Scan Matching Based Multi-robot Map Building

Batsaikhan Dugarjav and Soon-Geul Lee*

***Abstract*—**A 2D multi-robot cooperative localization and mapping framework of an unknown environment using iterative closest point (ICP) scan matching is proposed. Each robot is equipped with a 2D laser scanner and builds an individual local map by ICP algorithm. With the information of the known initial positions of robots, these local maps are merged into one global map. When both robots find common feature of the environment, map matching and merging to increase mapping accuracy are executed. Experiment shows that the mapping performance with multi robots is higher than that with a single robot.

Index Terms—map building, scan matching, multi-robot, iterative closest point

I. Introduction

Many applications in mobile robotics, require that robots have the capability of building a map of the environment to achieve their tasks more efficiently. In the practice, the team of multi-robots have the advantages of reducing the time of mapping, increasing the efficiency, and improving the accuracy of the map building with the collaboration positioning and information integration technology by comparing with single robot [1].

Many methods had been introduced for the cooperative mobile robots exploration over the last decade and those approaches can be categorized into two groups as a distributed and a centralized [2, 3]. First category where the all teammate robots are responsible for the individual mapping and when the robots are meeting physically each other exchanging individual information in order to build a complete global map model based on after establishing the common reference frame among them. In [2], distributed algorithm has presented where each robot unit estimates pose and map posteriors through unified Extended Kalman Filter (EKF) framework and if they are in communication range each map model is exchanged among teammate robots.

Second is centralized exploration approach where centralized host robot is responsible for mapping by collecting data from other teammate robots. In this category, related study is found in [4], in this work, traditional single robot EKF based mapping strategy is extended to multi-robot case and observations from the all robots are used to generate global map model.

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In the multi-robot area exploration field, the main challenging problem is map merging with unknown initial poses of the robots, furthermore finding common reference frame among the all teammate robots [5]. If the initial mutual poses of the robots are known they can merge maps immediately but it does not known map merging is unable to perform. Therefore it leads two ways to get common reference frame for each individual map to be merged [6]. First step, when the robots are meeting physically each other, one of the robots receives sensor data from the other robot and attempts to estimate its location by matching the received scan against its own map. Second the two robots supposed to meet at the expected location in an assumed common map. When they are succeeded, their maps are fused permanently.

For the map merging problem, some methods that uses matching algorithm are introduced in [7, 8, 9 and 10]. In [7], robot is initiate the SLAM process independently without knowing other robot's poses and map fusion technique is developed based on matching landmarks that are observed by stereo vision system. Specially, to make alignment of the individual two maps based on corresponding landmarks, some iterative methods are utilized such as the RANSAC and the ICP [8, 9]. Then each individual maps are merged into single one through estimation for alignment. To reduce the growth of errors in the location estimate and the mapping, hierarchical multi-robot mapping work is presented in [10], where at local mapping combination of the ICP scan matching and Kalman filter (KF) method is introduced and for global matching. They enhance histogram cross-correlation techniques, introducing entropy sequences of projection histograms and an exhaustive correlation approach for reliable matching in unstructured environments.

In this work, a centralized multi robot mapping and localization framework is proposed for exploration of unknown environment in which robots are moving their known initial poses. ICP scan matching based approach is used for each robot to estimate its pose and to build map incrementally. ICP is simple algorithm used to match two data set. Then each map solution is transmitted to the host PC where global solution produces. Generally, each individual maps are merged based on the known relative poses of the robots and when the robots are met in the expected region in the workspace the additional map matching is performed by ICP to improve the accuracy of the mapping.

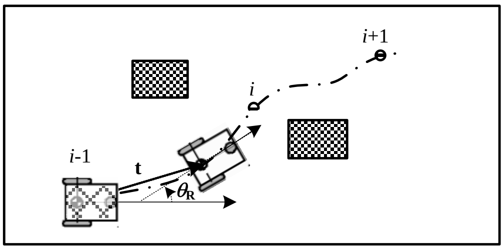
II. Incremental Map Building and Localization Based on ICP with Scan Matching

When the robot is building a map, sensor information received by the robot will be slightly different along with the different positions of the robot. To deal with this problem, the proposed method uses the global reference data and the new scan data to determine the overlapping area for alignment by ICP algorithm.

