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在多機器人同時定位與移動物體追蹤中的適應式估測與量測分享

Adapting Measurement and Belief Sharing in Multi-Robot Simultaneous Localization and Tracking

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本論文係張鈞凱君（學號 R02922039）在國立臺灣大學資訊工程學系完成之碩士學位論文，於民國 103 年 12 月 24 日承下列考試委員審查通過及口試及格，特此證明

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中文摘要

目前的多機器人合作感知的方法，根據機器人間分享資訊的方式，主要可以分為兩類：基於量測分享的合作感知與基於估測分享的合作感知。當通訊品質良好的時候，基於量測分享的方法可以達到理論上最佳的結果，然而基於估測分享的方法則不行。但是基於估測分享的方法在通訊不穩定的情況下，因為一組估測結果已經包含了多筆量測資料，所以相對來說表現比較穩定。啟發於量測分享與估測分享在不同情況下各有優劣，在本論文中，我們提出了適應式量測與估測分享的方法來考慮不同的通訊與感知情況，來整合量測分享與估測分享兩者的優勢，用以達到更好的效能與結果，並且處理通訊不穩定時所帶來的問題。然而要如何決定資訊分享的方式，是一種多機器人部分可觀察馬可夫決策過程的問題。我們藉由最大化地降低預期的不確定性，來決定要分享的量測資料或是估測資訊，透過有效通訊的期望值以及對於未來量測結果的預估，適應式量測與估測分享方法在複雜度上所面臨的問題可以被有效的處理，來即時地處理通訊上所遇到的問題。此外，我們也透過模擬實驗與真實數據實驗，來驗證所提出的適應式方法，透過模擬不同通訊情況以及資料映射的情境，可以發現我們提出的適應式量測與估測分享方法可以達到比只進行量測分享或只進行估測分享的演算法準確的結果。

關鍵字：通訊、多機器人、定位、追蹤、合作感知、部分可觀察馬可夫決策過程

ADAPTING MEASUREMENT AND BELIEF SHARING IN MULTI-ROBOT SIMULTANEOUS LOCALIZATION AND TRACKING

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ABSTRACT

EXISTING multi-robot cooperative perception solutions can be mainly classified into two categories, *measurement-based* and *belief-based*, according to the information shared among robots. With well-controlled communication, measurement-based approaches are expected to achieve theoretically optimal estimates while belief-based approaches are not. Nevertheless, belief-based approaches perform relatively stable under unstable communication as a belief contains the information of multiple previous measurements. Motivated by the observation that measurement sharing and belief sharing are respectively superior in different conditions, in this thesis an adapting algorithm, communication adaptive multi-robot simultaneous localization and tracking (ComAd MR-SLAT), is proposed to combine the advantages of both to tackle the unstable communication conditions. However, the decision process of what kind of information to share is only based on a probability distribution of states, which is estimated according to a set of observations and observation probabilities. Therefore, it could be seen as a multi-robot partially observable Markov decision process (POMDP) problem. The information to share is decided by maximizing the expected uncertainty reduction, based on which the algorithm dynamically alternates between measurement-sharing and belief-sharing without information loss or reuse. With using the expected effective communication and information receiving, the proposed ComAd MR-SLAT can tackle the complexity issue and online decide the sharing strategy to adapt different communication conditions. The proposed ComAd MR-SLAT is evaluated in communication conditions with different packet loss rates, bursty loss lengths, and data association conditions. The proposed ComAd MR-SLAT outperforms both measurement-based and belief-based MR-SLAT in both localization and data association accuracy. In addition, the real data are also collected and evaluated, the experimental results demonstrate the effectiveness of the proposed adapting algorithm and exhibit that the ComAd MR-SLAT is robust in the simulation and real data experiment.

Keywords: Communication, multi-robot, localization, tracking, cooperative, POMDP

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CHAPTER 1

Introduction

LOCALIZATION is one of the most essential capabilities for autonomous robots (Cox and Wilfong, 1990). In single-robot localization, the pose of the robot w.r.t. a given map can be estimated in a probabilistic manner by properly modeling the uncertainty of motion commands and measurements (Leonard and Durrant-Whyte, 1991)(Fox et al., 1999). With the ability to detect other robots, multi-robot cooperative localization has been proved to effectively outperform single-robot localization by incorporating relative measurements between a troop of robots (Fox et al., 2000)(Roumeliotis and Bekey, 2002)(Howard et al., 2002). Moreover, in our previous work, it has also been demonstrated that multi-robot simultaneous localization and tracking (MR-SLAT) can further improve the performance by exploiting the relative measurements between robots and moving objects in dynamic scenes (Wang et al., 2007)(Chang et al., 2011).

Existing multi-robot cooperative perception solutions can be mainly classified into two categories, *measurement-based* and *belief-based*, according to the information shared among the teammate robots. In the measurement-based approaches (Fox et al., 2000)(Howard et al., 2002)(Chang et al., 2011), the control data and measurements are shared. On the other hand, the belief-based approaches (Bar-Shalom and Li, 1995) (Roumeliotis and Bekey, 2002)(Thrun and Liu, 2005)(Nerurkar et al., 2009)(Aeberhard et al., 2012)(Govaers and Koch, 2012)(Cunningham et al., 2013), each robot firstly fuses its own control data and measurements into a local belief. Then the local beliefs are shared to the teammate robots, and the global state is inferred by merging the local beliefs.

However, with wireless communication, the packet loss is still a fundamental issue which may critically degrade the performance of multi-robot cooperation. There had discussed that it would have two types packet loss, independent packet loss and bursty packet loss (Yajnik et al., 1996). With the independent packet loss condition, packages get loss independently. Therefore, the duplicated transmission can effectively deal with the issue by receiving the lost information from following packages. In contrast, the bursty packet loss means that packages get loss continuously. Therefore, the problem caused by bursty packet loss cannot be tackled by duplicated transmission because of following packages are also lost.

By comparison with belief-based approaches, with well-controlled communication, in which the packet loss rate is low and there are merely consecutive packets lost, measurement-based approaches are expected to receive all control data and measurements from the other robots, and the global state is inferred in a centralized manner to achieve theoretically optimal estimation. Nevertheless, belief-based approach cannot achieve theoretically optimal estimation because the cross-correlations between beliefs are hard to be perfect estimated. On the other hand, with unstable communication, in which packets get lost continuously, measurement-based approaches would be critically degraded. However, belief-based approaches would be more stable than measurement-based approaches because one belief already contains several measurements.

This thesis is motivated by the different characteristics of the measurement-based and belief-based approaches against different communication conditions. Fig. 1.1 shows the performance of measurement-based and belief-based MR-SLAT under different packet loss rates. It can be observed that when the packet loss rate is low, the measurement-based approach outperforms the belief-based one. The main reasons are: (1) With perfect communication, centralized measurement-based approaches are expected to achieve theoretically optimal estimates while distributed belief-based approaches are not as the cross-correlations between local beliefs are hard to be perfectly estimated in practice (Chen et al., 2003). (2) Sharing beliefs generally requires more communication bandwidth, so under the same communication load, the measurement loss rate can be lowered by simple communication strategies such as duplicated transmission. In contrast, the advantage of belief-based MR-SLAT arises from the fact that a single belief contains the information equivalent to multiple measurements. While the performance of measurement-based MR-SLAT gets

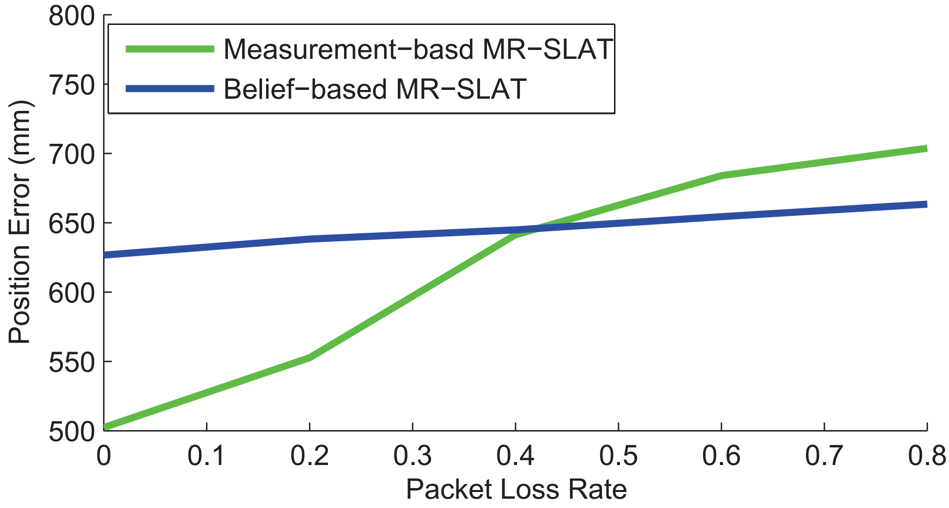


Figure 1.1. Comparison on the localization errors of measurement-based MR-SLAT and belief-based MR-SLAT under different packet loss rates.

worse when the packet loss rate gets higher, the performance of belief-based one performs relatively stable against packet loss as the information brought by the past measurements has been encoded in the latest local beliefs.

