2016 6th IEEE International Conference on Control System, Computing and Engineering, 25–27 November 2016, Penang, Malaysia

Obstacle Detection using a 2D LIDAR System for an Autonomous Vehicle

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***Abstract*—Obstacle detection is a requirement for Advanced Driver Assistance Systems (ADAS) which are the precursors to autonomous vehicle systems. A number of sensor systems have been used before to perform obstacle detection. One particular sensor system is the LIDAR system which is noted for its accuracy in measuring distances. However, most commercially available LIDAR (Light Detection and Ranging) systems are expensive and computationally intensive. This research characterizes an inexpensive 2D LIDAR system using the LIDAR-Lite v1 for use in obstacle detection for autonomous vehicles. Since data acquisition occurs only in a single plane, the system should be computationally fast. The field of vision should be capable of up to 360 degrees. The data acquired was median-filtered and pre-processed by the merging and segmentation of data points. Obstacle detection was then performed via clustering. Results show that obstacles with widths of 1 meter can be detected at distances of 10 meters.**

***Index Terms*—Autonomous Vehicle Sensor, 2D LIDAR System, Obstacle Detection.**

I. Introduction

Obstacle detection is the first step to local obstacle avoidance which is the significant embodiment of the mobile ground robot and the guarantee for it to perform various tasks [2]. An essential part of obstacle detection is the environment information from a sensor or a system of sensors.

Some of the commonly used sensor systems include computer vision (CV) systems using a camera, RADAR (Radio Detection And Ranging) systems, ultrasonic imaging systems and LIDAR systems. CV systems excel at object recognition which is far more complex than simple obstacle detection. However, CV systems require expensive processing and material costs, and have difficulty in ranging and measuring the distance of the recognized objects [3]. Ultrasonic imaging systems are cheaper and require lesser power; however, their accuracy and resolution are inferior to the others. RADAR and LIDAR systems have insignificant difference in terms of efficiency when used in Adaptive Cruise Control (ACC) [4]. This paper focuses on the use of the LIDAR systems in obstacle detection.

There are two types of LIDAR systems: 3D and 2D. 3D LIDAR systems are expensive to both processing power and material cost [2]. However, 3D systems are able to recover the height information of obstacle and their geometry whereas 2D systems only give distance information. For the purpose of decreasing costs, the proposal will use a 2D LIDAR system.

Commercial LIDAR systems are available such as the Velodyne HDL 64-E, the Sick LMS-511 and the Hokuyo UTM-30LX. These LIDAR systems are efficient enough for automated vehicle function but are very expensive. This research will use an inexpensive LIDAR-Lite v1 from Pulsed Light. The LIDAR-Lite has a maximum range of 40m, an accuracy of ± 2.5cm, a sampling rate of 50Hz [5].

As stated by Huang and Barth, the best approach to an obstacle detection system uses a LIDAR-camera fusion [3]. This research will complement existing research on CV.

In developing the LIDAR system for our autonomous vehicle, the following goals were set.

• 2D to decrease material and processing costs. With a 2D LIDAR system, the distance ranging information was taken at a single plane of measurement. This restricted the detection of obstacles to a minimum height and clearance as well as the false detection of high angled road sloping as obstacles. However, the scope of operation of the automated vehicle was for flat urban environments where obstacles such as other vehicles, buildings and people reach the minimum height clearance as well as roads having the enough clearance.

• Reliable and effective in the identification of obstacles. The accuracy of the distance measured for the identified obstacles must be tolerable. Detected obstacles were classified into three categories: vehicles, buildings and people. The LIDAR system should correctly classify each obstacle given an accurate distance map of the environment. The distance map of the environment should be reliable given that the LIDAR ranging does not occur simultaneously for the whole plane of measurement. Each degree sample was taken at a different time from the previous and therefore, inaccuracies may result when the environment has changed. This was especially crucial when dealing with moving obstacles or when the automated vehicle was moving. However, the scope of operation of the automated vehicle limited its speed to 30 kph and assumes that other vehicles were limited as well since fast paced driving was unnecessary in closed flat urban environment.

• Modular and can be easily integrated into a LIDAR-camera fusion as well as with other sensor systems. A fully automated vehicle requires multiple sensor systems and therefore, required each sensor system to be cooperative. The LIDAR system should easily be able to participate in a sensor network.

This work will thus focus on investigating the performance of low-cost LIDAR alternatives for obstacle detection.

II. Methodology

A. Hardware Design and Implementation

The LIDAR system was specified to be capable of a 360 degree field of vision for cost minimization instead of having multiple LIDAR systems with narrower fields of vision.