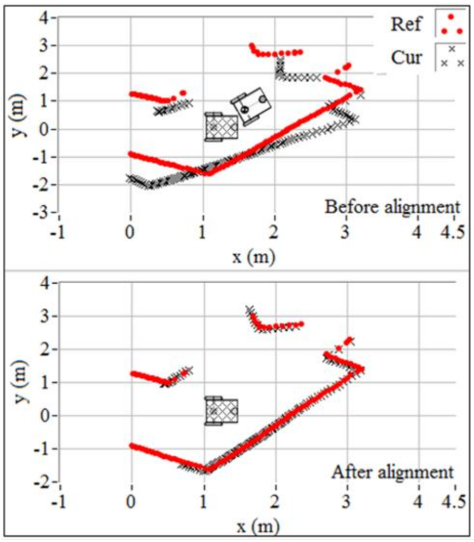
Let $\mathbf{M}^{i-1}$ be the reference data obtained at the previous node, where the robot is denoted as the shaded point in Fig. 1(a). The obtained $\mathbf{M}^{i-1}$ is denoted as the red dotted data points in Fig. 1(b). Let $\mathbf{S}_c^i$ be the scanned data at the current robot position between the nodes (i-1) and i as shown in Fig. 1(a). The gathered data $\mathbf{S}_c^i$ denoted as the black 'x'-marked points in Fig. 1(b) differ from $\mathbf{M}^{i-1}$ because the robot changes its position not only in terms of translation **t** but also in terms of rotation θ from the previous reference position. Given the rotation matrix $\mathbf{R} = \mathbf{R}_\theta$ and the translation **t**, the ICP algorithm iteratively computes the alignment error E between the two datasets and determines the proper rotation **R** and translation **t** that minimize Eq. (1).

$$E(\mathbf{R},\mathbf{t}) = \sum_{k=1}^{N_r}\sum_{j=1}^{N_c} w_{k,j} \left\| \mathbf{M}_k^{i-1} - (\mathbf{R}\mathbf{S}_{c,j}^i + \mathbf{t}) \right\|^2 , \qquad (1)$$

where N_r and N_c are the number of the points in $\mathbf{M}^{i-1}$ and



(a)



(b)

Fig. 1. ICP with scan matching: the reference scan and the current scan are matched.

$\mathbf{S}_c^i$, respectively. $w_{k,j}$ is 1, if $\mathbf{M}_k^{i-1}$ is the closest point to $\mathbf{S}_{c,j}^i$, and 0 otherwise.

If a 2D laser scanner is mounted on the robot, the robot moves through its way, and the laser scanner takes the measurements as a slice of the robot's workspace. Subsequently, the ICP algorithm calculates the relative position error between the two consequent recorded scans to determine the robot motion. That is, ICP with scan matching rotates the scanned data $\mathbf{S}_{c,j}^i$ by θ and translates the data by **t** to obtain the best alignment to the reference data $\mathbf{M}^{i-1}$. The second figure in Fig. 1(b) shows an example of an aligned result derived with the ICP algorithm.

Without any information, the robot can only partially detect its environment because of the limit of its sensing range and the occlusion caused by an object in the workspace. A local map can be obtained from such incomplete detection, that is, the scanned data of the sensor at each position as the robot moves. Thus, a local map is an incomplete representation of the partial workspace from the perspective of the current position of the robot. An incremental map is constructed by combining the successive local maps containing information on the position of the robot. Consequently, the succeeding incremental map becomes a more accurate and comprehensive representation of the workspace compared with the previous map, as all the previously built local maps are merged.

At the beginning of the mapping and localization, both the current and estimated poses of the robot are initialized into $[0\ 0\ 0]^T$ by matching the coordinate frame with the initial location. By executing ICP scan matching, a pose correction vector $\left[x_{sm}^i\, y_{sm}^i\, \theta_{sm}^i\right]^T$ is obtained. The homogeneous coordinate transformation matrix **H** can be derived from the components of the pose correction vector, which can combine multiplicative and translational terms for 2D geometric transformations into a single matrix representation by expanding the 2 x 2 matrix representations into 3 x 3 matrices, as shown in Eq. (2).

$$\mathbf{H} = \begin{bmatrix} \cos\theta_{sm}^i & -\sin\theta_{sm}^i & x_{sm}^i \\ \sin\theta_{sm}^i & \cos\theta_{sm}^i & y_{sm}^i \\ 0 & 0 & 1 \end{bmatrix} . \qquad (2)$$

Then the pose of the robot can be updated by Eq. (3).

