Painting Task Planning for Large Structure using a Mobile Manipulator

Hiroshi Tanaka
Graduate School of Engineering Science, Osaka University, Japan

Masato Tsuru
Graduate School of Engineering Science, Osaka University, Japan

Takuya Kiyokawa
Graduate School of Engineering Science, Osaka University, Japan

Kensuke Harada
Graduate School of Engineering Science, Osaka University, Japan
Email: {h.tanaka@hlab., tsuru@hlab., kiyokawa@, harada@}sys.es.osaka-u.ac.jp

Abstract

Painting a large structure with a robotic arm that is fixed to the ground is difficult due to its limited reachable range. To plan the robotic painting motion of such a large structure, we develop a robotic software system assuming a mobile manipulator to explore the environment using SLAM. Our software system includes both detection of AR markers and construction of the environmental map to determine the painting location. It can measure the error in self-position estimation that occurs during the movement. It can also generate spray trajectories for the recognized painting location and control the whole body using Model Predictive Control (MPC) to perform painting over a wide area.
Keywords: Painting, Large Structure, Mobile Manipulator, Model Predictive Control, SLAM

1. Introduction

While the manufacturing processes for a wide variety of industrial products have been automated in recent years, it is difficult to automate the painting of large structures. Large structures require the use of mobile manipulators because the painting area is so large that it exceeds the reach of the arm. Unlike a manipulator fixed to a pedestal, a mobile robot is subject to dynamic friction between its wheels and the ground, which causes errors in the position of the tip of the manipulator.

Figure 1 shows the large structure addressed in this study. It shows a bridge with several bridge girders placed on a platform. Although the shapes of the bridge girders themselves are known, it is difficult to accurately place them on the table, so the robot must perform the painting operation while recognizing in real time which position on the bridge girder is to be painted. In addition, such bridge girders often have few visual features, and it is often difficult for the robot to identify its own position by camera.

To address these problems, this study proposes a software system painting large structures using mobile manipulators. The proposed software system consists of three modules, 3D-SLAM[2], Model Predictive Controller (MPC)[1], and AR marker recognition[3]. The use of MPC enables a mobile manipulator to follow a target trajectory without being aware of the position of the dolly. In order to paint large objects with few visual features, the combination of AR markers and SLAM makes it possible to perform accurate painting operations while recognizing its own position.

In this paper, Section 2 describes related studies, followed by a description of the proposed method in Section 3. Finally, Section 4 describes the results of the evaluation of paint trajectories using physical simulations.

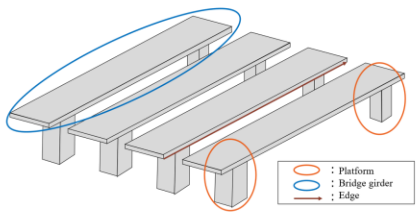


Figure 1 Large structures addressed in this study

2. Related Works

Researchers have used mobile manipulators to achieve various tasks [4]. Lin et al. researched spray painting using a robot manipulator [5]. Chen et al. also painted arbitrary free-form surfaces by approximating the shape of the object with a mesh model [6]. However, these studies on painting used a fixed robot arm, and did not consider using a mobile manipulator.

Dhanaraj et al. studied the spray painting using a mobile manipulator by fixing the cart section [7]. However, in this research, the position of the trolley had to be specified in advance, so it was not possible to paint while moving the trolley, and the painting took longer than when the trolley and arm were controlled simultaneously. Another study of painting using a mobile manipulator is the use of MPC in the agricultural field [8]. However, in a vineyard, the carts can only move in one direction, and the distance between the arm and the vines is always the same.

On the other hand, in this study, we propose a framework on spray painting using a mobile manipulator which actively explores the large structure by combining MPC and vision system.

3. Proposed Method

A schematic diagram of this research is shown in Figure 2. In this study, the following three ROS-based systems were created and combined for painting large structures, especially bridge girders, using mobile manipulators. The first is 3D-SLAM, which creates a map of the surrounding three-dimensional environment and estimates the robot's self-position based on this map. The second is an AR marker recognition system, which is necessary to identify the painting area. These systems enable the robot to obtain the position and orientation of AR markers on a 3D map of the environment generated by Simultaneous Localization and Mapping (SLAM), and to determine the position and orientation of multiple painted surfaces in the environment in 3D space. The third is a whole-body control system for mobile manipulators using Model Predictive Control (MPC). This allows the manipulator to follow the planned trajectory of the spray without explicitly providing the trajectory of the dolly, making it possible to easily paint over a large area beyond the reach of the arm. We propose a method to search for painting surfaces on multiple bridge girders by combining SLAM and AR marker recognition, and a method to generate spray launches for the shortest possible painting time by considering the next direction of movement for the recognized painted surfaces.

