Efficient Pedestrian Scanning by Active Scan LIDAR

Taiki Yamamoto, Yasutomo Kawanishi, Ichiro Ide, and Hiroshi Murase
Nagoya University
Graduate School of Informatics
Aichi, Japan

Fumito Shinmura
Nagoya University
Institutes of Innovation for Future Society
Aichi, Japan

Daisuke Deguchi
Nagoya University
Information Strategy Office
Aichi, Japan

Abstract— **Active Scan LIDAR is one of the actively developed distance measurement sensors in recent years. It has a great advantage that it can control the laser irradiation direction arbitrary and rapidly. By using this sensor, we will be able to scan distant pedestrians densely. However, an efficient scanning method nor strategy have not been established on obtaining dense point-clouds from pedestrians. Therefore, this paper proposes an efficient pedestrian scanning method based on pedestrian likelihood estimation using an Active Scan LIDAR. To evaluate the performance of the proposed method, Active Scan LIDAR was simulated using point-clouds obtained by a conventional LIDAR. The experiment results demonstrated the effectiveness of the proposed method.**

Keywords—Active Scan LIDAR; Stochastic sampling; Pedestrian likelihood estimation; Pedestrian detection;

I. INTRODUCTION

Traffic accident is one of the biggest problems remaining in the human society. Most victims are pedestrians, so it is expected to reduce the number of them as soon as possible. Therefore, pedestrian detection systems are becoming important to prevent such accidents. Such systems should detect pedestrians who may collide with a vehicle and warn the driver about their existence. In recent years, LIDAR-based pedestrian detection methods have been widely studied since it can measure the distance to target objects and their reflection intensity simultaneously. The most commonly used LIDAR has multiple laser irradiation ports in the vertical direction and it acquires point-clouds by irradiating lasers while rotating the sensor in the horizontal direction. According to the number of the laser ports, LIDAR can be classified into two types: High-resolution LIDAR with many ports, and low-resolution LIDAR with a few ports.

Kidono et al. [1] proposed a pedestrian recognition method using a high-resolution LIDAR, which combines a slice feature extracted from distant pedestrians and features related to the distribution of reflection intensities. The slice feature is extracted by dividing 3D point-clouds into multiple slice sections with a certain height. The whole-body shape of a pedestrian is expressed by the combination of the slice features. Furthermore, since the reflection intensity distribution is different for each object, they use this information for reducing misdetection against non-pedestrians. Although these features
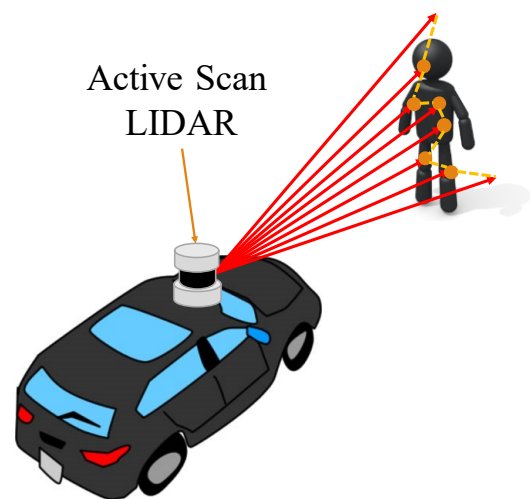

Fig. 1. Scanning point-clouds using an Active Scan LIDAR.

can also be extracted from a distant pedestrian, the detection accuracy will degrade if the pedestrian exists in a distance.

Tatebe et al. [2] proposed a method to improve the accuracy of pedestrian detection by integrating features calculated from multiple frames even for low-resolution LIDARs. However, this method does not work well against distant pedestrians whose point-cloud resolution is very low. Thus, to achieve accurate pedestrian detection, it is desirable that resolution of point-clouds should be as high as possible.

On the other hand, Active Scan LIDAR is one of the actively developing distance measurement sensors that can control the laser irradiation direction arbitrary and rapidly as shown in Fig. 1. This sensor enables us to freely design a scanning method to satisfy our need. For example, it can be used to scan distant pedestrians more densely for pedestrian detection purposes. However, an efficient scanning method to achieve this goal has not been established yet.

