Multi-robot Active SLAM based on Submap-joining for Feature-based Representation Environments

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Abstract

The ability to acquire knowledge of the environment actively is essential for autonomous system. In this paper, we propose a multi-robot active simultaneous localization and mapping (SLAM) algorithm based on mutual information for feature-based representation environments that do not depend on the grid map. A multi-layer motion planner and virtual landmarks are introduced to improve exploration efficiency and reduce planning time. To improve the system's accuracy and scalability, we also developed a decentralized version of the active SLAM based on the submap-joining approach. Both simulations and real-world experiments are performed to validate the effectiveness of the proposed methods.

1 INTRODUCTION

Multi-robot active SLAM problem has attracted lots of attention since it empowers robots with the ability to actively acquire knowledge of the environment which is essential for the current autonomous system [Dunbabin and Marques2012] [Tokekar *et al.*2013] [Bourne *et al.*2020]. In active SLAM, robots need to evaluate the utility of the available actions and choose the best action to improve SLAM estimation and, at the same time, perform other required tasks such as collision avoidance or area coverage. Utilizing multi-robot systems for active SLAM can leverage coordination between robots to improve accuracy and exploration efficiency [Bryson and Sukkarieh2007] [Bryson and Sukkarieh2009].

The early study of active SLAM problems dates back to the 2000s [Yamauchi1997] [González-Baños and Latombe2002]. In most of these researches, robot constructed an occupancy grid map with laser scanners to represent obstacles and free space. Then, the robot used the occupancy grid map to detect the frontier region (the region between known and unknown) for motion planning. The early approaches did not consider the SLAM performance and only focus on the coverage of the environment. Taking the SLAM accuracy into consideration, [Leung *et al.*2008] used model predictive control together with attractor strategy to generate trajectories that minimize the trace of the covariance matrix of the robot states. While [Stachniss2009] combined action information gain with the entropy of the map to construct the utility function of robot action. Later, [Singh *et al.*2009] extended the information based active SLAM to multi-robot systems to improve the SLAM performance and exploration speed. To further improve the SLAM estimation, [Chen *et al.*2020b] analyzed the relation between graph topology of the pose graph and utility metric to find out the weak connection in the graph and encourage robots to obtain extra observations related to these poses. Later work also further studied the combination of different utility functions for the active SLAM problem [Charrow *et al.*2015] [Carlone *et al.*2010] [Carrillo *et al.*2012].

For the motion planning part of active SLAM problem, researchers tend to formulate it as stochastic optimal control problem that maximize the utility of robot action [Atanasov *et al.*2015] [Kantaros *et al.*2019] [Chen *et al.*2020a] [Kantaros and Pappas2021]. When performing active SLAM, robots generate occupancy grid maps and use different sampling based motion planner (RRT* planner [Vallvé and Andrade-Cetto2015a], potential field planner [Vallvé and Andrade-Cetto2015b] and D* planner [Maurović *et al.*2018]) to generate collision free trajectories and achieve goal points. To speed up the decision process and at the same time guarantee the op-

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timality of the planning results, [Kantaros *et al.*2019] developed a sampling-based planner that explores both the robot motion space and the information space at the same time. Some researchers [Oßwald *et al.*2016] have also tried to exploit background information (the input topology graph of the environment) to speed up the exploration time by generating robot path and way points using a traveling salesman problem (TSP) solver. However, these active SLAM methods either used occupancy grid map for environment representation and information gain calculations or heavily relied on occupancy grid map for collision avoidance which introduced extra computation complexity.

In this paper, we propose a multi-robot active SLAM framework for feature map base on submap-joining approach. During the active SLAM process, robots keep performing non-linear least squares optimization (NLLS) to obtain localization results and feature positions estimation every period of time. With the estimated results, robots evaluate the utility of arriving candidate goal points that sampled from robots reachable set. The virtual landmarks are introduced in the prediction step to encourage the robots to explore unknown landmarks. We also use submap-joining SLAM approach to improve the scalability of the system and reduce the communication bandwidth.

The contributions of this paper can be summarized as follows:

- An information-based metric for motion utility evaluation in feature maps is proposed.
- A hierarchical sampling-based motion planner together with virtual landmark attractors is proposed to improve the exploration efficiency.
- Submap-joining based SLAM is introduced in the proposed multi-robot active SLAM approach to reduce communication bandwidth and improve real-time performance.

The remainder of the paper is organized as follows: Section II and III present the details of the proposed approaches, followed by experimental results and analysis in Section IV. The paper is concluded in Section V.