$$\begin{bmatrix} x_{est}^i \\ y_{est}^i \\ \theta_{est}^i \end{bmatrix} = \begin{bmatrix} x_{est}^{i-1} \\ y_{est}^{i-1} \\ \theta_{est}^{i-1} \end{bmatrix} + \begin{bmatrix} dx_{i-1}^i \\ dy_{i-1}^i \\ d\theta_{i-1}^i \end{bmatrix} + \begin{bmatrix} x_{sm}^i \\ y_{sm}^i \\ \theta_{sm}^i \end{bmatrix} , \qquad (3)$$

where $\left[x_{est}^{i-1}\, y_{est}^{i-1}\, \theta_{est}^{i-1}\right]^T$ is the estimated pose of the robot at (i-1)-th sampling time, and $\left[dx_{i-1}^i\, dy_{i-1}^i\, d\theta_{i-1}^i\right]^T$ is the difference between the i-th and the (i-1)-th pose of the robot that estimated through odometer.

Map merging is a process that combines the reference data set $\mathbf{M}^{i-1}$ and the current data set $\mathbf{S}_c^i$ into a new reference data set $\mathbf{M}^i$ for the next time step. This process is necessary to efficiently determine which points are the outlier points, and which new information on the workspace in the current scan can be integrated with the reference data for the map merging process. A sparse point map is used to avoid the duplication of stored points, which is achieved by conducting an additional correspondence search and by neglecting points that correspond to the data points already stored in the map.

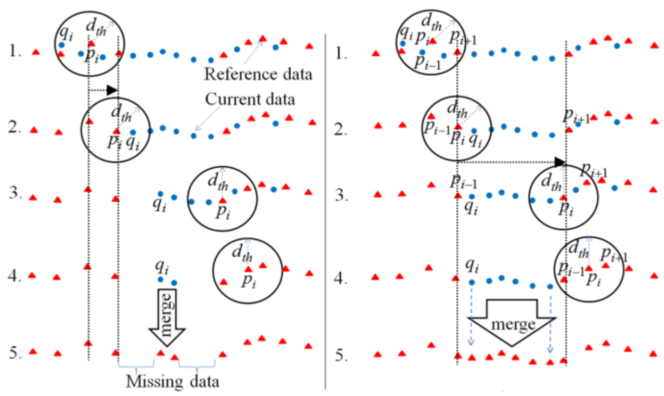
The map of the environment is incrementally built according to Eq. (4).

$$\mathbf{M}^i = \mathbf{M}^{i-1} \cup \{(x_q, y_q) \in \mathbf{S}^i{}_c \mid \nexists (x_p, y_p) \in \mathbf{M}^{i-1} : \|(x_q, y_q) - (x_p, y_p)\| < d_{th}\} \quad , (4)$$

where (x_q, y_q) is a data point of the current scan, $\mathbf{S}^i_c$, (x_p, y_p) is a data point in $\mathbf{M}^{i-1}$, and d_{th} is the threshold value for the map merging.

The proper value of d_{th} , based on the accuracy of the range sensor and the specification of the robot, will exclude the possibility of storing duplicated points in a precise manner, assuming that the correct alignment of the scanning range has been achieved. The process of modified map merging described by Eq. (4) is compared with the conventional merging method shown in Fig. 2(a). The result is shown in Fig. 2(b) in which the data points of the reference scan $\mathbf{M}^{i-1}$ are denoted by the red triangle, the data points of the current scan $\mathbf{S}^i_c$ are denoted by the blue circlet, and the sequence number of the merging process is represented by each line number. The data line "1" is thus the initial state, when a new scan $\mathbf{S}^i_c$ is obtained, and the threshold circle whose radius is d_{th} denotes the region, where the current merging is executed.

The merging is executed from left to right, and the threshold circle moves to the right as the number of the data line increases. The new reference $\mathbf{M}^i$ is finally obtained at



(a) (b)

Fig. 2. Map merging. a) Conventional merging rule. b) Modified map merging rule.

the data line "5." The larger the value of d_{th} , the more points stored in the map are reduced, as shown in Fig. 2.

