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Obstacle Classification Method Based On 2D LIDAR Database

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***Abstract*—**We propose obstacle classification method based on 2D LIDAR Database. The existing obstacle classification method based on 2D LIDAR, has an advantage in terms of accuracy and shorter calculation time. However, it was difficult to classifier the type of obstacle and therefore accurate path planning was not possible. In order to overcome this problem, a method of classifying obstacle type based on width data of obstacle was proposed. However, width data was not sufficient to improve accuracy. In this paper, database was established by width and intensity data; the first classification was processed by the width data; the second classification was processed by the intensity data; classification was processed by comparing to database; result of obstacle classification was determined by finding the one with highest similarity values. An experiment using an actual autonomous vehicle under real environment shows that calculation time declined in comparison to 3D LIDAR and it was possible to classify obstacle using single 2D LIDAR.

***Keywords*—**Obstacle, Classification, LIDAR, Segmentation, Width, Intensity, Database.

I. Introduction

IT is necessary to path planning constantly to make autonomous vehicles to drive for itself without intervention of a driver. The path planning technology is to generate an available route from a current location to a destination [1]. To path planning, an autonomous vehicle should be able to judge between drivable area and undrivable area on the road and avoid obstacles in driving, thus obstacle-perception technology is essential.

However, information on the type of the obstacles is needed in addition to obstacle perception. If they could obtain more efficient information on the type of obstacles, it is possible for vehicles to makea judgment appropriate for obstacles and situations.

As representative sensors to perceive the surrounding environment to path planning, there are LIDAR (LIght Detecting And Ranging), and VISION [2].As shown in the Fig. 1, performance of a sensor can be evaluated by range, scan angle, distance accuracy, range resolution, and angular resolution.

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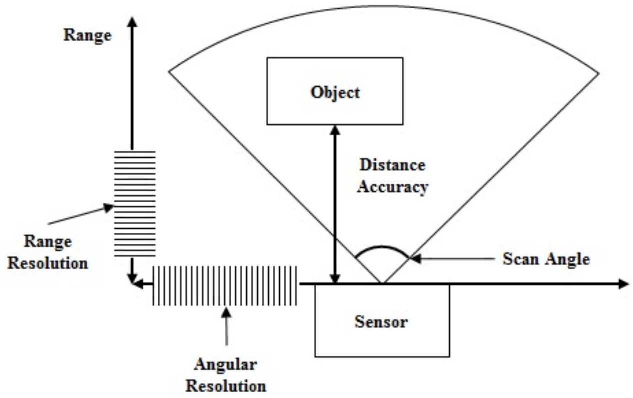

Fig. 1 Sensor Specification

LIDAR is able to acquire quite accurate distance information with a high range resolution and angular resolution, which is usually used in the map generating technique of the autonomous vehicles [3]. However, there are disadvantages that it is unable to obtain information on obstacles through forms or colors of them as it is only dependent on whether an obstacle exists or not, and distance information between LIDAR and the obstacles.

To overcome such disadvantages of LIDAR, techniques using multiple LIDAR [4], [5] or 3D LIDAR [6], [7] have been recently studied. But, cost of the sensor is high and the problem of difficulty in getting information on obstacles through their form or color is still remained. Therefore, information on the type of obstacles is acquired through convergence of LIDAR and a different sensor. The representative case among the different sensors is VISION.

VISION has an advantage which is able to perceive information like pedestrians or cars in slow driving unavailable in LIDAR through image data, which is mainly used in obstacle perception in autonomous vehicles [1]. However, there are also disadvantages that it is difficult to get distance-information (which is strength of LIDAR) and guarantee high speed due to much calculation in autonomous vehicles [8]. Also, it is impossible to get information through VISION in the dark environment where visibility is not secured.

If it is possible to classify the type of obstacles, beyond obstacle perception, which is able to obtain accurate information on obstacles, accordingly, an efficient and accurate path planning, not a simple version, is possible. For example, if the perceived obstacle is a person, the autonomous driving vehicle should stop, and if the obstacle is a car in slow driving or an accident area, it should avoid the situation like changing a lane. Like this, if accurate obstacle classification is possible, beyond obstacle perception, more efficient route generation is possible.

Therefore, this paper proposes an obstacle classification method which could provide safer autonomous driving by planning efficient and accurate path for autonomous vehicles, after perception of obstacles using the LIDAR data and classification of the type of obstacles.

