

Cost-effective Stationary Human Detection Using 2D LiDAR for Security Robots

Haruki Mochizuki

Graduate School of Kanagawa Institute of Technology
Atsugi, Japan

Ryozo Kiyohara

Kanagawa Institute of Technology
Atsugi, Japan
ORCID:0009-0004-3652-5615

Abstract—Since the COVID-19 pandemic, Japanese industries have been facing labor shortages across various sectors. In particular, the security industry has been affected due to an aging workforce and a lack of younger employees. This shortage has also impacted university security operations, where wide-area patrols place a considerable burden on security guards. Meanwhile, advancements in robotics have enabled not only the automation of simple tasks but also those involving human interaction. As a result, the development and deployment of patrol robots have been actively pursued, with high-precision situational recognition being a critical requirement for their practical implementation. However, existing robots are typically equipped with various sensors such as LiDAR and cameras, leading to high costs that hinder their adoption in university security. In this paper, we propose a cost-effective human detection method using multiple 2D LiDAR sensors. The proposed method focuses on the detection of stationary humans, an aspect that has not been sufficiently addressed in previous research. In addition, this paper outlines the key technical components necessary for the practical deployment of patrol robots in university security operations.

Keywords—patrol robot, human detection, 2D LiDAR, cost-effective sensing, campus security

I. INTRODUCTION

Since the COVID-19 pandemic, Japan has experienced labor shortages across various industries [1]. Among them, the security sector has been particularly affected due to an aging workforce and a lack of younger employees. This shortage has also impacted university security operations. In particular, universities with large campuses and partially uncontrolled entrances require a significant number of personnel for patrol duties. However, the industry-wide labor shortage makes it difficult to secure sufficient staffing, resulting in an increased workload for each security guard.

Meanwhile, advancements in robotics have enabled not only the automation of simple tasks but also the execution of tasks involving human interaction. For example, autonomous robots capable of obstacle avoidance have already been introduced in Japanese restaurants [2]. Leveraging such technologies, the development and deployment of patrol robots are being actively pursued, with the expectation of mitigating labor shortages and reducing the workload of security personnel.

For patrol robots to be practically implemented, high-precision situational recognition is essential. If a robot frequently misidentifies suspicious persons or objects, it will

require human verification more often, thereby failing to reduce the burden on security guards and potentially increasing it. Therefore, improving recognition accuracy is a critical requirement for effective deployment.

Additionally, patrol operations at universities are typically conducted during nighttime. During the day, most universities in Japan have minimal access control, allowing not only university personnel but also local residents to enter freely. In contrast, nighttime access is restricted, and only authorized personnel are permitted on campus. Unauthorized individuals are regarded as suspicious and are identified through regular patrols.

Existing patrol robots generally perform tasks such as human detection and anomaly recognition using various sensors, including LiDAR, cameras, and infrared sensors. However, the use of multiple types of sensors results in high costs, making their adoption in university security impractical. Since the primary objective of campus patrols is to detect suspicious persons or objects, there is a demand for low-cost robots equipped only with essential sensors.

In this study, we propose a human detection method using multiple 2D LiDAR sensors, which are commonly mounted on autonomous robots. While 3D LiDAR is typically used for SLAM in mobile robots, the point cloud data it generates is often too large for efficient human detection. Therefore, this study focuses on reducing data volume by utilizing multiple 2D LiDARs while maintaining effective detection performance. Many methods for detecting moving objects using LiDAR have been proposed [3]–[5]. However, research targeting stationary people is relatively limited [6], [7]. Although several prior studies have addressed this issue, they face challenges in terms of environmental conditions and detection accuracy [8]–[11].

In this paper, we present a method for detecting stationary people using multiple 2D LiDAR sensors and describe the technical components necessary for the practical application of patrol robots in university environments. The contributions of this paper are as follows:

- (1) A robotic human detection method
- (2) Establishment of a LiDAR ray selection method for classification
- (3) Demonstration of a security patrol robot in operation

II. RELATED STUDIES

Numerous studies have been conducted on human detection. Among them, image-based human detection is one of the most widely used approaches. With recent advances in camera and AI technologies, humans can be detected with high accuracy [12], [13]. These studies mainly focus on face or action recognition. A survey on pedestrian detection using monocular cameras is presented in [3]. However, in many campus environments, applying image-processing technologies for human detection can be challenging due to varying lighting conditions, including bright and dark areas. Processing images captured by low-cost cameras further increases the difficulty.