A simple rule to determine whether point q_i is a duplicated point in the current data set is proposed as a modified map merging. The current center point p_i and the adjacent points on both sides, p_{i-1} and p_{i+1} , of the reference data are involved in the rule explained in Fig. 2(b). If the Euclidian distances between p_i and p_{i-1} / p_{i+1} are less than the threshold d_{th} , the points inside the threshold circle of the current data set are deleted. This case is denoted by data lines "1" and "4" of Fig 2(b), and these points are assumed to be duplicates in the reference data set. The blue circlet within the threshold circle of the data line "1" is deleted after executing the merging process, as shown in the data line "2". At data line "2", the center of the threshold circle moves to the next data point denoted by the dotted arrow in Fig. 2(a) and as a result, the previous p_{i+1} of the data line "1" is set as p_i . Points can be assumed as newly scanned, when no corresponding point between p_i and p_{i+1} in the reference data set exists, such as those in the data lines "2" and "3" of Fig. 2(b). Whereas the conventional merging process regards all current scan points within the threshold circle as duplicates, the modified merging process counts the current scan points on the side, where no adjacent reference data point exists as newly scanned information within the threshold circle. Deleting duplicated points and merging new data points are efficiently executed by Eq. (4), and the reference data set for the next step is obtained as shown in the data line "5" of Fig. 2(b).

III. Multi Robot Map Building with Known Initial Poses

A single robot mapping problem as introduced in the Section II can readily be generalized to handle multiple robots with assumption that the initial poses of robots are known. If a same type robot collaborates with other robots, the workspace to be explored will be divided and the distances traveled by each robot will be reduced. Therefore the map will be built within less time and the odometer errors will be smaller. For that reason, it is evident that a team of cooperative robots can perform the same task in a more efficient way.

In this work, a centralized multi-robot mapping and localization framework is proposed for exploration of unknown environments in which robots are moving with their known initial poses. ICP scan matching based mapping is used for each robot to estimate its pose and to build map incrementally. Then each map solution is transmitted to the host PC where global solution produces with assumption of robots initial poses are known.

In a multi-robot system, in which each robot constructs its own local map, it is necessary to perform a later task, which consists in the fusion of those local sub maps into a global one. The fusion of the local maps is performed with two main steps. The first one is to compute alignment between the local maps. After the alignment between two maps is done, the second step is to merge the maps. However, in this work, initial poses of the each robot is known, hence alignment of the individual maps is executed by mutual poses of the robot when robots are not in the expected location. If the robot is entered in the expected location, additional map alignment is performed through the ICP. Because percentage to detect similar feature is high when the two robots are in the expected location. So, by matching those features, additional map matching is done.

Once the alignment is performed, the individual maps have the same reference system. In order to obtain a unique global map, these have to be merged. The map merging is done by same technique as explained in the Section II and the merging formulation as follow:

$$\mathbf{M}_i = \mathbf{M}_{r1} \cup \{(x_{r2}, y_{r2}) \in \mathbf{M}_{r2} \mid \nexists (x_{r1}, y_{r1}) \in \mathbf{M}_{r1} : \|(x_{r2}, y_{r2}) - (x_{r1}, y_{r1})\| < d_{th}\} \quad , (5)$$

where (x_{r2}, y_{r2}) is a data point of the local map of robot 2, $\mathbf{M}_{r2}$, (x_{r1}, y_{r1}) is a data point in $\mathbf{M}_{r1}$, and $\mathbf{M}_i$ is the merged global map at i-th sampling time.

IV. Experiment

The purpose of the experiment is to verify how efficient multi-robot area exploration versus single robot. In the experiment, each robot is equipped with 2D laser scanner, which is facing front to get perception of the environment and Wi-Fi communication module Raspberry to communicate host PC. Both robots are allowed to explore the environment and to send their sensorial information to the server by above communication module. Sketch of the experimental environment is shown in Fig. 3, which is described without metric. To provide metric real map, each part of the workspace of the robot is measured manually by

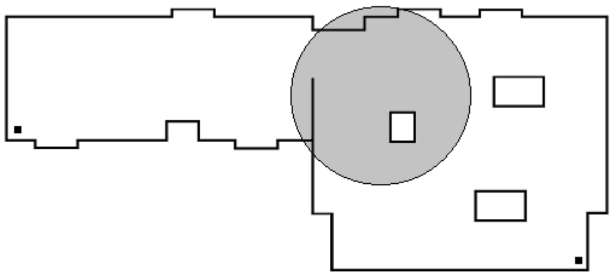


Fig. 3. Sketch of the experimental environment

Table. I Comparison Of The Single And Multi-Robots Exploration Time.

