3D Measurement System for Soil Loading by an Autonomous Backhoe using OPERA

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Abstract -

We developed a 3D measurement system for autonomous construction and conducted demonstration experiments of autonomous construction using OPERA (Open Platform for Earthwork with Robotics and Autonomy), which is a research and development platform developed by the Public Works Research Institute. As a use case, we carried out soil loading into a dump truck by a backhoe in a test field. In this paper, we give overviews of our system and the demonstration experiments.

Keywords -

3D measurement; OPERA; Autonomous construction; Point cloud; Soil loading; ROS 2

1 Introduction

The Japanese construction industry is facing a labor shortage because of a declining birthrate, an aging population, and youth job disengagement. To address this issue, the Ministry of Land, Infrastructure, Transport and Tourism is promoting i-Construction 2.0 [1] in order to establish efficient construction processes based on digital technologies. The aim of i-Construction 2.0 is to revolutionize construction sites via three types of automation, namely, automation of construction work, automation of data linkage, and automation of construction management, the expectations being reduced labor and improved productivity.

Extensive research has been conducted on the development of autonomous construction machinery and the utilization of 3D data. R. Heikkilä et al. [2] investigated case studies of automated construction in Europe, highlighting the increasing use of methods that employ 3D data, which plays a critical role in automation. I. Niskanen et al. [3] implemented the 3D LiDAR on the boom of the backhoe to recognize the shape of soil loaded on the vessel of the dump truck. A. Assadzadeh et al. [4] have employed deep learning to estimate the posture of the backhoe using RGB image data captured by cameras installed at the site.

In support of the aforementioned efforts, our work involves automating construction work by using autonomous construction machinery. As an implementation of autonomous civil construction work, we target soil loading associated with shield tunneling as shown in Figure 1. Soil excavated from the shield tunnel is transported to an external soil pit via pipelines and conveyor belts and then loaded into a dump truck by a backhoe and transported to a treatment plant. The backhoe operates depends on when the dump truck arrives, which in turn depends on traffic conditions, and this often causes waiting time for the backhoe operator. Therefore, automating these soil-loading tasks would increase efficiency and productivity. Furthermore, in this case the locations of the backhoe, truck parking, and soil pit hardly ever change. We can install sensors in the environment to detect the shape of the earth mound in the soil pit and the position of the dump truck. This requires fewer sensors than in more-dynamic situations, and this system is applicable even if the dump truck has no sensors of its own. For these reasons, our aims were to automate the soil loading involved in shield tunneling and conduct demonstration experiments in a test field. In this paper, we give an overview of our system the experiments performed in the test field.

2 System overview

We have developed three components for realizing autonomous construction OPERA (Open Platform for Earthwork with Robotics and Autonomy), which is a platform for autonomous construction; ROS2-TMS for Construction, which is a management system for controlling construction machinery; and a 3D measurement system. Figure 2 shows an overview of the system, in which two LiDARs detect the shape of the earth mound and three LiDARs detect the dump truck. The three components are on the same network and communicate using ROS 2 [5] to enable autonomous construction. In ROS 2, the communication method for sending and receiving commands and messages is called topic communication, and these commands and messages are called topics; sending topics is called publishing and receiving topics is called subscribing. In this paper, we use the same terminology.

2.1 OPERA

We use OPERA [6, 7] to control autonomous construction machines. Developed by the Public Works Research Institute (PWRI), OPERA is a research and development platform for automating earth works; it contains a set of common control signals, middleware, simulators, a demonstration environment, and autonomous construction machinery, and it is available on GitHub for open development [8]. Moreover, OPERA was developed in ROS 2, which allows construction machinery and sensors to be controlled by common commands independent of the manufacturer.

2.2 ROS2-TMS for Construction

We use ROS2-TMS for Construction [9] to manage the tasks of autonomous machinery developed by Kyushu University. This task management system enables the accumulation and management of environmental information from sensors in construction sites and machinery; it realizes autonomous construction by giving commands to robots and autonomous construction machinery based on the flowchart and data . TMS_IF for OPERA [10] is an interface developed to publish commands via OPERA based on the indicated tasks; it was also developed in ROS 2 and uses the open package Moveit2 [11] for motion planning and the open package Nav2 [12] for autonomous driving. We control the construction machinery by providing information from Mongo DB[13] as the database using ROS 2.

Figure 1. Use case.