Aiming at tackling practical scenes with unstable communication conditions, in this thesis we propose communication adaptive MR-SLAT (ComAd MR-SLAT), an online adapting algorithm combining the advantages of both measurement-sharing and belief-sharing by explicitly taking the communication condition into account. However, the sharing type decision process should be determined with only the probability distribution of multiple robot poses and the communication conditions between robots. Without perfect state information, multi-robot partially observable Markov decision process (multi-robot POMDP) is introduced to model the decision process. Nevertheless, the exact performance improvement in accuracy cannot be determined without the actual measurements are fetched and the packages are received. Therefore, the uncertainty reduction of the estimation is proposed to tackle the issue, as the estimation results with the smaller uncertainty are statistically expected to be more accurate. However, the complexity of the multi-robot POMDP problem is exponentially increased according to the communication conditions and the states of the MR-SLAT problem as the traditional approach should consider all possible reward for every possible states. Therefore, to determine the sharing mode, the expected approach is proposed to use the expected communication conditions and measurement receiving to calculate the reward and guide the multi-robot POMDP problem. The simulation approach is proposed to indicate the reward of uncertainty reduction for measurement-sharing, and the geometric distribution between communication conditions and uncertainty reduction is proposed to calculate the reward of belief-sharing. With the proposed expected approach, we can guide the POMDP problem, and the communication condition can be taken into account to adapt different situations.

The proposed ComAd MR-SLAT algorithm is evaluated under different communication and data association conditions in a multi-robot setting. Following the motion models and sensor models used in practical RoboCup scenes, various packet loss rates and bursty loss lengths (Yajnik et al., 1996) are simulated to verify the effectiveness of ComAd MR-SLAT. Note that not only packet loss rates but also burtsy loss lengths can influence the performance. In addition, the practical approach to do data association without information reuse or loss in the adapting scheme are also discussed. Accordingly, the factor is analyzed in the experiments. Moreover, the real experimental scenario is also evaluated to verify the practicability of the proposed ComAd MR-SLAT algorithm. The experimental results demonstrate that the proposed adapting solution outperforms both measurement-based and belief-based MR-SLAT in localization accuracy under different communication conditions, the ComAd MR-SLAT is more robust against unstable communication situations.

In our previous work (Chang et al., 2014), the concept for adapting measurement and belief sharing was adopted and verified only for given correct data association in simulation. In this thesis the multi-robot POMDP framework is introduced to model the problem theoretically. With integrating the communication condition and the states of the MR-SLAT problem, the complexity issue of the sharing mode determination is addressed. Moreover, the algorithm for generating correspondence of observations is also proposed and the derivation of the modelling between communication and localization uncertainty is conferred. Therefore, the ComAd MR-SLAT is able to tackle the communication issues by taking the communication into account. Accordingly, with the data association algorithm, the effectiveness of the proposed ComAd MR-SLAT is demonstrated in real data experiment.

CHAPTER 2

Related Work

In multi-robot cooperative perception, measurement-based algorithms have been proposed such as the particle filter (PF) based approach (Fox et al., 2000), the maximum likelihood estimation (MLE) based approach (Howard et al., 2002), and the extended Kalman filter (EKF) based approach (Chang et al., 2011). In these approaches, measurements, e.g. map feature detection and robot detection, are shared to the other robots, and then the global state is inferred in a centralized manner. Regarding communication considerations, the communication condition is not discussed in (Fox et al., 2000)(Howard et al., 2002) and is assumed well-controlled in (Chang et al., 2011).

On the other hand, various belief-based approaches have also been proposed based on different techniques, such as distributed EKF (Roumeliotis and Bekey, 2002), distributed Sparse Extended Information Filters (SEIF) (Thrun and Liu, 2005), distributed maximum a posteriori (MAP) (Nerurkar et al., 2009), track-to-track fusion (Bar-Shalom and Li, 1995)(Aeberhard et al., 2012)(Govaers and Koch, 2012) and distributed smoothing and mapping (SAM) (Cunningham et al., 2013). In these approaches, the measurements are first locally fused into beliefs in a decentralized manner. Then the beliefs are shared to the other robots and the global state is inferred by merging the local beliefs. Comparing to measurement-based approaches, one of the advantages of the belief-based approaches is that the computation can be distributed to multiple robots.

The comparison of measurement-based approaches and belief-based approaches has been discussed as follows: With well-controlled communication, the centralized measurement-based approaches are expected to achieve better performance than the decentralized ones as it is generally hard to accurately estimate the correlations between tracks of the same entity estimated by different robots in decentralized approaches (Chen et al., 2003). Though in (Govaers and Koch, 2012), an exact solution is proposed to decorrelate the cross correlations between tracks and is proved to be optimal based on Kalman filter (KF) assumptions. However, the correlation estimation is still approximate in practical non-linear applications. In contrast, regarding unstable communication conditions in practice, it has also been argued that the decentralized belief-based approaches have a higher tolerance to individual node failures due to the communication issues (Rabbat and Nowak, 2004).

Motivated by the different advantages of measurement-based and belief-based approaches, the idea is to switch the sharing strategy between measurement sharing and belief sharing according to the environment and communication conditions. However, the sharing decision should be made with only the probability distribution of the environment because the environment cannot be perfectly observed. Therefore, the proposed adapting algorithm could be treated as solving a partially observable Markov decision process (POMDP) problem in multi-robot scenario. For dealing with multi-robot scenario, the Decentralized POMDP (Dec-POMDP) model allows for fully decentralized execution (Bernstein et al., 2002), while the multi-agent POMDP (MPOMDP) takes a centralized approach (Pynadath, 2002). Inspired by a realistic sensor network coordination problem, the Networked Distributed POMDPs (ND-POMDPs) (Nair et al., 2005) is proposed to exploit local interactions in sensor networks. However, the number of states in a multi-robot POMDP scales exponentially which quickly leads to intractability even with state-of-the-art solvers (Hollinger and Singh, 2010). For dealing with the complexity, various approximate approaches are proposed in specific tasks such as (Nair et al., 2003)(Capitan et al., 2013), but the issues of communication between robots are not addressed. There also various approaches are proposed to consider the cost of communication such as (Xuan et al., 2001)(Nair et al., 2003)(Goldman and Zilberstein, 2003). However, although these algorithms consider the cost of communication, packet loss, which is a fundamental issue of wireless communication, is not addressed.

In addition, although some approximate algorithms are able to successfully handle the state spaces without the consideration of packet loss, the state spaces would be increased exponentially according to the consideration of communication and the MR-SLAT problem. Therefore, POMDPs ultimately face a complexity issue according to the large state spaces. Moreover, with unstable communication, which the conditions may change dramatically, the sharing mode decision should be made online to adapt different situations immediately. With modelling the problem as to maximize the uncertainty reduction, the expected approach is proposed to tackle the complexity issue by using the expected effective communication and predicted measurement receiving. With modelling the problem properly, the proposed adapting approach can adapt different communication conditions by online determining the information to share.

CHAPTER 3

Multi-Robot Simultaneous Localization and Tracking

IN this section, the theoretical foundations of multi-robot simultaneous localization and tracking (MR-SLAT) is introduced, and measurement-based MR-SLAT and belief-based MR-SLAT are described.

3.1. Augmented-State Representation

In MR-SLAT, the states of multiple robots and nearby moving objects are estimated simultaneously through the augmented state X_t:

$$X_t = \begin{bmatrix} (R_t^1)^T & \dots & (R_t^N)^T & (O_t^1)^T & \dots & (O_t^M)^T \end{bmatrix}^T \tag{3.1}$$

where t denotes the time index, N denotes the number of robots, M denotes the number of moving objects, $R_t^i = \begin{bmatrix} x_t^i & y_t^i & \theta_t^i \end{bmatrix}^T$ is the pose of the i^{th} robot at time t, and $O_t^j = \begin{bmatrix} x_t^j & y_t^j & vx_t^j & vy_t^j \end{bmatrix}^T$ contains the position and velocity of the j^{th} moving object at time t. In this thesis, we refer the *robots* to the entities that can communicate and share information with the others, and the *moving objects* to those that are not in the communication network.

3.2. Measurement-based MR-SLAT

In (Chang et al., 2011), following the theoretical framework of SLAMMOT (Wang et al., 2007) the extended Kalman filter (EKF) is used to integrate the uncertain data fetched from the robots, in which the covariance matrix maintains all of the pairwise correlations between the robots and moving objects. Regarding motion prediction, the odometry motion model is used for teammate robots in the communication network while the constant velocity (CV) model is used for the moving objects as the control data is not available. Regarding the measurement update, three types of measurements are aggregated: (1) relative information between the robot and the map (robot-to-map), (2) relative information between two teammate robots (robot-to-robot), and (3) relative information between the robot and the moving object (robot-to-moving-object).

In measurement-based MR-SLAT, the received odometry data and measurements are shared to the teammates at each time step. Accordingly, with well-controlled communication, at time t each robot is expected to receive all odometry data and measurements from all the other teammate robots. The global state, $Bel_{1:t}$, is inferred through the standard EKF procedure recursively in a centralized manner:

$$Bel_{1:t} \sim Pr(X_t | U^i_{1:t}, Z^i_{1:t}, \forall i = 1...N) \tag{3.2}$$

where $U^i_{1:t}$ denotes the control data of the i^{th} robot from time 1 to time t and $Z^i_{1:t}$ the measurements. In this thesis, we denote the suffix of the belief to indicate the time period during which the information has been fused into the belief.

3.3. Belief-based MR-SLAT

In belief-based MR-SLAT, for each robot its own odometry data and measurements are firstly fused into a local belief following the same procedure as described in the measurement-based approach. The local belief, $Bel^i_{1:t}$, contains the states of the i^{th} robot itself and nearby moving objects at time t:

$$Bel^i_{1:t} \sim Pr(X^i_t | U^i_{1:t}, Z^i_{1:t}) \tag{3.3}$$

Instead of sharing measurements, in belief-based MR-SLAT each robot shares beliefs to teammate robots, and then the global state is inferred by merging self and received beliefs:

$$Bel_{1:t} \sim BM(Bel^1_{1:t}, Bel^2_{1:t}, ..., Bel^N_{1:t}) \tag{3.4}$$

where $BM(\cdot)$ denotes the belief merging operator that can be realized through any existing track-to-track fusion algorithm (Matzka and Altendorfer, 2008).

