

Standing Human Detection Method Using 2D-LiDARs

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Abstract— Recently, autonomous vehicle technologies have been widely developed. Moreover, these technologies are applied to autonomous carts for security guards, guidance robots, delivery carts, etc. A variety of human detection technologies are important for these robotic carts. There are many studies on avoiding collisions with humans and other obstacles. However, technologies to distinguish between humans and other obstacles are especially important for security guard robots. In this paper, we propose a standing human detection method using 2D-LiDARs to reduce costs. We show the details of our methods and results of evaluation.

Keywords—2D-LiDAR, human detection, security guard robot, autonomous cart

I. INTRODUCTION

We are planning to introduce an autonomous cart for the Kanagawa Institute of Technology (KAIT) campus. The reason for introducing the autonomous carts is to reduce the cost of delivering services on campus, cleaning the campus and security guards. The campus consists of more than 10 buildings, outside squares, and grounds for sports as shown in Fig. 1.

It is necessary to deliver many things, such as lightweight paper and heavy loads, to buildings. Therefore, drones are

unsuitable. However, autonomous carts must be carefully operated to avoid collisions with humans or other obstacles.

Autonomous carts for delivery and cleaning are operated during the daytime. However, they also operate at night as security guards. Therefore, they must detect humans and obstacles during both the day and night. In particular, security guards must identify and distinguish suspicious humans.

Several devices are currently available for human detection. Cameras are the most commonly used. Many studies have been conducted on artificial intelligence (AI) technologies for image processing in human detection. However, a camera requires a light source. Therefore, camera devices are not suitable for nighttime. Autonomous vehicles use high-sensitivity cameras that require only a small amount of light. However, this method is expensive to use with autonomous carts.

We experimented with human detection at night using a low-cost web camera, and even with some light available, it was difficult to detect humans located a short distance away.

A thermal sensor camera can be used at night. However, it is difficult to detect humans near heat obstacles. Therefore, we adopt light detection and ranging (LiDAR) technologies for autonomous vehicles. The 3D LiDAR must be installed on autonomous carts for simultaneous localization and mapping (SLAM), which creates maps for autonomous movement. Therefore, if they could also be used for human detection, sensor costs would not be required.

The sensing data of LiDAR are point-cloud data that show obstacles relative to the LiDAR. The amount of point-cloud data from 3D LiDAR was too large. Therefore, the calculation costs are too large. We then propose a human detection method using part of the point-cloud data from 3D LiDAR as well as multiple 2D LiDAR.

II. LiDAR AND SLAM

Maintaining maps is important for autonomous movement in estimating location. Therefore, moving in unknown spaces where an autonomous cart has no map is difficult. SLAM technology, which generates maps and measures locations simultaneously, is very useful. Area maps must be generated for autonomous-car operation in advance using SLAM technology.



Fig 1. Map of KAIT Campus

SLAM technology measures relative obstacle maps using LiDAR and measures locations using GPS, blueprints, or other methods.

LiDAR emits light around itself and detects the light reflected from objects. Then, the LiDAR calculates the distance using the phase difference of the light. In other words, LiDAR can get 3D data that the image data from the camera does not have. Fig. 2 shows the point-cloud data from 3D-LiDAR and Fig. 3 shows the point-cloud data from 2D-LiDAR. The amount of point-cloud data from the 3D-LiDAR was too large. If the two legs and two arms of a human feature can be detected using a small amount of point-cloud data, the calculation cost can be reduced.

III. PATROL

Fig. 1 illustrates the KAIT campus. There are many buildings on the campus. Buildings 2 and 5 were used only for lectures. The other buildings contained lecture rooms, personal rooms for professors, and rooms for office workers.

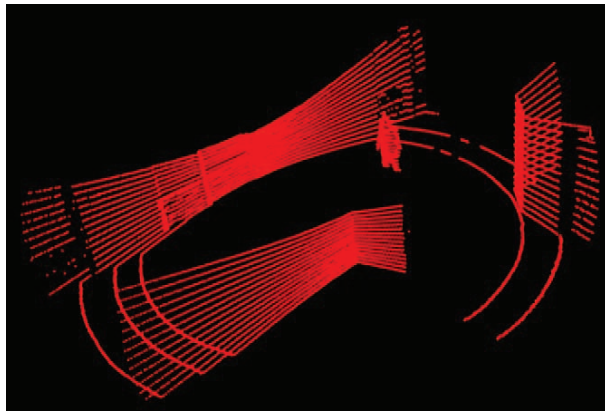


Fig. 2. Example of pointcloud data from 3D-LiDAR



Fig. 3. Example of pointcloud data from 2D-LiDAR

During the day, the main purpose of a patrol is to identify suspicious objects, including illegal parking. Because there are many students, teachers, office workers, and neighborhood residents on campus during the day, they are not required to go through an admission and confirmation process to enter the campus. However, all rooms except the lecture halls were locked, and only students and teachers with their approval could enter them.

