REAL-TIME MAPPING OF CONSTRUCTION WORKERS USING MULTILAYERED LIDAR

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ABSTRACT: In this study, we focus on intelligent construction vehicles to improve the safety of workers. Generally, global navigation satellite system positioning is utilized to obtain the position data of workers and construction vehicles in construction sites. However, construction fields in urban areas have poor satellite positioning environments. Therefore, we have developed a 3D sensing unit mounted on a construction vehicle for worker position data acquisition. The unit mainly consists of multilayered LiDAR. Moreover, we propose a real-time object classification and tracking methodology from temporal point clouds acquired with the multilayered LiDAR. We evaluated our methodology using temporal point clouds acquired from a construction vehicle in drilling works.

1. INTRODUCTION

Recently, the construction field has focused on technical and political issues, such as construction site management costs, productivity improvement, and reducing the number of accidents (Dong et al. 2018). Various actions are available to address these issues based on building information modeling (BIM). BIM uses terrestrial LiDAR, global navigation satellite system (GNSS) devices, unmanned aerial vehicles (UAVs), and intelligent construction vehicles (Doishita et al. 2010) for spatial data acquisition. Here, we focus on using intelligent construction vehicles to improve the safety of workers. Generally, GNSS positioning is applied to obtain the position data of workers and construction vehicles in construction sites. However, when position data are shared among construction vehicles and workers, instead of using GNSS devices, wireless communication systems and computing systems should be distributed to share position data between workers and construction vehicles. Thus, the sensing cost increases higher and the sensing system becomes more complex. Moreover, construction fields in urban areas have poor satellite positioning environments. Thus, we applied 3D sensing to provide more stable worker position data acquisition and sensing-avoid application of construction vehicles and incident prediction. UAVs and terrestrial LiDAR can acquire 3D data of static construction fields (Figure 1). However, with UAVs and terrestrial LiDAR, it is difficult to measure and represent changing objects and environments, such as moving workers, vehicles, and construction fields in real time.

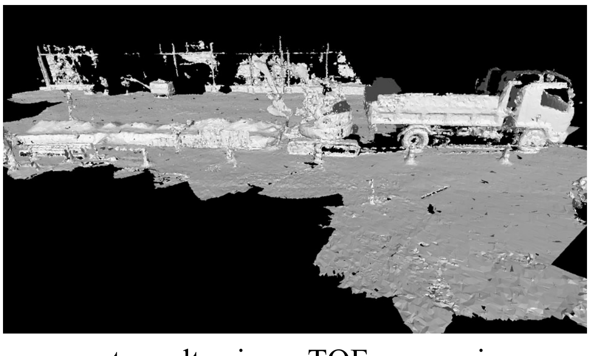

Figure 1. 3D measurement result using a TOF camera in a construction site

Therefore, we have developed a 3D sensing unit mounted on a construction vehicle for real-time worker position data acquisition. Our proposed unit mainly comprises multilayered LiDAR and iBeacon devices. Moreover, we propose a real-time object classification and tracking methodology from temporal point clouds acquired with a multilayered LiDAR and beacon devices. We evaluated our methodology using temporal point clouds and iBeacon data acquired from a construction vehicle in drilling works.

2. METHODOLOGY

Worker position data can be estimated directly from LiDAR data. However, object identification is impossible because LiDAR data have low spatial resolution and no color information. In contrast, although the accuracy of position estimation is unstable, beacon receivers can identify objects using a unique identifier sent from beacon transmitters. Therefore, we integrate LiDAR data and beacon data to identify objects.
Our proposed methodology is shown in Figure 2. First, temporal point clouds are acquired with multilayered LiDAR. At the same time, temporal distance data are acquired with beacon ranging devices. We focus on the use of LiDAR for autonomous vehicles and iBeacon for indoor positioning to improve the cost of 3D sensor units. Then, we distribute iBeacon transmitters to workers and mount LiDAR and iBeacon receivers on a construction vehicle to reduce the number of computing systems in a construction site. Second, simultaneous localization and mapping (SLAM) (Durrant-Whyte and Bailey 2006; Durrant-Whyte and Bailey 2006) and moving object extraction are applied to acquire point clouds in parallel. Moving object extraction results are used for directly sensing avoidance applications. Third, extracted objects are traced in moving object tracking. Lastly, moving objects are identified using temporal LiDAR and iBeacon data for incident evaluation and estimation in a construction site. When two or more PCs are used for sensing, we manage our measurement system with a GNSS clock to synchronize all sensors. When we use a PC, all sensors can be synchronized with the PC clock.