In the track-to-track fusion literature, the merged global belief can be fully-fed back, semi-fed back, or none-fed back. In our implementation the none-feedback scheme is applied in order to avoid the information reuse problem following the arguments in (Tian and Bar-Shalom, 2008): If the merged global belief $Bel_{1:t}$, which has already contained the information of $Bel^i_{1:t}$, is fed back or replaces the local belief of the i^{th} robot, then at the next time to merge local beliefs, the information in $Bel^i_{1:t}$ would be reused. On the other hand, in our implementation, we exploit the merged global state to improve the data association in local beliefs, which will be detailed in Section 4.2.

3.4. Communication Considerations in Practice

In this section, the foundations of two types packet loss are introduced, and the communication consideration for both measurement-based MR-SLAT and belief-based MR-SLAT are described. In addition, with the different superiors of measurement-based MR-SLAT and belief-based MR-SLAT, the necessity of adaptive sharing is described.

3.4.1. Communication Conditions

A critical issue for such multi-robot applications is the manner in which packet losses occur within the multicast network. With unstable communication, packet loss, which is the fundamental issue of wireless communication. The packet loss conditions can be roughly classified into two categories, independent packet loss and bursty packet loss according to the behavior of packet loss conditions.

With independent packet loss condition, which means that packages get lost independently, the information loss could be reduced effectively by using the duplicated transmission strategy as the information of the lost package could be received by following packages. In other words, with duplicate transmissions, robot sends a package containing not only current measurements but also previous measurements for several frames, and then the information loss rate could be exponentially decreased because the information could be received by following packages. However, with bursty packet loss, which means that packages get lost consecutively, the duplicated transmission strategy would not work well as the lost package is more likely followed by lost package. Namely, even if each package contains the information of sequential measurements, the information still gets lost after consecutive packet loss.

With the model of packet loss conditions, the measurement-sharing loss rate and the belief-sharing loss rate are introduced to represent the communication conditions. In general, the communication load of the measurement-based MR-SLAT is lower than belief-based MR-SLAT as the belief-based MR-SLAT should share the information contains the covariance to integrate previous measurements. For instance, in our application the bandwidth required by belief-based MR-SLAT is 6 times of that by measurement-based MR-SLAT in the case with 5 robots and 5 moving objects. Therefore, under the same communication load, the loss rate of sharing measurements can be lowered by duplicated transmission. Therefore, L_m, measurement-sharing loss rate, which is defined as the rate of unreceived measurements, would be equal to or less than the packet loss rate by using duplicated transmission strategy. On the other hand, L_b, belief-sharing loss rate is equal to the packet loss rate as the duplicated transmission strategy is not applied to belief-based MR-SLAT.

3.4.2. Communication Considerations for Measurement-based and Belief-based MR-SLAT

In theory, measurement-based MR-SLAT and belief-based MR-SLAT are expected to achieve similar performance in accuracy with well-controlled communication as the same amount of information is utilized. Nevertheless, in practice it can be observed that when the packet loss rate is low, the measurement-based approach outperforms the belief-based one as shown in Fig. 1.1. The first reason is that the communication bandwidth requirements for belief-sharing and measurement-sharing could be different and in general, belief-sharing requires more. Two other reasons making the measurement-based MR-SLAT better under well-controlled communication conditions are: (1) When merging two beliefs, it is hard to perfectly estimate the cross-covariance between two beliefs (Chen et al., 2003)(Matzka and Altendorfer, 2008), and (2) Measurement-based MR-SLAT maintains only one global state whose uncertainty is generally less than the local beliefs maintained in belief-based MR-SLAT, so Gaussian approximation and linearization are better in the measurement-based MR-SLAT.

In contrast, the advantage of belief-based MR-SLAT arises from the fact that a single belief contains the information equivalent to multiple measurements. For measurement-based MR-SLAT, once a measurement is lost, the information brought by it is permanently lost. As can be seen in Fig. 1.1, the performance of measurement-based MR-SLAT gets worse when the packet loss rate gets higher while the performance of belief-based MR-SLAT is relatively stable against packet loss as by definition, the information brought by the past measurements has been encoded in the latest local beliefs.

Motivated by these observations, the communication adaptive MR-SLAT (ComAd MR-SLAT) algorithm is proposed aiming at combining the advantages of measurement-based MR-SLAT and belief-based MR-SLAT. By explicitly taking the communication condition into account, the information to share is determined dynamically online.

CHAPTER 4

Adaptive MR-SLAT

To determine the sharing mode, the decision process is a multi-robot partially observable Markov decision process (POMDP) problem. Because robot can only partially observe the environment with the noise according to some physical or practical limitations, the estimator cannot have the perfect information of the environment. With only the probability distribution of multiple robot poses and the communication conditions between robots and uncertain results after the information shared, therefore, the decision process is a multi-robot POMDP problem.

To take the consideration of communication into account to determine the sharing mode dynamically, the notation introduced in (Bernstein et al., 2002) is used to formulate the problem, which defines a DEC-POMDP as a tuple $\langle \alpha, \beta, S, \{A^i\}, P, R, \{\Omega^i\}, O \rangle$ where α is the number of robots, β is the number of moving objects, S is the set of world state including poses and motions for all robots, moving objects, and the communication condition between every robot pairs:

$$S = R^{\alpha} \times O^{\beta} \times \phi^{\alpha^2} \tag{4.1}$$

where:

- R^{α} denotes the state space of all possible poses and velocity for all robots
- O^{β} denotes the state space of all possible positions and velocity for all moving objects
- ϕ^{α^2} denotes all communication conditions between robots

Note that both the MR-SLAT problem and the communication conditions should be integrated into the state space to consider take the communication conditions into account. A^i, which denotes the possible action set of the team, is different from the other POMDP problem, where each joint action, A^i, is composed of α individual sharing measurements or sharing beliefs:

$$\{A^i\} = \{A^1, A^2, ..., A^\alpha\} \tag{4.2}$$

where:

- A^i represents the possible action set for i^{th} robot including sharing measurements and sharing beliefs.

With the team action set $\{A^i\}$, P indicates a transition probability table according to the states and the sharing actions. $P(s, \{a^i\}, s')$ is the probability of transitioning from s to s' on taking actions $\{a^i\}$. Here $s, s' \in S$, $\{a^i\}$ represents the set of actions that each individual robot is sharing measurements or sharing beliefs. R is a reward function. $R(s, \{a^i\}, s')$ represents the overall performance improvement after taking the set of sharing actions $\{a^i\}$ from state s and transitioning to state s'. Ω^i is the set of possible observations for all robots, where each Ω^i is the set of possible observations for the $i^t h$ robot including map features, other robots, and moving objects. O is a table of observation probabilities. $O(s, \{a^i\}, s'\{o^i\})$ represents the probability of observing $\{o^i\}$ when taking the set of actions $\{a^i\}$ in state s and transiting to state s' as result, where $\{o^i\}$ represents the set of observations that are observed by each individual robot.

However, with the formulation, there are two main challenges. The first one is how to define the reward function. In some POMDP frameworks, the reward functions indicate the relation of target state and the design of the reward is well studied. However, in our problem domain, the reward function should be defined to consider the communication conditions and the MR-SLAT problem. The other challenge is that with combining the communication and MR-SLAT, the state space is large. Therefore, the complexity issue should be tackled. To tackle these issues, the communication adaptive MR-SLAT (ComAd MR-SLAT) is proposed to online determine the sharing mode by maximizing the uncertainty reduction with expected value approach. In addition, the proposed ComAd MR-SLAT should adapt different type of shared information ensuring the information would be used exactly once. In this section, the proposed ComAd MR-SLAT algorithm is described.

4.1. Online Sharing Mode Determination

In order to explain our developed algorithm, we start from analyzing the case of two robots. Assuming there are the i^{th} robot and the j^{th} robot, the reward function can be designed as following equation:

$$R(s, \{a^i, a^j\}, s') \sim R_u^{i \to j}(s, a^i, s^{i \to j}) + R_u^{j \to i}(s, a^j, s^{j \to i}) \tag{4.3}$$

where:

- $R_u^{i \to j}$ is the reward function of sharing information from the i^{th} robot to the j^{th} robot indicates the *expected uncertainty reduction*.
- $R_u^{j \to i}$ is the reward function of sharing information from the j^{th} robot to the i^{th} robot indicates the *expected uncertainty reduction*.
- a^i, a^j are the binary variables indicating the sharing mode with 0: *measurement-sharing* or 1: *belief-sharing* for $i^t h$ robot and $j^t h$ robot.
- s is composed of a tuple $\langle Bel^i_{1:t}, Bel^j_{1:t}, \phi^{i \leftrightarrow j} \rangle$.
- $s^{i \to j}$ is composed of a tuple $\langle Bel^i_{1:t}, {Bel^j_{1:t}}^{i \to j}, \phi^{i \leftrightarrow j'} \rangle$.
- $s^{j \to i}$ is composed of a tuple $\langle {Bel^i_{1:t}}^{j \to i}, Bel^j_{1:t}, \phi^{i \leftrightarrow j'} \rangle$.
- $Bel^i_{1:t}$ and $Bel^j_{1:t}$ are the estimation results before taking the sharing actions for i^{th} robot and j^{th} robot according to the MR-SLAT problem including the distribution of the poses and velocities for multiple robots and moving objects.
- ${Bel^j_{1:t}}^{i \to j}$ is the j^{th} robot's estimation results after the i^{th} robot taking the sharing action a^i.
- ${Bel^i_{1:t}}^{j \to i}$ is the i^{th} robot's estimation results after the j^{th} robot taking the sharing action a^j.
- $\phi^{i \leftrightarrow j}$ represents the packet loss conditions between i^{th} robot and j^{th} robot.
- $\phi^{i \leftrightarrow j'}$ represents the packet loss conditions after taking the sharing actions.