2 CENTRALIZED MULTI-ROBOT ACTIVE SLAM

2.1 Problem Statement

In this work, we focus on the multi-robot exploration problem in 2D environment that aim to locate more features with minimal time cost and at the same time provide accurate localization results. The robots are assumed to navigate in the environment with point features on the boundary. After each decision interval, the robots perform non-linear optimization with odometry and feature observations to obtain SLAM results and calculate the utility of each candidate sub-goal points. The sub-goal points with highest utility are chosen to plan the robots actions in the exploration task.

For each robot i at time t, we assume that it follows the differential motion model:

$$X_{i,t+1} = f(X_{i,t}, u_{i,t}) + \omega_u \tag{1}$$

$$f(X_{i,t}, u_{i,t}) = \begin{bmatrix} x_t^i \\ y_t^i \\ \theta_t^i \end{bmatrix} + \begin{bmatrix} v_t^i/\omega_t^i \cos(\theta_t^i) + v_t^i/\omega_t^i \sin(\omega_t^i \delta t + \theta_t^i) \\ v_t^i/\omega_t^i \sin(\theta_t^i) - v_t^i/\omega_t^i \cos(\omega_t^i \delta t + \theta_t^i) \\ \omega_t^i \delta t \end{bmatrix} \tag{2}$$

where $X_{i,t} = [x_t^i, y_t^i, \theta_t^i]^T$ is the pose vector of robot i and $u_{i,t} = [v_t^i, \omega_t^i]$ is the control of the robot consist of linear and angular velocity. $\omega_u \sim N(0, \Sigma_u)$ is the zero-mean Gaussian control noise with covariance Σ_u.

At each time step, robot i may obtain observation $\{Z_{x_j,t}^i\}$ $(j \neq i)$ from peer robot j in limited range and field of view (FOV) and observations $\{Z_{F_k,t}^i\}$ from feature $F_k \in F$ with observation model:

$$Z_{x_j,t}^i = h_r(X_{i,t}, X_{j,t}) + \omega_r \tag{3}$$

$$h_r(X_{i,t}, X_{j,t}) = \begin{bmatrix} \cos(\theta_{i,t}) & -\sin(\theta_{i,t}) & 0 \\ \sin(\theta_{i,t}) & \cos(\theta_{i,t}) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{j,t} - x_{i,t} \\ y_{j,t} - y_{i,t} \\ \theta_{j,t} - \theta_{i,t} \end{bmatrix} \tag{4}$$

$$Z_{F_k,t}^i = h_f(X_{i,t}, F_{k,t}) + \omega_c \tag{5}$$

$$h_f(X_{i,t}, F_{k,t}) = \begin{bmatrix} \cos(\theta_{i,t}) & -\sin(\theta_{i,t}) \\ \sin(\theta_{i,t}) & \cos(\theta_{i,t}) \end{bmatrix} \begin{bmatrix} x_{f,i} - x_{i,t} \\ y_{f,i} - y_{i,t} \end{bmatrix} \tag{6}$$

in the local coordinate frame, where $\omega_r \sim N(0, \Sigma_r)$ and $\omega_c \sim N(0, \Sigma_c)$ are the zero-mean Gaussian observation noise for relative observations and feature observations.

In the centralized case, we assume that robots can maintain stable communication and therefore, each robot is able to obtain all the synchronized observations data and the wheel encoder data. Under this assumption, we consider the state of all n robots at time-step t as $S_t := [X_{1,t}, ..., X_{n,t}]$ $(t = 1 : m)$, the observed features as F, the transition function of the robots state can be denoted as $S_{t+1} = \mathbb{T}(S_t, U_t, \omega_u)$, where $\mathbb{T}$ is the combination of robots' motion model and the $U_t := [u_{1,t}, ..., u_{n,t}]$ is the union control of n robots at time step t.

Therefore, we can formulate the multi-robot exploration problem as a stochastic optimal control problem that maximize the utility $\mathbb{U}$ of the union action in time horizon T.

$$\underset{U_t}{\text{Max}} \sum_{\delta t=1}^{T} \mathbb{U}(S_{t+\delta t}, F|S_t, U_{t:t+\delta t-1}, \hat{Z}^S_{F,t+\delta t}, \hat{Z}^S_{X,t+\delta t})$$
$$\begin{aligned} s.t.\ S_{t+\delta t} &= \mathbb{T}(S_t, U_{t:t+\delta t-1}) \\ \hat{Z}^S_{F,t+\delta t} &= Q^F(S_{t+\delta t}, F) \\ \hat{Z}^S_{X,t+\delta t} &= Q^R(S_{t+\delta t}). \end{aligned} \tag{7}$$

where the $Q^F(S,F)$ is the combined observation function of features and $Q^R(S)$ is the combined relative observation function for the involved robot. $\hat{Z}^S_{F_k,t+\delta t}$ and $\hat{Z}^S_{X_j,t+\delta t}$ are the predicted observations of feature and robots after δ_t.