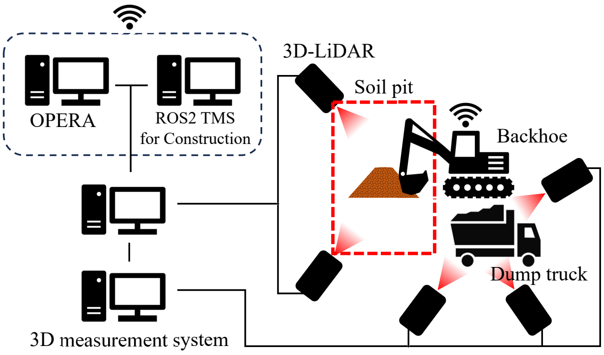

Figure 2. Overview of system.

2.3 3D measurement system

We developed the measurement system by using multiple 3D LiDARs to detect the shape of the earth mound and the location of the dump truck. The resulting point-cloud data enable accurate recognition of the shapes of the targets, and this allows calculation of the best position for the backhoe to excavate more soil. We explain the registration method for the point-cloud data from the multiple 3D LiDARs in Section 2.3.1, the excavation recognition methodology in Section 2.3.2, and the loading recognition methodology in Section 2.3.3.

2.3.1 Registration of point-cloud data

Because the LiDAR coordinate system uses the sensor center as the origin, the point-cloud data obtained by each LiDAR are in different coordinate systems. In this study, we define the center of the backhoe as the origin of the world coordinate system W, and we calculate the homogeneous transformation matrix $H_{L\to W}$ from each LiDAR coordinate system L to W.

As shown in Figure 3, we placed three spheres in the scan range of all the LiDARs , and we estimate the center coordinates of each sphere from the obtained point-cloud data as shown in Figure 4; Figure 4(b) shows the cropped point-cloud data around one of the spheres from Figure 4(a). Using four points selected randomly from the cropped point-cloud data of the sphere, we obtain its center coordinates $s(a, b, c)$ by solving the following equation:

$$\begin{pmatrix} x_1 - x_0 \\ x_2 - x_0 \\ x_3 - x_0 \end{pmatrix} \begin{pmatrix} a \\ b \\ c \end{pmatrix} = \begin{pmatrix} x_1^2 - x_0^2 + y_1^2 - y_0^2 + z_1^2 - z_0^2 \\ x_2^2 - x_0^2 + y_2^2 - y_0^2 + z_2^2 - z_0^2 \\ x_3^2 - x_0^2 + y_3^2 - y_0^2 + z_3^2 - z_0^2 \end{pmatrix} /2. \quad (1)$$

Next, we calculate the L_2 norm between s and each cloud point and count the points for which the L_2 norm is within threshold. This process is iterated 1000 times, after

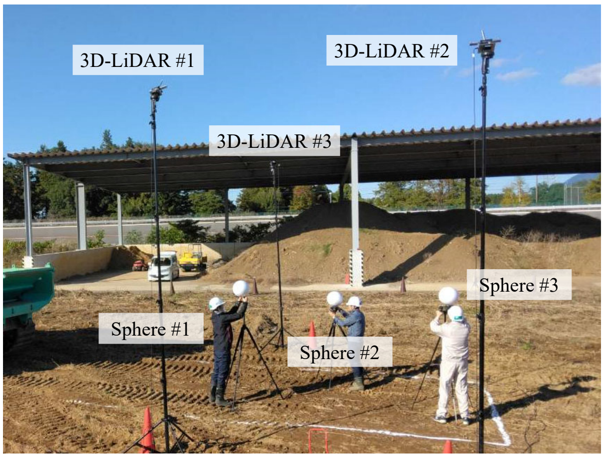

Figure 3. Installation of spheres.

