Stationary Human Detection Method by 2D-LiDARs

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***Abstract*—Post COVID-19 pandemic, the labor shortage has become increasingly serious in Japan because many people have quit their jobs. In particular, a shortage of personnel such as security guards, taxi drivers, bus drivers, and delivery personnel is noticeable. Therefore, introduction of self-driving taxis, self-driving buses, and security robots are being considered. In this study, we focus on human detection function, a function of a security guard robot. Battery-based robot carts require a small resource of calculation. We proposed a human detection method using a 2D-LiDAR with point cloud data for small resource of calculation. Moreover, we presented the evaluation results of our method.**

Keywords—Human detection, pointcloud, 2D-LiDAR

I. Introduction

Currently, the importance of the security industry in society is increasing along with its demand. However, in the current security industry, the number of security guards in Japan has decreased by 7,824 (1.3%) in 2020 compared to the previous year. In addition, issues such as the abundance of jobs preventing people from continuing for a long period, unpaid wages, not being required to undergo legal training, and being forced to work long hours exist. Consequently, a severe manpower shortage exists owing to the aging of security guards and a lack of young people. Therefore, to solve the problem of manpower shortages, the development of security systems using IT is being considered.

A decrease in the number of security guards is likely to affect the security of university campuses. Therefore, by substituting university security services with IT, we aim to solve the problem of a decrease in the number of security guards for university security services.

At Kanagawa Institute of Technology, incidents of elderly people with dementia or other conditions intruding into the campus without malicious intent were observed approximately a few times a year. Various security and countermeasure methods exist to prevent intrusion from outside the facility. To prevent intrusions, Kanagawa Institute of Technology uses surveillance cameras and conducts three patrols three times during night security. However, because these incidents occur only a few times a year, daily monitoring of surveillance cameras and patrol is burdening.

Therefore, the purpose of this study was to reduce the number of patrols required by security guards and the number of personnel required, by replacing the security guards by security robots to detect suspicious persons and objects. Thus, the burden on security guards and the number of security guards required will be reduced. However, if the sensors installed in a security robot are expensive, the cost of security will exceed the cost of hiring a security guard. Therefore, the sensors mounted on robots must be inexpensive.

When moving on campus, this robot must travel according to a plan and avoid obstacles and people. To satisfy these demands, the accuracy of object recognition and self-position estimation must be improved. Therefore, we used LiDAR that is used in autonomous driving. To reduce the amount of information and cost, we used a 2D-LiDAR that is inexpensive and requires only a small amount of information to be acquired.

When identifying a person in a real environment, judging and aligning in front of the target person is difficult for a security robot. Moreover, the target person may face the front of the LiDAR or another direction. Furthermore, because the amount of information acquired differs depending on the angle, erroneous recognition may occur when identifying the person. Therefore, learning each angle is necessary for accurate judgement. However, as the number of learning angles increases, the amount of information in the point cloud and the number of learning calculations increase. Therefore, in this study, we propose a method for detecting a stationary person at any angle by learning a small number of angles..

II. Related Studies

Research has been conducted on the use of 3D-LiDAR to drive autonomous robots [1]. 3D-LiDAR was used to detect the surrounding environment and situation for autonomous driving systems. This study proposed an environment recognition system that can measure the shape, distance, and infrared reflection intensity of objects within a range and perform real-time mapping for autonomous driving. However, determining a person detected by 3D-LiDAR requires a large number of calculations.

Research on person identification using a 2D-LiDAR has been conducted that simultaneously performs self-position estimation and map creation to track passing objects in indoor environments [2]. This study used simultaneous localization and mapping (SLAM), the simultaneous execution of self-localization and mapping. This study measured the distance of the surroundings, such as people and walls, using LiDAR and performed mapping from the acquired data. The location of the target was determined from the information obtained from the LiDAR on the generated map, a route for the robot was created, and human tracking was performed.

However, the target might be lost owing to the influence of noise because the amount of movement of the point cloud was acquired for each acquisition cycle, and a threshold was determined. Additionally, in this study, the moving object was assumed to be a person. Therefore, false detection could occur if the moving object was other than a person. Moreover, because it detects moving objects, it cannot detect stationary objects. Therefore, it cannot identify stationary people.