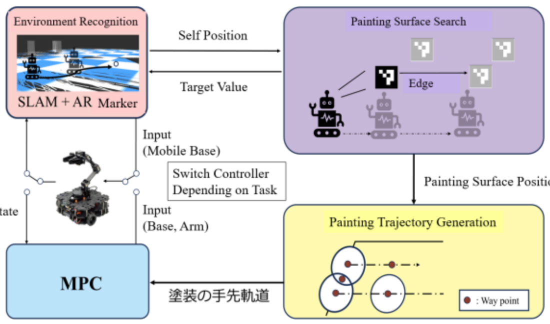


Figure 2 System overview

3.1. *Environment*

In this study, painting task is performed in the environment shown in Figure 1 where several bridge girders to be painted are placed on fixed temporary platforms. In such an environment, it is difficult to identify the pose of each bridge girder by aligning the point cloud using the CAD model of the bridge girders because only a portion of the bridge girders can be observed by the vision sensor. Therefore, this study uses the information on the edge of the bridge girder to identify the location of the bridge girder. The layout of the bridge girders is difficult to completely fix due to the huge size of the structure, and each bridge girder has multiple painted areas on its underside. For this reason, AR markers are placed at the four corners of each painted surface to recognize the painted surface. In this study, a mobile manipulator is used to paint over a wide range of painting trajectories beyond its own size without being aware of the position of the dolly.

3.1.1. Combined System of SLAM and Marker Recognition

By using a wheeled mobile robot, the robot's current position can be obtained using wheel odometry. However, errors occur in the self-position due to the effects of wheel slippage. SLAM can be used for compensating the error in self-position using a vision sensor. In particular, we use RTabMap[2] as a 3D-SLAM. RTabMap uses both wheel odometry and an RGB-D camera to obtain point cloud data of the map.

Figure 3 shows a system that combines 3D-SLAM and AR marker recognition. In this study, two types of RGB-D cameras are used: a SLAM camera (Camera 1) installed so that it faces horizontally and a camera (Camera 2) installed so that it faces vertically to recognize AR markers. With this camera configuration, we aim to avoid the large error in the self-position estimation because the accuracy of estimating the camera position based on the feature values is reduced when the camera faces the ceiling.

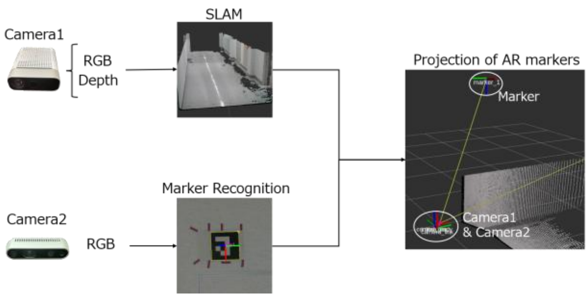


Figure 3 System diagram of combined 3D-SLAM and AR marker recognition

3.1.2. Motion of Mobile Manipulator during Painting Action

In this study, OCS2[9] is used as the MPC, and the MPC is used to provide state feedback and robot control. The robot was modified to send input commands to the end-effector. The trajectory to be followed by the end-effector and the target time are taken as inputs. The inputs are calculated by using the internal kinematics model and optimizer in MPC, and convergence to the target position is measured by receiving feedback from the robot. MPC is a control method that calculates the optimal input by solving optimization problems for the predictive model at each time to predict future responses.

OCS2 automatically computes the system dynamics from the geometric model of the mobile manipulator and calculates the inputs satisfying the constraints. The state variables of the system are the position and posture of the cart and the joint angles of the manipulator, as well as the translational and rotational speeds of the cart as input, and the manipulator.

3.2. *Painting Trajectory Generation*

This section describes a method for generating the shortest possible spray trajectory for a recognized painting location. Figure 4 shows an overview of the proposed method. The MPC takes as inputs a list of the coordinates of the four corners of the recognized painting area, the average Z-coordinates (height) of the corners, and a list of candidate points to be searched for next, and generates a set of square-wave like trajectories with minimum travel distance to paint the rectangular area. When we plan the square-wave like trajectory, we consider the spray width for overlapping with neighbor spray trajectory with the predefined amount. Finally, the tool tip trajectory can be obtained from the painting trajectory. The tool-tip trajectory becomes the input to the MPC.