Although the theoretical optimal decision should consider the influence on accuracy to optimize the estimation result. However, for practical algorithms, the exact performance improvement in accuracy cannot be determined before actual measurements are fetched and the packages are received. Without the way to represent the performance directly, the uncertainty reduction is introduced to indicate the reward. Because the estimation results with the smaller uncertainty based on proper models, are statistically expected to be more accurate.

In other words, the sharing mode is determined by maximizing the *expected uncertainty reduction* with choosing measurement-sharing or belief-sharing respectively. With traditional POMDPs, using the discretization approach to consider the distribution of state, the decision process could be represented:

$$a^{i*} = \arg\max_{a^i} \sum_{s \in S} b(s) R_u^{i \to j}(s, a^i, s^{i \to j})$$

$$\begin{cases} \sum_{s \in S} b(s) R_{u,m}^{i \to j}(s, s^{i \to j}) & \text{if } a^i = 0 \\ \sum_{s \in S} b(s) R_{u,b}^{i \to j}(s, s^{i \to j}) & \text{if } a^i = 1 \end{cases} \tag{4.4}$$

where:

- a^{i*} is the decision of sharing measurements or beliefs.
- $R_{u,m}^{i \to j}$ is the reward function of sharing measurements from the i^{th} robot to the j^{th} robot indicates the *expected uncertainty reduction*.
- $R_{u,b}^{i \to j}$ is the reward function of sharing beliefs from the i^{th} robot to the j^{th} robot indicates the *expected uncertainty reduction*.
- b is the function that each state is indicated a probability according to current estimation result.

However, with the discretization determination process, the complexity issue would be critical. Because of the dynamics of the MR-SLAT problem and the communication conditions, the decision should be made online. Nevertheless, the state space is enormous according to the communication conditions and the MR-SLAT problem, therefore, the discretization way to summarize the reward is not feasible. To tackle the complexity issue, an expected value approach is proposed to calculate the *expected uncertainty reduction* by using the expected values of the frequency of the information receiving based on the predicted measurements and the expected effective communication instead of using discretization approach. With the uncertainty reduction as the reward function and the Kalman filter assumption, the reward indicates the Gaussian distribution of states, therefore, the reward value is possible to be calculated by evaluating the predicted covariance matrix:

$$a^{i*} = \arg\max_{a^i} R_{u,expected}^{i \to j}(s, a^i, s^{i \to j})$$

$$\begin{cases} R_{u,m,expected}^{i \to j}(s_{mean}, s_{covariance}, s_{covariance}^{i \to j}) & \text{if } a^i = 0 \\ R_{u,b,expected}^{i \to j}(s_{mean}, s_{covariance}, s_{covariance}^{i \to j}) & \text{if } a^i = 1 \end{cases} \tag{4.5}$$

where:

- $R_{u,m,expected}$ is the function indicates the uncertainty reduction of measurement-sharing according to expected packet loss, predicted observations, and current estimation uncertainty.

- $R_{u,b,expected}$ is the function indicates the uncertainty reduction of belief-sharing according to expected packet loss, predicted observations, and current estimation uncertainty.
- s_{mean} is the mean value of current estimation result.
- $s_{covariance}$ is the estimated covariance matrix based on the Kalman filter assumption.
- $s_{covariance}^{i \to j}$ is the predicted covariance matrix after the sharing action.

Regarding sharing measurements, $R_{u,m,expected}^{i \to j}$, based on the common practice that measurements are assumed without cross correlations and are processed independently in the measurement-based MR-SLAT, we firstly generate the *predicted observations* which follows the common practice in POMDP works, and then according to the L_m, measurement-sharing loss rate, the *expected uncertainty reduction* of the teammate robot could be predicted. For instance, assuming that there are 2 entities in view, the recall rate of object detection is 0.5, and the packet loss rate is 0.5, the estimated time of receiving one measurement is $1/(2*0.5*0.5) = 2$ time steps. In addition, for generating data associations for the predicted measurements, without loss of generality we assume that the objects in the current state are equally-likely to be observed. Based on the generation of the *predicted observations*, the predicted uncertainty reduction through sharing measurements considering the packet loss effects can be estimated following the standard measurement-based MR-SLAT procedure.

Different from sharing measurements, it would be incorrect to estimate the cases of sharing beliefs by predicted beliefs as there are obviously strong correlations between beliefs to share: At time T_1, once $Bel_{1:T_1}^i$ has been successfully received by the j^{th} robot, the effects of $Bel_{1:1}^i$, $Bel_{1:2}^i$, ..., $Bel_{1:T_1-1}^i$ should be ignored as their information has already been contained in $Bel_{1:T_1}^i$. More specifically, considering the belief-sharing loss rate L_b, the effect of each belief on uncertainty reduction follows the geometric distribution, and accordingly the predicted uncertainty reduction of sharing beliefs can be estimated as:

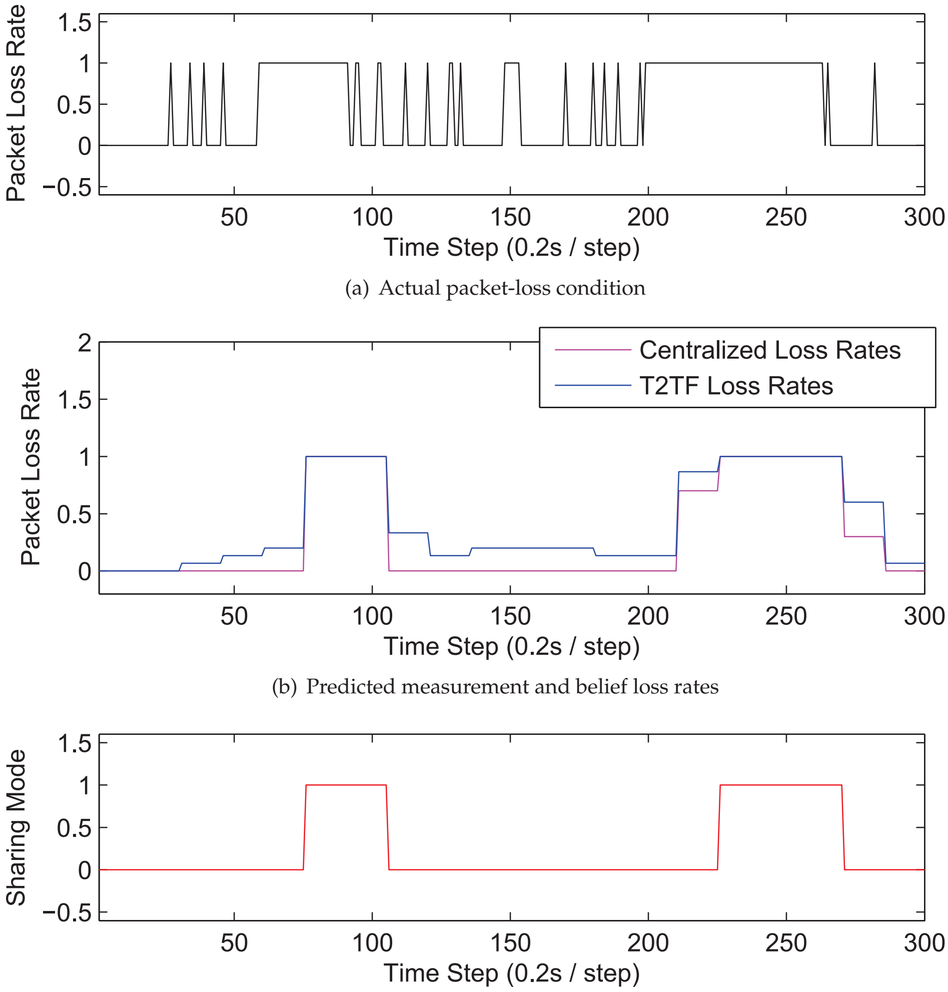
$$\sum_{t=1}^{T} (L_b)^{T-t}(1-L_b)I_b(Bel_{1:t}^i, Bel_{1:t}^j, t, T) \tag{4.6}$$

where I_b is the function estimating the predicted uncertainty reduction by sharing beliefs when the last successfully received belief occurred at time t. Similarly, I_b can be inferred by firstly generating the *predicted observations*, and then following the belief-based MR-SLAT procedure, the predicted uncertainty reduction considering the loss rate can be estimated.

With the statistical model, the uncertainty reduction is proposed to guide the POMDP problem as the estimation results with smaller uncertainty are statistically expected to be more accurate. Moreover, to tackle the complexity issue according to the large state space, we propose to use the expected communication conditions and predicted measurements to calculate the uncertainty reduction instead of using the discretization approach to considering the state space. With the expected value approach, the uncertainty reduction of measurement-sharing is simulated accordingly, and the geometric distribution is proposed to describe the reward of belief-sharing. Therefore, with the expected value algorithm, we are able to determine the sharing strategy dynamically to adapt different situations.