In research on people flow measurement using 2D-LiDARs, a solid-state 2D-LiDAR was installed on the ceiling, and information on the number of people passing through the 2D-LiDAR measurement range, direction, and speed was measured [3]. By using a solid-state 2D-LiDAR, this could be performed more compactly and at a lower cost than that using a rotating 2D-LiDAR. However, using this method, the 2D-LiDAR is fixed to the ceiling, creating blind spots, and several LiDARs must be installed for security purposes. Therefore, a fixed LiDAR is not suitable for security patrol operations.

A previous study on stationary person detection used a single 2D-LiDAR [4]. One 2D-LiDAR was attached to an autonomous robot to acquire the point clouds. The proposed method performed deep learning on the acquired 2D point cloud information using the PointNetAutoEncoder [5], a library of MATLAB [6], to determine stationary people. The 2D point cloud information was obtained from the 2D-LiDAR at the waist of an adult at a height of 90 cm and used to characterize the shape of the human waist, such as "convexity" and "dog" shape at the front of the waist and on the sides of the waist, respectively, to judge the person. With a single LiDAR, the accuracy was 93.6% when using only waist-shaped features; however, the accuracy might decrease depending on the learning conditions. The detection accuracy of a standalone 2D-LiDAR is limited.

Therefore, previous study on stationary person detection used features other than the front of the waist for detection [9]. Multiple 2D-LiDAR units were used to detect a frontal person at two heights: a waist height of 95 cm and a shin height of 40 cm of an adult person. This created 3D data by complementing the 2D point cloud data with the z-axis coordinates at each height. Using this method, a person standing in front of the 2D-LiDAR could be identified using two factors: waist height and shin height. However, judging angles other than the front is difficult; the angle of the person to be judged must be learnt..

III. Proposed Method

In previous study, we used two 2D-LiDARs to focus on two features of an adult: a waist height of 95 cm and a shin height of 40 cm, and to perform human recognition by learning the frontal orientation in advance [7]. However, the shape of the point cloud differs depending on the angle the person is facing. In addition, because the width and shape of the point cloud differ for each body type, various angles and body types must be assumed in advance to prepare the data for learning.

First, pointclouds for learning and judgment must be acquired. In this study, we acquired point clouds of human and tree data as training data. When acquiring information from a human point cloud, the information on the arms, torso, and shins were used. The height of the installation for acquiring this information changed depending on the height and standing posture of the person being measured. Therefore, we measured students standing on university campuses at night. The participants had to be between 1.5 m and 1.8 m tall and standing still with their hands down at their sides. Therefore, two 2D-LiDARs were installed at heights of 95 cm and 40 cm to acquire point clouds. Three human body types were prepared: thin, normal, and obese. A specific example of human point cloud acquisition is shown in Figure 1, and a plot of the point cloud is shown in Figure 2. Figure 3 shows the point cloud acquisition of the tree, and Figure 4 shows a plot of the point cloud.

The height information was added to the 2D point cloud data acquired at each height to create 3D point cloud data. To judge the created 3D point cloud data, we used PointNet, that was published in the MATLAB library, and PointNetAutoEncoder, that compressed and decompressed the point cloud, extracted only the features, and classified them. This was used to identify the participants.

Fig. 1 Example of a Human

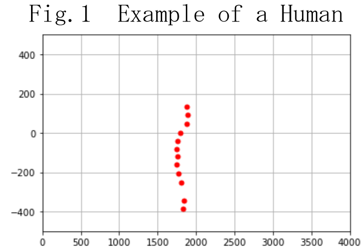

Fig 2. Pointcloud data of Fig. 1

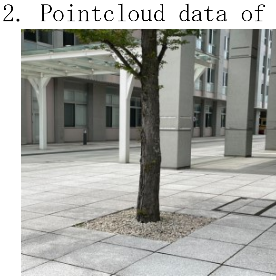

Fig 3. Example of a tree

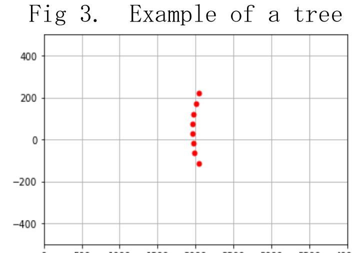

Fig. 4 Pointcloud data of Fig. 3

In addition, as the number of angles that must be learned increases, the amount of information in the point cloud to be learned increases, the amount of calculation required for learning increases, and the ambiguity increases, resulting in a decrease in accuracy. Hence, the minimum angle required for learning must be determined.