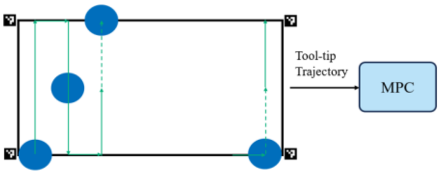
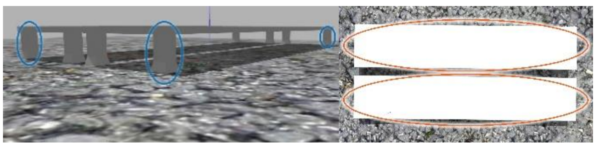


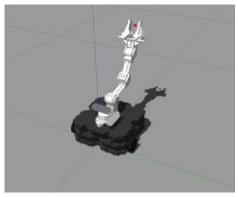
Figure 4 Paint Trajectory Generation for Recognized Paint Locations

4. Simulation

In this study, Gazebo was used as a physics simulator to evaluate the proposed method. Figures 5 shows the painting environment in Gazebo. The red and blue circles indicate bridge girders and temporary abutments, respectively. The dimensions of the bridge girder is 0.7 m high, 2.35 *m* deep, and 12 *m* wide. In this study, forward and vertical upward facing RGB-D cameras were added to the model. The control horizon of MPC was set to 15.0[*s*]. Figure 6 shows the painting environment used in Experiment 1. Markers are placed in the four corners of the painted area with red circles, and the number of the painted area inside the marker is defined as 1 to 6, as in "Pait Area 1". Similarly, Figure 7 shows the painting environment shown in Experiment 2. The difference between these experiments is the position of AR markers.



(a) Bird's-eye view (b) Top view



(c) Mobile manipulator

Figure 5 Painting environment in the simulator

4.1. *Results*

Figure 8 shows a scene from Experiment 1. The red line in the figure shows the ideal trajectory of MPC, and it can be seen that the coordinate system, which is the result of marker recognition, has increased. These results show that the painting locations have been searched based on the markers and edges in the environment, and that the mobile manipulator can appropriately control the whole body in relation to the ideal trajectory of the tip of the hand using MPC. Figure 9 shows the ideal and actual tip trajectories. The gray rectangles represent the painting area calculated from the placement of markers, and the red and orange dots represent the start and end points of each painting activation, respectively. This figure shows that this method can be used to adjust the painting path appropriately to the starting position of the mobile manipulator. This figure also shows that each coating point is able to follow the track with little error.

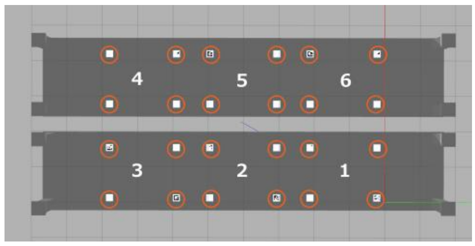


Figure 6 Painting environment in Experiment 1

Figure 10 shows a scene from Experiment 2. From these figures, it can be confirmed that the system can search and paint appropriately even when the size of the painted area changes in the horizontal direction. Figure 11 shows the position of the painting tip in the entire environment, the ideal tip trajectory used as input to MPC, and the painting location using the marker positions in the simulation. From this figure, it can be seen that the method is able to calculate trajectories appropriately for the size of the coating area and that it is able to follow the ideal trajectory at each coating area. These results confirm that the method successfully searches for paint locations by using the edges of the environment and performs painting operations on the recognized paint locations.