Fig. 4.1 shows a result of the developed mode decision for two nodes in a 300-frame sequence. Note that because of the different communication load requirements of measurement-sharing and belief-sharing, the measurement-sharing loss rate is less than or equal to the belief-sharing loss rate by simple duplicated transmission under the same communication bandwidth. It can be observed that the measurement-sharing mode is selected when there is no packet loss or the packet loss rate is low while the belief-sharing mode is selected when the packets are lost in a burst, which reflects the intuition that when consecutive packets are lost, sharing-beliefs is preferred as the beliefs carry the information of multiple previous lost measurements. The result also demonstrates that the proposed *expected uncertainty reduction* approach is able to guide the POMDP problem online determining the sharing mode and adapt different communication situations.

In the case with two nodes, the proposed decision module resorts to the optimal solution in the probabilistic point of view by modelling the communication conditions and the MR-SLAT problem properly. However, the consideration between two robots cannot be extended to many robots directly. With the multi-robot POMDP formulation, the problem of generating optimal policies for multi-agent POMDPs is known to be NEXP-complete (Bernstein et al., 2000), so making exact solutions with the existing multi-agent POMDP is unfeasible and necessitating the use of heuristics. In our scenario, robots communicate with each other via broadcasting information, so their only one type of information to share for all robots. Therefore, in order to maximize the uncertainty reduction between multiple robots, the theoretically optimal decision is regarding all possible sharing-modes of all the



(a) Actual packet-loss condition

(b) Predicted measurement and belief loss rates

(c) Decided sharing modes

Figure 4.1. The result of the developed mode decision for two nodes in a 300-frame sequence

robots, which scales poorly to many robots. To deal with the scale up issue, the summations approach is proposed:

$$a^i = \arg\max_{a^i} \sum_{j, j \neq i} R^{i \to j}_{u,expected}(s_{mean}, s_{covariance}, s^{i \to j}_{covariance}) \tag{4.7}$$

With the Equation 4.7 offering a trade-off between optimality and applicability, the proposed ComAd MR-SLAT can online provide satisfactory results, which is important under unstable environment, to adapt different communication conditions. In addition, the effectiveness of the proposed sharing mode decision process is demonstrated in our experiment. Based on the decided sharing modes for multiple robot scenario, the scheme of our adapting measurement and belief sharing algorithm is introduced in the next section.

4.2. Adapting Measurement and Belief Sharing

This section describes our adapting MR-SLAT that can dynamically alternate between sharing measurements and beliefs given the online decided sharing modes. The main requirement for the algorithm design is that in the condition of perfect communication, the information of each measurement should be used exactly once, which means it should be guaranteed that there is no information loss or reuse in the designed algorithm. For clarity, the algorithm is explained in two different views, the sender's view and the receiver's view, but note that in practice each robot plays the sender and the receiver at the same time.

In addition, the approach to deal with the data association issue is required as that exact correspondence between observations and entities cannot be applied in some MR-SLAT applications. Therefore, the algorithm for generating correspondence in our adapting MR-SLAT scheme is proposed. The main requirement is that all information, which robot can have, should be considered without the risk of information double-counting or loss.

4.2.1. Information Sender's View

When the i^{th} robot is in the measurement-sharing mode, the robot simply sends the new measurements and odometry data to the teammate robots as in measurement-based MR-SLAT. When the i^{th} robot is decided to switch from the measurement-sharing mode to the belief-sharing mode from T_1 to T_2, a separate local EKF is created to integrate its measurements and odometry data between T_1 and T_2:

$$Bel^i_{T_1:t} \sim Pr(X^i_t | U^i_{T_1:t}, Z^i_{T_1:t}), \text{ for } T_1 \leq t \leq T_2 \tag{4.8}$$

The beliefs, $Bel^i_{T_1:t}$ for $T_1 \leq t \leq T_2$, are shared to the teammate robots between T_1 and T_2. Note that these beliefs do not fuse the measurements before T_1 in order to prevent the information reuse.

In our implementation, the created local EKF is initialized with sufficiently large uncertainty. However, one critical issue is that the uncertainty of these newly created EKFs could be larger than those in the original measurement-based or belief-based approaches because less measurements are fused, so the data association gets more challenging as the data association uncertainty is increased. Accordingly, we exploit the merged global state to assist data association in local-belief EKFs by only applying the measurements that satisfy the Mahalanobis distance gating in both of the local belief and the merged-global state. The computation of the merged global state is explained in the information receiver's view in the following.

4.2.2. Information Receiver's View

Each robot always maintains a state, $Bel_{1:t}^{M}$, which integrates the odometry data and measurements of the robot itself and those in the measurement-sharing mode:

$$\begin{aligned} & Bel_{1:t}^{M} \sim \\ & \quad Pr(X_t | \{U_{1:t}^{i}, Z_{1:t}^{i}, \forall i \in M\}, \{U_{1:T_j}^{j}, Z_{1:T_j}^{i}, \forall j \notin M\}), \\ & M = \{i | \theta_i = 0\} \end{aligned} \tag{4.9}$$

where M denotes the set of robots in the measurement-sharing mode, and T_j denotes the last time from which the j^{th} robot switched to the belief-sharing mode. At each time step the global state is inferred by merging $Bel_{1:t}^{M}$ with the other beliefs received from the robots in belief-sharing mode:

$$Bel_{1:t} \sim BM(Bel_{1:t}^{M}, \{Bel_{T_j:t}^{j} | \forall j \notin M\}) \tag{4.10}$$

For preventing the information reuse problem, the merged global state $Bel_{1:t}$ would not be replaced or fed back to $Bel_{1:t}^{M}$ to keep $Bel_{1:t}^{M}$ containing information only from the robot itself and those in the measurement-sharing mode.

In the proposed scheme, the global state $Bel_{1:t}$ is exploited during data association gating for robustness as described in the previous section. In addition, when the j^{th} robot is decided to switch from the belief-sharing mode to the measurement-sharing mode at T_3, our algorithm fuses its local belief $Bel_{T_j:T3}^{j}$ into $Bel_{1:t}^{M}$ to make sure that its odometry data and measurements contained in $Bel_{T_j:T3}^{j}$ are not lost.

4.2.3. Data Association Generation

To generate the correspondence the likelihood-based approach is applied, and the appearance of observations such as color of robot, type of map feature is used. In addition, all information from all robots is considered to generate the global consistent correspondence, besides, the differences between measurement-based and belief-based MR-SLAT are described.

For the measurement-based MR-SLAT, the likelihood could be calculated directly because the estimation already contains all measurements. Different from the measurement-based MR-SLAT, the local estimation of the belief-based MR-SLAT doesn't contain all measurements it can have, therefore, generating correspondence with the local estimation would not consider the information from other robots. On the other hand, the global belief is generated by merging all local estimation at each frame instead of updating previous global belief to prevent the information reuse, therefore, fusing the observations into the global belief would indicate the information loss. In order to take all information into account without the risk of information reuse or loss, the belief-based MR-SLAT should merge all beliefs into a global estimation to generate the correspondence, and then update the observations into the local estimation according to the correspondence. With the same concept, the algorithm for the proposed ComAd MR-SLAT to generate the correspondence is similar to the belief-based MR-SLAT.

Although the likelihood-based approach can generate correspondence adequately, there still has some issues according to the communication conditions. For the measurement-based MR-SLAT, once the bursty packet loss condition is occurred, the tracking result may drift or miss. On the other hand, the belief-based MR-SLAT can recover the information after bursty packet loss via belief-merging to get the correspondence more robustly after bursty packet loss. However, the calculation of likelihood for belief-based MR-SLAT would be deflected because when different teammate robots observe the same entity, the prediction model cannot be estimated with all information accordingly. Even if the information could be incorporated by belief-merging, the deviation comes from the prediction step is hard to be recovered. Therefore, in general, the measurement-based MR-SLAT has an advantage in doing data association when the communication condition is not bursty. By comparison, the belief-based MR-SLAT has the superiority after the bursty packet loss because the risk of track missing can be reduced by belief-merging.

With the online decision process to combine the measurement-based MR-SLAT and the belief-based MR-SLAT, the proposed ComAd MR-SLAT tends to share the measurements when the packet loss conditions aren't bursty then the robot can estimate the prediction model with all information accordingly. On the other hand, with bursty packet loss, the proposed ComAd MR-SLAT is likely to share the belief, and then the risk of track missing can be reduced. Therefore, the proposed ComAd MR-SLAT could generate the correspondence more reliable under different communication conditions.

CHAPTER 5

Evaluation

In order to verify the effectiveness of the proposed adapting algorithm, the proposed ComAd MR-SLAT is evaluated under different packet loss rates, different bursty loss lengths, and different data association conditions. In addition, the real data experiment is also evaluated to verify the practicability of the proposed ComAd MR-SLAT algorithm.

5.1. Simulation Experimental Scene Setting

The experimental scene follows the RoboCup Standard Platform League (SPL) scenario, in which two teams of robots move in the soccer field consisting several map features, e.g. four goal posts, the center circle, corners, and white lines. In order to get statistically meaningful results, 80 runs of Monte Carlo simulations are conducted for each communication setting. The algorithm is executed at the frame rate of 5 Hz. Each run lasts 60 seconds, i.e. 300 frames, and in each run, the robots are placed randomly at the beginning with a random moving direction. If the robot moves outside the field, the moving direction is randomly decided again. The odometry motion model is used for teammate robots that can share information to each others and the constant velocity (CV) model for opponent robots. Relative range and bearing measurements to nearby map features and robots are extracted and the correspondence between measurements and entities is given. The motion and sensor models follow the parameters we applied in practical RoboCup competitions (Chang et al., 2011).