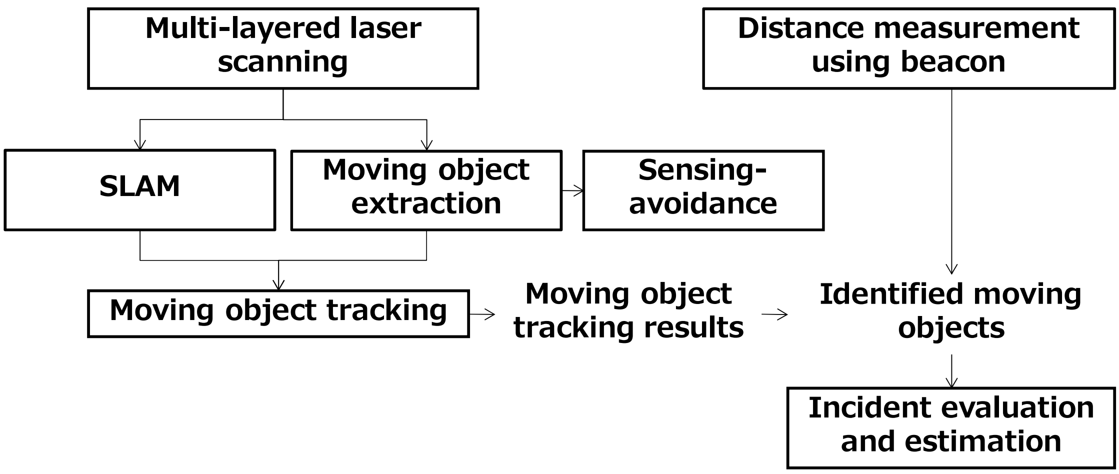

Figure 2. Proposed methodology

2.1 Moving object extraction

Moving object extraction consists of four steps (Figure 3). First, temporal point clouds are projected into temporal range images. The temporal range image is prepared as 7D spaces consisting of 3D coordinate values (X, Y, and, Z), intensity values, scanning directions (horizontal angles), scanning layers (vertical angles), and scene numbers. Second, point clouds higher than ground height are labeled in the range images. The ground height is determined using a major horizontal plane estimated with robust plane fitting. Third, labeled point clouds are clustered to generate moving object candidates with voxel segmentation processing, and we apply the region-growing methodology for the voxel segmentation. Fourth, moving objects, such as workers and construction vehicle buckets, are extracted from moving object candidates. The closest moving object candidate from a scanner is assumed to be a bucket, while the other moving object candidates are assumed to be workers with geometric constraints such as height and volume.

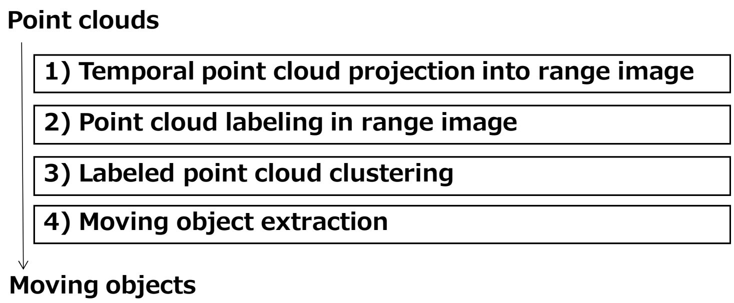

Figure 3. Moving object extraction

2.2 Moving object tracking

Candidates of moving objects, such as buckets and workers, are tracked to be constantly fixed as buckets and workers during several scenes in a temporal 3D space. When a scanner position is fixed, the nearest cluster tracking can be applied for simple object tracking. However, when the scanner translates and rotates, tracking results using acquired point clouds would be unstable (Figure 4). Thus, SLAM is integrated to detect and track moving objects (Vu et al. 2011) to improve the stability of moving object tracking from a moving scanner. In our methodology, rotation and translation parameters are estimated with SLAM. Then, the nearest clusters are searched from rotated and translated point clouds. At the same time, spike noises and unclear points can be rejected from moving object candidates.

