

Calibration of Networked Sensors in an Intelligent Space Based on Interactive SLAM

Fumitaka Hashikawa¹, Kazuyuki Morioka²

^{1,2} Meiji University, Kanagawa 214-8571, Japan
(Tel: +81-44-934-7304, Fax: +81-44-934-7304)

¹ce01073@meiji.ac.jp, ²morioka@isc.meiji.ac.jp

Abstract: For human-robot coexistent environments, intelligent spaces including networked laser range sensors, cameras and the other sensing device have been developed. So, we consider the intelligent spaces with Fast-SLAM based on Particle Filter. Especially, on the map construction based on a grid map is more accurate than normal SLAM. However, those methods use only sensing data from the mobile robot to achieve SLAM. In this study, a new method of SLAM, which uses distributed sensors fixed in an environment as intelligent space, is introduced. This method shares information with SLAM of mobile robot. And we introduce calibration method of distributed sensors.

Keywords: mobile robot, SLAM, intelligent space

1 Introduction

Recently, as one of the methods for achievement of human-robot coexistent environments, intelligent space including distributed sensors has been considered [1][2]. In order to build intelligent space and to perform human tracking with distributed sensors, it is required to know positions of distributed sensors in world coordinate system of intelligent space. Then, calibration of distributed sensors must be achieved for development of intelligent spaces. However, it is generally complicated works. Easy calibration method is required for spreading the intelligent space. Especially, since distributed laser range sensors are widely used for human tracking in intelligent spaces, geometrical calibration of many laser range sensors in unified world coordinate system must be achieved. This study focuses on easy calibration of networked laser range sensors.

In this study, structural map building of intelligent space with a mobile robot is exploited for sensor calibration. Maps built by the distributed sensors are compared with the map built in SLAM process of the robot. Then, positions of the distributed sensors are estimated according to matching results.

Also, the map built by the robot is improved accurately according to estimation results of the distributed sensors. This study aims to improve position estimation of the mobile robot itself and the distributed sensors of intelligent space based on interactively communicating each other.

2 Interactive FastSLAM with intelligent space

2.1 Outline

In this study, FastSLAM[3] is used for map building by the mobile robot and localization. SLAM is a method to make a map of the environment, and estimate position of mobile robots simultaneously based on matching between sensing results and environmental maps previously generated. FastSLAM based on particle filter can achieve SLAM with high speed and high accuracy. Especially, grid-based Fast SLAM is more promising. This method includes building a probabilistic grid map based on environment information obtained by a laser range sensor on the mobile robot. Then, the grid map and new sensing results are compared every sampling time, and the grid map is updated. Mobile robot's self-position is also presumed based on this map.

This study considers extending FastSLAM by robot itself to an interactive SLAM with the intelligent space. The interactive SLAM uses grid-maps built by the networked laser range sensors of the intelligent space in addition to grid-maps built by robot itself. When the mobile robot is in the networked sensor's monitoring area, grid maps built by the networked sensors are shared with the mobile robot and used as the constraints of the mobile robot's SLAM. In that case, grid map by networked sensor and sensing results of the mobile robot are compared in each particle in addition to matching with local maps in SLAM process by robot itself with laser sensing results. Particles that match both maps will be preserved as good particles in the FastSLAM. This is effective for improving accuracy of grid maps,