Here, let us assume that there is a pedestrian inside the field-of-view. If we can estimate the existence of a pedestrian from a small number of laser irradiations, we can scan their surroundings to find the pedestrian precisely. In addition, the density of the point-cloud becomes higher after the scan, so we can expect the pedestrian location prediction to improve.
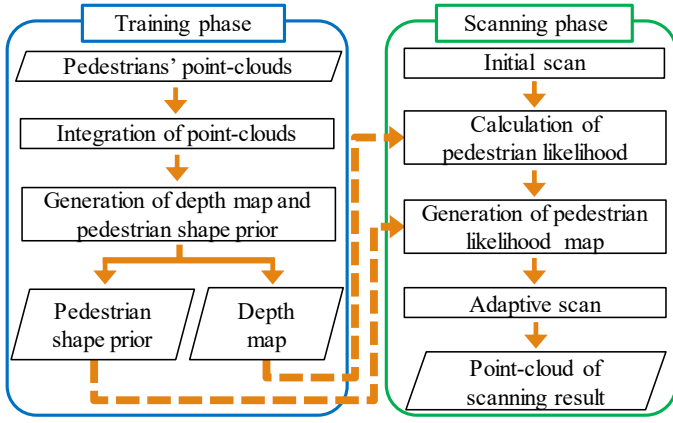
Fig. 2. Process-flow of the proposed method.

Therefore, by repeating this process, it will become possible to find pedestrians progressively starting from a sparse point-cloud. Based on this idea, this paper proposes a method to scan distant pedestrians efficiently and accurately. The contributions of this paper are as follows:

1. Proposal of a progressive pedestrian scanning method using an Active Scan LIDAR.

2. Estimation of a pedestrian likelihood map from sparse point-clouds based on the probability calculated from the shape of the pedestrian.

3. Adaptive laser irradiation control based on stochastic sampling according to a pedestrian likelihood map.

II. SCANNING METHOD BASED ON PEDESTRIAN LIKELIHOOD

As shown in Fig. 2, the proposed method can be divided into two phases. The first phase is called the training phase, where we generate a depth map and a pedestrian shape prior from pedestrians' point-clouds. The second phase is called the scanning phase, where the adaptive scanning is performed.

A. Training phase

This section describes the process for the generation of a depth map and a pedestrian shape prior. The depth map is used to calculate the likelihood of a measured point and the pedestrian shape prior is used to calculate the likelihood of a neighborhood position of a measured point. In the following explanations, the center of LIDAR is used as an origin of the coordinate system. Here, x-, y-, z-axes are defined as the lateral, the vertical, and the depth directions of the vehicle, respectively.

The training phase of the proposed method consists of two steps:

1) *Integration of pedestrians' point-clouds:* First of all, all pedestrians' point-clouds are aligned by shifting the smallest vertical coordinate (y-axis) and depth coordinate (z-axis) of each point-cloud to zero (y = 0 and z = 0). Next, the proposed method extracts points that exist in the area of 1.5 m × 2.0 m in the x, y-coordinates from the origin. Finally, by merging all the pedestrian's point-clouds, the integrated point-cloud is obtained.

2) *Calculation of depth map and pedestrian shape prior:* A depth map and a pedestrian shape prior are calculated

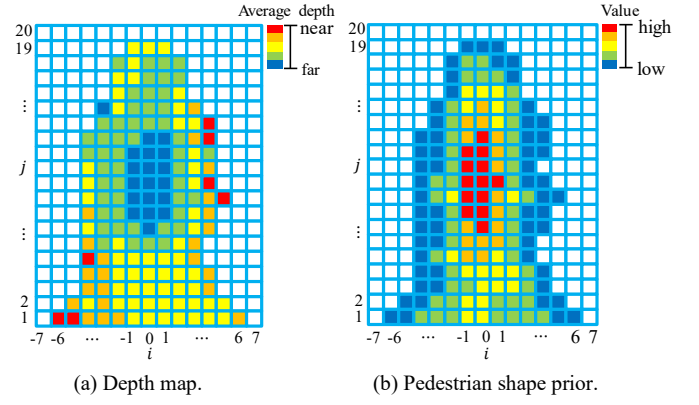
(a) Depth map.　　(b) Pedestrian shape prior.