The LIDAR unit used is the LIDAR-Lite v1 from PulsedLight which uses I2C communication at 100 Kbps and an accuracy of 2.5cm with a maximum range of 40m [5]. A single board computer Raspberry Pi 2 Model B handles the processing of the obstacle detection algorithm, the motor control and the I2C communication to the LIDAR-Lite v1.

Figure 1. PulsedLight LIDAR-Lite v1 [5]

The mechanical design for the mounting and the casing of the LIDAR system valued simplicity and cost minimization. The LIDAR-Lite was mounted on the stepper motor using a custom mount. The stepper motor was placed in a casing to stabilize its position from vibrations. The individual components of the mechanical design were computer modelled and 3D printed using PLA thermoplastic. The mounting position of the LIDAR system was on the top of the automated which has 1.5-meter elevation from the ground and directed 5 degrees below the horizontal so as to achieve the proper and unobstructed plane of measurement but still sufficiently low enough to detect short obstacles.

B. Software Design of Obstacle Detection

1) LIDAR Data Acquisition

The Raspberry Pi 2 Model B was used to control the stepper motor and the LIDAR unit by producing PWM signals and implementing the I2C communication, respectively. A continuous PWM signal was used to move the stepper motor every distance sample taken. Furthermore, the stepper motor used is capable of 400 data points per sweep at half-wave operation. Distance samples were continuously taken and the speed of the LIDAR's acquisition puts the motor speed to lower than the rated value. Thus, the half-wave operation of the stepper motor encountered irregular step errors. By running the stepper motor at full-wave operation or at 200 samples per revolution, the irregular step errors were removed. Thus, the objective accuracy of one degree per sample is compromised in favor of consistency and precision. In terms of the speed of each sweep, the LIDAR system takes one sweep in 1.7s. The data acquisition time of the LIDAR was considerably longer compared to the processing time of the subsequent software operations.

2) Data Filtering

A median filter is typically used to remove salt and pepper noise or occasional noise peaks. [2] used a 3-neighbor median filter to eliminate noise points in the distance map. In the software implementation, a dynamically allocated array takes the values of the current distance point and its two neighbors. The array is sorted using the quicksort method and the median replaces the value of the current distance point.

3) Data Pre-processing

Each point or sample in the distance map has a relative position to the LIDAR system computed from the distance and the angle of the sample. Thus, each point or sample has a coordinate. [2] considered the distance between each point . If the distance exceeded a given maximum, the points were segmented and placed into different blocks. Similarly, if the distance was less than the given maximum, the points were merged into one block. This maximum distance value was proposed to be 1.5 m which was the width of the autonomous vehicle plus and additional clearance value since it would be impossible for it to pass through spaces narrower than this.

4) Data Clustering

Each block after pre-processing was subjected to shape association. [2] has three shaping rules: circle, line and rectangle for simplicity. Each shape corresponded to a classification defined for the obstacle detection algorithm. The circle shape was associated with a person, the line associated with the forward vehicle and road barriers, and the rectangle for other vehicles and buildings. If the block has five or less points, the shape association was a circle. The radius of the circle was the maximum distance of the points in the block from the center. If there were more than five points, a main feature line of the block was designated as the line connecting the first and last points. If the distance between all the points and the main feature line was less than 20% of the length of the main feature line, the shape association was the main feature line. If the distance exceeded the 20%, the shape association was a rectangle with a length and width that minimally encompasses all the points. Once every block has been shape associated, an output file was created listing the obstacles and their classifications and positions.

5) Testing

An indoor testing procedure was designed to check the accuracy of the obstacle detection. A sample obstacle with a height of 2.2m and width of 1.26m was placed at varying distances in front of the vehicle. In addition, the features of the indoor room was checked for consistency. Five trials each for four different obstacle distances were conducted. Finally, the results of the obstacle detection of the LIDAR system were compared to the true distances of the sample obstacle.

An outdoor testing procedure was designed to test the LIDAR operation in actual operation. The LIDAR system was tested on both stationary and moving states of the automated vehicle. For the stationary vehicle test case, the output clustered map was compared to the actual distances of select obstacles. There were four selected obstacles. Obstacle 1 was a forward vehicle while obstacles 2, 3 and 4 were people. Each obstacle was stationed at a randomly chosen position away from the automated vehicle. For the moving vehicle test case, the output clustered maps were compared with the preceding samples to determine the changes in distance of a selected obstacle and ascertain the effect of vehicle motion. The selected obstacle used was a parked forward vehicle.

III. Results and Analysis

A. Consistency of Features in Distance Maps

Before testing the obstacle detection accuracy of the LIDAR system, the consistency of the acquired distance map was first considered. Figure 6 shows an approximation of the features of the topology of the indoor testing area at a height of 1.5 m. The orange rectangle represented the automated vehicle and the green square was the LIDAR system. The red obstacle's position was varied during the testing of the obstacle detection.