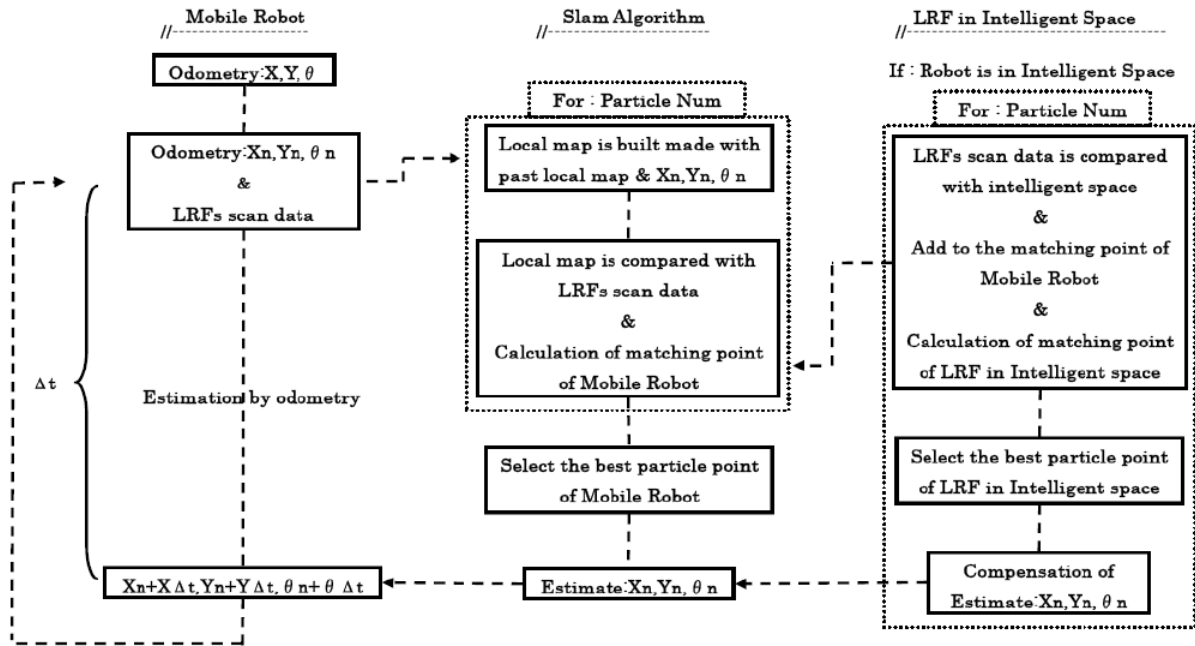


Fig.1 outline of interactive SLAM

because maps built by networked sensors fixed in the environments are integrated to map built by robot itself.

Next, it is assumed that positions of networked sensors in intelligent space are unknown. While interactive SLAM process, positions of networked sensor can be also estimated simultaneously in addition to positions of mobile robots.

2.2 System Configuration

System configuration of interactive SLAM with networked laser range sensors is shown in Fig.1. This system is configured with three processes: mobile robot control including data acquisition, SLAM process of mobile robot itself, mapping with distributed sensor.

In the robot control process, moving distance by odometry and range data by the sensor is measured for every sampling time. The measured data is sent to the SLAM process. At this time, the time stamps of sending data are saved in order to consider calculation time for estimation in the SLAM process. In the SLAM process, Grid Based FastSLAM is exploited for estimating robot positions and maps. Grid Based FastSLAM is based on a particle filter, and robot positions and maps are estimated as state variables. The computed state variable is retransmitted to the robot control process. Robot position in the robot control process is updated with considering the computation time for estimating position in the SLAM process.

Interactive FastSLAM is performed when a mobile robot moves in a monitoring area of a distributed sensor. Then, an occupancy grid map from the distributed sensor

and a sensing result from a mobile robot are compared. Although matching between past maps generated by the mobile robot itself and the current sensing data is used for likelihood calculation of a particle in the usual SLAM, comparison with the map of the distributed sensor is also add in the interactive SLAM. Difference between a map estimated by the robot side and a map of the distributed sensor is reflected to estimation result of the interactive SLAM.

2.3 Construction of Grid Map in FastSLAM

Matching between current sensing data by the laser range sensor in the robot and a local map based on past position estimation is performed in map estimation of usual Grid Based FastSLAM. Likelihood is calculated based on the number of sensing points, which matched with the grids with high occupancy probabilities in the local map. This likelihood calculation is performed in each particle of a particle filter. Robot position is estimated by the weighting average based on likelihood of each particle. Fig.2 shows an example of the sensing data by the mobile robot in environment where moving objects, such as humans and the other static objects are exist. Fig.3 shows an example of matching between the sensing data and a local map. In this figure, red points represent grids that the local map and the sensing points are corresponding.