Mutual information (MI) [MacKay1992] is an evaluate metric of information gain that defined as the relative entropy between two joint distribution. The entropy [Shannon1948] is the measurement of uncertainty of a random variable x which is defined as $H(x) = \int p(x)log(p(x))dx$. For the Gaussian distribution $x \sim N(\mu_x, \Sigma_x)$, the entropy can be calculated with:

$$H(x) = 1/2(log(2\pi e) + log(det(\Sigma_x))). \tag{8}$$

Where e is the Euler's number. Since the aim of our active SLAM algorithm is to minimize the uncertainty of the feature and robot localization results, we can transform the Equation (7) to maximising the difference between prior and posterior entropy of the robot poses and feature positions after adopting the union action. Therefore, with MI $\mathbb{I}$ as the evaluation metric of the action utility, we have:

$$\mathbb{I} = H(S_t, F_t) - H(S_{t+\delta t}, F_{t+\delta t}|\hat{Z}_{t+\delta t}). \tag{9}$$

In our case, the $H(S_t, F_t)$ and the $H(S_{t+\delta t}, F_{t+\delta t}|\widehat{Z_{t+\delta t}})$ are the entropy of the robots joint state and the features before and after taking union action $U_{t:t+\delta t-1}$. Σ is the covariance matrix of robot state and features which can be calculated with SLAM method. Therefore, for our multi-robot exploration problem, the evaluation metric of the joint action U is:

$$\begin{aligned} &\sum_{\delta t=1}^{T} \mathbb{I}(S_{t+\delta t}, F|S_t, U_t, \hat{Z}^S_{F,t+\delta t}, \hat{Z}^S_{X,t+\delta t}) \\ &= H(S_t, F_t) - H(S_{t+\delta t}, F_{t+\delta t}) \\ &= log\ det(\Sigma^{S_t,F_t}) - log\ det(\Sigma^{S_{t+\delta t},F_{t+\delta t}}). \end{aligned} \tag{10}$$

Thus, our goal is to find the best union of action that can achieve maximum utility.

2.2 Method

Measurement prediction

Although $H(S_t, F_t)$ of the current state can be calculated with the covariance matrix of robot poses and features obtained with the weighted non-linear least squares (NLLS) method, such as Gauss-Newton method or Levenberg-Marquardt method, we cannot obtain the $H(S_{t+\delta t}, F_{t+\delta t})$ directly. In order to obtain predicted observations $\hat{Z}^S_{F,t+\delta t}$ and $\hat{Z}^S_{X,t+\delta t}$, we use the prior distribution of the landmarks to calculate the landmark observation and current distribution of robot positions for the relative observation.

In addition, unlike the lidar-based active SLAM methods [Kantaros *et al.*2019] [Kantaros and Pappas2021] that generate grid maps, we cannot guarantee that the MI is always positive. When the robot cannot obtain any observation of landmarks or other robots in the predicted position $S_{t+\delta t}$, the utility of current union action $U_{t:t+\delta t-1}$ would increase and result in negative utility. In the worst case, the utility of all available union actions could be negative and the control algorithm would degenerate to stochastic exploration.

To handle these situations, we introduce the virtual landmarks in the prediction step to ensure the positivity of union action utility and guide the robots for exploration as shown in Fig. 1.

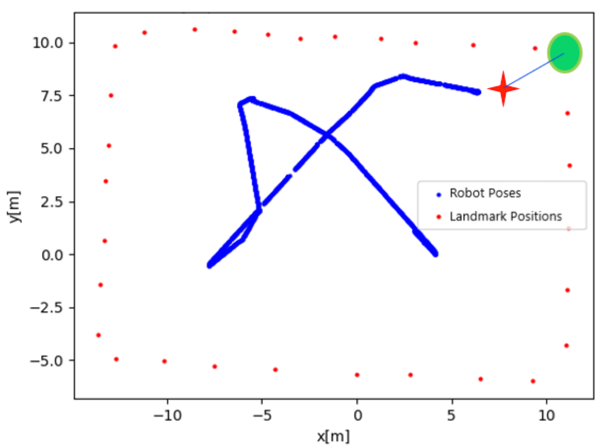


Figure 1: Illustration of the virtual landmark (represented by red star). The green circle indicates the unobserved landmark and the red dots represent the previously observed landmarks.