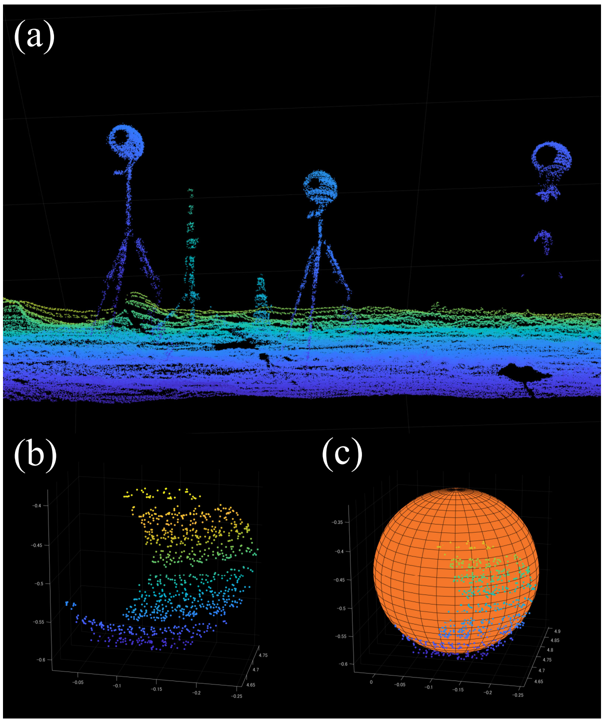

Figure 4. Point-cloud data of spheres: (a) LiDAR-obtained point-cloud data; (b) cropped point cloud of a sphere; (c) estimated sphere.

which the s with the most points is adopted. We estimate $S_L = \{s_1, s_2, s_3\}$ by calculating for the three spheres.

We then placed prisms at a mechanically known point on the backhoe and the center positions of the spheres. The sphere coordinates S_W in the world coordinate system were obtained by using a total station.

We obtain the homogeneous transformation matrix $H_{L\to W}$ from S_L and S_W and transform each LiDAR coordinate system into the world coordinate system. Figure 5 shows the point-cloud data transformed by the homogeneous transformation matrix.

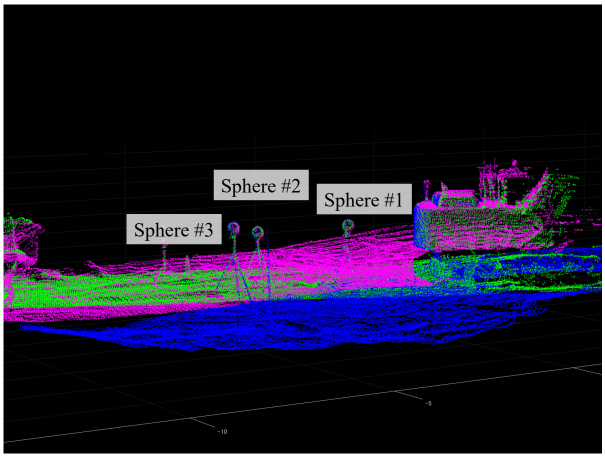

Figure 5. Integrated point-cloud data.

2.3.2 Recognition for excavation

We estimate the excavation points from the shape of the earth mound by using the point-cloud data transformed to the world coordinate system. We extract the point-cloud data in the soil pit and divide them into a planar grid. At each grid location, the lowest z coordinate is the height of the grid, and these grid data form the height map from which the highest grid point is estimated as being the excavation point. Figure 6 shows the height map of the earth mound. The excavation points are published constantly in the database of ROS2-TMS for Construction as the ROS 2 topics.

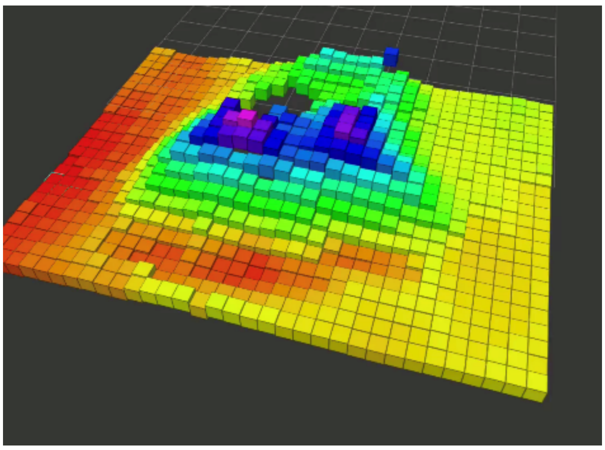

Figure 6. Height map of earth mound.

2.3.3 Recognition for loading

First, we estimate the current position of the dump truck. We obtain the point-cloud data of an empty dump truck P_d in advance and find the coordinates at the four corners of the vessel O_d from P_d. RANSAC is used to derive the homogeneous transformation matrix that converts P_d into the current point-cloud data P_r. By using the matrix to transform O_d, the current position of the dump truck is estimated as the current vessel coordinates O_c.

Next, we estimate the loading point by using O_c to extract the inlier point-cloud data in P_r, and the extracted point-cloud data are divided into a planar grid. The points with the highest z coordinate give the height of the grid, and these gird data form the height map. In this study, the grid map was padded and smoothed via convolution. From the height map, the lowest grid point is estimated as being the loading point. In addition, the loading volume inside the vessel is estimated by comparing P_d and P_r.

