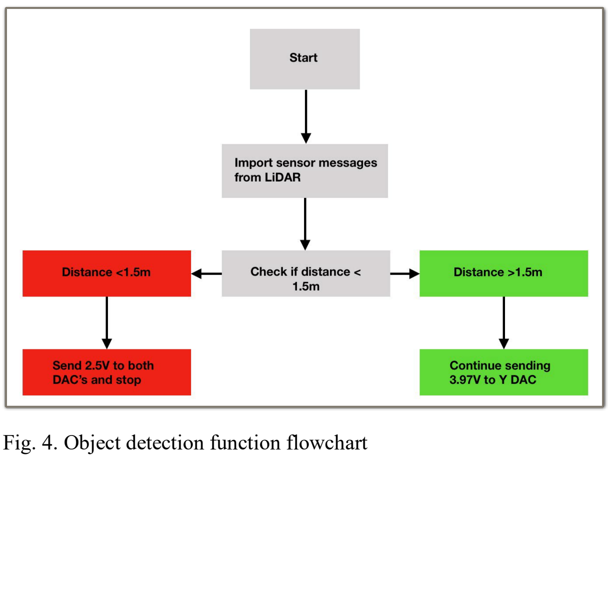

Fig. 4. Object detection function flowchart

This middle range value takes the distance to the nearest object directly in front of the vehicle but the entire spectrum of live range values can be displayed by using the inbuilt echo command within ROS as shown in Fig. 5. The script imported only allows one or all range values to be imported and as the vehicle was located within the housing, only the middle range value was used to prevent false positives.

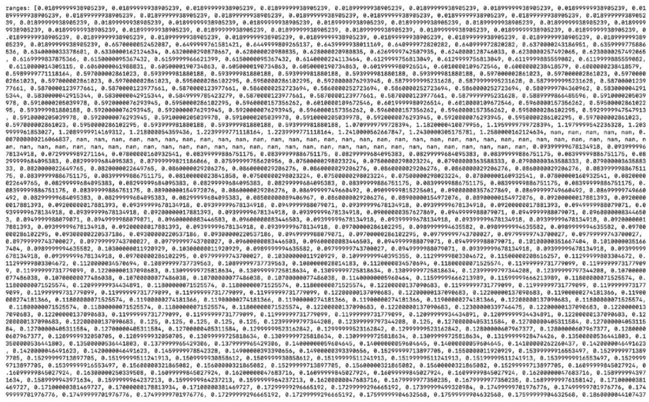

Fig. 5. LiDAR range values from a single 240° scan

The LiDAR was secured onto the vehicle housing and connected to the Pi via power and data transfer over USB, a 5V portable battery provided power for both the LiDAR and the Pi. The packages mentioned above are run along with the autonomous script. If the range imported from the LiDAR is less than a predefined value (e.g. 1.0m), a stop function is executed sending 2.5V to the DAC for a set amount of time, otherwise the vehicle will continue in a forward trajectory at a set speed defined by the voltage passing through the Y DAC.

IV. Experiments, Results and Discussion

The experiments focused on the ability of the LiDAR to detect objects and its effect on the vehicle's ability to avoid collisions. Various scenarios with low light conditions, reflective surfaces at multiple angles, simple stopping tests and different motion paths at varied speeds were tested in order to analyse the LiDAR's object detection capabilities. Further, dynamic objects such as pedestrians were also tested to emulate real world scenarios. LiDAR's generally do not respond well to reflective surfaces as the laser light is deflected and doesn't always find its way back to the receiver resulting in varied distance measurements, providing diverse results for analysis [18].

All tests were run at either speed 4 (3.2mph) or 5 (4mph) on the vehicle microcontroller which corresponded to DAC voltages of 3.97V and 5.17V respectively. The variables measured for this test were LiDAR recorded stopping distance, actual stopping distance, accuracy of range measurements and clock time of the Pi. Stopping distance was then compared to our previous work [4] to ultrasonic sensors. The LiDAR range information was recorded using 'rosbag', a feature of ROS to track all range measurements, diagnostic messages and errors over the time the test took place. A 3m track was used for the vehicle with objects placed at the 3m mark as seen in Fig. 6. 3m was chosen as quoted range accuracy for the LiDAR drops off after 1000mm to ±1% between 1000mm-4095mm. 1.0m was used as the distance threshold for when the vehicle motors would stop due to a command issued by the Pi.

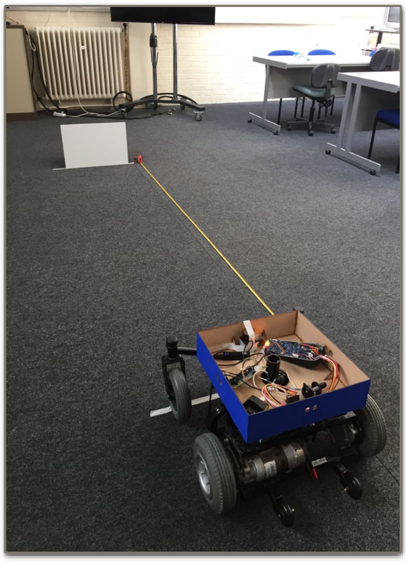

Fig. 6. Autonomous vehicle testing environment

By measuring clock time using the inbuilt Python function, it could be observed if the variables implemented had any effect on processing times for the Pi. The experiments are designed to emulate scenarios within the real world with objects that autonomous vehicles would encounter daily. Due to the limitations of working inside a controlled environment, these results give a general idea of LiDAR's capabilities on a small scale that are applicable to real world scenarios.