In order to evaluate the proposed ComAd MR-SLAT under different communication conditions, packets are randomly selected to be lost in each run. Different packet loss rates (0.0, 0.2, 0.4, 06, and 0.8) and different bursty loss lengths (1, 20, 30, and 40 frames) are verified, where the packet loss rates denote the overall ratio of lost packets, and the bursty loss lengths denote the average lengths of consecutive lost packets, except that with bursty length 1, the packet loss is simulated to occur independently for each time frame.

5.2. Five-vs.-Five with Homogeneous Communication

This experiment simulates a five-vs.-five scenario as shown in Fig. 5.1. Blue circles denote robots that can share information to each other, and black circles denote the moving objects. In this experiment, homogeneous communication conditions between each paired robots, which means the packages for all receivers would get lost at the same time, are assumed. The homogeneous communication is to simulate the case in which communication is realized through one centralized device such as the WiFi device used in practical RoboCup competitions.

The performance of localization accuracy averaged from 80 Monte Carlo runs under different packet loss rates and bursty loss lengths is shown in Fig. 5.2. Firstly, regarding packet loss rates, it can be seen that the measurement-based MR-SLAT outperforms belief-based MR-SLAT when the packet loss rate is low while belief-based MR-SLAT performs more stably when the packet loss rate increases, which is consistent with our understanding of the characteristics of the two approaches. Regarding bursty loss lengths, it can be observed that as the bursty loss length increases, the advantage of sharing beliefs approach gets more significant as when consecutive packets are lost, beliefs containing multiple previous measurements can prevent the measurements from being permanently lost. In the other extreme case where the bursty length is 1, in which each packet gets lost independently, the measurement-based approach is preferred as by simply retransmission, the measurement loss rate can be much lowered comparing to the belief-based approach with the same communication load.

It can be seen that our proposed ComAd MR-SLAT outperforms measurement-based and belief-based approaches. In the case with independent packet loss, ComAd MR-SLAT correctly decides to share measurements and achieves the same performance as the measurement-based MR-SLAT. While in the cases with other bursty lengths, ComAd MR-SLAT achieves better results. It is also worth mentioning that ComAd MR-SLAT can achieve more accurate results than the better one of measurement-based and belief-based MR-SLAT as even in one sequence with the same communication condition, the optimal sharing mode could be interleaved by measurement-sharing and belief-sharing, e.g.

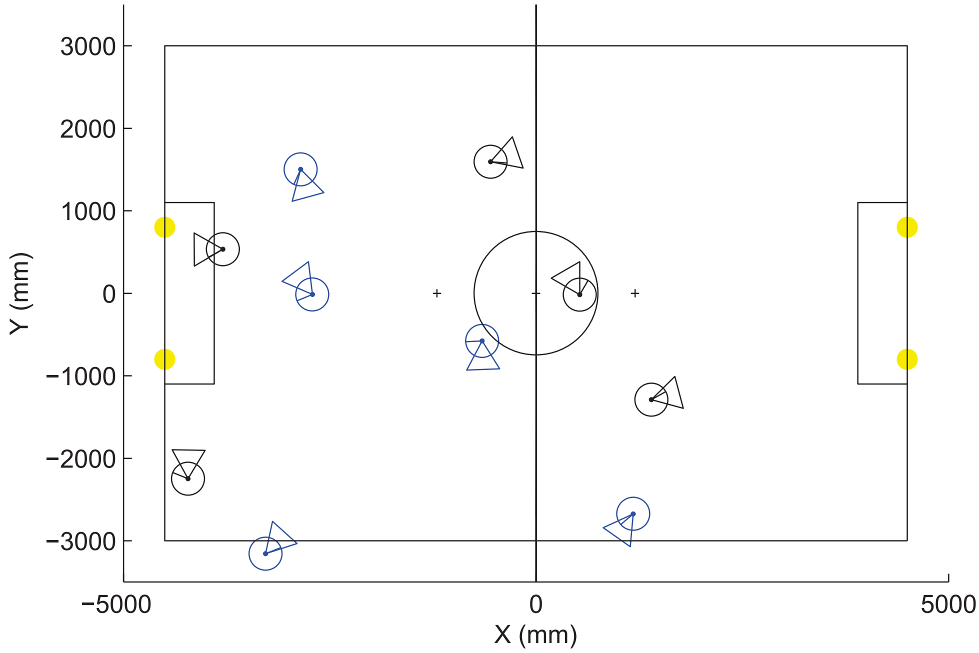
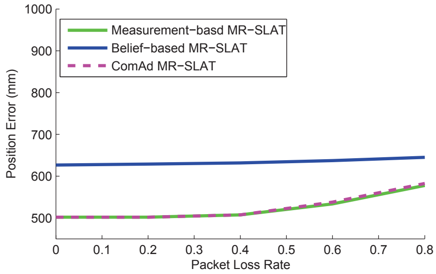


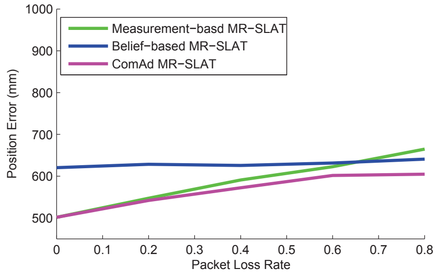
Figure 5.1. Setting of the multi-robot scene for evaluation. Following the motion models and sensor models used in practical RoboCup scenes, e.g. odometry noises, feature extraction noises, detection recall rates, various packet loss rates and bursty loss lengths are simulated. Blue circles denote robots that can communicate with each other, and black circles denote the moving objects.

measurement-sharing in the first half and belief-sharing in the second half, which can only be achieved by the communication adaptive algorithm. This experiment demonstrates the effectiveness of the developed sharing mode decision module and that the proposed Co-mAd MR-SLAT successfully combines the advantages of measurement-based and belief-based MR-SLAT.

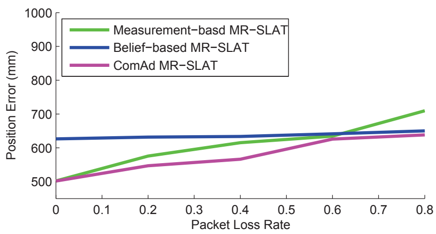
In addition, with different noise level of motion models and sensor models, the experimental results are also discussed: With lower noise level of odometry data, the measurement-based approach would be relatively promoted because the odometry data are applied to all teammate robots. By comparison, for the prediction step, the belief-based approach uses CV model instead of odometry data for teammate robots. On the other hand, with higher detection noise, the belief-based approach would be relatively worse than the measurement-based approach because the motion model of belief-based approach is estimated only with



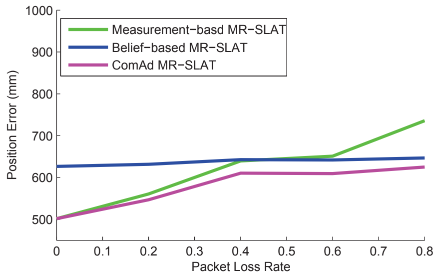
(a) Independent packet loss



(b) Bursty loss length = 20



(c) Bursty loss length = 30



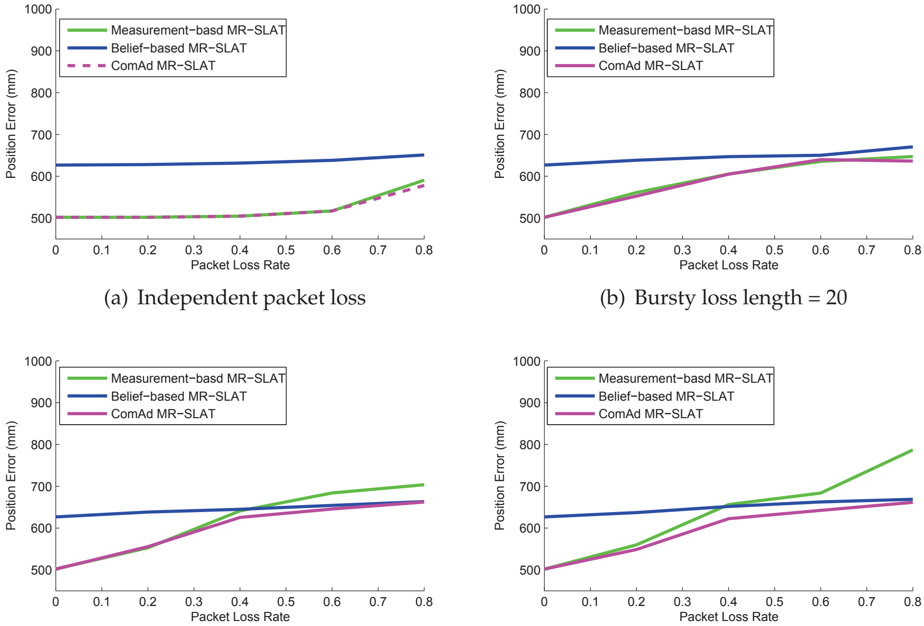
(d) Bursty loss length = 40

Figure 5.2. Five-vs.-five with homogeneous communication. Comparison on the localization errors of measurement-based MR-SLAT, belief-based MR-SLAT, and the proposed ComAd MR-SLAT under different packet loss rates and different bursty loss length.

observation results. At the same time, the recall of detection modules are also characterized. With lower recall of moving objects detection, the algorithm cannot estimate the motion model well. Therefore, the influence on belief-based approach is relatively critical because the measurement-based approach uses odometry data as the motion model for teammate robots and only estimates the motion model for those without odometry data.