Fig. 3. Generation of depth map and pedestrian shape prior.

using the integrated point-cloud. Figure 3 shows the generation of them. The integrated point-cloud is divided into 15×20 cells where each cell is a rectangle with an edge of $W = 0.1$ m. Each cell is identified using horizontal and vertical indices ($i = -7, -6, \dots, 6, 7$, $j = 1, 2, \dots, 20$). Next, the average depth $d_{i,j}$ and the number of points $n_{i,j}$ in each cell are calculated. Here, in order to reduce noise, the proposed method ignores cells with $n_{i,j} < 10$, by treating them as $d_{i,j} = \infty$ and $n_{i,j} = 0$. After all $d_{i,j}$ and $n_{i,j}$ are calculated, the pedestrian shape prior $s_{i,j}$ of each cell is calculated as,

$$s_{i,j} = \begin{cases} \dfrac{n_{i,j}}{\sum_{k,\ell} n_{k,\ell}} & \text{if } n_{i,j} \geq 10 \\ 0 & \text{otherwise} \end{cases}. \quad (1)$$

By following the above steps, the depth map and the pedestrian shape prior are obtained.

B. Scanning phase

This section describes the process of the scanning phase. In the following, $\mathcal{P}_0$ indicates the point-cloud measured by the initial scan, and $\mathcal{P}_m$ indicates the point-cloud measured until the m-th scan. The scanning phase of the proposed method consists of five steps:

1) *Initial Scan:* This step aims to find a pedestrian by a small number of laser irradiations and to obtain the rough shape of existing pedestrians. Specifically, with a certain height h, N points of lasers are irradiated with certain intervals along the horizontal direction. After this step, dense point-cloud at a certain height h can be obtained.

2) *Calculation of pedestrian likelihood using depth map:* This step calculates the pedestrian likelihood corresponding to each measured point to generate the pedestrian likelihood map. First, for each measurement point $\boldsymbol{p} \in \mathcal{P}_m$, the pedestrian likelihood $f(\boldsymbol{p})$ is calculated as,

$$f(\boldsymbol{p}) = \frac{1}{|\mathcal{N}(\boldsymbol{p})|} \sum_{\boldsymbol{q} \in \mathcal{N}(\boldsymbol{p})} g(\boldsymbol{p}, \boldsymbol{q}), \quad (2)$$

where $\mathcal{N}(\boldsymbol{p})$ is a set of neighbors of $\boldsymbol{p}$ and $|\mathcal{N}(\boldsymbol{p})|$ the number of elements (points) in $\mathcal{N}(\boldsymbol{p})$. $\mathcal{N}(\boldsymbol{p})$ is selected as,
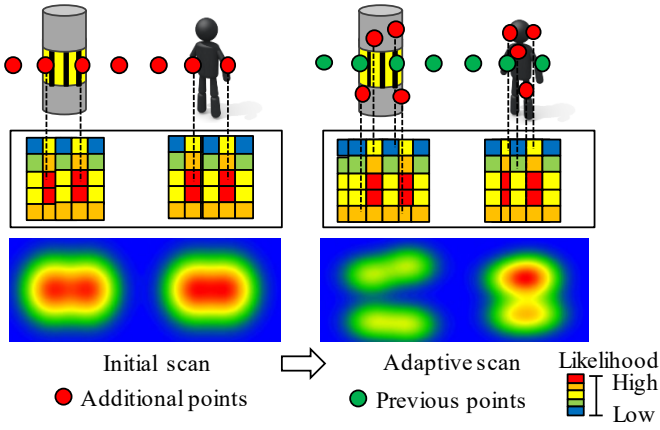
Fig. 4. Updating measured points and pedestrian likelihood map by adaptive scan.

- Initial scan ⇨ Adaptive scan
- ● Additional points
- ● Previous points
- Likelihood: High / Low

$$\mathcal{N}(\boldsymbol{p}) = \{\boldsymbol{q} \mid \boldsymbol{q} \in \mathcal{P}_m,$$
$$|q_x - p_x| \le 0.75, 0 \le q_y \le 2, |q_z - p_z| \le 1\}, \quad (3)$$

where $\boldsymbol{p} = (p_x, p_y, p_z)$ and $\boldsymbol{q} = (q_x, q_y, q_z)$. $g(\boldsymbol{p}, \boldsymbol{q})$ is calculated using a normal distribution whose average and variance are $\mu = d_{i,j} - d_{0,j}$ and σ^2 as,

$$g(\boldsymbol{p}, \boldsymbol{q}) =$$
$$\begin{cases} \exp\left(-\dfrac{((q_x - p_x) - \mu)^2}{2\sigma^2}\right) & \text{if } d_{i,j} \ne \infty, \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

where $d_{0,j}$ is the depth value of cell $(0, \hat{\jmath})$ containing $\boldsymbol{p}$, and $d_{i,j}$ is the depth value of cell (i, j) containing $\boldsymbol{q}$. Here, the index of each cell is calculated as,

$$\hat{\jmath} = \left\lfloor \frac{p_y}{W} \right\rfloor, \quad (5)$$

$$i = \left\lfloor \frac{q_x - p_x}{W} \right\rfloor, \quad j = \left\lfloor \frac{q_y}{W} \right\rfloor. \quad (6)$$

Note that $\lfloor \cdot \rfloor$ is floor function defined as,

$$\lfloor x \rfloor = \max\{n \mid \forall n \in \mathbb{Z}, n \le x\}, \quad (7)$$

where $\mathbb{Z}$ represents a set of whole integers.