During the night, only teachers and students with permission were allowed to stay on campus. Thus, patrol services are required. The purpose of such a patrol is described in Section 1.

Identifying suspicious individuals is difficult. However, robots may also encounter non-malicious individuals. This is because they do not think that the individual is illegal. We hope that the robot can deter and identify non-malicious individuals. Examples of non-malicious individuals include elderly wanderers and children.

IV. RELATED STUDIES

Numerous studies have been conducted regarding human detection. Human detection using image processing is one of the most commonly used methods. Recent camera and AI technologies can detect humans with high accuracy [1][2]. These studies have focused on face or action recognition. Studies on pedestrian detection by monocular cameras are surveyed [3]. However, in the case of many campuses, image-processing technologies with cameras may be difficult to apply for human detection. The campus had a mixture of bright and dark fields. Processing images using low-cost cameras is challenging.

There are some studies on human detection with 3D-LiDAR. Pedestrian recognition using 3D-LiDAR for autonomous vehicles [4] uses a support vector machine (SVM) for human detection. Other approaches use 3D LiDARs as multiple 2D-LiDARs [5]. This study gathered point-cloud data from many different heights and achieved a classification rate of up to 96%. An example of using reduced point-cloud data is dividing 3D point clouds in the target into parts, that is, the trunk and legs, to achieve robust in situ pedestrian recognition [6].

All these studies used 3D point-cloud data, which requires a powerful CPU. Because 3D LiDAR can acquire a point-cloud of an entire human image, it is possible to discriminate a human regardless of its shape, such as clothes. However, it is not necessary to have multiple human shapes that can be acquired from locations at similar heights. Therefore, in this study, we propose a human detection method that uses multiple 2D-LiDARs to reduce the calculation costs.

In a previous study [7], we proposed a human detection method based on low-resolution 2D-LiDAR and a PointNet-based autoencoder [8]. 2D-LiDAR was used to gather data from a height of 90 cm, which is considered the typical waist height of humans, both frontally and laterally. The proposed method successfully detected humans within 5 m of LiDAR. However, robotic applications require detection over long distances. This issue was addressed in this study.

V. HUMAN FEATURES AND PROPOSED METHOD

The human features used in this paper are not only the convex shape of the human waist, which was mentioned in previous research [7], but also the shape of two legs. The reason for adding the shape of the two legs is that people dress differently depending on the season. Therefore, it is easy to acquire the human shape because the clothes are thin in the hot season, but it is difficult to acquire the original shape of a human being in the cold season because the clothes are thick.

Multiple trouser layers are rarely worn on the feet. Therefore, similar foot shapes can be obtained in both the cold and hot seasons. Therefore, we assume that, by combining the shapes of the torso and feet, it is possible to distinguish people regardless of their clothes.

VI. PRELIMINARY EXPERIMENTS

A. Equipment

The 2D LiDAR used in this experiment was the RP-LiDAR A1M8 [9]. This inexpensive LiDAR system can acquire data up to a distance of 12 m. However, when the distance is long, the number of point clouds that can be acquired decreases; however, this is not a problem if the data are acquired for a sufficient time.

The autonomous mobile cart used in the experiment was equipped with a Jetson-AGX [10] and a portable power supply. Because the CPU is also used for SLAM, if SLAM and person judgment calculations are performed on the same device, the performance will be poor. If multiple devices are used, the power consumption increases and affects the running time of the cart. Therefore, we aimed to reduce the amount of computation required and run it for a long time.

B. Basic Experiment

The data used in the experiment consisted of a human, wall, and two sticks, as shown in Fig. 4 and Fig. 5. For data learning, we use the 3D point-group classification method published in MATLAB [11].



Fig.4 Example of human

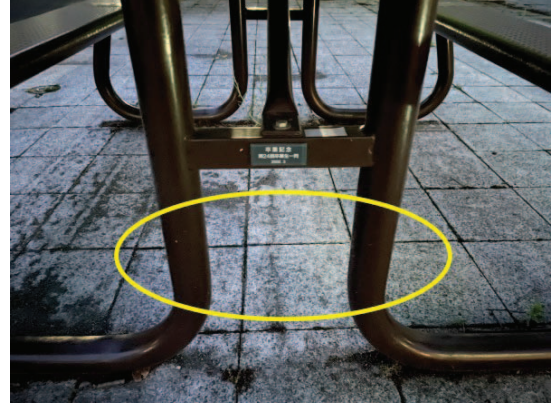


Fig. 5 Two sticks

Because the information that could be acquired by 2D LiDAR was only two-dimensional information in the x and y coordinates, the z-axis coordinates complemented the acquired data.