Several studies have also addressed human detection using 3D LiDAR. For example, [4] proposed a pedestrian recognition method for autonomous vehicles that employs a support vector machine (SVM) to classify human point-cloud data. As a human-following technique for mobile robots, [5] proposed the use of a single laser range finder to detect and track human legs. This approach employs an SVM to learn leg features and leverages human gait models for efficient tracking. Accordingly, humans are detected based on motion information obtained through temporal comparison of point-cloud data.

Other work has collected point-cloud data from multiple heights and achieved a classification rate of up to 96%. Another study [6] divided 3D point clouds of targets into parts—specifically, the trunk and legs—to achieve robust pedestrian recognition in real environments. While these approaches demonstrate strong performance, they rely on high-resolution 3D point-cloud data, which requires powerful computational resources. Although 3D LiDAR can capture the full shape of a human, enabling recognition regardless of clothing or posture, such detailed information is not always necessary in campus patrol scenarios. Therefore, in this study, we propose a human detection method using multiple 2D LiDARs to reduce computational costs while maintaining sufficient detection accuracy.

In our previous work [8], we proposed a human detection method using low-resolution 2D LiDAR and a PointNet-based autoencoder [14]. The 2D LiDAR sensors were positioned at a height of 90 cm—approximately the waist height of an adult—to collect data from both frontal and lateral directions. The proposed method successfully detected humans within 5 m of the sensor. In another study [9], we proposed a human recognition method using multiple 2D LiDARs; however, both methods required detection from the exact front. In this paper, we propose an improved method capable of recognizing humans regardless of the sensing angle.

Previous research [10], [11] has also proposed methods for detecting stationary humans by focusing on two physical features and two observation directions. By extracting these physical features, stationary humans could be recognized from various orientations while minimizing the amount of data required. In this paper, we extend this approach by expanding the detection range through adjustment of the LiDAR data acquisition cycle and evaluate the proposed method experimentally.

In [15], a high-precision localization method for autonomous mobile platforms based on SLAM was proposed. In university campus security applications, accurate localization is essential both for autonomous navigation and for providing precise positional information to security personnel. The study demonstrated that the system can dynamically update maps in response to obstacles, such as those arising during campus events, thereby achieving robust localization in changing environments.

In [16], a system for detecting suspicious individuals using Bluetooth technology was proposed. In this system, university personnel such as students and faculty members register their information in advance via a dedicated application that transmits Bluetooth signals. Security guards then verify this information using a receiver device. The system estimates the distance to each individual based on the received signal strength indicator (RSSI) value and distinguishes between registered and unregistered individuals. This approach enables contactless verification of entry authorization during nighttime patrols, minimizing physical contact.

In [17], the acoustic characteristics of robots operating in indoor environments were investigated. The study measured sound pressure levels and frequency characteristics during robot operation and found that these acoustic properties influence human perception of a robot's presence. The results also suggested that certain sound characteristics may cause discomfort within human personal space.

Based on the findings from these previous studies, this paper proposes a low-cost human detection method using multiple 2D LiDAR sensors

III. PURPOSE OF PATROL SECURITY ON THE KAIT CAMPUS

This section describes the security patrol operations conducted on the Kanagawa Institute of Technology (KAIT) campus and their objectives. Figure 1 shows a schematic diagram of the campus, which contains lecture rooms, laboratories, faculty research labs, and other facilities. Access to these rooms is restricted to university employees or those with a permit.

The main purpose of daytime security patrols is to detect suspicious objects and illegal parking. During the day, not only students and faculty but also high school students and local

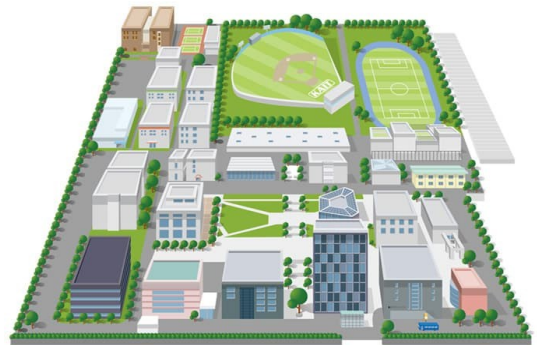


Fig. 1. Map of KAIT campus

residents may be present on campus. While access to lecture halls and faculty laboratories is restricted, other areas are generally open, so verifying residence permits is unnecessary. Consequently, security guards often focus on other tasks during daytime patrols. Therefore, if robots are deployed during the day, they are considered more suitable for delivery or guidance rather than security patrols.