A. *LiDAR sensor testing for stopping distance*

Stopping distance tests shown in Table I measured the final recorded distance by the LiDAR to the object that was to be detected. Angular reflective and reflective tests used a sheet of aluminum for detection set at 45° and 90° to the vehicle's path respectively. All angular reflective tests were errors with incorrect range values recorded throughout resulting in the vehicle crashing.

TABLE I. LIDAR STOPPING DISTANCES

Test type	Speed	Test 1	Test 2	Test 3	Test 4	Test 5	Range threshold (m)
Angular reflective	4	2.3	0	2.9	2.5	3	1
Pedestrian	4	0.5	0.3	0.1	0.3	0.5	1
High voltage	5	0.6	0.6	0.6	0.6	0.6	1
Low light	4	0.4	0.1	0.5	0.6	0.4	1
Reflective	4	1	2.1	1	1	3.5	1
Stationary	4	0.9	0.8	0.8	0.8	0.8	1

Reflective tests performed better with only one crash and successful stops but recorded range values were still incorrect at times. Pedestrian tests involved an individual walking in front of the vehicle during motions and this resulted in low recognition times with the final stopping distances to the pedestrian being significantly below the range threshold. Low light tests involved a dark object for detection in a blacked out room and showed a diverse range of final distances to the object. The object was often not recorded until around 0.5m away. Stationary and high voltage tests both used a wooden square for detection and produced uniform results across all tests with minor variation.

TABLE II. HIGH VOLTAGE STOPPING DISTANCES

Actual	0.45	0.47	0.49	0.46	0.46
LiDAR recorded	0.4	0.4	0.4	0.4	0.4
%age error	11.1	14.9	18.4	13	13

High voltage tests shown in Table II used a voltage of 5.17V to run the vehicle at the preset speed setting 5. This test was run in order to test stopping distances at higher speeds and show the actual vs recorded range measurements. Due to the range measurements only being displayed to 2 significant figures, it can be assumed that the LiDAR is reasonably accurate at recording the actual distance to the object, subject to ±1% as quoted previously but round ups to the nearest 0.1m. ROS automatically rounds range values up when not viewed in their raw format therefore reducing accuracy.

B. *LiDAR sensor clock test*

Clock time was measured against stopping distance and the number of range values recorded. As seen below in Fig.7 there is very little variation in results as only one message is being imported into the script making it not very computationally intense.

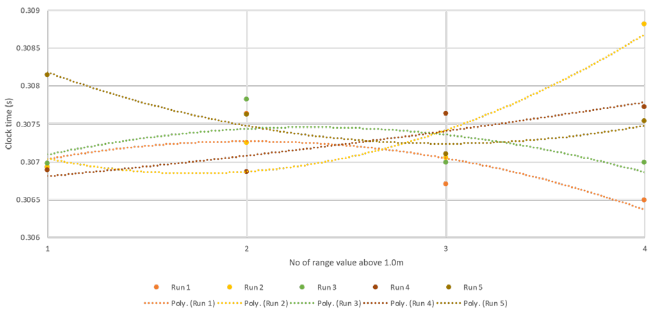

Fig. 7 Clock time results against number of measurements

However earlier range values show more diverse results in terms of clock time. Differences in clock time values are very small however, when put into the context of how long the Pi takes to complete these operations, they display significant variation.

C. *Ultrasonic vs LiDAR sensor stopping distance*

Results from the LiDAR sensor were then compared to the ultrasonic sensors at speeds 4 and 5 over three different tests shown in Fig.8. The stopping distance results show the distance taken to stop when given a range threshold of 1.0m. Points that are on the black line would count as crashes. Ultrasonic results can be seen to take further to come to a complete stop once the range threshold of 1.0m has been reached when compared to LiDAR data and both the 4 and 5 speed tests show more variation in stopping distances for ultrasonic data. Pedestrian tests show more variation for LiDAR data and performs worse when compared to ultrasonic tests possibly due to the use of only one laser being used for LiDAR range measurements.