During the prediction process, to reduce the computational complexity, we directly sample the reachable position set $\mathbb{P}_i$ for each robot i according to the robot's motion model with its current position and velocity. Then, the predicted union position set can be calculated by Cartesian production of the reachable position sets. For systems involve two robots, $\mathbb{P}_U = \mathbb{P}_i \times \mathbb{P}_j$ where "$\times$" is the Cartesian production. For each $P^k_U \in \mathbb{P}_U$, we generate virtual landmarks on the line segment between the closest unobserved features for each robot i and its position. Then, we can calculate the predicted observation according to the observation model as well as the utility of these union positions.

Algorithm 1 Centralized Multi-robot Acitve SLAM

```
for Every time period t do
  Perform NLLS optimization to obtain SLAM result and calculate H(S, F).
  Calculate predicted union position set P_U = P_i × P_j
  for each P_U^k ∈ P_U do
    for each Robot_i ∈ P_U^k do
      Find the closest unobserved landmark F_l and generate virtual landmark V_l.
      Predict observation Ẑ^S_{F,t+δt}, Ẑ^S_{X,t+δt} for robots with P_U^k and V_l.
    end for
    Perform SLAM to obtain predicted estimation result S_{t+δt} and correspondence Σ^{S_{t+δt}}.
    Calculate the expected mutual information of P_U^k with Equation 10.
  end for
  Select the P_U^k with highest utility.
  Generate the motion control command for each robot with ORCA planner to arrive P_U^k.
end for
```

Motion controller

In this work, we adopt a hierarchical planner with two layers. The upper layer is a greedy planner that chooses the best union position P_U^* with the highest utility as temporary goal points for robots. Since the predicted union positions are calculated with the motion model, the actions that drive robots to these positions cannot guarantee collision-free property. The local motion controller, Optimal Reciprocal Collision Avoidance (ORCA) [Van Den Berg *et al.*2011] controller, is adopted as the lower layer of the hierarchical planner. After the selection of the best union positions, the local planner generates collision-free motion commands for each robot to reach these positions. The proposed centralized multi-robot active SLAM method is shown in Algorithm 1.

3 DECENTRALIZED MULTI-ROBOT ACTIVE SLAM

In order to reduce the communication bandwidth and improve the scalability of the multi-robot active SLAM system, we adopt the submap-joining scheme in [Zhao *et al.*2014] and develop a decentralized version of the proposed method.

3.1 Generating and Maintaining Submap

In the decentralized active SLAM case, each robot i maintains a local submap containing the poses of the current robot i at different time step ($\mathbf{P}^i = \{X_2^i, ..., X_t^i\}$), the poses of other observed robots $\mathbf{P}_r^i = \{X_{j,t_j}^i, ..., X_{s,t_s}^i\}$ observed at time step t, and the positions of the observed features $\mathbf{F}^i = \{F_1^i, ..., F_k^i, ...F_m^i\}$ in robot i local coordinate frame:

$$\mathbf{M}^i = \{\mathbf{P}^i, \mathbf{P}_r^i, \mathbf{F}^i\} \tag{11}$$

The optimal solution of the submap state $\hat{\mathbf{M}}_i$ and the corresponding information matrix I_{S^i} can be obtained by solving the NLLS problem with the objective function:

$$g(\mathbf{M}^i) = \left\| Z - H^M(\mathbf{M}^i) \right\|_{I_Z}^2 \tag{12}$$

where $Z = \{..., Z_{F_k,t}^i, ..., O_t^i, ..., Z_{X_j,t}^i, ...\}$ combines all the observations and odometry. The $H^M(\mathbf{M}^i)$ combines all the observation functions corresponding to Z and $I_Z = P_Z^{-1}$, where $P_Z = (..., P_{Z_{F_k,t}^i}, ..., P_{O_t^i}, ..., P_{Z_{X_j,t}^i}, ...)$ combines all the covariance matrices.

3.2 Multi-robot Submap Joining

When global map is needed, robots can communicate with each other to share the state vector together with the corresponding information matrix $\{\hat{\mathbf{M}}_i, I_{S^i}\}$, which reduce the communication bandwidth for message sharing.