After applying the above process to all m-th measurement points $\mathcal{P}_m$, the normalized pedestrian likelihood $F(\boldsymbol{p})$ is calculated as,

$$F(\boldsymbol{p}) = \frac{f(\boldsymbol{p})}{\sum_{\boldsymbol{p} \in \mathcal{P}_m} f(\boldsymbol{p})}. \quad (8)$$

3) *Generation of pedestrian likelihood map:* This step estimates positions where pedestrians exist by using the pedestrian likelihood calculated in step 2. First, the local map $m_{i,j}$ is calculated using the pedestrian shape prior as,

$$m_{i,j} = F(\boldsymbol{p}) s_{i,j}. \quad (9)$$

Since the position on the z-axis of each local map is different, we cannot integrate each map as it is. Thus, for a certain depth z, we assume the X-Y plane and project each local map on the X-Y plane. The likelihood at areas where each local map overlaps is the sum of the values of each local map. By integrating local maps as described above, the pedestrian likelihood map is generated.

4) *Adaptive scan based on pedestrian likelihood map:* This process irradiates lasers according to the pedestrian likelihood map. Here, stochastic sampling is used for selecting irradiation directions.

5) *Repeat step 2 to step 5:* This step aims to update measured points and the pedestrian likelihood map progressively. As shown in Fig. 4, a pedestrian is progressively scanned by repeating the pedestrian likelihood map calculation and laser irradiation based on stochastic sampling.

III. EXPERIMENT AND DISCUSSION

This section describes experiments that were conducted to evaluate the effectiveness of the proposed method with discussions on the results.

A. Experimental procedure

Unfortunately, we could not use an actual Active Scan LIDAR since it is still under development. Therefore, we prepared a dataset by simulating its function using point-clouds obtained from a high-resolution uniform-scan type LIDAR. Actually, point-clouds from KITTI dataset [3] were used. This dataset includes point-clouds corresponding to pedestrians, vehicles, and other objects. From this dataset, 600 frames including a pedestrian closer than 30 m in front of the vehicle were selected. After the selection, point-clouds corresponding to the vehicle's front-view were cropped. Then, all points corresponding to pedestrians were labeled manually as the ground-truth.

The proposed method was compared with a uniform-scan method (comparative method). $N = 100$ and $N_{\max} = 1,000$ were used as the numbers of laser irradiation points with each scan and the total scan, respectively. As the height of the initial scan, $h = 1.0$ m from the ground-plane was used. In addition, $\sigma = 0.05$ m was used in (7). The performance of each method was evaluated by two-fold cross validation.

B. Evaluation metrics

We evaluated methods using three metrics: hit rate, region overlap rate, and pedestrian extraction rate, defined as follows:
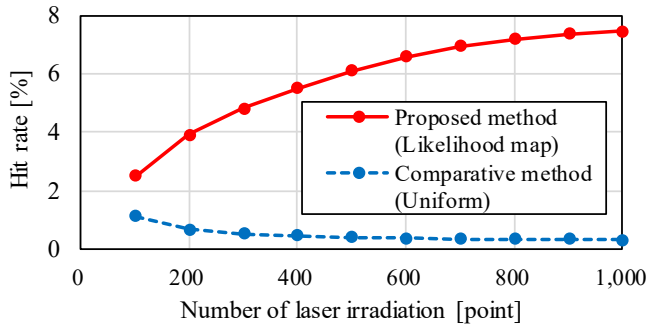
1) Hit rate R_{hit} is defined as,

$$R_{\text{hit}} = \frac{N_{\text{ped}}}{N_{\text{laser}}}, \quad (9)$$

where N_{laser} is the number of irradiation lasers, and N_{ped} is the number of measured points that actually hit the ground-truth pedestrian points.
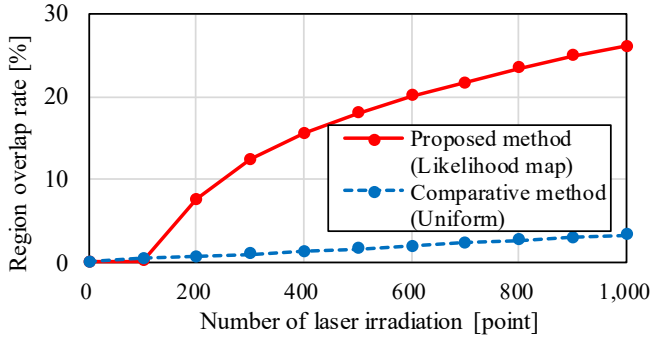
2) Region overlap rate R_{over} is defined as,

