

SLAM-based Mapping in Truck-and-Robot System for Last-Mile Delivery Automation



Ryo Nakamura¹
Takeshi Kambe²
Masafumi Hashimoto²
Kazuhiko Takahashi²

¹ Graduate School of Science and Engineering, Doshisha University

² Faculty of Science and Engineering, Doshisha University



Presenter

Masafumi Hashimoto

mhashimo@mail.doshisha.ac.jp

- He received the M.Eng. and D.Eng. degrees in aeronautical engineering from University of Osaka Prefecture, Japan, in 1981 and 1988, respectively.
- He is currently working as a Professor with Department of Intelligent Information Engineering and Deputy Director of Mobility Research Center in Doshisha University, Kyoto, Japan.
- His research interests and expertise include LiDAR-based sensing, sensor fusion, and sensor network with applications in active safety and autonomous driving of vehicles and mobile robots.

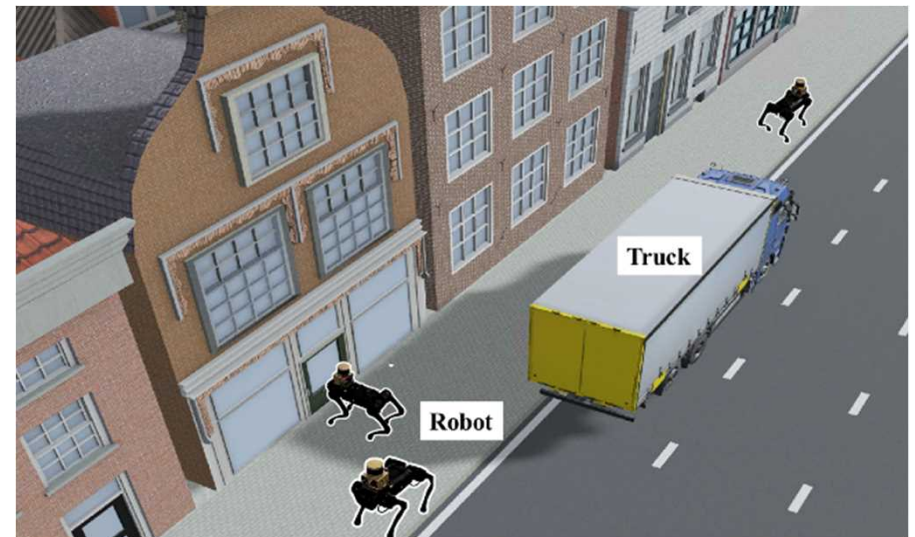
Agenda

1. Motivation
2. Experimental system
3. Map building and correction
4. Loop detection
5. Experimental results
6. Conclusion and future work



Motivation (1)

- Last-mile delivery automation using wheeled and legged robots has progressed due to increased e-commerce and demand for contactless delivery during the COVID-19 pandemic.
- Delivery robots are designed to move short distances at pedestrian speed. Owing to their low speed and limited range, delivery robots are usually combined with trucks to enable a fast and efficient delivery process (see figure):
 - A truck transports delivery goods with robots and releases the robots at dedicated drop-off locations (robot depots).
 - The robots deliver goods to customers and return to the robot depots by themselves.



- In such truck-and-robot delivery systems, map building (mapping) using Light Detection And Ranging (LiDAR)-based Simultaneous Localization And Mapping (SLAM) is an important technology for autonomous navigation of delivery robots.

Motivation (2)

- In this study, a **LiDAR SLAM-based mapping method for truck-and-robot delivery systems** is presented.
- The LiDAR SLAM-based mapping method involves integrating components that we previously proposed (Refs. 9–11 in the conference paper):
 - Distortion correction of LiDAR scan data,
 - Extraction of scan data related to stationary objects from the entire corrected LiDAR scan data, and
 - Point cloud mapping based on Normal Distributions Transform (NDT) Graph SLAM.
- Other contributions of this study are that
 - The performance of loop detection in our previous Graph SLAM is improved by introducing Fast Point Feature Histograms (FPFH), and
 - The mapping accuracy of robot-mounted LiDAR is improved using scan data from truck-mounted LiDAR.