II. Relevant Research

To planning efficient and accurate path, it is necessary to acquire not only obstacle perception but also information on the type of obstacles. However, the LIDAR's distance data based obstacle classification method has problems that it is not enough to acquire information on the type of obstacles. To resolve such problems, researches studying methods to classify obstacle by using distance-data to get outline of the obstacles and geometric information and subsequent use of the information to classify the type of obstacles are ongoing, however, the problems are still remained to classify obstacles accurately [9]. As solutions for the problems, a new method to acquire other information to perceive obstacles from the distance data is studied, not a method simply using the distance data through the 3D LIDAR data. Looking into a paper using the 3D LIDAR and a paper using the MLP network of them, it is found that they have a disadvantage of complicated calculation from big data caused by the 3D LIDAR [10]. Consequently, a new data which is able to classify the type of obstacles and expected to have less complication from small size is needed.

There is already a method classifying obstacles using the LIDAR intensity data [11], [12]. The method used the probability distribution of the LIDAR intensity data and dispersion to perceive and classify obstacles [11], [12]. However, less complicated calculation is not guaranteed to classify obstacles by calculating the probability distribution of the intensity data and dispersion. If it is difficult to guarantee real-time response, quick planning of a path for autonomous vehicles is impossible as well as safety related issues. For this reason, a new obstacle classification method based on the single LIDAR is necessary, which should be able to classify obstacles accurately and guarantee high processing speed.

Therefore, this paper proposes a new method to planning a path efficiently and accurately for autonomous vehicles and secure safe autonomous driving through high real-time response in comparing LIDAR data to DB. A new method to classify obstacles is suggested by comparing data generated from DB to data acquired by LIDAR, after creating DB of obstacles using LIDAR data. For the method, width data of obstacles is extracted from the LIDAR's distance data, and the first classification is conducted based on the data. Here, it is difficult to classify obstacles accurately only by the width data, thus the second classification is conducted using the LIDAR intensity data.

As a solution to the biggest problem of the LIDAR's distance data based method that it is unable to acquire information on the type of obstacles, this paper uses the LIDAR intensity and KNN-Classification. We propose a new method to classify obstacles, combining the advantage of resolving the VISION based method's problem with high real-time response of the LIDAR based method as another advantage.

III. Obstacle Classification Algorithm

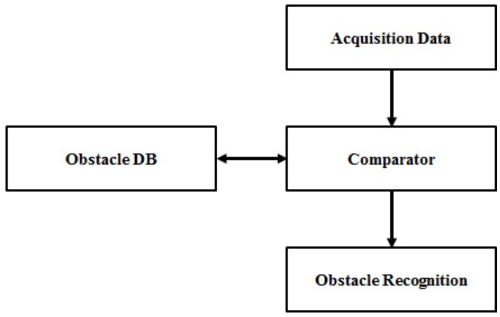

Fig. 2 Obstacle Classification Algorithm

Obstacle classification algorithm in this paper proceeds in the way shown in the Fig. 2 . First, data in the front area is acquired through the 2D LIDAR, and final obstacles are classified through comparison to the pre-generated DB. To conduct the process, obstacle classification algorithm in the paper is composed of 3 systems; data acquisition system, classified data input system, and data classification system.

Under the data acquisition system, data in the front area is acquired through the 2D LIDAR, and noise unnecessary for the 2D LIDAR is removed through segmentation, enabling data acquisition within the needed perception range. Also, it generates width data through the 2D LIDAR data and conducts the first overall classification.

The classification data input system levels data within the needed perception range to generate the obstacle DB after the acquired noise is removed by the data acquisition system.

The data classification system classifies final obstacles through comparison between the firstly classified 2D LIDAR data from the data acquisition system and the obstacle DB generated from the classification data input system. Details on each system are as follows.

A. Data Acquisition System

The data acquisition system acquires data on information of obstacles in the front area through the 2D LIDAR show in the Fig. 3.

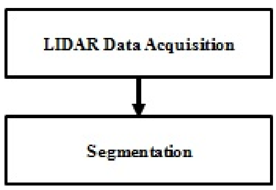

Fig. 3 Data Acquisition System

2D LIDAR data, acquired through the whole system initialization, is divided into two types of data; distance data between obstacles and the 2D LIDAR and the intensity data presenting features of obstacles. LIDAR used in this paper is SICK LMS, a product of 2D LIDAR. As it has a FOV(Field of

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View) within 270° and accuracy of 0.5, 541 distance data and the corresponding 541 intensity data can be acquired. Distance data and intensity data are acquired for each range from 270° to0.5°. Distance data and intensity data are acquired in the form of a character string and each form is hexadecimal number.