Therefore, in addition to the point cloud information facing forward (0°), the system learnt point clouds facing sideways (90°) to identify people at angles other than front-facing.

IV. Experiment and Evaluation

We conducted an experiment to determine the possibility of identifying people from any angle. The LiDAR was installed at heights of 95 cm and 40 cm to obtain point clouds. For the LiDAR, point clouds were acquired using RPLiDAR A1M8, a 2D-LiDAR from SLAMTEC. Considering the maximum measurement distance of the LiDAR used, 6 m, the measurement range to be acquired was set to 5 m, and the point cloud was acquired by measuring at distances of 1 m from 1 m to 5 m. The human data used for classification were obtained from the point clouds of three body types: thin, normal, and obese.

The evaluation procedure involved removing the necessary portion of the point cloud from the acquired point cloud data, compressing and decompressing the point cloud, and extracting the features. We evaluated person recognition by classifying the extracted features using the PointNetAutoEncoder that was published in the MATLAB library.

A. *Changes in accuracy depending on body type*

We confirmed the changes in the classification rate based on the body shape of the person being judged. Because the width and shape of the point cloud change depending on the body type, we obtained point clouds for three body types–thin, normal, and obese–and divided them into classes. Each point cloud was acquired approximately 2 m from the RPLiDAR A1M8.

For classification, we prepared 150 pieces each of human and tree data as learning data, with each rotation of the 2D-LiDAR serving as one piece of data. The human data used as training data were trained for three body types, one each. The number of training iterations was 100, and 300 point cloud data of humans and trees were trained in advance. Human data that differed from the training data were used as the test data; 150 pieces of each of the three body types were prepared, and each type was divided into classes. Table 1 presents the accuracy of the classification rates for each body type.

We confirmed that the classification rate for other body types decreased when learning one body type. We also confirmed that a determination was possible even if the body types were different. However, the accuracy of judgment changes depending on the body shape of the person being judged. Therefore, if the human data to be trained have only one body type, the recognition rate will be affected. Therefore, each of the three body types must be learned. Table 2 presents the accuracy of the classification judgment rate after learning about the three body types.

By learning the three body types, the recognition accuracy improved, and we confirmed that 100% recognition was possible.

B. *Changes in accuracy depending on learning angle*

We confirmed the change in the classification judgment rate when only the front angle (0°) and sideways angle (90°) were used as the training data. We also confirmed changes in the classification rate when learning both orientations. Each point cloud was acquired approximately 2 m from the RPLiDAR A1M8. For classification, we prepared 150 training datasets of human data facing front, sideways, and front facing and horizontal and 150 pieces of tree data each for one rotation of the 2D-LiDAR. A total of 300 pieces of human and tree data were trained in advance. For the test data, we prepared 150 pieces of human data each at 0°, 45°, and 90° as correct data and 150 pieces of tree data that differed from the training data as incorrect data. Table 3 presents the results of the F value for classification judgment when learning the frontal, sideways, and frontal and sideways angles.

We confirmed that accuracy improved by learning frontal and sideways orientations and that people could be identified even when facing at an angle of 45°. Judging other angles when only facing forward was difficult; however, when only facing sideways, front facing could also be determined with a certain degree of accuracy. When both orientations were learned, the accuracy increased, confirming that by learning multiple angles, the accuracy of person recognition from angles other than the learned angles increased. Therefore, if the angles cannot be determined, multiple angles must be learned.