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Doshisha
University

Experimental system

Light Detection AND Ranging (LiDAR) Velodyne VLP-16

- Layer : 16
- Scanning frequency: 10 Hz
- Maximum range : 50 m
- Horizontal view angle: 360°
- Vertical view angle : 41.3 °

Inertial Measurement Unit (IMU) Xsens Mti-300

- Measurement
 - Roll and pitch angles
 - Roll, pitch, and yaw velocities
- Sampling frequency: 100 Hz



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Map building and correction (1)

Local map building by robot-mounted LiDAR

Sequence of local map building

1. Capture LiDAR scan data

2. Correct distortion in LiDAR scan data

- The LiDAR obtains range measurements by scanning laser beams.
- Thus, when a robot moves and swings, LiDAR scan data are distorted.
- The distortion is corrected based on information from normal distributions transform (NDT) SLAM and an IMU.

3. Identify self-pose of robot using NDT SLAM

4. Extract stationary object scan data

- LiDAR scan data consist of scan data relating to stationary objects, moving objects, and road surfaces.
- For map building, stationary object scan data are extracted from the entire LiDAR scan data

5. Mapping of stationary object scan data using NDT SLAM

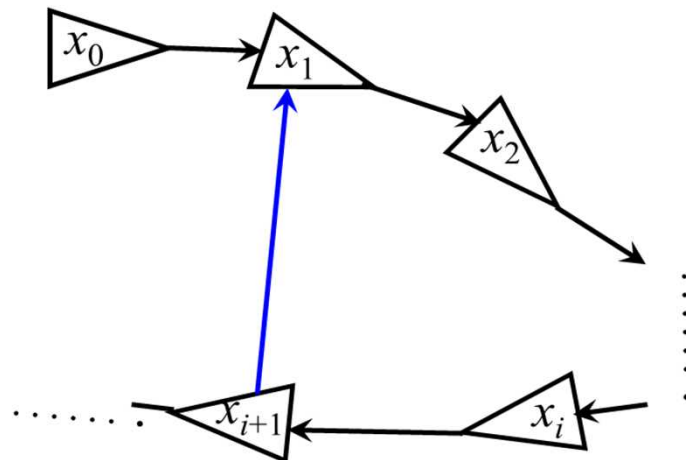
Map building and correction (2)

Local map building by robot-mounted LiDAR

6. Correction of NDT SLAM-based mapping

NDT SLAM degrades mapping accuracy over time due to accumulation errors. To reduce the error, **Graph SLAM** is employed by the following steps:

- The robot poses, which are calculated by NDT SLAM, are mapped onto a pose graph.
- When revisit places (loops), where the robot has already visited places during map building, are detected, the current robot's pose relative to its pose at the revisit node is set to the pose graph as a loop constraint.
- The accuracy of the map built by NDT SLAM is improved using pose graph optimization.



Pose graph for map building

- Black triangle (node): robot pose obtained by NDT SLAM
- Black arrow (edge): relative pose of robot obtained by NDT SLAM
- Blue arrow (loop constraint): relative pose of the robot at the revisit node obtained by NDT scan matching

Map building and correction (3)

Local map correction by truck-mounted LiDAR

When the robot returns to the robot depot, the local map built by the robot is corrected in Graph SLAM framework using the LiDAR scan data captured by the truck-mounted LiDAR.