The primary goal of nighttime patrols is to detect suspicious individuals and objects. At night, non-university personnel, including high school students and local residents, are not allowed on campus except in emergencies. Even if such individuals have no malicious intent, their presence on campus is unauthorized. To prevent unauthorized access, most entrances and exits are locked, with only a limited number remaining open. Under these conditions, anyone entering campus without permission is considered suspicious.

Nighttime patrols are particularly important but require multiple rounds to ensure safety. The large campus size and other duties of security guards make it difficult to patrol as scheduled. Introducing patrol robots is expected to reduce workload and manpower requirements, while maintaining effective security. Robots are intended to detect suspicious individuals and objects and report them to security personnel.

Person detection is performed using point-cloud data acquired by LiDAR. We assume that intruder behavior differs depending on intent. Malicious intruders tend to avoid surveillance and may flee when a robot approaches. Existing methods [8] can detect such moving individuals by observing changes in point-cloud data. In contrast, non-malicious intruders may remain stationary even when a robot passes nearby. Our previous person detection method [12] often fails to detect such stationary individuals.

Therefore, in this study, we propose a method for detecting non-malicious stationary people. In actual campus incidents, non-malicious intruders include, for example, elderly individuals with dementia who occasionally get lost and are later found by security guards. Stationary postures include standing, sitting, and lying down; here, we focus on upright postures, which are the most commonly observed by campus security personnel.

IV. PROPOSED METHOD

Based on the challenges identified in campus patrol operations, particularly the difficulty of detecting non-malicious stationary individuals during nighttime patrols, it is necessary to develop a robust human detection method. The following section presents the proposed method, which leverages multiple 2D LiDAR sensors to achieve accurate and cost-effective detection of stationary people while maintaining real-time performance for practical deployment on patrol robots.

A. Human Physical Characteristics

When acquiring data using 2D LiDAR, it is important to consider which body parts provide stable point-cloud data. The head is relatively small and, depending on the person's height, is more susceptible to variations, making stable data acquisition difficult. Therefore, this study focuses on the torso and legs, and

LiDAR sensors are installed at heights that allow reliable acquisition from these body parts.

Additionally, the subject's body type affects the shape of the point cloud. Different body types (thin, average, obese) result in subtle variations in point-cloud patterns. For instance, obese individuals have wider torsos and legs than thinner individuals. Training a classifier on a single body type may lead to misclassification; therefore, training data should include samples representing diverse body types.

B. LiDAR Installation Location

The mounting height of each LiDAR unit must account for the stature of target individuals. As discussed previously, the primary targets are non-malicious intruders on campus, many of whom are elderly individuals with dementia. Table I summarizes their average heights; based on this data, we assume a height range of 145–170 cm. To acquire point clouds of the torso and legs, we mount two LiDAR units at approximately 90 cm and 45 cm above the floor, respectively. This configuration enables reliable data acquisition even when the subject's height varies within the assumed range.

C. LiDAR Rotation

The point density in a single LiDAR scan cycle is often low, and it decreases with distance. Consequently, a single scan may fail to accurately capture a human's shape, potentially causing misclassification and reducing recognition accuracy. To address this, the robot approaches the target and collects point-cloud data over multiple consecutive scan cycles. Aggregating multiple scans increases the effective point density and improves human detection accuracy.

D. Human Learning in Classification

Human identification is performed using point-cloud classification. We employ the publicly available PointNet-based system "Classify Point Clouds Using PointNet" [12], which extracts features from point clouds regardless of point order by compressing and reconstructing the data. In our approach, human features are trained in two directions, enabling broader recognition coverage and discrimination from other objects. This two-way training model is used to classify suspicious individuals and other objects in the environment.