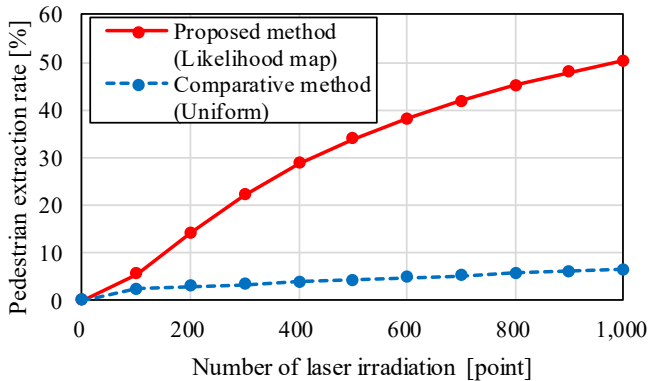$$R_{\text{over}} = \frac{|V|}{|V_{\text{true}}|}, \quad (10)$$

where $|V|$ is the volume of the smallest cuboid containing all measured pedestrian points, and $|V_{\text{true}}|$

(a) Hit rate.

(b) Pedestrian extraction rate.

(c) Region overlap rate.

Fig. 5. Experimental results by evaluation metrics.

is the volume of the smallest cuboid cover the true pedestrian region.

3) Pedestrian extraction rate R_{ext} is defined as

$$R_{\text{ext}} = \frac{M_{\text{ped}}}{N_{\text{sum}}}, \qquad (11)$$

where M_{ped} is the number of measured pedestrian points, and N_{sum} is the total number of pedestrian points in the ground-truth. Here, if a certain pedestrian point is measured, pedestrian points whose distance is less than 0.1 m are considered to be measured.

In the each of above metrics, the higher the value is, we consider that the more effective the pedestrian can be scanned. In addition, if the number of laser irradiations becomes smaller, we consider that the method can scan pedestrians efficiently.
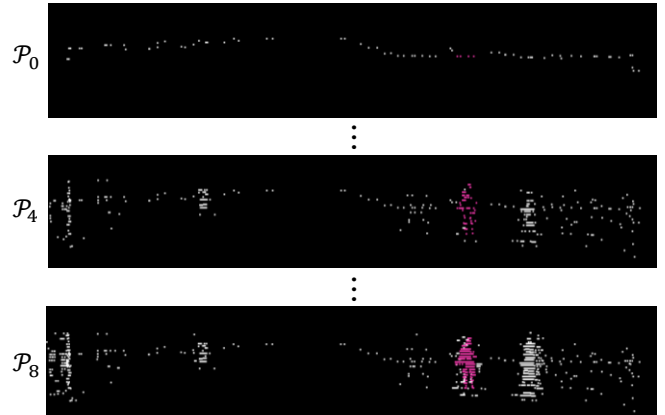

Fig. 6. Image captured during scanning.

Fig. 7. Scanning result by the proposed method. Pink dots represent pedestrians while white dots represent other objects.

C. Results and discussions

Figure 5 shows the results by each evaluation metric. We confirmed that the proposed method outperformed the comparative method in all metrics. Figure 7 shows the scanning results of the proposed method against the situation shown in Fig. 6. As the results demonstrate, the proposed method could scan pedestrians progressively and efficiently.

IV. CONCLUSION

This paper proposed an efficient and accurate pedestrian scanning method based on the pedestrian likelihood map estimated from the shape of a pedestrian. Specifically, by learning the shape of a pedestrian, it is possible to estimate a probable position where a pedestrian exists from a sparse point-cloud, and then scan progressively by controlling laser irradiation. Through experiments using the KITTI dataset, we confirmed the effectiveness of the proposed method.

Future work includes the improvement of the map construction in the learning phase and the development of the pedestrian detection method for point-clouds obtained by the proposed method.

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