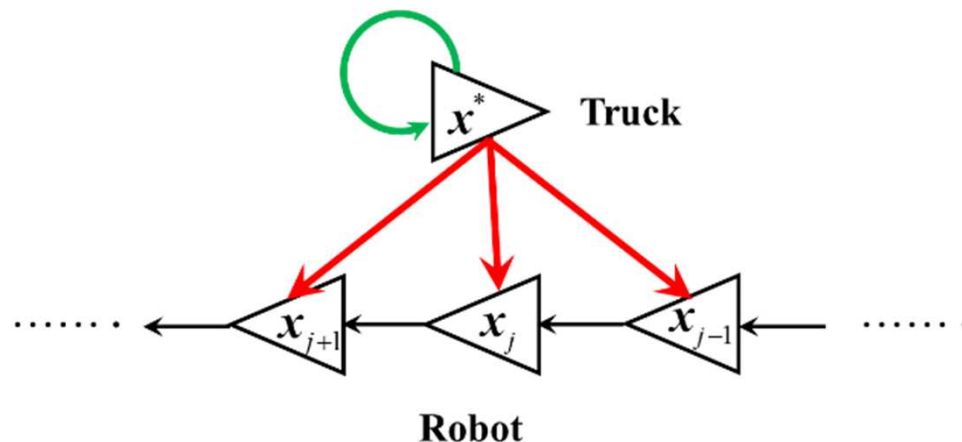
Sequence of local map correction

1. Mapping by truck-mounted LiDAR

Map is built using the truck-mounted LiDAR at the robot depot, and the truck poses are mapped onto a pose graph.

2. Encounter node detection

Nodes, where the robot encounters the truck, are detected in the pose graph.



- Black triangle (node): poses of robot and truck
- Black arrow (edge): relative poses of robot
- Red arrow: relative pose of the robot at the encounter node obtained by NDT scan matching
- Green arrow : truck pose obtained by map matching using high-definition map

Pose graph for map correction

Map building and correction (4)

Local map correction by truck-mounted LiDAR

3. Relative pose estimation

The robot's poses relative to the truck at encounter nodes are estimated from scan data captured by the truck and robot-mounted LiDARs using NDT scan matching.

4. Map correction

The local map built by the robot is corrected using pose graph optimization.

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Loop detection (1)

The method of encounter node detection during map correction by truck-mounted LiDAR is similar to the method of revisit node detection by robot-mounted LiDAR. Therefore, we describe the method of revisit node detection by robot-mounted LiDAR.

Sequence of loop detection

1. Candidate detection by self-location information of the robot

A candidate for revisit nodes is first obtained using the self-location information of the robot by NDT SLAM.

If the distance of an old node from the current node is less than 10 m, the old node is recognized as a candidate for revisit nodes.

2. Candidate detection by Loop Probability Indicator (LPI)

see next page (page 15)

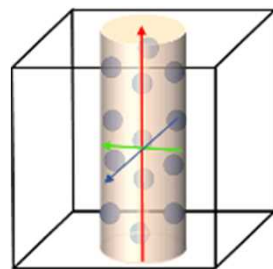
3. Loop detection by Matching Distance Indicator (MDI)

see page 16

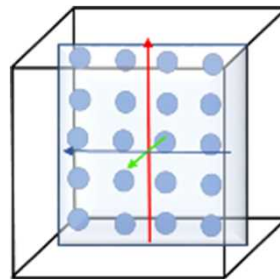
Loop detection (2)

Candidate detection by Loop Probability Indicator (LPI)

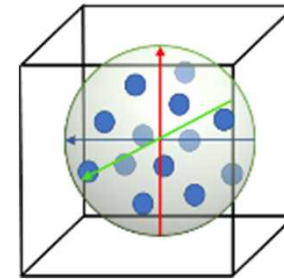
- Each grid of the voxel map, on which stationary object scan data captured at the candidate for the revisit and current nodes are mapped, is classified into three types: **line**, **plane**, or **other voxels** based on principal component analysis.
- The LPI is calculated from the feature descriptors related to classified voxels.
- A higher degree of similarity between the LiDAR scan data at both nodes (the candidate for the revisit and current nodes) leads to a larger LPI.
- Thus, the loop can be detected from the candidate of the revisit nodes using a large LPI value (a threshold of 80% in this study).