C. *Test for each angle*

We confirmed the changes in the classification judgment rate based on the changes in the characteristics of the point cloud for each angle. To determine the classification rate for each angle, point clouds were acquired approximately 2 m from the RPLiDAR A1M8. When classifying into classes, we prepared 150 human data points for each angle and body type, with one rotation of 2D-LiDAR as one data point for three types of human data, frontal and sideways. We also prepared 150 pieces of 2 m tree data and trained them 100 times in

Table 1 Accuracy for each body type

Learning \ test	thin	standard	fatness
thin	1.00	1.00	0.14
standard	1.00	1.00	0.27
fatness	0.18	0.54	1.00

Table 2 Accuracy for body types

Learning \ test	thin	standard	fatness
thin standard fatness	1.00	1.00	1.00

Table 3 F values depending on the angles of training data

Learning \ test	0°	45°	90°
front	1.00	0.01	0.00
sideway	0.95	0.76	0.95
front and sideways	1.00	1.00	0.98

advance with 300 pieces of human and tree data. For the test data, we prepared 150 pieces of human data that differed from the training data as correct data, for each 10° from 0° to 180°, and we also prepared tree data that differed from the training data as incorrect data.

By learning the frontal and sideways orientations, individuals could be identified at angles other than 0° and 90°, that were learned in advance. The F value decreased slightly at 110° and 120°. However, because the F value was close to 1, no problem occurred with human recognition. Thus, we confirmed that by learning the data of front-facing and sideways-facing individuals, people could be identified from any angle.

D. Test for each distance

In the experiment, we confirmed that people could be identified from any angle, both frontal and sideways. Therefore, we confirmed a change in the classification judgment rate when the number of point clouds changed depending on the distance. Point clouds were acquired every 1 m at distances ranging from approximately 1 m to 5 m from the RPLiDAR A1M8. The data to be prepared were human data, 2 m long, with three body types facing forward and sideways and one rotation of 2D-LiDAR as one data point, for a total of 150 pieces for each angle and body type. We also prepared 150 pieces of 2 m tree data and trained them 100 times in advance with 300 pieces of human and tree data. For the test data, we prepared 150 pieces of human data that differed from the training data as correct data, each measuring 1 m from 1 m to 5 m at 0°, 45°, and 90°, and the learning data as incorrect data. We prepared 150 pieces of tree data under similar conditions. Individuals were determined using the same distance between the prepared human and tree data. Tables 4, 5, and 6 present the classification results for angles of 0°, 45°, and 90° for each distance. Figure 5 presents a graph of the F values for each distance.

As a result of the judgment, we could obtain F values higher than 0.95 for up to 4 m at 0° and 90°. However, the F value decreased at 5 m. We believe that as the distance increases, the number of point clouds decreases. The number of point clouds decreased considerably compared with that at 1 m, resulting in a low-density point cloud and thus decreasing the F value. Moreover, the F value might decrease further if the distance was further increased. In addition, the F values obtained at 45° were close to those at 0° and 90°, except for the decrease in the F value for 1 m at 90°. When the angle was 45°, clear distinction was difficult if the distance was extremely close.

Table 4 F values at 0˚

	Recall	Precision	F
1m	1.00	1.00	1.00
2m	1.00	1.00	1.00
3m	1.00	1.00	1.00
4m	0.99	0.93	0.96
5m	1.00	0.70	0.82

Table 5 F values at 45

	Recall	Precision	F
1m	1.00	1.00	1.00
2m	0.96	1.00	0.98
3m	1.00	1.00	1.00
4m	1.00	0.93	0.96
5m	1.00	0.70	0.82

Table 6 F values at 90˚

	Recall	Precision	F
1m	0.17	1.00	0.29
2m	1.00	1.00	1.00
3m	0.96	1.00	0.98
4m	0.97	0.93	0.95
5m	1.00	0.70	0.82

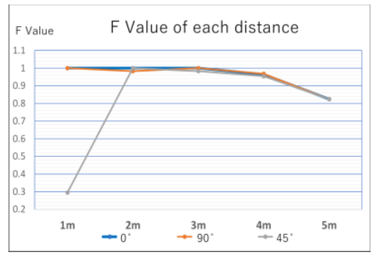

Fig. 5 F values of each distance

V. SUMMARY

To solve the problem of manpower shortage in the security industry, we verified whether people could be identified from various angles using a security robot equipped with 2D-LiDAR. Using 2D-LiDAR, we focused on the characteristic shapes of human hips and shins and learned frontal and sideways orientations to identify people from various angles. The results of the experiments indicated that stationary people could be identified from various angles: frontal and sideways. We proposed a method to identify a stationary person by learning a small number of angles, irrespective of the angle of the person.

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