Fig. 6 shows the point-cloud information when input into MATLAB. We confirmed that the 152 pieces of data used for the evaluation were properly classified as humans. Thus, we can detect humans using the shapes of the waist and legs.

C. Experiment in Various Environments

Through basic experiments, we confirmed that 2D LiDAR could detect humans if they were directly in front of humans, and the distance between the humans and 2D LiDAR was fixed. However, this was difficult to achieve. Moreover, it is difficult to distinguish between people and trees, which are similar to the human body. In addition, MATLAB requires significant CPU resources. Therefore, we repeated the experiment to detect humans correctly.

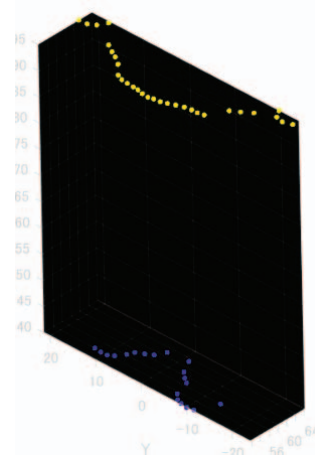


Fig. 6 Pointcloud data for input

To confirm that the difference between humans and trees can be discriminated, we introduced the PointNet technology [11].

1) Various Distance between LiDAR and Human

We tested the recall rate for human detection at various distances. The LiDAR sensing time was adjusted to the same point-cloud density. Two types of training data, namely waists seen from the front and waists seen from the side, were prepared for each distance, which ranged from 1 m to 6 m. The number of data points corresponded to 150. The number of epochs is set to 200. Fig. 7 shows the recall rate of the experiment. The waist was better at the front than at the sides. However, at distances greater than 6 m, the recall rate is poor. This is because of the low density of the point-cloud data.

2) Human with jacket or not

The clothes with which a human wears the jacket should be tested. Figs. 8 and 9 show that the human was not wearing a jacket and wearing a jacket, respectively. This result indicates that clothing is not important for human detection. However, training data should include various humans and clothes.

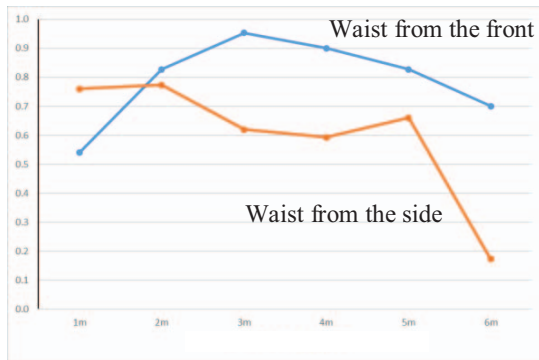


Fig.7 Recall rate at each distance

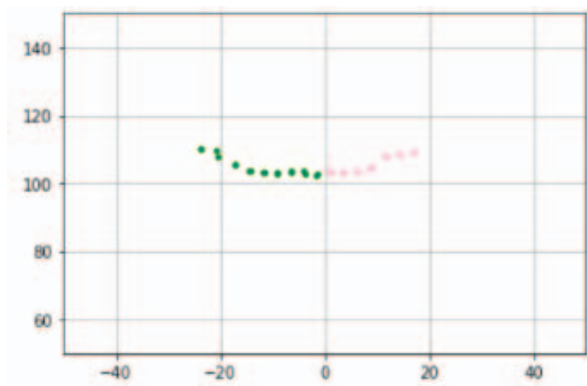


Fig. 8 Pointcloud data without jacket

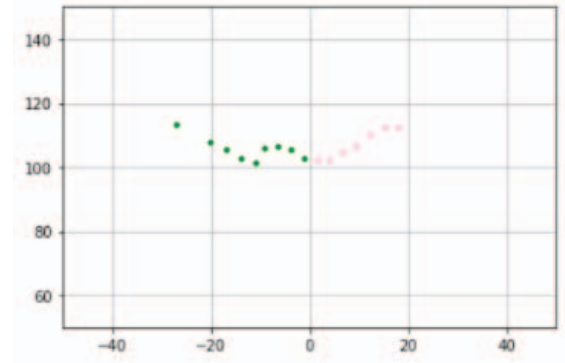


Fig9. Pointcloud data with jacket

VII. EXPERIMENTS

A. Experiment in Various Directions

Through preliminary experiments, standing humans could be detected using waist and leg information from the front. However, the robot cart must move in front of the robot. However, this approach is unrealistic.