3 Overview of experiment

We conducted the task of excavating and loading soil with one autonomous backhoe (ZX200, Hitachi Construction Machinery Co., Ltd.) and one crawler carrier (IC200, Kato Works Co., Ltd.) at the PWRI DX field in Tsukuba City, Ibaraki Prefecture, Japan. Figure 7 shows the experiment. The earth mound was surrounded by pipes that simulated the soil pit. Five LiDARs (Livox) were installed to detect the shape of the earth mound and the location of the crawler carrier and estimate the excavation and loading points. Those points were then published to the database of ROS2-TMS for Construction as the ROS 2 topics. The backhoe generated a trajectory based on the target coordinates in the database and performed excavation and loading operations. When the inside of the vessel reached a certain loading capacity, a loading completion flag was published to the database, and the operation was completed.

3.1 Excavation test

Figure 8 shows the excavation by the backhoe, which avoided the pipes by us preparing walls as obstacles in the simulation environment in advance. Figure 8(a) shows the backhoe waiting for the start flag of ROS2-TMS for Construction, and Figure 8(b) shows the excavation task starting and the backhoe having subscribed the excavation point from the database. Figure 8(c)–(f) show the backhoe executing the excavation tasks twice and excavating the top of the earth mound. In the study of Niskanen et al.[3], the 3D LiDAR was installed on the boom of the backhoe to measure the vessel. In contrast, we install the 3D LiDAR at the site. By installing the 3D LiDAR at the site, it is possible to recognize the entire soil mound, including the backside, which cannot be observed from

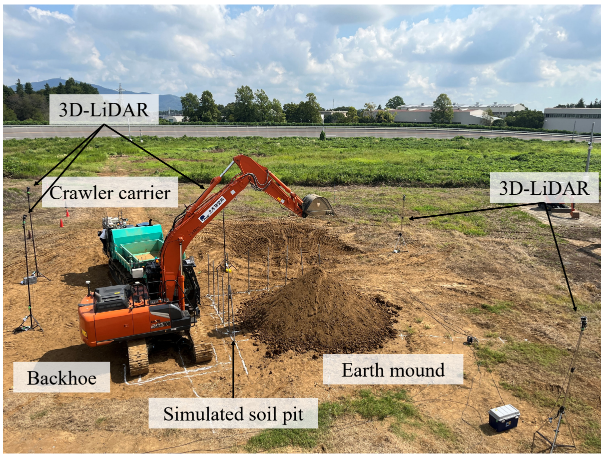

Figure 7. Overview of experiment.

the backhoe. Additionally, since point cloud data of the soil mound can be continuously acquired regardless of the backhoe's posture, the backhoe can operate without waiting for measurement and estimation times.

In this study, the backhoe is assumed to remain stationary. Since the coordinate system of the backhoe is obtained through prism measurements, it is necessary to perform measurements each time the backhoe moves. This is our future work, and we will explore methods to automatically recognize the position and orientation of the backhoe in the future.

3.2 Loading test

Figure 9 shows the point-cloud data at different times; in each panel, the purple rectangle is the estimated outline of the vessel and the red sphere is the loading point at the relevant time. The vessel is recognized when the evaluation value exceeds a certain level from the registration results, and the lowest point inside the vessel is estimated as the loading point in the height map in this rectangle. By performing coordinate transformation from the position and orientation of the vessel, it is possible to continuously estimate the position and orientation of the dump truck. Acquiring point cloud data from multiple angles using three LiDARs improves the accuracy of registration, thereby stabilizing the estimation of position and orientation. The vessel is not recognized in Figure 9(a) but is recognized in Figure 9(b). In Figure 9(c), the loading point is estimated in the vessel and published to the database. In Figure 9(d)–(h), the position of the loading point changes as the soil is loaded. Figure 10 shows the inside of the vessel before and after loading, and the loading volume was estimated from the point-cloud data after the loading operation.