As for the acquired 2D LIDAR data, every data within the perception range of the 2D LIDAR is acquired. Therefore, we need to remove unnecessary data like noise and extract data within the range with possibility of obstacles out of the wide 270°. The process is segmentation, which generates width data of obstacles using the 2D distance data and makes grouping through the generated outcome, in addition to removing noise of the 2D LIDAR data. The first classification is briefly conducted through the width data of obstacles. Segmentation technique used in this paper is sequential classification, which is able to obtain point cloud, connecting sequentially measured points out of the 2D LIDAR data [13]. Looking into the segmentation process, from the 541 2D LIDAR data, it is assumed that the i-th scanned point is P_i, a point scanned prior to the i-th one is P_{i-1}, and a point scanned after the i-thone is P_{i+1}. As the 2D LIDAR data is measured sequentially by nature, we can figure out location of points previously/after measured based on a random point of P_i. Through this process, a line connecting between points can be considered or width data of obstacles can be extracted through the length of the line.

B. Classification Data Input System

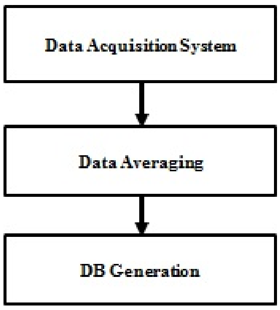

Fig. 4 Classification Data Input System

Classification data input system is initially one-time performance system, under which the acquired 2D LIDAR data is collected and obstacle DB is generated show in the Fig. 4.

First, obstacles for DB generation are measured through the data acquisition system and the 2D LIDAR data is leveled after noise and unnecessary data are removed. In the real environment experiment, the 2D LIDAR data is not in the same value due to air penetration ratio for each moment or noise of channels. Therefore, each obstacle DB is generated after ten-times perceived data is added along with leveling. Reliability of the DB is expected from the process.

Obstacles put into the DB are selected as pedestrians, vehicles, two-wheel vehicles, and rubber cone.

When generating the obstacle DB, two factors were considered. First, distance between autonomous vehicles and obstacles. Under this paper, maximum perception range of the 2D LIDAR is 20m, and breaking distance in slow driving (30km/h) is 15m, thus it was considered that obstacle classification should be made at least within 20m ahead. Also, we had the obstacle DB generated with the interval of 5m from 20m to 5m for unexpected obstacles appearing within 20m. The second factor is a direction of the obstacle. In general, expectable directions are narrowed to 4 when the 2D LIDAR perceives obstacles; front, side, rear, and side-back of the obstacles. In case of side, as each obstacle has quite different size, classification accuracy is high. Considering pedestrians, two-wheel vehicles, and vehicles, size difference of the obstacles is clear. Therefore, the obstacle DB was generated based on rear direction which is generally perceived in autonomous driving in this paper. Based on the rear of obstacles, this paper is to classify obstacles using intensity data according to obstacle features, not the size of them.

The obstacle DB saves data acquired from the data acquisition system by leveling, and its saving format is as the (1), (2) stated below.

$$Data_{DB} = \frac{\sum_{i=1}^{10} Data_i}{10} \tag{1}$$

$$Data_{variance} = \frac{\sum_{i=1}^{10} (Data_i)^2}{10} - \left(\frac{\sum_{i=1}^{10} Data_i}{10} \right)^2 \tag{2}$$

In the (1)~(2), $Data_{DB}$ is a result of generating DB from leveling the 2D LIDAR data, $Data_{DB}$ is the 2D LIDAR data acquired the data acquisition system, and $Data_{variance}$ is dispersion of the 2D LIDAR data which can be acquired through leveling.

The obstacle DB includes information on intensity of the obstacles. As the 2D LIDAR data having been through segmentation is composed of values for each distance of 0.5°and intensity about the obstacle's range, the obstacle DB is composed of values of intensity for each 0.5° regarding each obstacle's range.

C. Data Classification System

Data classification system classifies final obstacles by comparing the intensity of the firstly classified 2D LIDAR data through the data acquisition system, to that of the obstacle DB generated through the classification data input system.