Line voxel



Plane voxel



Other voxel

Loop detection (3)

Loop detection by Matching Distance Indicator (MDI)

- From two LiDAR scan data captured at the current node and each candidate for revisit nodes, the relative pose of the robot is calculated using NDT scan matching. The **Matching Distance Indicator (MDI)** is given by

$$\text{MDI} = \frac{1}{N} \sum_{i=1}^N d_i$$

where N represents the number of measurements in the LiDAR scan data captured at the candidate for revisit nodes. d_i denotes the nearest neighbor distance.

- A higher degree of similarity between the LiDAR scan data captured at two nodes leads to a smaller MDI.
- The loop is finally detected by a smaller MDI value (a threshold of 1.5 m in this study).
- In NDT scan matching, if an initial value of the relative pose is given incorrectly, both the relative pose estimate and MDI become inaccurate due to local minima issues.
- To correctly set an initial value of the relative pose, a **Fast Point Feature Histograms (FPFH)** is used.

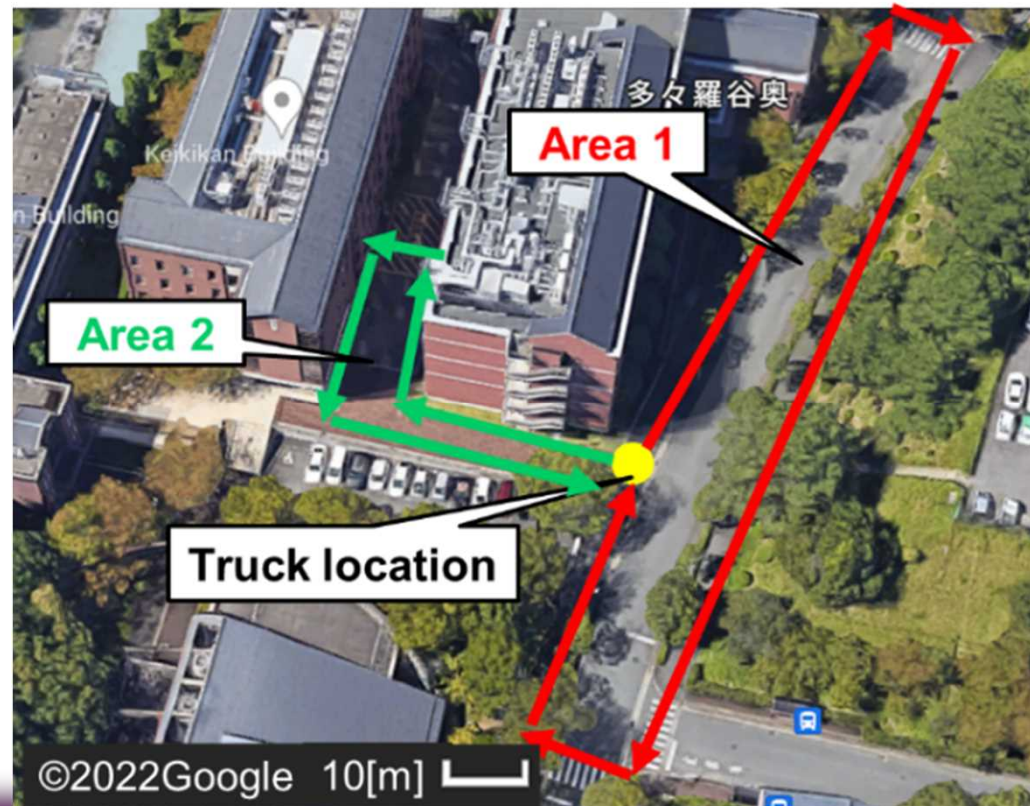
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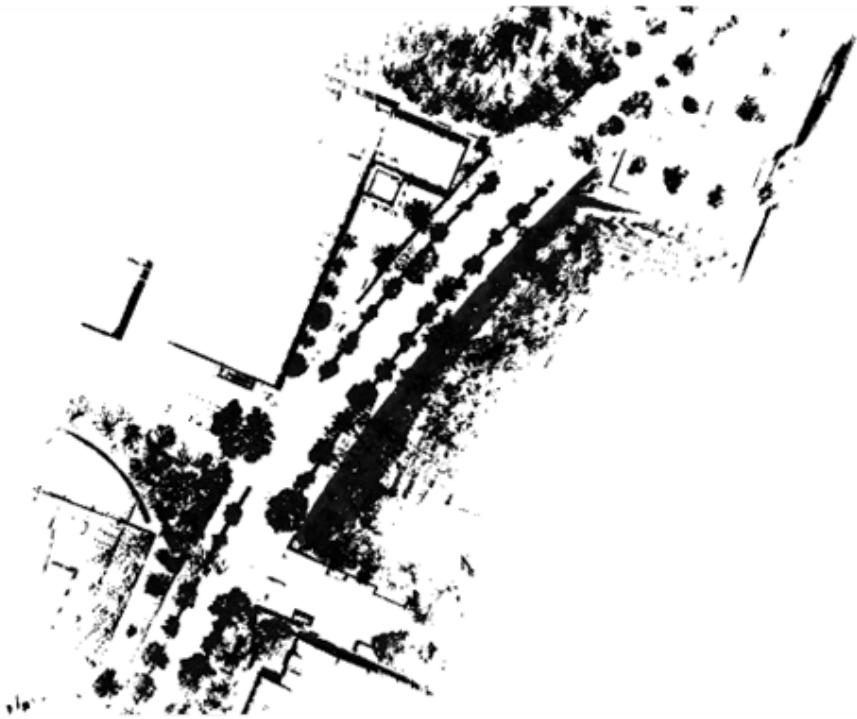
Experimental results (1)