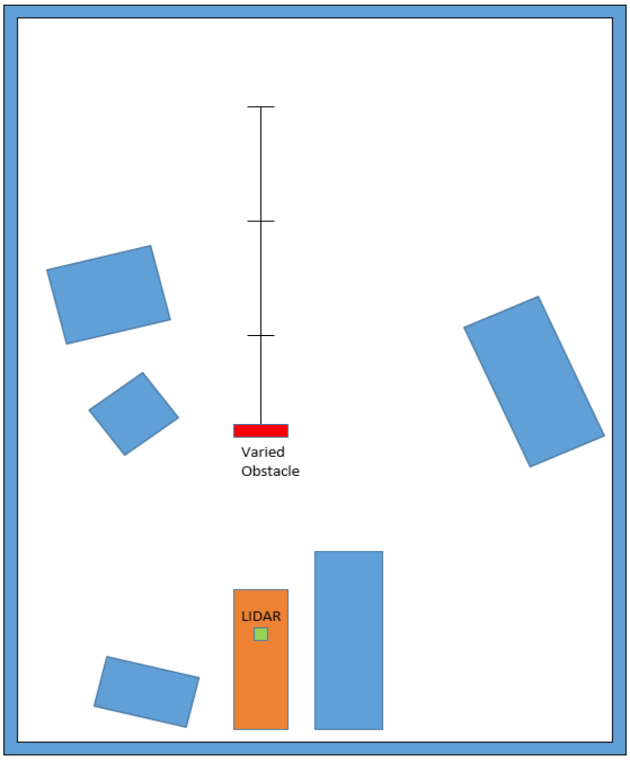

Figure 2. Approximation of the Features in the Laboratory at a Height of 1.5m

In testing the consistency of the output of the LIDAR system, five comparisons of different distance map acquisitions were made. Figure 3 shows one of the distance maps acquired by the LIDAR system. It was observed that the distance map resembles the approximation. The distance maps were compared by calculating the distance between each corresponding point.

Table 1 shows the distance errors as calculated from the LIDAR acquired distance and the actual measured distance. It was observed that the differences in the features of the topology in the acquired distance map averagely differ within 1.5 m to 3 m. The difficulty in increasing the consistency and precision of the LIDAR system was due to the occasional noise points of the LIDAR-Lite and the lack of positional feedback and absolute starting position of the stepper motor. The raw distance map was passed through the median filter to remove the occasional noise points. However, the filter also smoothened out the distance map data that were significant especially the singular isolated peaks that occur when the system samples far narrow obstacles. The lack of positional feedback and absolute starting position also served to decrease the consistency of features in the distance map.

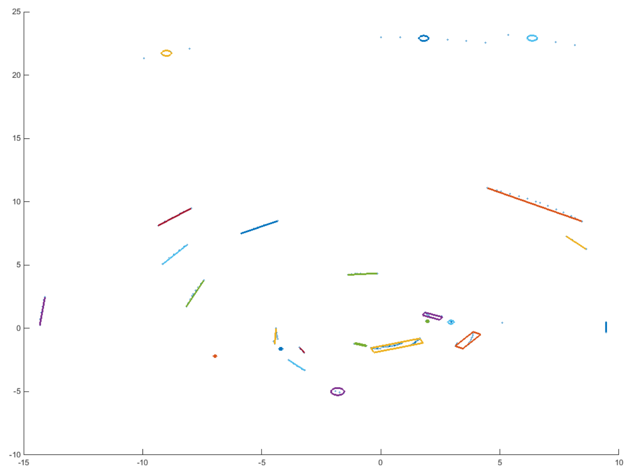

Figure 3. Sample Distance Map Acquired by the LIDAR System

Table 1. Consistency of Features in Distance Maps

Distance Map Comparisons	Average Distance Error
After 4 sweeps	238.65 cm
After 6 sweeps	176.35 cm
After 8 sweeps	246.70 cm
After 10 sweeps	294.83 cm
After 12 sweeps	204.88 cm

B. Reliability of Obstacle Detection

The reliability of the obstacle detection of the LIDAR system was based on its capability to detect the obstacle, the accuracy of the detected distance from the obstacle and the proper classification of the obstacle type. The indoor testing used a rectangular sample obstacle with a height of 2.2 m and a width of 1.36 m and placed at varied distances from the automated vehicle. The test was designed to check reliability of the LIDAR system by its the capability to detect vehicle type obstacles, its ability to classify an obstacle as a vehicle and its accuracy in measuring the distance from the obstacle. There were five trials for each of the four different distances used in the testing. Table 2 shows the results.