The second classification uses Euclidean Distance. Equation (3) is expression of Euclidean Distance. $Data_{DB}$ from (3) is the obstacle DB generated through the classification data input system, and$Data_i$ means the 2D LIDAR data acquired through the data acquisition system. After calculating error by comparison between the acquired 2D LIDAR data and the generated obstacle DB, the system classifies final obstacles with the obstacle DB having the least value out of the calculated errors.

$$d_{ED}(Data_{DB}, Data_i) = \sqrt{\sum_{i=1}^{N} (Data_{DB} - Data_i)^2} \tag{3}$$

Euclidean Distance is a general method used in comparing two data. It has a disadvantage of causing complication in square calculation while it has an advantage of intuitive calculation of data difference and simplicity compared to other KNN-Classification. Also, it is efficient in comparison between data with high immobility like a DB. It calculates error between the obstacle DB and the intensity data and classifies final obstacles by judging obstacles with the least error out of the calculated error.

TABLE I
ACCURACY OF EXISTING ALGORITHM

Obstacle	Accuracy (%)
Pedestrian	96.96
Vehicle	91.65
Building	88.13
Light Pole / Trees	88.12
Others	81.81

TABLE II
ACCURACY OF PROPOSED ALGORITHM

Obstacle	Accuracy (%)
Pedestrian	82.83
Vehicle	92.79
2-wheel Vehicle	79.73
Rubber Corn	88.25

IV. EXPERIMENT

D. Experiment Environment

Fig. 5 2D LIDAR

Fig. 6 Test Vehicle

This paper uses a model of LMS 111 in SICK as shown in the Fig. 5 for obstacle classification. As for the autonomous vehicle, we used a renovated Sportage R like in the Fig. 6. We mounted the 2D LIDAR at the front bumper and tested it by using LabVIEW and installing an industrial PC. The test venue is a road in the campus of Yeongnam University, and obstacles were displayed with an interval of 5m from 5m to 20m. The experiment was conducted in the condition that autonomous vehicle and obstacles are static.

E. Experiment Result

This experiment is to compare the method using the 3D LIDAR regarding the accuracy of the obstacle classification [10].

The accuracy of the obstacle classification was judged by perception ratio of the type of obstacles in the front area, through comparison between the existing obstacle DB and the acquired obstacle data from the 2D LIDAR.

While the Table I shows classification accuracy about the obstacle classification method, using 3D LIDAR[10] and the Table II shows classification accuracy for each 4 obstacle selected by this paper. By coming together the experiments in the range of 5m, 10m, 15m, and 20m, classification accuracy for each obstacle was percentage.

It was found that classification accuracy of vehicles was highest, which is due to its biggest size compared to other obstacles. As its size is relatively big compared to other obstacles, a good result was presented in the first classification from using the width data of obstacles.

The reason for the second highest level of the classification accuracy of rubber cone is that the intensity data is regular compared to the two-wheel or pedestrians in similar sizes. Based on the regular intensity data, we could obtain a good result at the second classification.

As for the pedestrians and the two-wheel vehicles, it was found that classification accuracy was lower than vehicles and rubber cone. In case of vehicles, classification was easier by using the bigger width data than other obstacles and rubber cone was easily classified based on its mediums and colors. However, as for pedestrians and two-wheel vehicles, difference in width data was not clear and difference in intensity data was not regular, either. Detailed result is as follows. Pedestrians and two-wheel vehicles have various mediums and colors.

Mediums and colors of pedestrians are differentiated according to clothes of drivers. In case of two-wheel vehicles, they have various mediums and colors by itself, but intensity is not regular as the diversity is increased by clothes of drivers. This fact is the reason that classification accuracy of pedestrians and two-wheel vehicles is lower than other obstacles. To resolve this problem, we used DB dispersion generated from the classification data input system. When comparing pedestrians and two-wheel vehicles, we considered that a medium of the two-wheel vehicles was more varied than that of pedestrians. If two-wheel vehicles are perceived in rear, three types of medium are perceived including wheels of the two-wheel vehicles, the vehicle itself, and legs of riders. Then, dispersion value can be calculated according to the different intensities of the three mediums. Classification of pedestrians and two-wheel vehicles were conducted through the dispersion value.

When comparing to the obstacle classification method using the existing 3D LIDAR, the algorithm in the paper showed little difference in classification accuracy. However, in case of pedestrians, if was found that more accurate result was presented as a result of classification after detailed extraction of pedestrians' features using the 3D LIDAR data. Ho wever, we considered a problem that the 3D LIDAR data has complicated calculation according to its big data. Given that the 3D LIDAR data has a bigger amount and more complicated structure than those of 2D LIDAR data, we expect this paper could supplement the lower classification accuracy by algorithm strength of using the 2D LIDAR data.