First, the data were gathered by placing the LiDAR in front of a standing human in the same manner, as shown in Fig. 4. The point-cloud data of a human and a tree at a distance of 1.5 m from the LiDAR were trained. Point-cloud data from humans and trees at a distance of 3 m were then tested. Fig. 10 shows the learning process for a human at a distance of 1.5 m away. Fig. 11 shows the point-cloud data used for the learning and evaluation processes.

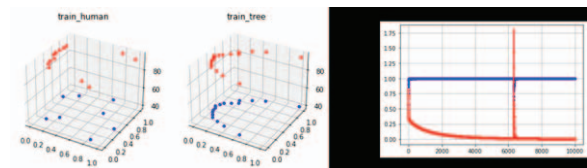


Fig. 10 Learning process with standing front of LiDAR

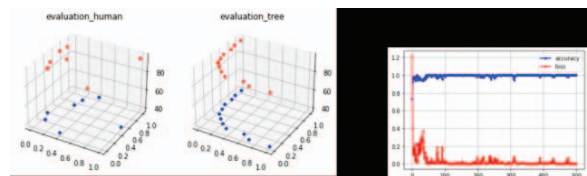


Fig. 11 Evaluation with standing front of LiDAR

Noise, such as the background or other pedestrians, was removed from the raw point-cloud data that were captured by LiDAR, as shown in Fig 12.

Subsequently, the human turned 45 °and placed in front of the LiDAR, as shown in Fig. 13. Fig. 14 shows the results of the evaluation. This result shows that even if a model is trained with the data of the standing front of the LiDAR, it can be distinguished from humans. However, this is clearly distinguishable from that of humans using LiDARs. This is because the features of the legs are unclear.

B. Experiment in Various Poses

We experimented with detecting humans in various poses. Because, standing human might have various poses, such as raising both hands as shown in Fig. 15. Humans stood with their backs to the LiDAR with raising both hands as shown in Fig. 16. Fig. 17 shows point-cloud data and the result of evaluation.

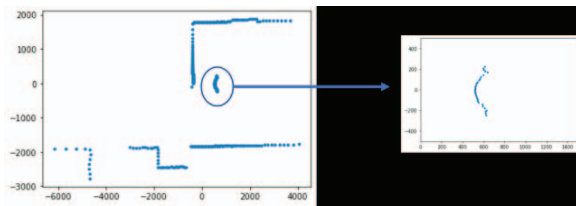


Fig. 12 Noise have been removed



Fig. 13 Human turned 45° and standing in front of LiDAR

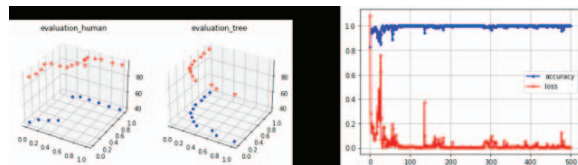


Fig. 14 Evaluation - standing turned 45°

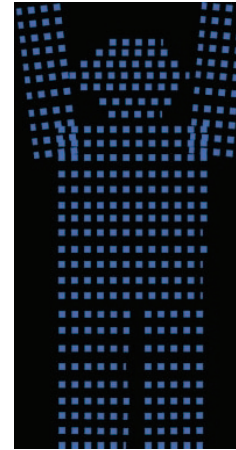


Fig. 15 Standing with raising both hands



Fig. 16. Standings their backs of LiDAR

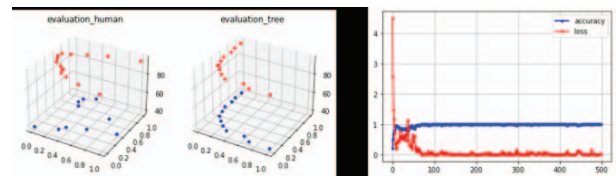


Fig 17 Evaluation with humans standing with their backs

It can be detected in humans using two LiDARs. This was because the features of the two legs were clear. Therefore, it is difficult to detect humans in various poses clearly if the two legs are not clear. However, in such cases, it is difficult to clearly detect the human using 3D-LiDAR.

VIII. CONCLUSION

We demonstrated a human detection method using 2D-LiDARs for autonomous carts as security guards. We conducted experiments under various scenarios. In many cases, it is difficult to clearly detect humans. However, if the possibility of human involvement is high, robot carts can move

in front of the human. Therefore, this method may be useful and can reduce the calculation costs.

In the future, we will conduct experiments with more actual cases and autonomous robot carts. Moreover, it is important to distinguish between suspicious and authorized individuals.

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