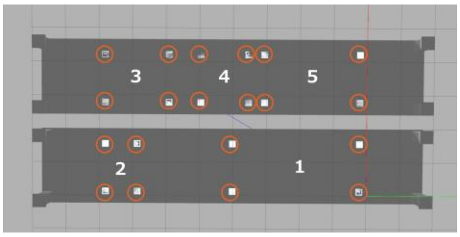
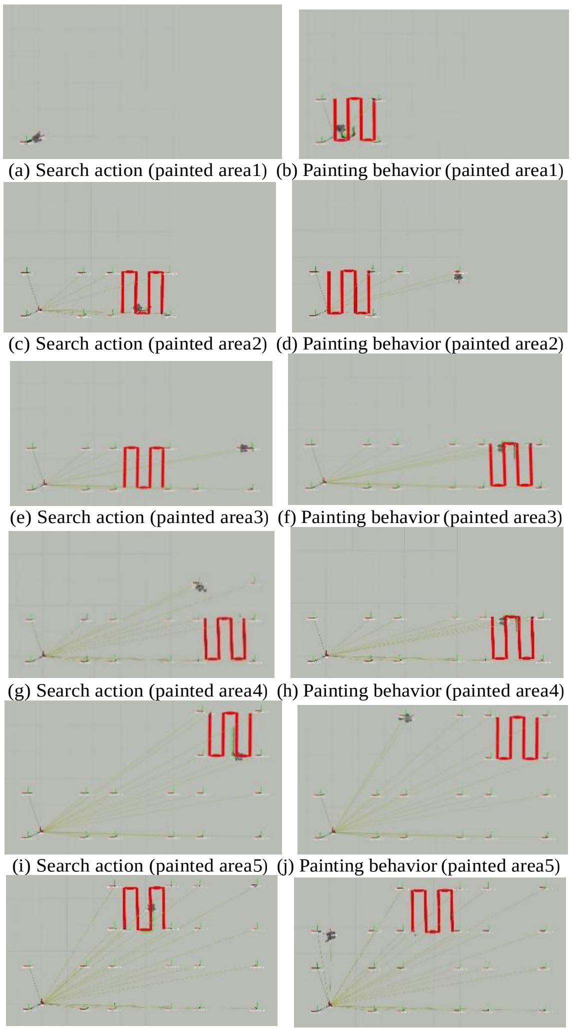


Figure 7 Painting environment in Experiment 2



(a) Search action (painted area1) (b) Painting behavior (painted area1)
(c) Search action (painted area2) (d) Painting behavior (painted area2)
(e) Search action (painted area3) (f) Painting behavior (painted area3)
(g) Search action (painted area4) (h) Painting behavior (painted area4)
(i) Search action (painted area5) (j) Painting behavior (painted area5)
(k) Search action (painted area6) (l) Painting behavior (painted area6)

Figure 8 Result of Experiment 1

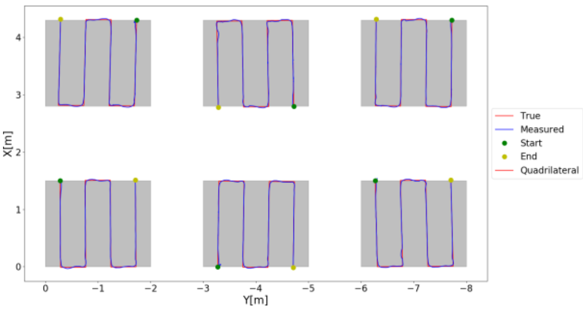
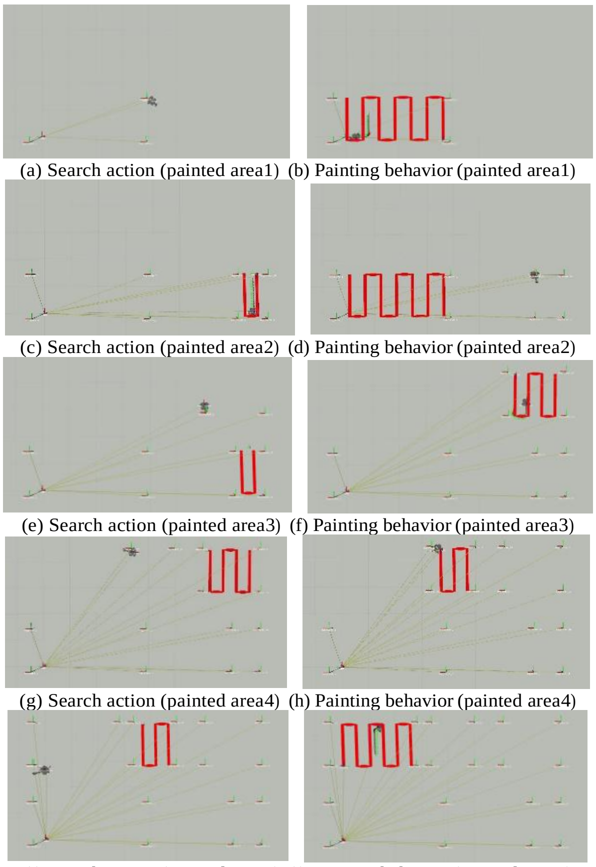