Table 2. Results for the Indoor Testing of the LIDAR System using a 2.2m X 1.36m Rectangular Obstacle

True Distance	Trial	Obstacle Detected?	Shape Classification	Measured Distance
430 cm	1	YES	LINEAR	439 cm
	2	YES	LINEAR	434 cm
	3	YES	LINEAR	441 cm
	4	YES	LINEAR	437 cm
	5	YES	LINEAR	438 cm
826 cm	1	YES	CIRCLE	836 cm
	2	YES	CIRCLE	830 cm
	3	YES	CIRCLE	836 cm
	4	YES	CIRCLE	842 cm
	5	YES	CIRCLE	830 cm
1230 cm	1	YES	CIRCLE	1152 cm
	2	NO	-	-
	3	YES	CIRCLE	1237 cm
	4	NO	-	-
	5	YES	CIRCLE	1242 cm
1626 cm	1	NO	-	-
	2	NO	-	-
	3	NO	-	-
	4	NO	-	-
	5	NO	-	-

At a distance of 4.30 m and 8.26 m, the LIDAR system was able to detect the obstacle for all trials while at 12.30 m, the LIDAR system was able to detect only 60% of all trials. At a distance of 16.26 m, the LIDAR system was unable to detect the obstacle. It was observed that the capability of the LIDAR system to detect obstacles is inversely proportional to the true distance of the obstacle. The number of points per sweep and the width of the obstacle also affected the performance. Since the step resolution of the motor was limited, the number of points per sweep of the LIDAR system was constrained. Thus, an obstacle, of width ***w***, was only detectable by the LIDAR system, which has a stepper motor resolution of ***r***, at a distance limit of ***d***. Furthermore, since the distance map was passed through a 3-neighbor median filter, the obstacle was surely detected if its width was greater than four times the minimum detectable width and stochastically detectable if its width was greater than three times the minimum detectable width. Equation 5 shows the 100% detectability condition for an obstacle on the given LIDAR system specifications and Equation 6 shows the stochastically detectability condition. Therefore, given that the sample obstacle has a width of 1.36 m and the stepper motor has a 1.8 degree resolution, the sample obstacle was 100% detectable at distances less than 10.82 m and was stochastically detectable at distances less than 1443 cm.

$$d < \frac{w}{\left[4\sin(r)\right]} \tag{5}$$

$$d < \frac{w}{\left[3\sin(r)\right]} \tag{6}$$

It was only at a distance of 4.30 m that the LIDAR system was able to properly classify the obstacle as a linear or a vehicle-type obstacle. Since a linear type obstacle requires more than five points of the distance map to be part of the obstacle, a distance limit was again defined. Given the smoothening effect of the 3-neighbor median filter, the distance limit required at least 8 points of the distance map to be part of the obstacle. Therefore, the distance limit for the proper classification of vehicle-type obstacles is shown in Equation 7. The distance limit for the proper classification of a 1.36 cm wide obstacle was 5.41 cm.

$$d < \frac{w}{\left[8\sin(r)\right]} \tag{7}$$

In testing the accuracy of the obstacle's distance measured by the LIDAR system, data from misclassified obstacles were included since the type of the obstacle was unrelated to the measured distance by the LIDAR system. Table 3 shows the error statistics of the measured distances to the true distances.

Table 3. Accuracy of the Measured Distance of the LIDAR System

True Distance	Mean of Measured Distances	Percent Error	Standard Deviation
430 cm	437.8 cm	1.81%	2.59 cm
826 cm	834.8 cm	1.07%	5.02 cm
1230 cm	1210.3 cm	1.60%	50.58 cm

The errors for the mean of the measured distances for all true distances were in the range of 1% to 2% which was relatively negligible. Furthermore, the standard deviations of the measured distances for each trial at true distance values of 4.30 m and 8.26 m were negligible compared to the mean. However, at a true distance of 12.30 m, the standard deviation increased but was still relatively small compared to the mean. This increase may have been due to limit of 100% detectability which was at 10.82 m and given that only three trials showed the detection of the obstacle.

IV. Conclusion

The LIDAR system was composed of the LIDAR-Lite v1, the Raspberry Pi 2 Model B and a stepper motor. The LIDAR system was designed to be an obstacle detection module for the automated vehicle. The system was 2D and operated on a single plane of measurement. The reliability of the 2D LIDAR system was based on its performance on detection of obstacles, classification of obstacles and ranging of obstacles. Based on the results of indoor testing, reliable detection of a 1.36 m wide obstacle was achieved at distances of less than 10.82 m. Reliable classification of obstacles was achieved at distances of less than 5.42 m. Given the detection of an obstacle, the ranging of the obstacle was achieved to be reliable up to the range of the LIDAR-Lite v1 sensor.

V. References

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