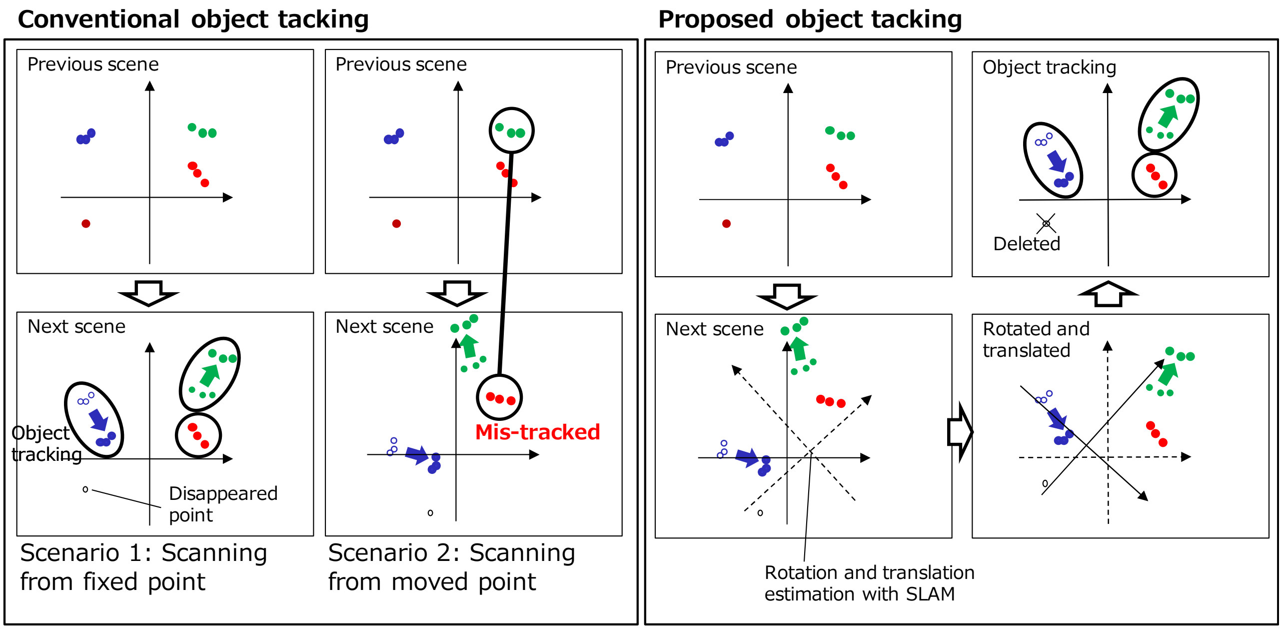

Figure 4. Moving object tracking and filtering

2.3 iBeacon ranging

In wireless communication-based indoor positioning systems, popular positioning algorithms include time of arrival (ToA), time difference of arrival (TDoA), angle of arrival (AoA), and received signal-strength indication (RSSI) positioning (Golden and Bateman 2007). In an actual environment, ToA, TDoA, and AoA positioning are strongly affected by precise synchronization between transmitters. In contrast, RSSI positioning (Vaidya et al. 2014) is more robust than the other methods. While three or more fixed transmitters are required for triangulation-based positioning, cheap transmitters, such as iBeacon, have recently been used for RSSI positioning because RSSI can provide position data without precise synchronization between transmitters. However, in our study, a moving receiver receives signals from moving transmitters. Thus, we only focus on only beacon ranging and omit the positioning calculation using iBeacon.

An iBeacon receiver can receive signals from many transmitters without interference because of spectrum spreading signal processing. iBeacon transmitters send data consisting of unique identifiers such as universally unique identifier (UUID), distance labels, and received signal-strength (RSS) values. Although an approximate distance from a transmitter can be determined from the distance labels, such as near (< 1 m from a transmitter), far (> 1 m), and unknown (the precise distance from transmitter to receiver can be estimated using RSS values from a transmitter). The distance can be calculated using the following equation based on the Friis transmission formula:

$$D = 10^{((TxPower - RSS)/20)},$$

where D is the estimated distance value from an iBeacon transmitter to the receiver and $TxPower$ is the RSS value 1 m from an iBeacon transmitter.

2.4 Moving object identification

Each UUID of iBeacon data is linked to tracking results estimated from LiDAR data using iBeacon ranging data in the moving object recognition step. Generally, the estimated distance accuracy of iBeacon data is lower than that of LiDAR data. However, the trends of temporal distance data are approximately the same. Thus, moving objects are identified based on pattern matching using tracking results and temporal distance data of iBeacon (Figure 5).