Figure 9 Relationship between the ideal trajectory and the position of the tool-tip during painting in the entire environment of Experiment 1



(a) Search action (painted area1) (b) Painting behavior (painted area1)
(c) Search action (painted area2) (d) Painting behavior (painted area2)
(e) Search action (painted area3) (f) Painting behavior (painted area3)
(g) Search action (painted area4) (h) Painting behavior (painted area4)
(i) Search action (painted area5) (j) Painting behavior (painted area5)

Figure 10 Result of Experiment 2

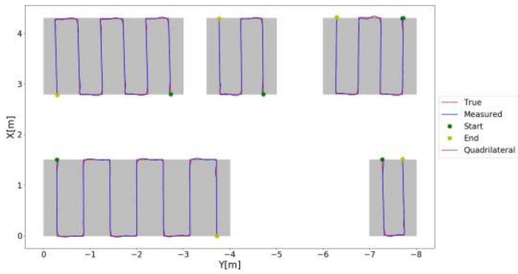


Figure 11 Relationship between tool-tip position and ideal trajectory during painting in the entire environment of Experiment 2

5. Conclusions

In this study, a software system was developed to plan painting operations on large structures using mobile manipulators. The proposed software system consists of three modules, 3D-SLAM, Model Predictive Controller (MPC), and AR marker recognition. In the action planning, the robot recognizes AR markers with its vision sensor and can plan the trajectory of the manipulator to paint within the range indicated by the markers. Future work includes testing the proposed method on actual bridge girders to verify its effectiveness.

References

1. J. Pankert and M. Hutter. Perceptive Model Predictive Control for Continuous Mobile Manipulation, Robotics and Automation Letters, 5(4), 2020.
2. M. Labb´e and F. Michaud. Rtab-map as an open-source lidar and visual simultaneous localization and mapping library for large-scale and long-term online operation. *J. Field Robotics*, 36(2):416-446, 2019.
3. R. Munoz-Salinas and R. Medina-Carnicer. Ucoslam: Simultaneous local- ization and mapping by fusion of keypoints and squared planar markers. *Pattern Recognition*, 101:107193, 2020.
4. S. Chitta, B. Cohen, and M. Likhachev. Planning for autonomous door opening with a mobile manipulator. *IEEE Int. Conf. on Robotics and Automation*, pp. 1799-1806, 2010.
5. W. Lin, A. Anwar, Z. Li, M. Tong, J. Qiu, and H. Gao. Recognition and pose estimation of auto parts for an autonomous spray painting robot. *IEEE Trans. on Industrial Informatics*, 2019.
6. H. Chen et al., Automated robot trajectory planning for spray painting of free-form surfaces in automotive manufacturing. In *Proc. of IEEE Int. Conf. on Robotics and Automation*, vol. 1, pp. 450 -455 vol.1, 2002.
7. N. Dhanaraj, Y. Yoon, R. Malhan, P. Bhatt, S. Thakar, and S. Gupta. A mobile manipulator system for accurate and efficient spraying on large surfaces. *Procedia Computer Science*, 200:1528-1539, 2022.
8. V. Ivo, V. Goran, and K. Zdenko. task space model predictive control for vineyard spraying with a mobile manipulator. *Agriculture*, 12(3), 2022.
9. https://github.com/leggedrobotics/ocs2

Authors Introduction

Mr. Hiroshi Tanaka

He received his Bachelor's and Master's degree in Engineering in 2022 and 2024, respectively, from Osaka University in Japan.

Dr. Masato Tsuru

He received his M.S., and Ph.D. degrees from Osaka University, Japan, in 2021 and 2024, respectively.

Prof. Takuya Kiyokawa

He received his Ph.D degree from Nara Institute of Advanced Science and Technology in 2021. Currently, he is an Associate Professor at the Graduate School of Engineering Science, Osaka University, Japan.

Prof. Kensuke Harada

He is a Professor at the Graduate School of Engineering Science, Osaka University, Japan, a Fellow of the IEEE, and a Cross-Appoint-ment Fellow at the National- Institute of Advanced Industrial Science and Technology (AIST), Japan.