V. PRELIMINARY EXPERIMENT

A. Background Subtraction

For patrol security, autonomous robots must identify objects in their environment. We conducted an experiment comparing point-cloud data from a reference map with data from the current environment to extract differential points. Figure 2 and 3 show examples of point-cloud data at the same location. Since exact

TABLE I. AVERAGE HEIGHT OF JAPANESE ELDERLY PEOPLE

Age	Height (cm)	
	Male	Female
60–69	167. 4	154. 0
70–79	163. 1	149. 4
80+	161. 1	146. 6

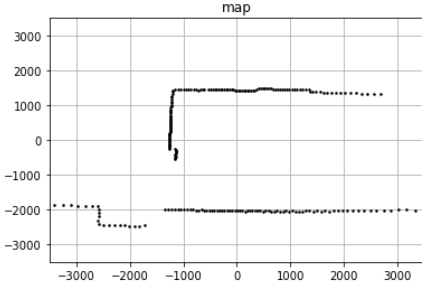


Fig. 7. Comparison point cloud data 1

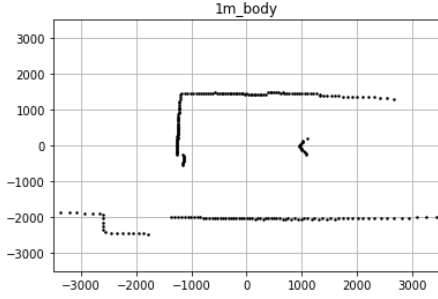


Fig. 8. Comparison point cloud data 2

point matching is difficult, an appropriate threshold was applied. Figure 4 illustrates the differential points extracted for detection.

B. Personal Space

To evaluate discomfort caused by robot noise, students measured the distance at which they did not want the robot to approach. This simulated nighttime patrol conditions. The robot (Figure 5) approached the subject from 10 m under three conditions: (i) facing the robot with visual recognition, (ii) facing the robot with eyes closed, and (iii) back to the robot. Measurements were conducted on both cobblestone and asphalt surfaces.

Table II summarizes the results. Personal space was approximately 2–3 m, and it increased when eyes were closed. These findings indicate that, at night, suspicious individuals should be detected before the robot enters their personal space. The robot's appearance was not particularly unpleasant; running noise was the main source of discomfort.

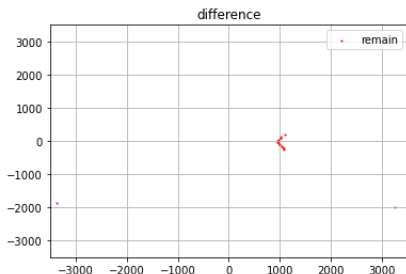


Fig. 5. Background subtraction point cloud data



Fig. 6. Security Robot

TABLE II. AVERAGE DISTANCE

	Stone	Asphalt
Front (Open)	229.3	239.2
Front (Close)	280.4	312.8
Behind	227.8	250.4

C. Bluetooth Reception by Multiple Persons

Accurate positioning using RSSI alone is difficult due to device variability. We tested directional reception to estimate locations of authenticated smartphones. The receiver was partially covered with aluminum foil to restrict reception direction (Figure 6). Measurements were conducted by pointing the receiver alternately toward each transmitter. Figures 7 and 8 show that RSSI values depend on receiver orientation, enabling

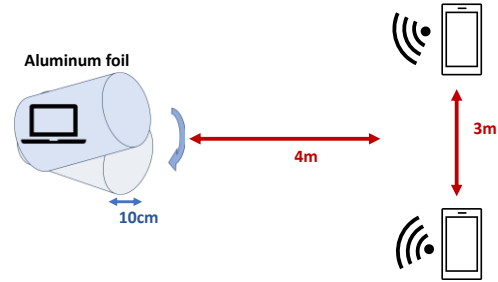


Fig. 2. Experiment Image

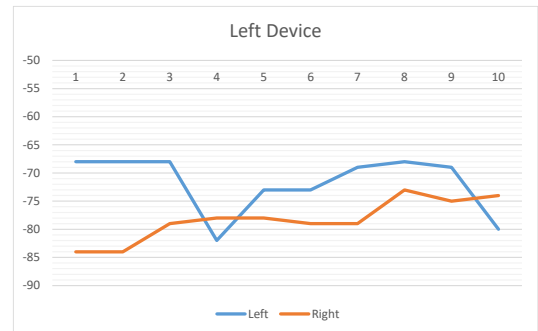


Fig. 3. RSSI of receiving left device

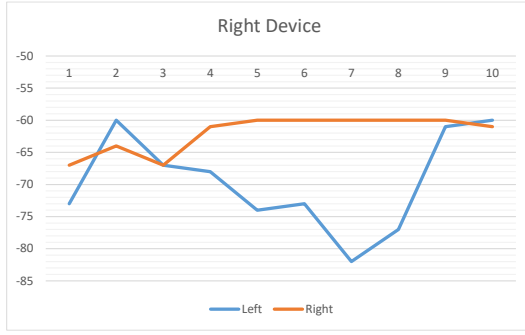


Fig. 8 RSSI of receiving left device

estimation of the location of multiple smartphones by sequential directional scanning.

