3D-Simulation Data-Making Trial to present and analyze Small-sized Farmlands Fields with Car-shaped Robot, ROS2, SLAM and Foxy for Real agricultural workers

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Abstract — In this study, we create various application systems focusing on agricultural (agri-) field data digitalization issues that will benefit traditional agri-researchers, workers, and their respective managers. We obtain three-dimensional (3D) information on agri-environments (e.g., rice fields, farmlands) via roaming robots with sensors. Robot-controlled middleware, such as robot operating systems (ROS), are often used for such robots. Thus, we selected car-shaped robot (NANO-RT1), ROS2, and the SLAM-based system. The car-shaped robot-based system operates sensor units uniformly. With this technology, we can recognize our location at an unknown place, and the robot can run. There are challenges in accurately presenting quantitative accuracy data for this type of study. We address this by providing average and standard deviation (SD) data for certain situations using five algorithms: (1) Hector-SLAM, (2) G-mapping, (3) Karto-SLAM, (4) Core-SLAM, and (5) Lago-SLAM. We believe the proposed holistic system has the potential to improve not only agri-businesses, but also agri-skills and overall security levels.

Keywords — 3D-Simulation data-making, car-shaped robot, NANO-RT1 Robot, ROS2, SLAM, Foxy, agricultural site.

I. INTRODUCTION

Over several decades, various hardware agricultural (agri) systems have been developed to help manage agri-business [1]-[11].

Obtaining and sharing diverse digital three-dimensional (3D) agri-field information is a crucial factor for success in practical modern agri-management. One approach to achieving this is to use an autonomous mobile robot. Thus, we develop a robot using simultaneous localization and mapping (SLAM) systems.

When developing such self-controlled locomotive robots, researchers and engineers often utilize middleware of robot control as robot operating systems (ROS) or the more advanced ROS2 [12]-[21].

In this study, considering past technical concepts and trends, we develop and implement a ROS2 SLAM-based agri-fields' record producing system for common agri-workers and managers.

Specifically, we use the car-shaped NANO-RT1 Robot (Shenzhen XiaoR Geek Technology Co. Ltd., Shenzhen, China), which can integrate and handle diverse sensors and electric modules. This allowed us to execute these trials with

an assimilation, to some extent.

II. METHOD

A. Outline

First, we reviewed past academic and industry novel accomplishments and met with predecessors who have engaged in primary industries. Then, we selected promising ROS2 and SLAM-based techniques. Next, we developed approximate schedules, designed, and mechanically constructed the systems, and performed various processing.

Although diverse similar systems and commercial goods exist, none are optimized for small- to middle-sized, non-trimmed (i.e., not well prepared for running car-shaped machines) agri-fields with 3D-SLAM systems or cooperate with network-connected systems. Thus, we create new integrated structures that support these options and enhance their utility and flexibility against sudden accidents in real situations.

We implemented certain distributed smartphone applications on the car-shaped NANO-RT1 Robot. As preliminary trials, we conducted practical experiments to judge the systems' utility in an indoor (sufficiently flat home) situation and an outdoor asphalt road.

Thinking of recent technical trends [12]-[21], we considered the following five algorithm-based SLAM approaches to compare diverse items, particularly error estimation value: (1) Hector-SLAM, (2) G-mapping, (3) Karto-SLAM, (4) Core-SLAM, and (5) Lago-SLAM.

The following main features of the SLAM framework for this study were considered as criteria for selection: (a) sensors' installation; (b) data gathering mechanism, including an odometer; (c) algorithm; (d) mapping methods; and (e) looping back directions.

B. System

Fig. 1-3 illustrate the main structure of our approach and proposed system. Fig. 1 shows the fundamental flow of the system's methodology, Fig. 2 illustrates the model of the proposed ROS2 car robot, and Fig. 3 shows the set of systems used to achieve SLAM-based operations.

This study consists of five phases: (1) designing and confirming the validity of the entire system; (2) constructing and integrating mechanical parts, including tuning and

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revising minor system settings; (3) conducting preliminary experiments in both indoor and outdoor settings; (4) conducting main trials in outdoor farmlands; and (5) evaluating output datasets with consideration to similar research.

We mounted a Raspberry Pi (Raspberry Pi Foundation, Cambridge, England (UK)) and a Jetson Nano (Nvidia Corporation Inc., California, USA) as the microcomputer board. We flexibly coded in both Python and C++ languages.

The NANO-RT1 was 300×240×325 mm, weighing 3.1 kg. The main camera had 1,080 pixels. The Inertial Measurement Unit (IMU) was a nine-axis gyroscope sensor. The driver board was STM32F105. The motor torque was 3.5 N · m. Finally, the radar was XR_Lidar S1.

Fig. 1. Fundamental flow of this system's methodology.

Fig. 2. Model of the Raspberry Pi-based ROS2 car-shaped robot.

Fig. 3. Set of systems for SLAM-based operations.

Fig. 4–7 illustrate the real parts of the study, i.e., the actual built components.

Fig. 4 presents the distributed smartphone application software used to build electronic maps. Fig. 5 shows the Ubuntu operating system (OS) version 18.04 installed on the Raspberry Pi board. Fig. 6–7 present the deep learning-based car-shaped machines that we tested through successive studies.