In comparison of Fig.2 and Fig.3, Fig.2 detects the moving objects in the measurement result. Since occupancy grid probabilities matched with any sensing points are updated in the grid map shown in Fig.3, influences of moving objects decrease in map building.

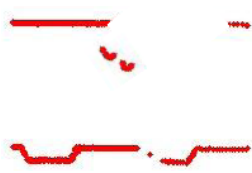


Fig.2 sensing result

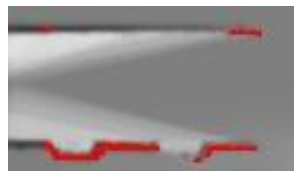


Fig.3 matching of local map and sensing data

2.4 Matching with maps by distributed laser range sensors

In the interactive FastSLAM using intelligent space, when a mobile robot moves into an area of a distributed laser range sensors, likelihood of each particle is computed from comparison with grid maps which the distributed sensors generate in addition to comparison with the local maps which the mobile robot itself generate as mentioned above. That is, when the mobile robot runs in the measuring range of a distributed sensor, it is aimed that accuracies of position and map estimations in SLAM process are improved by evaluating the matching points with the grid map from the distributed sensors. The grid maps of distributed sensors are generated by a method of literature [3]. Fig.4 is an example situation of matching with the map from the sensor fixed in intelligent space. In this figure, red points are current sensing points by the mobile robot. Blue points show the grids, which the map by distributed sensor and the sensing points are corresponded. It is enough when many correspondent points are measured as shown in Fig.4. However, as shown in left figure of Fig.5, there are many cases that correspondent points between the map by the distributed sensor and sensing data are small because of orientation differences between maps and sensing data especially. It means that the number of correspondent points is not enough to evaluate matching with the maps of distributed sensors.



Fig.4 sensing data corresponding to map by a distributed sensor

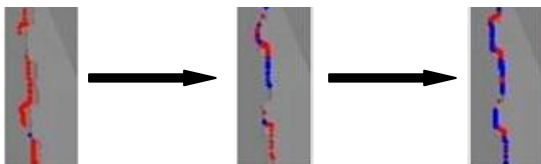


Fig.5 matching correction

So, in this study, orientation differences between maps of distributed sensors and sensing data are used for evaluation of matching. Two grids with the highest occupancy probability in the map of distributed sensor are

selected as representative points. In the sensing data observed by the robot side, the points nearest to selected two points are searched. Average errors of two points are reflected to likelihood of each particle. At this time, each particle is also recording slopes of lines between each two points in the grid map or sensing data. State compensation based on the slopes is performed at the update of state variables in the robot side. Both the maps of distributed sensors and the map built by the robot itself are evaluated by performing this process for every cycle of the SLAM process. Matching result is corrected on running of the robot as shown in Fig.5. The number of matching points is shown by blue points increase in this figure. In the monitoring area of distributed sensors, particles, which match with both of the past local map by SLAM and the maps by distributed sensors will be selected as a result.

2.5 Estimating position and orientation of distributed laser range sensors

When positions and orientations of distributed laser range sensors in a world coordinate system are known, position estimation of a mobile robot and accuracy of map building improve according to the map of distributed sensors in the interactive FastSLAM as described above. In this case, the map of distributed sensors becomes constraints in SLAM process. However, when many sensors are distributed in the environment, it becomes a complicated work to know positions and orientations of all sensors in unified world coordinate system. Then, the case, that positions and orientations of distributed sensors are unknown, is considered. This study introduces estimating both positions and orientations of the mobile robot and distributed sensors simultaneously with interactive SLAM.

When a mobile robot enters into an area of distributed sensors, an initial position of the distributed sensor is measured by the mobile robot in the coordinate system of the map generated by the usual SLAM. A measurement result is sent to the distributed sensor. In Grid Based FastSLAM mentioned above, a mobile robot's position and the grid map are used as state variables. In addition to these state variables, positions and postures of distributed sensors are also added as state variables and estimated simultaneously. When the mobile robot runs into the areas of distributed sensors, correction of positions and orientations of distributed sensors are performed.