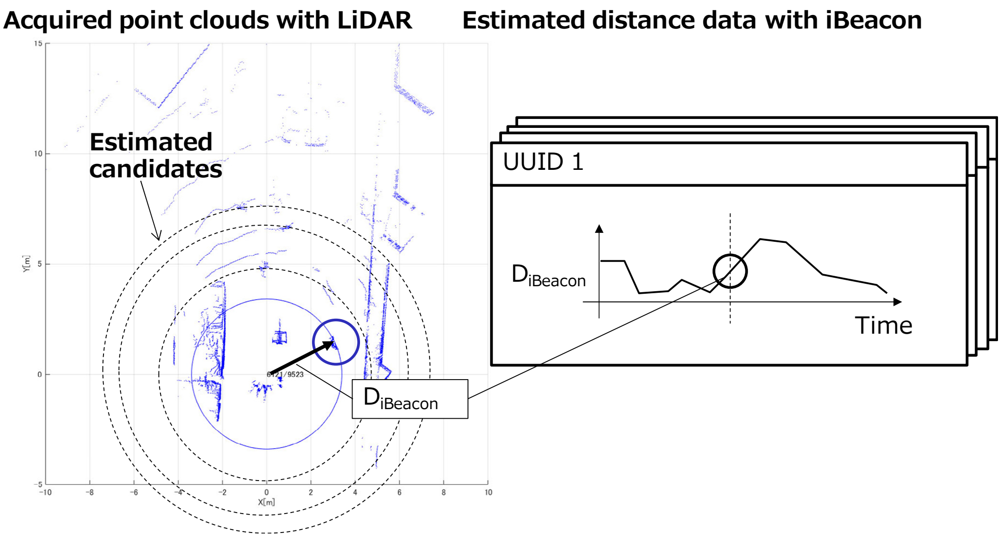

Figure 5. Moving object identification

3. EXPERIMENTS

We prepared simulated construction environments in an urban area (Figure 6). Point clouds and iBeacon data were acquired from the backhoe under general construction operation with translation and rotation of construction vehicles during construction work.

Figure 6. Simulated construction environment

A multilayered LiDAR (VLP-16, Velodyne) was mounted on a backhoe (Figure 7). A laptop computer (MacBook Air, Apple) was used to acquire point clouds with LiDAR. We acquired point clouds during construction work, such as excavation, piping, and filling works, for 30 minutes (approximately 18,000 scenes). Altogether, we used 134,955,204 points (9,523 scenes) in all acquired point clouds for our data processing. We distributed iBeacon transmitters (MyBeacon MB004 Ac, Aplix) to four workers and had each worker carry two iBeacon receivers in their front pockets. *TxPower* was adjusted as –63 dBm. We also used the laptop computer with the bleacon Node.js library as an iBeacon receiver. The laptop computer received signals from all iBeacon transmitters within approximately 1 Hz (approximately 1,800 epochs). All LiDAR and iBeacon data were synchronized with the PC clock.

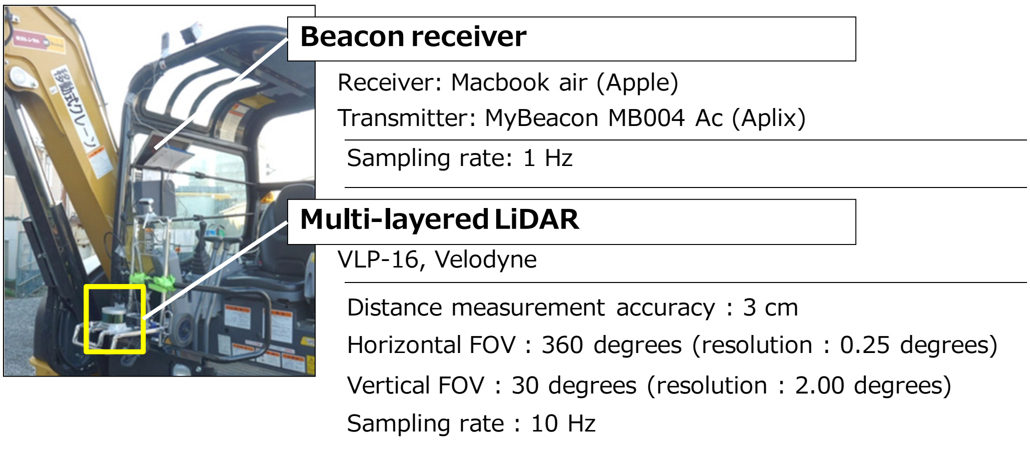

Figure 7. Multilayered LiDAR and beacon receiver mounted on a construction vehicle

4. RESULTS

Acquired temporal point clouds are shown in Figure 8. The upper image shows a scene of acquired point clouds and the extracted moving objects. The bottom image shows a range image and extracted moving objects. The vertical axis indicates scanning layers extended 8.0 times with linear interpolation, and the horizontal axis indicates horizontal scanning angles with 0.25 resolution. Figure 9 shows a part of the results after segmentation and clustering.