- Mapping experiments are conducted on our university campus.
- A truck stops at the **yellow circle** in the figure, and the robot starts from the **yellow circle**, moves on the **red** and **green** paths in areas 1 and 2, respectively, and returns to the **yellow circle**.
- The distances travelled by the robot in areas 1 and 2 are 250 and 95 m. respectively, and the maximum velocity is approximately 5 km/h.

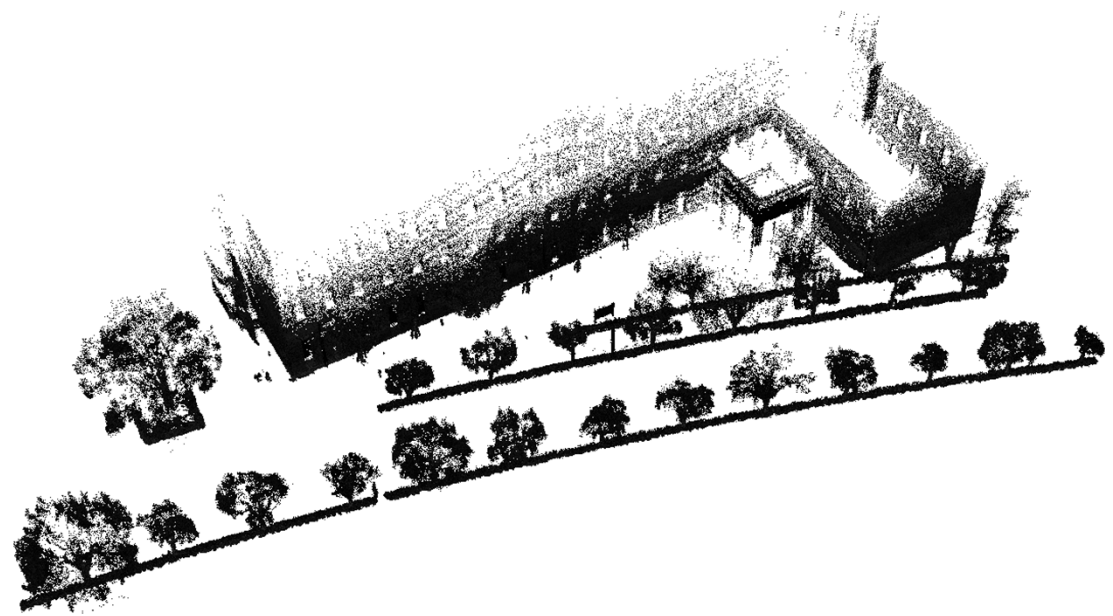


Experimental results (2)