3 Experiment

As a preliminary experiment on the conditions which positions and orientations of distributed laser range sensors are known, the system of interactive FastSLAM is implemented and the experiment of self-position estimation and map generation was conducted. As experiment environment, the mobile robot moved a squared course in one floor of building of our university. A length of the course is about 100 m. Four distributed sensors were installed in yellow points of Fig.7. Fig.6 shows the map generated by usual FastSLAM only.

On the other hand, Fig.7 is a map built by information sharing with four distributed sensors with the interactive FastSLAM. A part of a red dotted circle in Fig.6 has matching errors when the mobile robot revisited this area. However, an accurate map is shown in a part of a yellow dotted circle in Fig.7, because the robot position and map are obtained by particles, which also matched with the maps from the intelligent space. Fig.8-11 is examples of map matching in the measurement areas of four distributed sensors in the interactive SLAM. These shows find that matching of a sensing result, a map by robot itself, and a map by the distributed sensor is performed in each part. Also, in the case that positions and orientations of distributed sensors are unknown, positions and orientations of the distributed sensors updated to actual values according to robot movement with the similar system.

In this experiment, the number of particle in a particle filter of the interactive SLAM is 50, and the grid size of is set to 50 mm x 50 mm. Pioneer3-DX was used for the mobile robot. UTM30-LX was used for the sensor installed in the robot. URG04-LX was used for the distributed sensors.

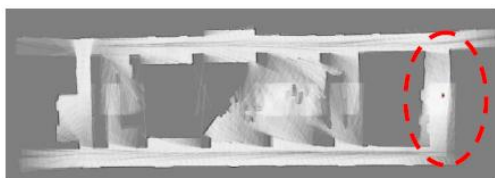


Fig.6 SLAM result (only Mobile robot)

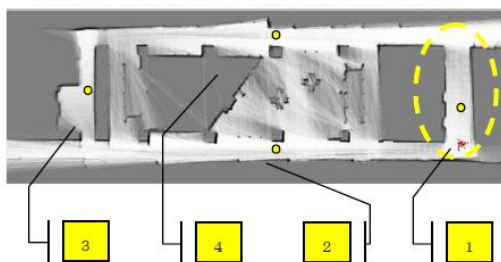


Fig.7 SLAM result (information sharing)

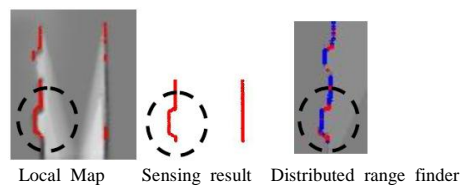


Fig.8 Scan matching in "1" of fig.7

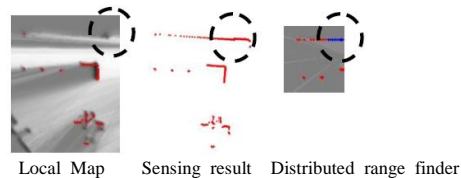


Fig.9 Scan matching in "2" of fig.7

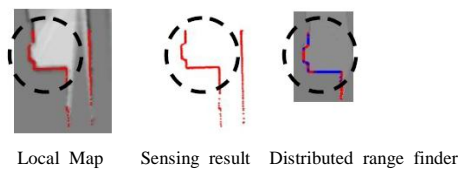


Fig.10 Scan matching in "3" of fig.7

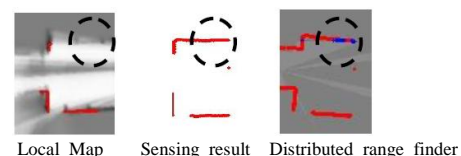


Fig.11 Scan matching in "4" of fig.7

4 Conclusion

In this paper, it was shown that it is effective in improving the accuracy of SLAM by using information of distributed laser range sensors in intelligent space in the SLAM problem. This paper also described a possibility that the proposed SLAM is utilizable to estimating positions and orientations of distributed sensors in intelligent space.

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