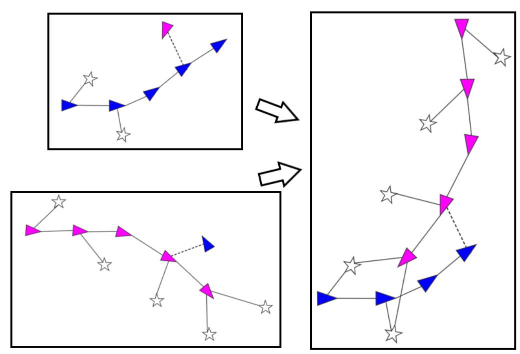


Figure 2: Illustration of the Submap-joining process of two local maps. The landmarks are represented by star. The blue and pink triangle represent robot 1 and robot 2 respectively.

Suppose the submap built from the robot i is denoted by $\{\hat{\mathbf{M}}_i, I_{M^i}\}$, $(i = 1 : n)$, in the map joining process, the state of the joined global map contains all the robots poses and the feature position in the first robot's coordinate frame:

$$\mathbf{G} = \{\mathbf{P}_1^G, ..., \mathbf{P}_n^G, \mathbf{F}^G\} \tag{13}$$

where $\mathbf{P}_1^G$ and $\mathbf{P}_i^G$ (for $i >= 2$) contain the poses of all the robots to be joined at all the timesteps and the $\mathbf{F}^G$ $(k = 1 : m)$ contains all the observed features.

Using $\{\hat{\mathbf{S}}_i, I_{S^i}\}$ as an integrated observation, submap-joining process for multiple robots can also be formulated as a nonlinear optimization problem which minimizing the objective function:

$$g(\mathbf{G}) = \sum_{i=1}^{n} \left\| \mathbf{M}^i - H^{M_i}(\mathbf{G}) \right\|_{I_i}^2 . \tag{14}$$

Where $H^{M_i}(\mathbf{G})$ is a combination of transformation functions $\{..., H^{F_k^i}(\mathbf{G}), ..., H^{X_t^i}(\mathbf{G}), ..., H^{X_{j,t_j}^i}(\mathbf{G}), ...\}$ corresponding to the state of each submap that transform from global coordinate to corresponding submap coordinate frame. Then, the optimal solution of the global map together with the corresponding information matrix $\{\hat{\mathbf{G}}, I_G\}$ can also be obtained using the Gauss–Newton iteration method.

3.3 Motion planner

Algorithm 2 Decentralized Multi-robot Active SLAM

for Every time period t **do**
  for each $Robot_i$ **do**
    Share submaps $\{(\hat{\mathbf{M}}^i,\ I_{M^i})\}$ and observed features F^i with other robots.
    Perform submap-joining to construct a global map $\hat{G}^i$ in $Robot_i$'s coordinate frame.
    Sample reachable position set $\mathbb{P}_i$.
    for each $p_i \in \mathbb{P}_i$ **do**
      Find the closest unobserved landmark F_l that is not selected by other robots.
      Generate virtual landmark V_l and share F_l with other robots.
      Predict observation $\hat{Z}^{G_i}_{F,t+\delta t}, \hat{Z}^{G_i}_{X,t+\delta t}$ for $Robot_i$ with p_i and V_l.
    end for
    Perform SLAM to obtain predicted estimation result $G_{t+\delta t}$ and correspondence $\Sigma^{G_{t+\delta t}}$.
    Calculate the expected mutual information of p_i with equation 10.
  end for
  Select the p_i with highest utility.
  Generate the motion control command for each robot with ORCA planner to arrive p_i.
end for

In the decentralized multi-robot active SLAM scenario, we use a planner similar to the one in the centralized case. As shown in Algorithm 2, for each decision time period, robots share their local submaps and perform submap-joining to construct a global map. Then robots perform measurements prediction and select the candidate position with the highest utility as the goal point. We also use the ORCA planner for each robot to generate collision-free actions to achieve the goal point.

4 SIMULATIONS AND EXPERIMENTS

4.1 Simulation Setup

To verify the performance of the proposed method we conduct two simulation scenarios in MATLAB and one simulation in the Gazebo simulator as shown in Fig. 3 and Fig. 4. In the first MATLAB simulation scenario, robots move in an environment that is surrounded by features. In the second scenario, features are located at both the boundary of the environment and inside the environment. In both simulations, we use two robots that move following the differential kinematic model and assume robots are able to observe features and other robots within a certain range (10m) within FOV (120 degrees) with the observation model. Since the compared method in experiment 2 directly evaluates the utility of the candidate actions instead of sampling goal points for robots, we adopt the same action sampling scheme for the proposed method in MATLAB simulation for better comparison.