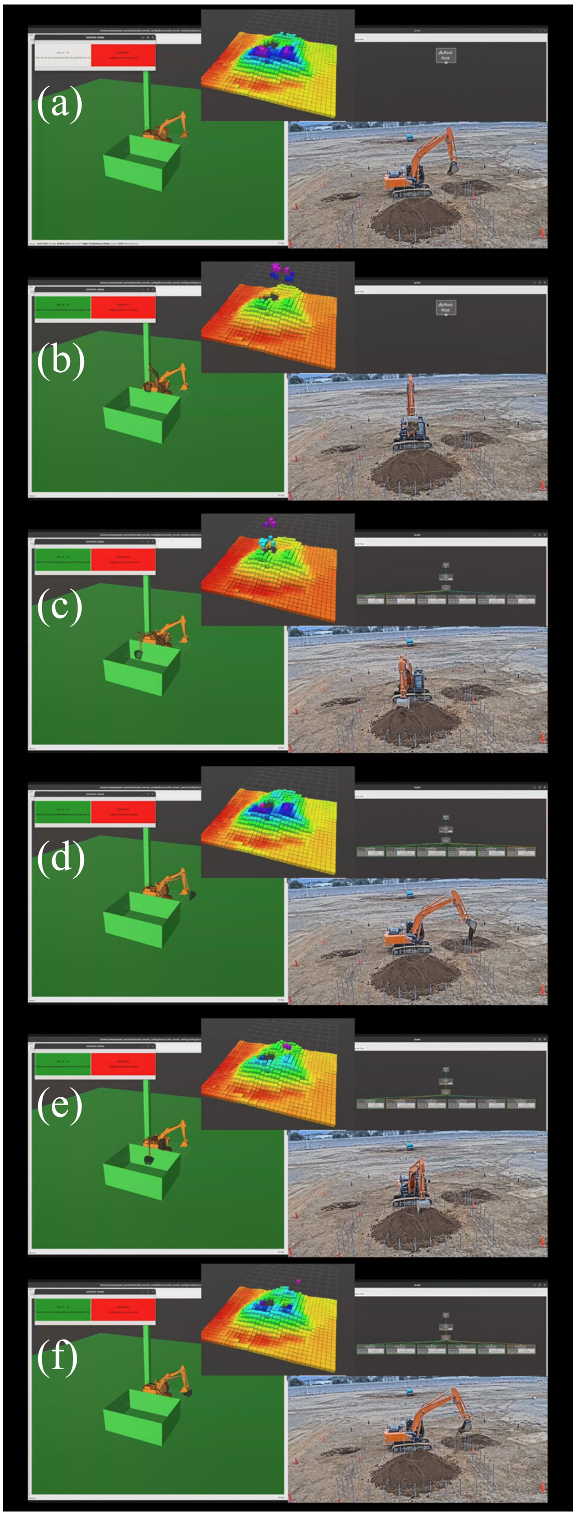

Figure 8. Each figure shows the simulation (left), the actual backhoe (right), and the height map (center).

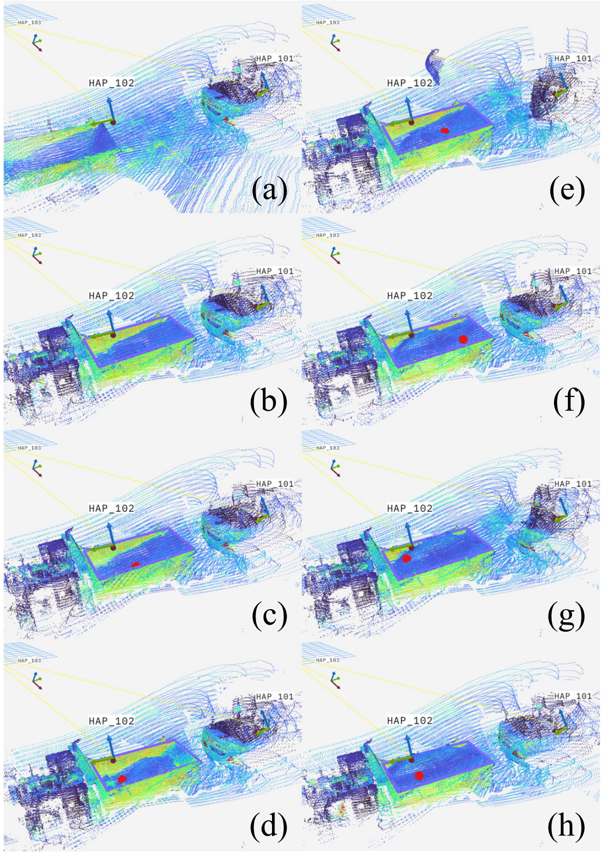

Figure 9. Estimating the loading point at each time. The purple rectangle is the estimated outline of the vessel and the red sphere is the loading point at each time.