Fig. 8 shows a simplified map of the target agri-field. The gray areas are a common, non-specific, stiff plastic-sheet road (corridor) that we placed to reduce the physical barriers of the car-shaped robot's movement.

Fig. 4. Distributed smartphone application to build electronic maps.

Fig. 5. Setting of Ubuntu OS ver. 18.04 on Raspberry Pi board.

Figs. 6-7. Deep learning-based car-shaped machines that the authors tested through successive studies.

Fig. 8. Simplified map of target agri-field.

C. Theory

We compared the usefulness and characteristics of five algorithms: (1) Hector-SLAM, (2) G-mapping, (3) Karto-SLAM, (4) Core-SLAM, and (5) Lago-SLAM.

Here, note that Hector-SLAM's navigation technologies are sometimes combined with other two-dimensional (2D) SLAM methodologies for better robustness and inertial sensing.

Note that 3D spatial navigation state estimation is based on Extended Kalman Filter (EKF), which is only necessary when the IMU exists. Thus, we only discuss 2D SLAM in this study.

Fig. 9. ROS2 system.

III. RESULTS

As described, we created a SLAM system with a car-shaped robot that included sensors to realize ROS2.

Fig. 10 presents the error-estimation data for the five SLAM-based approaches, where the bars indicate the average values with standard deviations. The number of trials (N) is five.

Fig. 11–12 present typical sample pictures of ROS2 operations. The arrow-shaped marks indicate the location of the robot.

Based on our results, the proposed approaches could realize moderate accuracy compared with similar approaches found in the literature and industry. However, we could not quantify the difference between our proposed system and past similar systems using specific statistical items. We did not define appropriate trial time ranges; the trial area was rather narrow. Qualitatively, we confirmed the usefulness and

We initially obtained 2D map data in target fields to set the laser beam lattice (vertical position) and estimate the representation of laser points on the mapping data. Then, we assumed the probability (%) of matching each squared grid.

In this study, we used a Gauss-Newton-based methodology to resolve the scan-matching data and identify the rigid body transformation of the laser pointer to set the current map to existing map data.

We performed scan matching by finding the rigid transformation presented in (1).

$$\xi = (x, y, \theta)^T = (p_x, p_y, \Psi)^T \quad (1)$$

We then aim to minimize ξ as in (2).

$$\xi^* = \operatorname{argmin}(\xi) = \sum_{i=1}^n \|1 - M(Si(\xi))\|^2 \quad (2)$$

In Equation (2), $Si(\xi)$ is a global coordinate of the i -th scan endpoint $s_i = (s_{i,x} - s_{i,y})^T$, and $M(Si(\xi))$ returns the map value for these coordinates. The problem is solved using the Gauss-Newton equation:

$$\Delta \xi = H^{-1} [\nabla M(Si(\xi))]^2 \quad (3)$$

The Hessian Matrix H is given by (4).

$$H = [\nabla M(Si(\xi)) \frac{\partial Si(\xi)}{\partial \xi}]^T \cdot [\nabla M(Si(\xi)) \frac{\partial Si(\xi)}{\partial \xi}] \quad (4)$$

Fig. 9 presents the methodology of the ROS2-based system.

feasibility of the proposed system.

Fig. 10. Comparative graph of average error estimation for 5 SLAM algorithms with standard deviation whiskers (N = 5).

Figs. 11-12. 3D data from prototype ROS2 system.

IV. DISCUSSION AND CONCLUSION

To gather ambient, agri-situation 3D data, we accumulated basic data from several digital methodologies with the aim of future practical applications. We calculated and compared various patterns using five SLAM-based algorithms: (1) Hector-SLAM, (2) G-mapping, (3) Karto-SLAM, (4) Core-SLAM, and (5) Lago-SLAM.

However, the agility, cost-performance, and usefulness of the proposed approach is promising and could easily be applied by agri-managers or agri-researchers.

As we could not present item-oriented (scientifically numerical) sets of fixed quantitative data, we must seek more suitable and valid methods to assess the systems' operations.

Another remaining problem is attaining more data from diverse settings and situations (such as breeding farms, plastic farms, construction sites, or in situations with more intense or sudden natural impacts).

Our desktop analyses and interviews with key experts and users could be incorporated into computer systems and fed back to experimental users.

We could also undertake further experiments and practical applications of the system to understand how to enhance the system for use in real settings.

V. FUTURE TASKS

For future scalabilities, we have been planning consultation and supporting projects to improve the security and productivity of agri-workers. Above all, we hope to start launching practical discussions, consultations, and proposals with real agri-users, both in Japan and globally.

The techniques we have examined are economically robust, scalable, and distributed flexibly. Therefore, they could be applied to other fields and settings, such as factories or residential districts, to identify sudden accidents or crimes and to solve diverse social problems.

In the future, we will attach small solar panels to the robot's body to support long-term operation.

Additionally, as part of troubleshooting the system's limitations, we will consider various non-fixed factors, such as utilizing locations, and sudden incidents, such as the system's tumbling or sudden halting.

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