Figure 8. Acquired point clouds and extracted moving objects

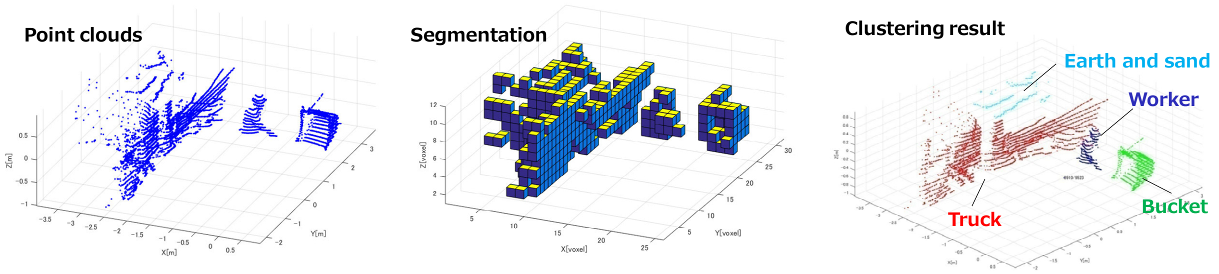

Figure 9. Results after segmentation and clustering of point clouds

Figure 10 shows the estimated distances from the iBeacon transmitters to the receiver. The vertical axis indicates estimated distance values, while the horizontal axis indicates the signal received time.

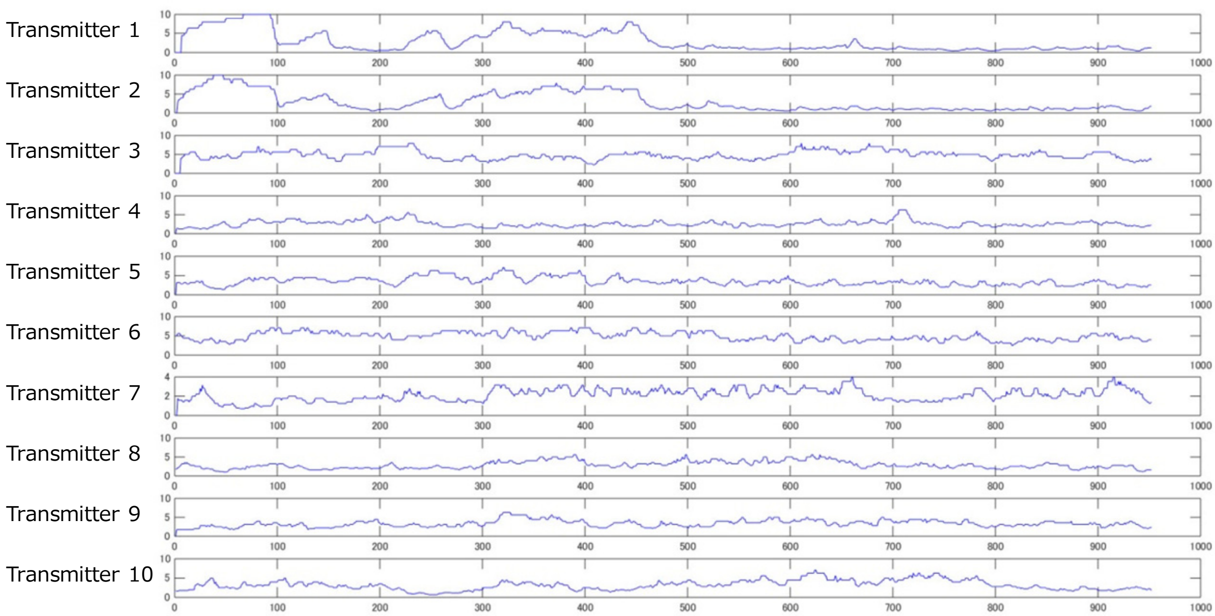

Figure 10. Estimated distances from the iBeacon transmitters to the receiver

Object tracking and recognition results are shown in Figure 11, and indicates that our methodology can stably trace workers. The processing time is shown in Table 1. Our processing environment was Intel Core i7-6567U (3.30 GHz). We confirmed that object extraction was processed with a frequency of approximately 10 Hz and overall processing with a frequency of approximately 5 Hz.