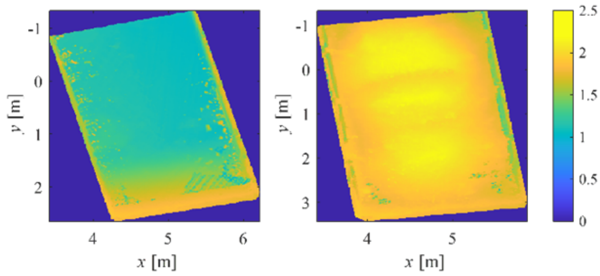

Figure 10. Inside of vessel.

4 Conclusion

We have developed a 3D measurement system for autonomous construction. We configured the task of loading soil into a dump truck by an autonomous backhoe as the use case, and we conducted demonstration experiments of this task in the test field.

Installing multiple LiDARs around the targets enabled the latter to be measured without any blind spots. The coordinate transformation method using spheres facilitated registration of the point-cloud data obtained by the LiDARs.

The obtained point-cloud data allowed detection of the shape of the earth mound. The excavation points were published to ROS2-TMS for Construction as the task management system, and the backhoe excavated autonomously based on the excavation points.

The obtained point-cloud data allowed detection of the vessel position and the shape of the loaded soil. The loading points were also published to ROS2-TMS for Construction.

The integration of multiple point-cloud data which was achieved by our developed system, ensured reliable data acquisition. We will focus on exploring optimal excavation methods using the acquired data.

In this measurement system, the LiDAR-obtained point-cloud data are large and can overload the network. Therefore, in future work we will construct a robust network and continue to develop the system for application to actual construction sites.

References

[1] MLIT. i-construction 2.0. On-line: `https://www.mlit.go.jp/tec/constplan/content/001738240.pdf`, Accessed: 01/11/2024.

[2] R. Heikkilä and M. Jaakkola. Automation of road construction - the state of the art in europe. In *Proceedings of the 23rd International Symposium on Automation and Robotics in Construction(ISARC2006)*, pages 7–10, Tokyo, Japan, 2006.

[3] I. Niskanen, G. Duan, H. Suzuki, D. Endou, M. Immonen, Hiltunen M., G. Yamauchi, P. Tyni, T. Hashimoto, and R. Heikkilä. Determining payload on platform of lorry in real time using integrated 3-d lidar from excavator boom. In *IEEE Transactions on Instrumentation and Measurement*, volume 73, pages 1–7, 2024.

[4] A. Assadzadeh, M. Arashpour, H. Li, R. Hosseini, F. Elghaish, and S. Baduge. Excavator 3d pose estimation using deep learning and hybrid datasets. *Advanced Engineering Informatics*, 55:101875, 01 2023. doi:10.1016/j.aei.2023.101875.

[5] Open Robotics. Ros 2 documentation: Humble. On-line: `https://docs.ros.org/en/humble/index.html`, Accessed: 01/11/2024.

[6] G. Ymauchi, D. Endo, H. Suzuki, and T. Hashimoto. Proposal of an open platform for autonomous construction machinery development. In *Proceedings of the 40th International Symposium on Automation and Robotics in Construction(ISARC2023).*, pages 186–191, 2023.

[7] D. Endo, Y. Matsusaka, G. Ymauchi, and T. Hashimoto. Research on an open source physical simulaotr for the autonomous construction machinery development. In *Proceedings of the 41th International Symposium on Automation and Robotics in Construction(ISARC2023).*, pages 1303–1306, 2024.

[8] github. pwri-opera. On-line: `https://github.com/pwri-opera`, Accessed: 01/11/2024.

[9] github. irvs/ros2_tms_for_construction. On-line: `https://github.com/irvs/ros2_tms_for_construction`, Accessed: 01/11/2024.

[10] Y. Kasahara, T. Itsuka, K. Shibata, T. Kouno, R. Maeda, K. Matsumoto, S. Kimura, Y. Fukase, T. Yokoshima, G. Ymauchi, D. Endo, T. Hashimoto, and R. Kurazume. Task management system for construction machinery using the open platform opera. In *Proceedings of the IEEE International Conference on Robot Human Interactive Communication (RO-MAN)*, August 2024.

[11] PickNik Robotics. Moveit 2 documentation. On-line: `http://abcd.efg.hij`, Accessed: 01/11/2024.

[12] Open Navigation. Nav2. On-line: `https://docs.nav2.org/`, Accessed: 01/11/2024.

[13] Mongo DB. Documentation. On-line: `https://www.mongodb.com/docs/`, Accessed: 01/11/2024.