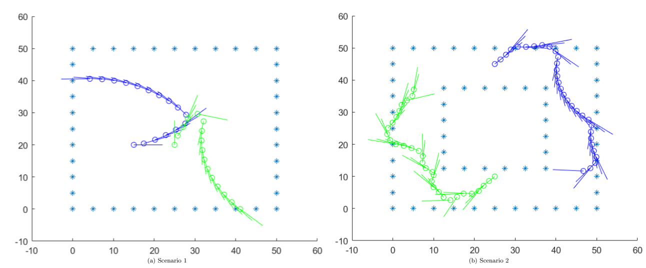


Figure 3: Illustration of the two simulation scenario (Left: Scenario 1; Right: Scenario 2) in MATLAB. In both figures, the "*" represent the features in the environment, and the blue and the green circles represent the Robots 1 and Robot 2 whose poses are illustrated with bar.

In the Gazebo simulator, we also use two robots for multi-robot active SLAM. Robots equipped with kinect RGB-D sensor and differential wheel chassis navigate in the environment with Apriltags [Wang and Olson2016] on the wall. The tags within 4m and in the field-of-view of 90 degrees can be detected at each time step. For each decision period, robots sample 6 positions based on their current pose, velocity, and motion model. Then, ORCA motion controller is used as the lower layer of the hierarchical motion planner to generate control commands.

4.2 Comparative experiments

To verify the performance of the proposed method in an environment with different feature distributions, we test the proposed method in scenario 1 and scenario 2 (experiment 1). We also compare the average steps for coverage and the root mean square error (RMSE) of

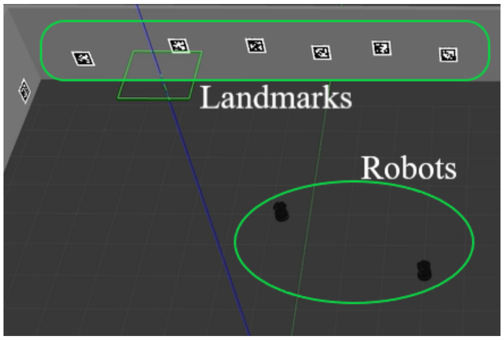


Figure 4: Illustration of the simulation scenario in Gazebo. The robots move on the floor and obtain observation data of landmarks (Apriltags [Wang and Olson2016]) on the surrounded wall with Kinect RGB-D sensor.

the robot state of our multi-robot active SLAM method with the method in related work [Atanasov *et al.*2015] that use both occupancy grid map and feature map for active SLAM in MATLAB scenario 1 (experiment 2). For the MATLAB simulation experiments, the configurations of parameters used are the same as work [Atanasov *et al.*2015] and shown in TABLE 1.

Table 1: PARAMETER SETTINGS FOR MATLAB SIMULATION

Term	Value	Term	Value
Robot Radius	0.25m	Sensing range	10.0m
V_{max}	3m/s	ω_{max}	$\pi/2$
V_{min}	1m/s	ω_{min}	0
Action Samples	10	Environment size	50m*50m

Table 2: PARAMETER SETTINGS FOR GAZEBO SIMULATION

Term	Value	Term	Value
Robot Radius	0.5m	Sensing range	4.0m
V_{max}	2m/s	ω_{max}	$\pi/2$
V_{min}	0m/s	ω_{min}	0
Goal Samples	6	Environment size	25m*17m

In the Gazebo simulator, we compare the proposed method with the single robot active SLAM that utilizes MI as evaluation metric and the multi-robot SLAM with two robots following a predefined circle path (experiment 3). In experiment 3, two robots move on a circle with an ever-increasing diameter to obtain sufficient landmark observations as well as relative observations. For the Gazebo simulation experiments, the configurations of parameters used are shown in TABLE 2.

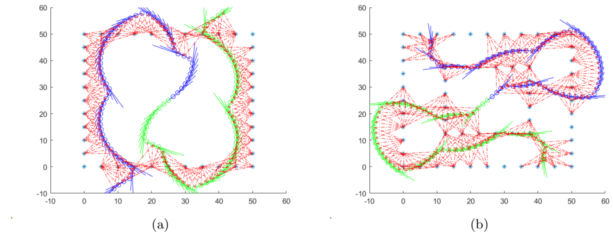


Figure 5: Two MATLAB simulation experiments. The red lines represent the observations of features.