V. Conclusion

This paper developed the 2D LIDAR based obstacle classification method for autonomous driving. Quick planning for path is an important part in autonomous driving related with safety. For such quick planning for path, accurate classification of obstacles is necessary. We classified obstacles using the 2D LIDAR's distance data and intensity data. By replacing the obstacle classification method using the existing 3D LIDAR data with the method through the distance data of LIDAR, intensity data, and KNN- Classification as shown in the Fig. 2, we could see overall calculation reduced.

The future research will be classification of obstacles such as lane, speed bump, traffic sign, and traffic lights in addition to general obstacles like drivable area for improved path planning. Also, factors like obstacles or motion of autonomous driving vehicles influencing on th e classification accuracy should be studied. It is required to devel op a classification algorithm through modeling on intensity for each obstacle by finding out features of the intensity data. Lastly, research on the lear ning system to generate the obstac le DB should be conducted. It is expected to provide higher obstacle classification accuracy through real-time DB gen eration and updating. The r esearch will be helpful to the system which a real-time path planning in autonomous driving.

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References

[1] Z. Yankun, "A Single Camera Based Rear Obstacle Detection System," Intelligent Vehicle Symposium, Baden-Baden, 2011, pp. 485-490.
[2] J. Wenger, "Automotive Radar-Status and Perspectives," Compound Semiconductor Integrated Circuit Symposium, 2005.
[3] A. Kirchner, T. Heinrich, "Model Based Detection of Road Boundaries with a Laser Scanner," IEEE International Conference on Intelligent Vehicles, Stuttgart, 1998, pp. 93-98.
[4] K. Chu, J. Han, M. Lee, D. Kim, K. Jo, D. Oh, E. Yoon, M. Gwak, K. Han, D. Lee, B. Choe, Y. K im, K. Lee, K. Huh, M. Sunwoo, "Development of an Autonomous Vehicle: A1," Transactions of KSAE, Vol.19, No.4, pp. 146-154, 2011.
[5] D. M. Cole, P. M. Newman, "Using Laser Range Data for 3D SLAM in Outdoor Environment," Robotics and Automation, Orlando, pp. 1556-1563, 2006.
[6] S. Thrun, M. Montemerlo, H. Dahlkamp, D. Stavens, A. Aron, J. Diebel, P. Fong, J. Gale, M. Halpenny, G. Hoffmann, K. Lau, C. Oakley, M. Palatucci, V. Pratt, P. Stang, S. Strohband, C. Dupont, L. E. Jendrossek, C. Koelen, C. Markey, C. Rummel, J. v anNiekerk, E. Jensen, P. Alessandrini, G. Bradski, B. Davies, S. Ettinger, A. Kaehler, A>Nefian, P. Mahoney, "Stanley: The Robot that Won the DARPA Grand Challenge," Journal of Field Robot, Vol. 23, No. 9, pp. 661-692, 2006.
[7] R. Halterman, M. Bruch, "Velodyne HDL-64E LIDAR for Unmanned Surface Vehicle Obstacle Detection," SPIE Defense, Security and Sensing, pp. 76920D-76920D-8, 2010.
[8] L. Iocchi, S. Pellegrini, "Building 3D Map with Semantic Elements Integrating 2D Laser, Stereo Vi sion and IMU on a Mobile Robot," 2nd International Society for Photogrammetry and Remote Sensing International Workshop 3D-ARCH, 2007.
[9] H. Moon, J. Kim, "Obstacle Detecting System for Unmanned Ground Vehicle using Laser Scanner and Vision," 2007 International Conference on Control, Automation and System, 2007.
[10] D. Habermann, A. Hata, D. Wolf, F. Osorio, "Artificial Neural Nets Object Recognition for 3D Point Cloud," Intelligent System, pp. 101-106, 2013.
[11] J. Hancock, "Laser Intensity-based Obstacle Detection and Tracking," Carnegi Mellon University, 1999.
[12] A. Carballo, A. Oh ya, S. Yuta, "People Detection using Range and Intensity Data fr om Multi-Layered Laser Range Finders," Intelligent Robots and System, Taipei, 2010, pp. 5849-5854.
[13] O. Hadjiliadis, I. Stamos, "Sequential Classification in Point Cloud of Urban Scenes," Proceeding of 3DPVT, 2010.