Mapping result in area 1 (local map 1)



(a) Overall map (top view)



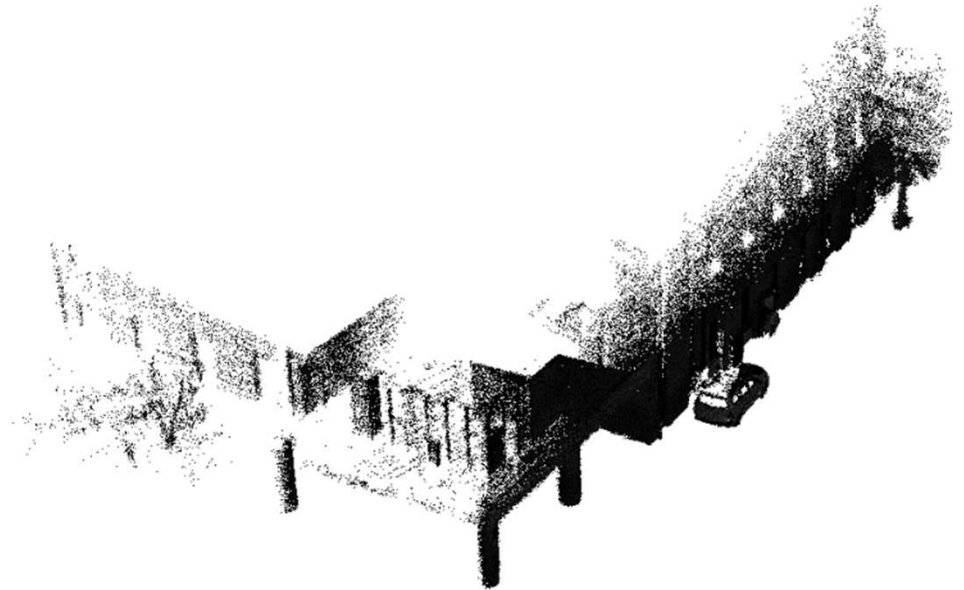
(b) Enlarged map (bird's-eye view)

Experimental results (3)

Mapping result in area 2 (local map 2)



(a) Overall map (top view)



(b) Enlarged map (bird's-eye view)



Experimental results (4)

- In SLAM-based mapping, the mapping accuracy is equivalent to that of the self-pose estimate of the robot.
- To evaluate the mapping accuracy, the error of position estimate of the robot at the goal position is obtained (see table).
- From the table, case 3 provides better results than cases 1 and 2. Furthermore, case 4 (proposed method) provides better results than case 3.

Error in position estimate of robot at goal position in **Local map 1** and **Local map 2**

	CASE 1	CASE 2	CASE 3	CASE 4
Run 1	3.09 m 0.92 m	3.63 m 1.17 m	0.15 m 0.28 m	0.13 m 0.10 m
Run 2	3.30 m 0.47 m	4.54 m 1.89 m	0.10 m 0.25 m	0.10 m 0.13 m

where

- Case 1: NDT SLAM-based local map building using robot-mounted LiDAR,
- Case 2: NDT SLAM-based local map building without distortion correction of LiDAR scan data,
- Case 3: NDT Graph SLAM-based local map building,
- **Case 4: Correction of local map using truck-mounted LiDAR (proposed method)**

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Conclusion and future work

- A LiDAR SLAM-based mapping method in truck-and-robot system was presented for last-mile delivery systems.
- The efficacy of the presented mapping method was demonstrated through experimental results using quadruped robot in our university campus.

As our future studies,

- Quantitative evaluations of the proposed method will be performed through experiments in various environments.
- Map building using small and lightweight solid-state LiDAR instead of the mechanical LiDAR used in this paper will be performed.
- Map update and maintenance will be studied.