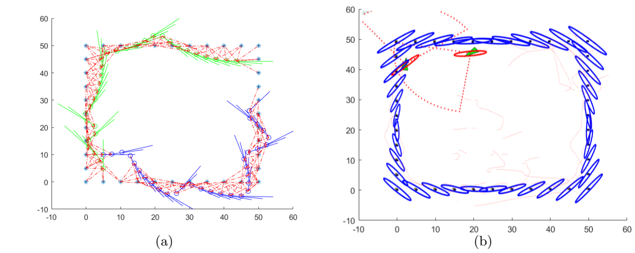


Figure 6: The feature map and robot trajectory generated by the proposed method (a) and the related work [Atanasov *et al.*2015] (b). The red lines represent the observations of features.

4.3 Simulation Results

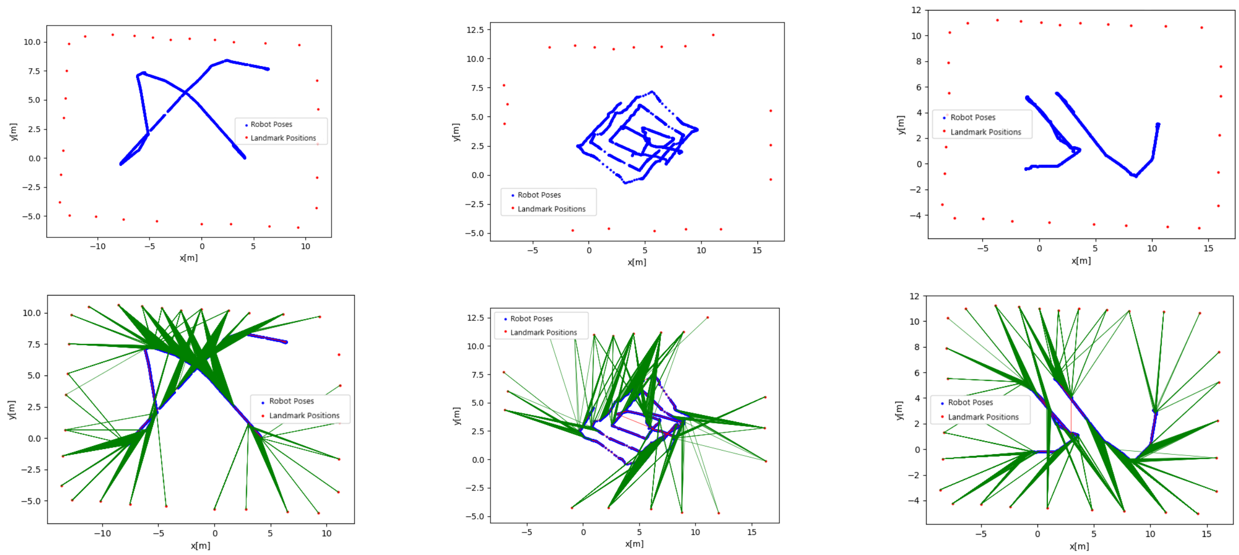
The simulation results (Fig. 5) of experiment 1 show that our proposed method can handle environments with different feature distributions and achieve good coverage as well as SLAM accuracy.

Table 3: RESULTS IN SIMULATION 2

Method	Average steps for coverage	RMSE of State
Related work [Atanasov *et al.*2015]	463	0.23m
Centralized multi-robot active SLAM	75	0.11m
Decentralized multi-robot active SLAM	81	0.14m

The comparison between the proposed method and the method in [Atanasov *et al.*2015] is shown in Fig. 6 and TABLE 3. The method in [Atanasov *et al.*2015] takes 463 steps to finish the exploration while the proposed method only takes 75 steps in the centralized version and 81 steps in the decentralized version. The proposed method also has a smaller RMSE compared to the method in [Atanasov *et al.*2015]. Therefore, our proposed method has higher accuracy and better coverage speed.