VI. EXPERIMENTS AND EVALUATION

A. Classification Accuracy for Various Person Orientations

To evaluate classification accuracy for different orientations, point cloud data were acquired at approximately 5 m from the LiDAR to prevent discomfort during robot approach. The LiDAR specifications (VLP-16) are listed in Table III. For the proposed method, a single 3D LiDAR beam was selected to capture data at the required height. Five LiDAR rotations were aggregated to increase point density, corresponding to a scan time of less than 1 s.

The target classes were people, trees, and signs. Training data included frontal and side views of six subjects with diverse body types. Test data covered multiple orientations from 0° (front) to 180° (rear) in 30° increments. Trees were included due to their torso-like point-cloud shapes, and signs as common campus objects. Classification used the PointNet pipeline with 100 epochs and batch size 32, training/validation ratio ~2:1.

Results are summarized in Table IV. High accuracy was achieved for humans across all orientations, and humans were

TABLE VII. PERFORMANCE OF LiDAR

Name	VLP-16
Range	100m
View Angle (Vertical)	30° (±15°)
View Angle (Horizontal)	360°
Rotational Speed	5Hz-20Hz

TABLE VIII. F VALUE BY EACH ANGLE (HUMAN)

Class	Observations	Average number of pointcloud
Human	400	182
Tree	400	308
Sign	400	259

correctly distinguished from trees and signs. These results show that training on frontal and profile orientations enables accurate classification across multiple orientations.

B. Classification Accuracy at Different Distances

We evaluated classification accuracy at distances of 5 m, 10 m, 15 m, and 20 m. The same LiDAR system and aggregation method (five rotations per point cloud) were used. People were tested at four orientations (0°–90° in 30° increments), and trees and signs were included at various distances. Training data were acquired at 5 m.

Tables V–IX summarize the results. High accuracy was maintained across distances despite reduced point cloud density, demonstrating that aggregation of multiple scans mitigates

TABLE III. F VALUE BY EACH ANGLE (HUMAN)

Angle	F-Value
0	1.00
30	1.00
60	1.00
90	1.00
120	1.00
150	1.00
180	1.00

TABLE IV. F VALUE BY DISTANCE (5M)

Angle	Recall	Precision	F-Value
0	1.00	1.00	1.00
30	1.00	1.00	1.00
60	1.00	1.00	1.00
90	1.00	1.00	1.00

TABLE V. F VALUE BY DISTANCE (10M)

Angle	Recall	Precision	F-Value
0	1.00	1.00	1.00
30	1.00	1.00	1.00
60	0.99	1.00	0.99
90	1.00	1.00	1.00

TABLE VI. F VALUE BY DISTANCE (15M)

Angle	Recall	Precision	F-Value
0	1.00	1.00	1.00
30	1.00	1.00	1.00
60	1.00	1.00	1.00
90	1.00	1.00	1.00

TABLE IX. F VALUE BY EACH ANGLE (HUMAN)

Angle	F-Value
0	1.00
30	1.00
60	1.00
90	1.00
120	1.00
150	1.00
180	1.00

accuracy loss. Training on frontal and side views alone was sufficient for accurate classification at all distances, supporting robust LiDAR-based detection in practical patrol scenarios.

VII. SUMMARY

To address labor shortages in the security industry, we investigated the ability of an autonomous mobile robot equipped with 2D LiDAR to classify humans in various poses. Humans were classified by training on two standard poses—frontal and side—based on torso and leg features captured by LiDAR.

Experimental results demonstrated that the system can classify stationary people not only in the trained poses, but also in other orientations. This approach enables stationary person classification independent of orientation, using a small set of standard training poses.

In future work, we plan to evaluate classification performance against non-human obstacles and investigate classification for subjects in non-upright postures (e.g., sitting or lying).

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