Experiment type	Exploration time (sec)	RMS error (mm)	Traveled distance (m)	
Single robot exploration	498.51	570.81	38.25	
Multi robots exploration	350.08	348.27	Robot 1	17.69
			Robot 2	15.68

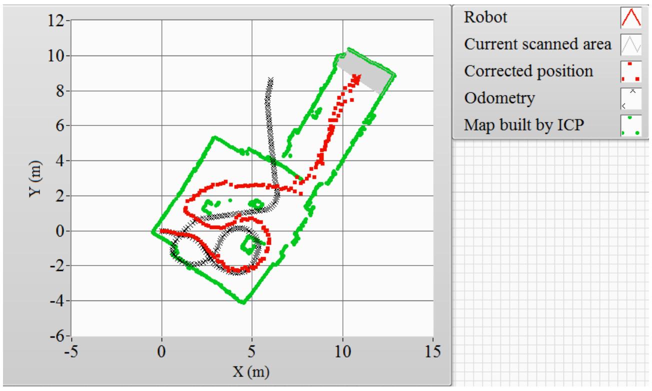


Fig. 4. Single robot exploration.

tape measure after experimental environment is set up.

The initial poses and the expected location of the robots are shown in Fig. 3 as marked as black dots and shaded circlet, respectively. Both robots are not aware until they encountered in the shaded region. When the robots are encountered in the shaded region additional map alignment is done where their common features are used to realign the

individual maps. After single and multi-robot exploration are performed, to verify the performance of the mapping in terms of accuracy, time efficiency and traveled distances, the RMS feature errors and exploration time of the merged map

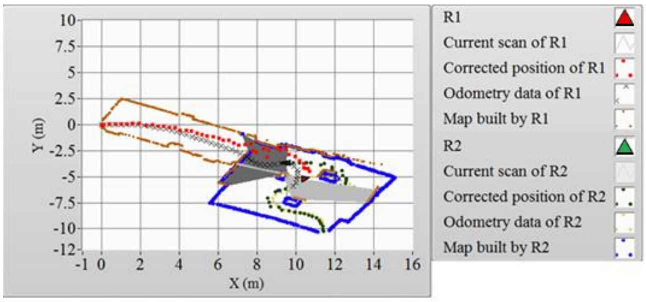


Fig. 5. Multi robots exploration

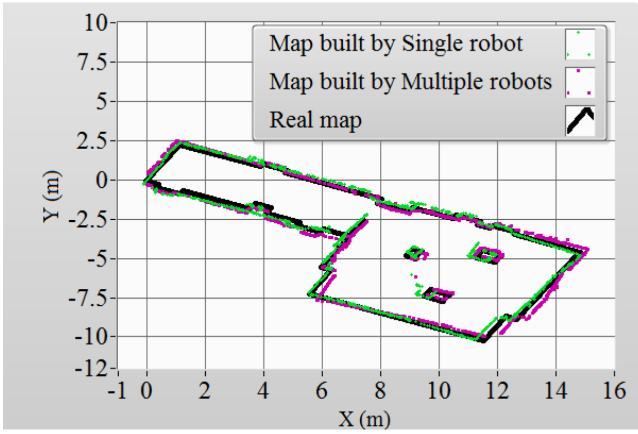


Fig. 6. Comparison of the single and multi-robots mapping accuracy versus real map.

by proposed algorithm were compared and summarized in Table I.

Also, the total traveled distance of single and multi-robot are compared. The RMS error is calculated through corresponding corner features in the single, dual and real map then the RMS error between the single robot mapping and real map is around 570 mm but the multi robots mapping and real is around 348 mm. The total required times for mapping the whole environment by a single robot and two robots were 498.51 sec and 350.08 sec, respectively. Therefore, the two-robot case reduced the total required time by 22.77%, which is one of the advantages of multi-robot SLAM in terms of time efficiency. The single robot and dual robots exploration results are shown in the Fig. 4 and 5, respectively and three maps that single, dual robots and real are shown in the Fig. 6.

V. Conclusion

This paper presents centralized multi robot mapping and localization framework that uses ICP scan matching in unknown environment where mutual poses of the robot are known to each other. Basically, mutual poses of the robot are utilized for the map alignment and when robots are entered in the expected location additional map alignment have performed. Experiment results show that the multi robot mapping higher performance than single robot. Future work will be handled cooperative mobile robot exploration with unknown mutual poses of robot.

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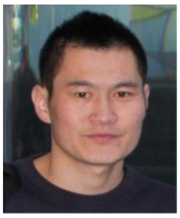

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