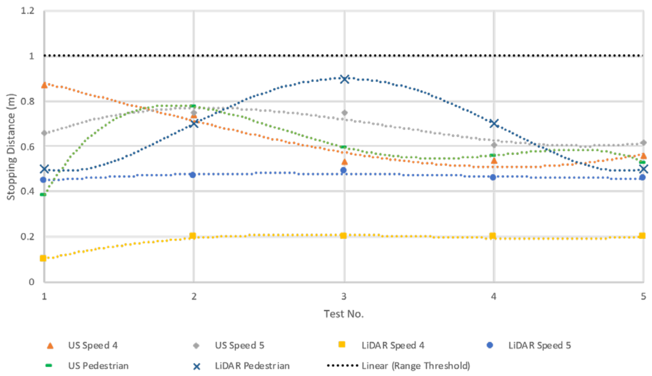

Fig. 8. Ultrasonic and LiDAR sensor stopping distance comparison

D. *RViz scenario comparison*

RViz images were captured for each scenario with the corresponding object for detection placed at a distance of 0.5m from the vehicle to show differences in how the LiDAR perceived each object. On each image the U shaped point cloud distribution is the inside of the vehicle housing being picked up by the LiDAR. Pedestrians as shown in Fig.9a show point cloud points, but they are grouped together allowing the LiDAR to easily detect the object. Reflective tests shown in Fig.9b have some interference between the object and the vehicle displaying point cloud data where no object is present. Angular reflective results shown in Fig.9c and stationary tests in Fig.9d also show the same trend, possibly due to reflections or dust. Low light tests shown in Fig.9e show some anomalous point cloud points and the object was not picked up by the LiDAR.

Fig. 9a. RViz pedestrian test image

Fig. 9b. RViz reflective test image

Fig. 9c. RViz angular reflective test image

Fig. 9d. RViz stationary test image

Fig. 9e. RViz low light test image

E. *Discussion*

Testing the LiDAR's effectiveness in a range of conditions adequately displayed the sensors advantages and weaknesses when compared with other technologies. The LiDAR sensor was fairly accurate at recording range measurements and subsequently issuing stop commands to the motors however this could be improved. The vehicle suffers with only being able to stop the motors and not apply brakes when an object comes within the range threshold leading to an average distance of 0.34m required to come to a complete stop amongst the speed 4 tests. Average stopping distance based on data from the RAC [19] when scaled for the vehicle equates to an average stopping distance of 0.48m. This data however, does not take into account weight, ground surface, etc. but still provides a good benchmark for comparison.

Errors were mostly seen in the reflective and low 1light tests. Figures 9a, 9c and 9e show the LiDAR has difficulty with accurately locating and portraying these objects in point cloud format. This could be possibly due to the lasers deflecting and not reaching the receiver or being absorbed by the dark object due to the laser signal weakening with distance from the LiDAR, as range measurements were only ever recorded below 0.6m for these tests. Point cloud data suffers from errors mainly due to reflections, an uncalibrated LiDAR possibly due to vibrations on the vehicle and mixed pixels whereby the depth coordinate of point cloud data is incorrectly displayed resulting in the effect seen in Fig.8e [20].

A study using a 2D LiDAR for the Defense Advanced Research Projects Agency (DARPA) grand challenge proved LiDAR's effectiveness in low light conditions when detecting road markings [21], but due to the use of only one datapoint and the type of LiDAR used, the vehicle range information in these conditions was not viable and did not perform as expected. Work presented in [22] investigated the effect of dust particulates on LiDAR data and found that information transmittance of point cloud data was as low as 2% for high reflective surfaces and 6% for black surfaces. These studies used a more advanced LiDAR so these figures may not be directly transferrable but show significant limitations of LiDAR for certain surfaces. Similar studies have alleviated the issue via filtering techniques that do not rely on trajectory data, using processes of segmentation, clustering and feature recognition for reflective road signs [23].

Small percentage errors were observed between actual and recorded high voltage range measurements but this was due to the LiDAR range measurements only publishing to two significant figures.

LiDAR and ultrasonic sensor results show remarkably lower stopping distances as well as more uniformity in stopping distances for LiDAR. The LiDAR runs at a high refresh rate, did not have RViz running during testing and dealt with only one range value compared to the ultrasonic sensor, which had to trigger multiple sensors resulting in more computational processing time and therefore, an increased time and distance to stop. Data streaming via USB for the LiDAR was more reliable than the pins used for the ultrasonic sensor connections that would often come loose resulting in slow or no data transfer. LiDAR does struggle with pedestrian recognition compared to ultrasonic sensors but it is believed this is due to the fact that only one laser signal was measured.

These results agree with similar studies [24] comparing ultrasonic and LiDAR sensors demonstrating LiDAR's superior accuracy and high efficiency, however it is also noted that ultrasonic sensors are generally more user-friendly and cheaper than LiDAR due to their software and hardware requirements. Most common errors encountered with LiDAR technology appear to be alleviated via filtering algorithms. Filtering algorithms would increase processing times but could possibly be reduced by upgrading or overlocking the computer used.

V. CONCLUSIONS

In this paper a Hokuyo LiDAR has been successfully implemented as a range sensor for the Raspberry Pi 3B microcontroller on an autonomous vehicle. The vehicle was then tested across a range of scenarios avoiding collisions with objects. LiDAR proved to be a superior technology when compared to ultrasonic sensors demonstrating high accuracy and clock time but was limited by fidelity of point cloud data and its perception of reflective or dark surfaces. The use of only one range value from the LiDAR hindered its performance when detecting pedestrians but it still managed to maintain a low overall stopping distance.

LiDAR has proved to be a viable technology for an autonomous vehicle of this scale and appropriately meets the function of a scalable testbed for autonomous technologies. Our future work will focus on filtering algorithms and other forms of sensors to improve its overall detection performance.

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