5.3. Heterogeneous Communication and Scalability

The proposed ComAd MR-SLAT is also evaluated in the case of heterogeneous communication that the packet loss conditions between each pair of robots are independent, which simulates the scenario where communication links are established in a robot-to-robot way. The results under different packet loss rates and bursty loss lengths are shown in Fig. 5.3. The results again demonstrate that the proposed ComAd MR-SLAT outperforms measurement-based and belief-based MR-SLAT, which verifies the effectiveness of



(a) Independent packet loss

(b) Bursty loss length = 20

(c) Bursty loss length = 30

(d) Bursty loss length = 40

Figure 5.3. Five-vs.-five with heterogeneous communication. Comparison on the localization errors of measurement-based MR-SLAT, belief-based MR-SLAT, and the proposed ComAd MR-SLAT under different packet loss rates and different bursty loss length.

the ComAd MR-SLAT with heterogeneous communication links between robots. However, it can be observed that comparing to the homogeneous communication case, the performance of the ComAd MR-SLAT is closer to the better one of the measurement-based and the belief-based MR-SLAT, and the reason is that when the robot tries to decide the sharing mode in the heterogeneous communication case, it is possible that some of its teammates prefer measurement-sharing while the others prefer belief-sharing, so the performance difference between the two sharing modes could be less obvious. However, the proposed method still selects the sharing mode expected to be better and mostly achieves the preferable performance among the three approaches under comparison.

In addition, the scalability of the ComAd MR-SLAT is also evaluated in a 10-vs.-10 scene as the setting illustrated in Fig. 5.4. The results are shown in Fig. 5.5. Due to the page limits of the thesis, only the results of independent packet loss and bursty lengths 40 are shown, but the results of other bursty lengths are similar. In this experiment, the

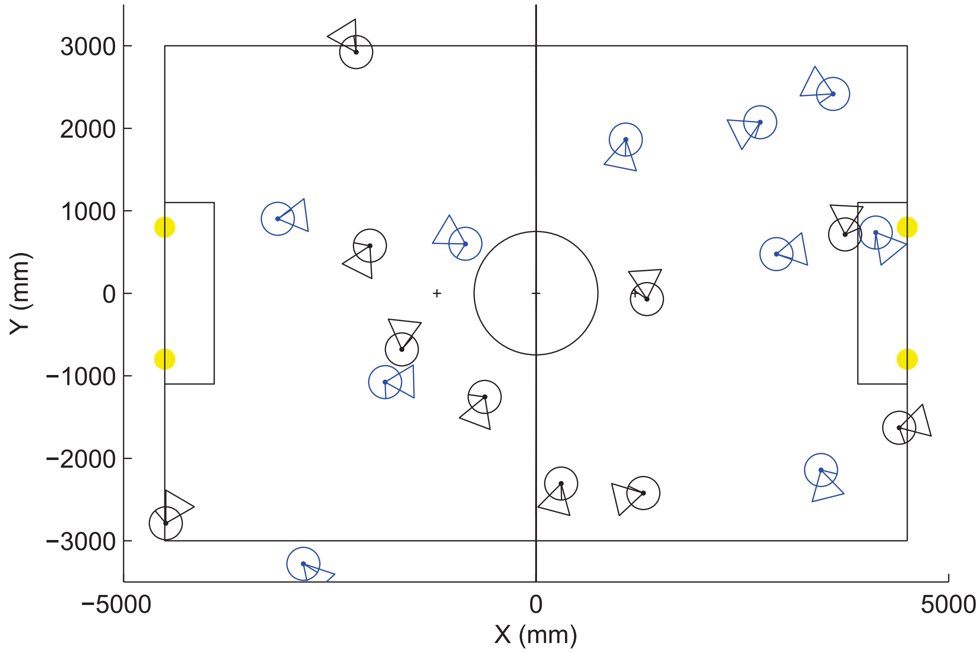
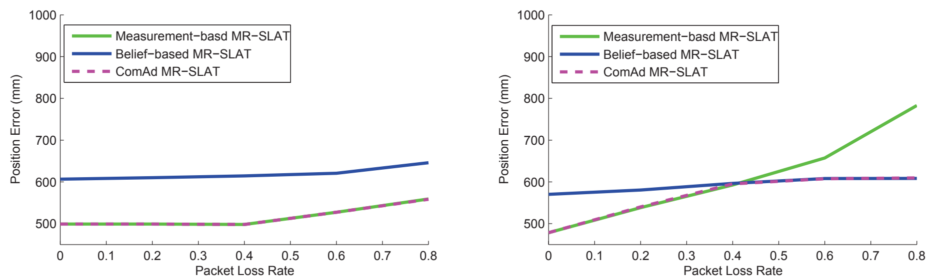


Figure 5.4. Setting for scalability evaluation: Ten-vs.-ten with heterogeneous communication.

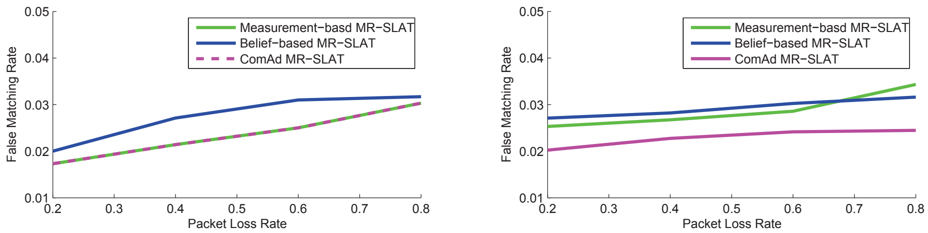


(a) Independent packet loss

(b) Bursty loss length = 40

Figure 5.5. Scalability evaluation: Ten-vs.-ten with heterogeneous communication. Comparison on the localization errors of measurement-based MR-SLAT, belief-based MR-SLAT, and the proposed ComAd MR-SLAT under different packet loss rates and different bursty loss length. Robots are with heterogeneous communication conditions.

proposed adapting algorithm also works and based on the decided sharing-modes, the ComAd MR-SLAT outperforms both measurement-based and belief-based approaches.



(a) Independent packet loss (b) Bursty loss length = 30

Figure 5.6. Data association evaluation: Five-vs.-five with heterogeneous communication. Comparison on the false matching rate of the measurement-based MR-SLAT, the belief-based MR-SLAT, and the proposed ComAd MR-SLAT under different packet loss rates.

5.4. Data Association Evaluation

In previous experiment, the algorithms are evaluated with correct correspondence for all observations to evaluate the effectiveness of the proposed adapting algorithm. However, exact data association sometimes cannot be obtained, the influence on the capability for generating correspondence should also be considered. For verifying the utility of the data association module, with the same setting as previous experiment 5.1, the false matching rate is evaluated under different packet loss and bursty length with the heterogeneous condition shown in Fig. 5.6. In general, for doing data association in RoboCup scenario, the likelihood-based approach is effective, and the result also shows that the correspondence can be generated appropriately.

Nevertheless, it can also be observed that with independent packet loss shown in Fig. 5.6(a), the capability of doing data association for the measurement-based MR-SLAT and the proposed ComAd MR-SLAT are better than the belief-based MR-SLAT as the likelihood could be calculated adequately. On the other hand, with bursty packet loss shown in Fig. 5.6(b), the difference between the measurement-based MR-SLAT and the belief-based MR-SLAT becomes much closer and the belief-based MR-SLAT outperforms the measurement-based MR-SLAT with bursty lengths 30 and loss rate 0.8. By switching communication mode properly to combine both benefits from the measurement-based MR-SLAT and the belief-based MR-SLAT, the proposed ComAd MR-SLAT outperforms both measurement-based and belief-based approaches with bursty packet loss conditions.

In addition, the influence on the position error of correspondence is also evaluated. The behavior of the result shown in Fig. 5.7 is similar to the result shown in Fig. 5.6 because the estimation and data association would complement each other. The result also demonstrate that the proposed ComAd MR-SLAT outperforms the measurement-based MR-SLAT and the belief-based MR-SLAT in both cases of data association conditions, which exhibit the capability of the ComAd MR-SLAT working in the real environment.

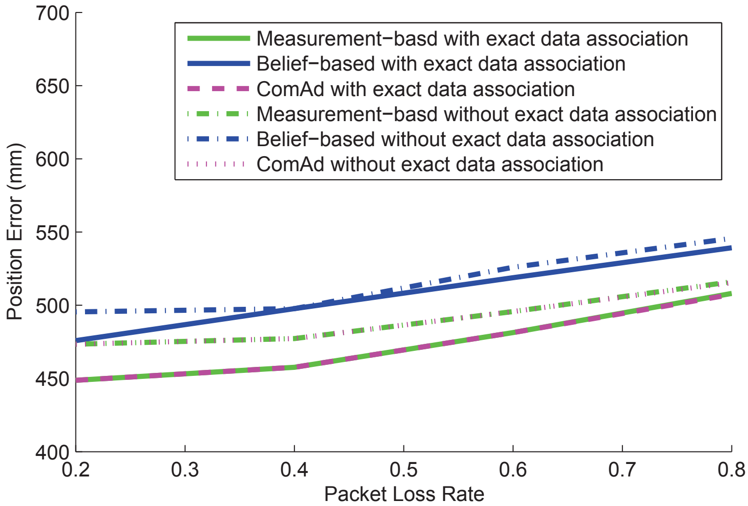
5.5. Real Experimental Evaluation

To verify the effectiveness of the proposed approach in the real environment, the real data experiment is concluded. The experimental scene follows the RoboCup Standard Platform League (SPL) scenario, in which two teams of robots move in the soccer field as the setting illustrated in Fig. 5.8(a). In order to demonstrate the real scenario, there are two robots configured as goal keepers. In the scenario, goal keepers would stay in the penalty area and other robots would move back and forth, and the walking patterns of robots are designed as Fig. 5.8(b). In the experiment, robots follow the pattern to collect the perception data and then the perception algorithms would process those data under different communication conditions to evaluate the measurement-based MR-SLAT, the belief-based MR-SLAT, and the proposed ComAd MR-SLAT.