The Gazebo simulation results are shown in Fig. 7 and TABLE 4. For the single robot active SLAM, it takes 2080 steps to finish the exploration (Fig. 7 (a)) while the proposed method takes only 816 and 940 steps per robot (Fig. 7 (c)) in centralized and decentralized scheme respectively. As shown in Fig. 7 (b), although follow-



(a) (b) (c)

Figure 7: The simulation results in Gazebo environment with one robot performing active SLAM (a), two robots following predefined path (b) and two robots performing active SLAM with proposed method (c). The blue dots represent the robot positions, the red dots represent the landmark positions and the green lines demonstrate the robot observations of landmarks.

Table 4: RESULTS IN SIMULATION 3

Method	Average steps for coverage	RMSE of State
Single robot active SLAM	2080	0.075m
SLAM with predefined path	over 3500	0.059m
Centralized multi-robot active SLAM	816	0.021m
Decentralized multi-robot active SLAM	940	0.043m

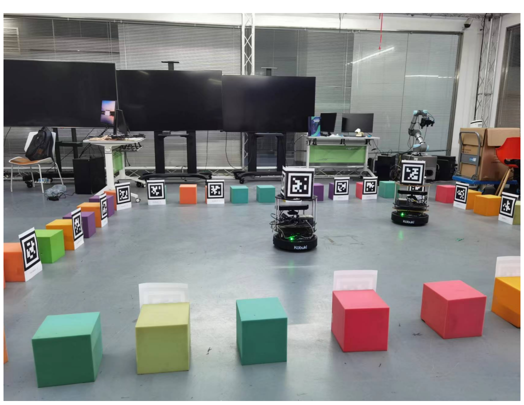


Figure 8: Illustration of the experimental scenario, the tags in the environment act as the features, and the robots need to observe all the features during the active SLAM process. The tags on the robots are used to obtain relative observations.

ing predefined goal points can guarantee more landmark observations and relative observations, the multi-robot SLAM done in this scheme cannot cover all the features until it exceeds the step limit (3500 steps). The comparisons of RMSE show that our proposed method can obtain better SLAM results than the single robot active SLAM method and the decentralized method have similar accuracy compared to the centralized method.

The results show that our proposed method can not only improve the coverage speed but also the accuracy of the SLAM results than the single-robot active SLAM method and the multi-robot SLAM methods with predefined paths.

4.4 Real World Experiment

In this section, we present the real world experiments with two Turtlbot2 ground robot and 21 Apriltag landmarks in a $5.2 \times 4.8\ m^2$ environment as shown in Fig. 8. During the active SLAM task, robots tagged with Apriltags can obtain landmark observations and relative observations with Kinect V1 RGB-D sensor and odometry data from wheel encoder. The robot communication and data synchronization are performed using ROS operation system [Stanford Artificial Intelligence Laboratory et al.] with message filter. To verify the performance of the proposed method, we adopt the motion capture system to obtain ground truth positions of robots and features.

The trajectories of the robots and the positions of the observed landmark in the experiment are shown in Fig.

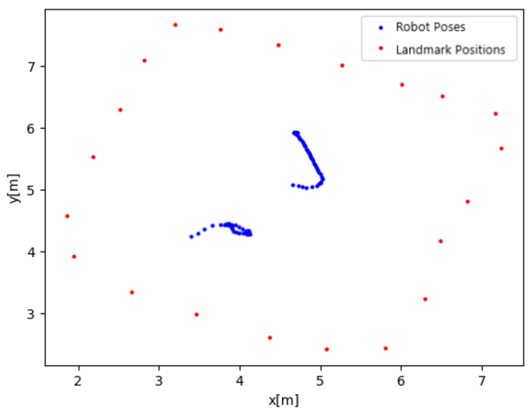


Figure 9: The real world experiment results in environment shown in Fig. 8. The blue dots and the red dots represent the robot positions and the landmark position respectively.

9. The robots finish the active SLAM task in 137 steps with RMSE of 0.146 m for the robot positions and 0.098 m for landmark positions. The result shows that our proposed method is also capable of handling real-world environment with noisy sensor data.

5 CONCLUSION

In this work, we present a multi-robot active SLAM method together with the method for calculating the utility of robots' actions for feature map representation. A decentralized version of the multi-robot active SLAM that adopts a submap-joining scheme is also proposed to improve the scalability and reduce the communication bandwidth. MATLAB and Gazebo simulations show that our approach can achieve better performance in coverage speed and at the same time maintain good SLAM estimation results.

However, the current approach did not consider the relative measurement between robots in the evaluation of action utility. Besides, joining the submaps in each decision-making process may not be the best solution. In future work, we will take the differential entropy of the common feature in different submaps into consideration to decide when to visit the commonly observed features and when to merge the submaps.

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