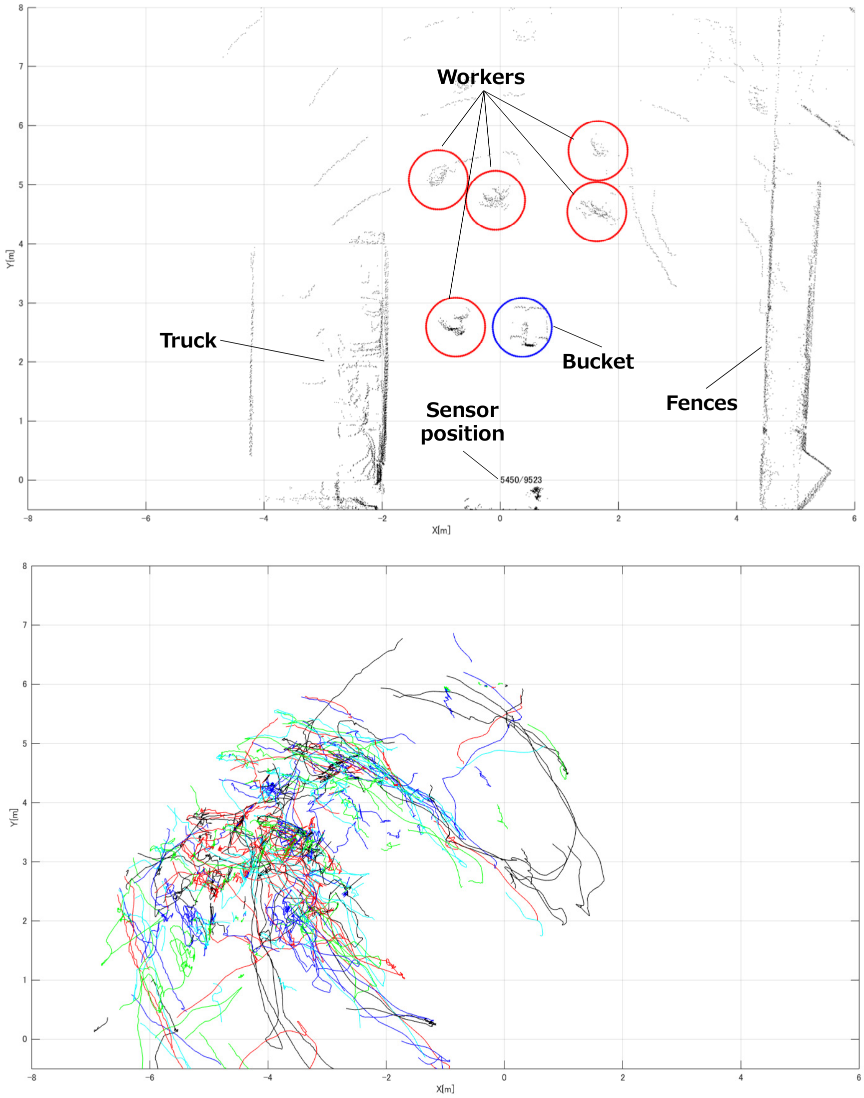

Figure 11. Worker tracking and identified results. Upper image: results of object extraction on point clouds; Bottom image: results of identified tracking

Table 1. Processing time

	SLAM	Moving object extraction	Moving object tracking	Total
Processing time [sec]	1023.690	759.050	13.130	1795.870
Processing time (average) [sec]	0.107	0.080	0.001	0.187

5. CONCLUSION

In this study, we developed a real-time 3D sensing unit mounted on a construction vehicle for worker position data acquisition. In addition, we proposed a real-time object classification and tracking methodology from temporal point clouds acquired with multilayered LiDAR and iBeacon data. We conducted an experiment to evaluate our methodology using temporal point clouds and iBeacon data acquired from a construction vehicle in drilling works. We confirmed that our methodology can extract and track static and kinematic objects with multilayered LiDAR and beacon devices with real-time processing.

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