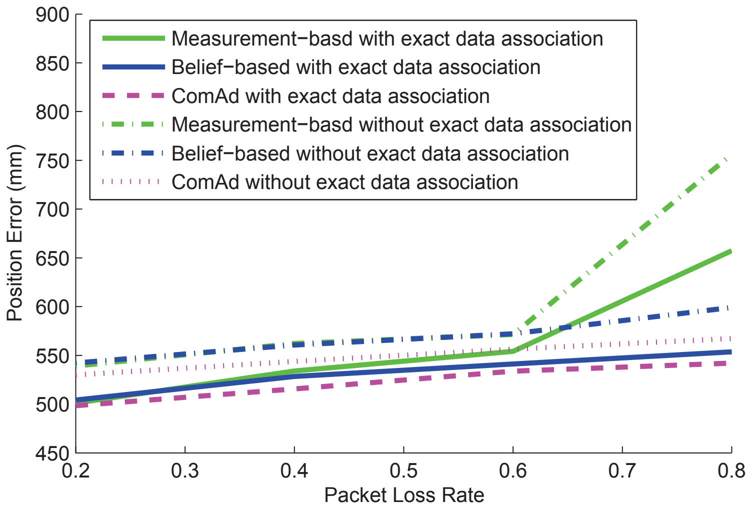
In order to evaluate the proposed algorithm in the real environment, two SICK LMS 100 laser scanners are placed on both sides of the field to provide the position ground truth of the robots. These two laser scanners are circled and shown in Fig. 5.8(a), the angular sensing ranges of SICK laser scanners is 270 degrees and the distance sensing range is 20 meters, which is sufficient to cover the whole field. The data collected from these two laser scanners are clustered into segments and the mean positions of the clustered points are viewed as the candidates of the ground truth locations of robots. These candidates are then associated with the closest estimates from the result with centralized fusion and perfect communication conditions, and the incorrect associations are re-labeled manually.

The practical performance of the ComAd MR-SLAT is evaluated in a four-vs.-four scene as the setting of Fig. 5.8. Although the real data experiment is evaluated under four-vs.-four instead of five-vs.-five scenario, the results shown in Fig. 5.9, are also similar to the simulation results.

With the results of real data evaluation, it can be seen that the proposed ComAd MR-SLAT outperforms both the measurement-based MR-SLAT and the belief-based MR-SLAT as the results shown in simulation evaluation. The Fig. 5.9(a) shows that with the independent packet loss condition, the ComAd MR-SLAT correctly decides to share measurements and achieves the same performance as the measurement-based MR-SLAT. On the other hand, the Fig. 5.9(b) can be observed that with the increasing of bursty loss length, the advantage of our adapting sharing scheme gets more significant. The proposed ComAd MR-SLAT can decide the sharing mode appropriately to deal with the issue of packet loss in the real environment.

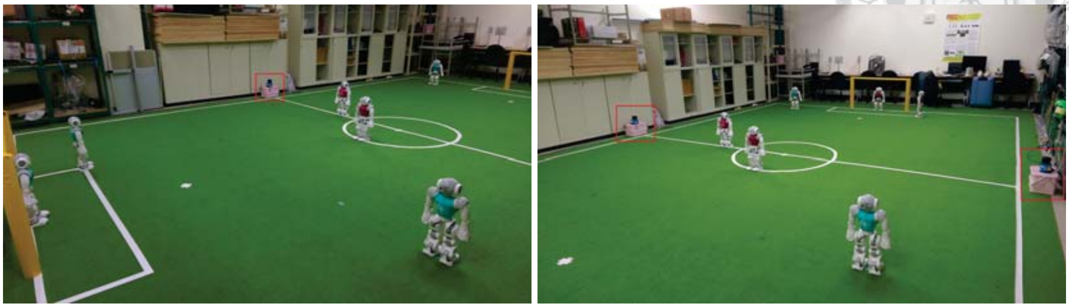


(a) Independent packet loss

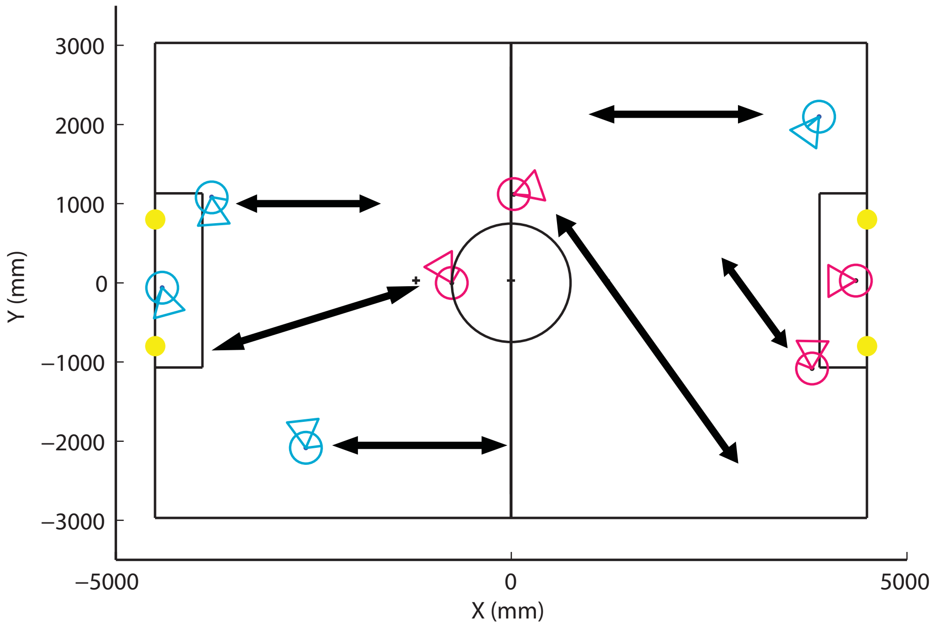


(b) Bursty loss length = 30

Figure 5.7. Data association evaluation: Five-vs.-five with heterogeneous communication. Comparison on the position error of the measurement-based MR-SLAT, the belief-based MR-SLAT, and the proposed ComAd MR-SLAT under different communication conditions.

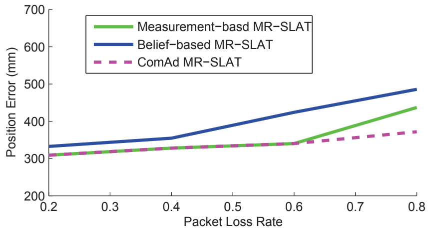


(a) The standard site of RoboCup standard platform league

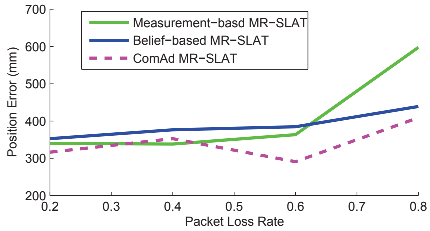


(b) The setting of robots for the real experiment evaluation.

Figure 5.8. Setting for real experiment evaluation: Four-vs.-four with heterogeneous communication.



(a) Independent packet loss



(b) Bursty loss length = 30

Figure 5.9. Real data evaluation: Four-vs.-four with heterogeneous communication. Comparison on the localization errors of measurement-based MR-SLAT, belief-based MR-SLAT, and the proposed ComAd MR-SLAT under different packet loss rates.

CHAPTER 6

Conclusions

In this thesis, a communication adaptive multi-robot simultaneous localization and tracking (ComAd MR-SLAT) algorithm is proposed to deal with practical scenes in which the communication condition is unknown or unstable. Motivated by the observation that sharing measurements and sharing beliefs are respectively superior in different communication conditions, an adapting approach is developed to combine the advantages of both. With the uncertainty of the estimation, to decide sharing mode in multi-robot scenario is known as a multi-robot partially observable Markov decision process (multi-robot POMDP) problem. To consider the influence of the communication, the uncertainty reduction is proposed to guide the POMDP problem. However, with the communication conditions and the MR-SLAT problem, the state space would lead to the complexity issue. Therefore, with the expected effective communication and predicted measurements, the simulation approach with geometric distribution is proposed to online calculate the *expected uncertainty reduction*. By using the expected value approach, the proposed ComAd MR-SLAT can online decide the sharing mode to adapt different communication conditions by switching between measurement-sharing and belief-sharing without information loss or reuse. Moreover, the algorithm for generating data association is proposed to consider all measurements from all robots without the risk of information loss or double-counting.

The proposed algorithm is evaluated in the RoboCup scenario under different packet loss rates, bursty lengths, and correspondence conditions. Following the models used in the practical RoboCup competitions, Monte Carlo runs are simulated. In addition, the real data are also collected and evaluated. In the experiments, the proposed ComAd MR-SLAT outperforms the measurement-based MR-SLAT and the belief-based MR-SLAT in both localization and data association accuracy. The experimental results demonstrate the effectiveness of the proposed adapting algorithm and exhibit that the ComAd MR-SLAT is robust under different communication conditions and is effective in real data experiment.

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