2014 IEEE International Conference on Robotics & Automation (ICRA)
Hong Kong Convention and Exhibition Center
May 31 - June 7, 2014. Hong Kong, China

Communication Adaptive Multi-Robot Simultaneous Localization and Tracking via Hybrid Measurement and Belief Sharing

Chun-Kai Chang, Chun-Hua Chang and Chieh-Chih Wang

***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 because the cross-correlations between beliefs are hard to be perfectly estimated in practice. 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 paper a hybrid algorithm, communication adaptive multi-robot simultaneous localization and tracking (ComAd MR-SLAT), is proposed to combine the advantages of both. To tackle the unknown or unstable communication conditions, the information to share is decided by maximizing the expected uncertainty reduction online, based on which the algorithm dynamically alternates between measurement-sharing and belief-sharing without information loss or reuse. The proposed ComAd MR-SLAT is evaluated in communication conditions with different packet loss rates and bursty loss lengths. In our experiments, ComAd MR-SLAT outperforms measurement-based and belief-based MR-SLAT in accuracy. The experimental results demonstrate the effectiveness of the proposed hybrid algorithm and exhibit that ComAd MR-SLAT is robust under different communication conditions.**

I. Introduction

Localization is one of the most essential capabilities for autonomous robots [1]. 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 [2][3]. 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 [4][5][6]. In addition, 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 [7][8].

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 measurement-based approaches [4][6][8], the control data and measurements are shared once after they are fetched. With well-controlled communication, in which the packet loss rate is low and there are merely consecutive packets lost, each robot is expected to receive all control data and measurements from the other robots, and the global state is inferred in a centralized manner. In belief-based approaches [9][5][10][11][12][13][14], each robot firstly fuses its own control data and measurements into a local belief in a distributed way. Then the local beliefs are shared to the teammate robots, and the global state is inferred by merging the local beliefs.

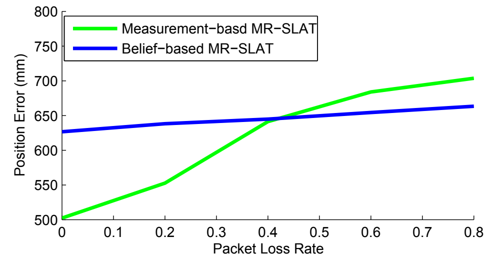


Fig. 1. Comparison on the localization errors of measurement-based MR-SLAT and belief-based MR-SLAT under different packet loss rates.

This paper is motivated by the different characteristics of the measurement-based and belief-based approaches against different communication conditions. Fig. 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[15]. (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 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.

C.-K. Chang, C.-H. Chang and C.-C. Wang are all with the Department of Computer Science and Information Engineering, and the Graduate Institute of Networking and Multimedia, National Taiwan University, Taiwan [gene9216,alan]@pal.csie.ntu.edu.tw, bobwang@ntu.edu.tw

This work was supported in part by Taiwan National Science Council, National Taiwan University and Intel under grants NSC103-2623-E-002-010-D, NSC102-2221-E-002-179, NSC100-2221-E-002-238-MY2, NSC100-2911-I-002-001 and NTU102R7501.

978-1-4799-3684-7/14/$31.00 ©2014 IEEE

Therefore, aiming at tackling practical scenes with unstable communication conditions, in this paper we propose communication adaptive MR-SLAT (ComAd MR-SLAT), a hybrid algorithm combining the advantages of both measurement-sharing and belief-sharing by explicitly taking the communication condition into account. An online sharing mode decision module is designed. Although theoretically optimal sharing modes should be determined by optimizing the localization and tracking accuracy, for practical online applications, the exact performance cannot be determined until actual measurements are fetched. Accordingly, we instead reduce the problem from optimizing the performance in accuracy to maximizing the *expected uncertainty reduction* in order to select from measurement-sharing and belief-sharing. With proper uncertainty models, estimates with the smaller uncertainty are statistically expected to be more accurate. In addition, based on the decided sharing modes, a hybrid scheme is developed, in which the algorithm can dynamically alternate between measurement-sharing and belief-sharing without information loss or reuse.

The proposed ComAd MR-SLAT algorithm is evaluated under different communication conditions in a multi-robot setting. 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 [16] 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 bursty loss, consecutive packets are lost due to communication interference such occlusion. Under the same communication load, measurement loss rates can be lowered by duplicate transmission, but in bursty loss, the loss rate of measurement-sharing would be closer to that of belief-sharing. Accordingly, these two factors are analyzed in our experiments. The experimental results demonstrate that the proposed hybrid solution outperforms the measurment-based MR-SLAT and belief-based MR-SLAT in localization accuracy under different communication conditions and is more robust against unstable communication conditions.

II. Related Work

In multi-robot cooperative perception, measurement-based algorithms have been proposed such as the particle filter (PF) based approach [4], the maximum likelihood estimation (MLE) based approach [6], and the extended Kalman filter (EKF) based approach [8]. In these approaches, measurements, e.g. map feature detection and robot detection, are shared to the other robots after being fetched, and then the global state is inferred in a centralized manner. Regarding communication considerations, the communication condition is not discussed in [4][6] and is assumed well-controlled in [8].

On the other hand, various belief-based approaches have also been proposed based on different techniques, such as distributed EKF [5], distributed Sparse Extended Information Filters (SEIF) [10], distributed maximum a posteriori (MAP) [11], track-to-track fusion [9][12][13] and distributed smoothing and mapping (SAM) [14]. 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 in the literature. 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 [15]. Though in [13], an exact solution is proposed to decorrelate the cross correlations between tracks and is proved optimal based on Kalman filter (KF) assumptions, 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 [17].

Motivated by the different advantages of measurement-based and belief-based approaches, in this paper we propose a hybrid algorithm combining the merits of both. By considering the communication condition online, the proposed communication adaptive approach dynamically determines the information to share and achieves better performance in accuracy as demonstrated in our experiments.

III. 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.

A. Augmented-State Representation

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

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

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 paper, 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.

B. Measurement-based MR-SLAT

In [8], following the theoretical framework of SLAMMOT [7] 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 fetched 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:

$$Bel_{1:t} \sim Pr(X_t | U^i_{1:t}, Z^i_{1:t}, \forall i = 1...N) \quad (2)$$

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 paper, we denote the suffix of the belief to indicate the time period during which the information has been fused into the belief.

C. 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:

$$Bel^i_{1:t} \sim Pr(X^i_t | U^i_{1:t}, Z^i_{1:t}) \quad (3)$$

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:

$$Bel_{1:t} \sim BM(Bel^1_{1:t}, Bel^2_{1:t}, ..., Bel^N_{1:t}) \quad (4)$$

where $BM(\cdot)$ denotes the belief merging operator that can be realized through any existing track-to-track fusion algorithm [18].

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 [19]: 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 IV-B.

D. 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. 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. 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 simple communication strategies such as duplicated transmission. 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 [15][18], 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 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, 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.

IV. Communication Adaptive MR-SLAT

In this section, the proposed communication adaptive MR-SLAT (ComAd MR-SLAT) algorithm is described.

A. Online Sharing Mode Determination

An online decision module is designed in order to appropriately determine the sharing mode, i.e. *measurement-sharing* or *belief-sharing*, given the current state and the communication condition. To explain our developed algorithm, we start from analyzing the case of two robots. Assuming that the i^{th} robot is sharing information to the j^{th} robot, the theoretical optimal sharing mode can be determined according to the following equation:

$$\theta_{i \rightarrow j} = \arg\max_{\theta} f(\theta; Bel^i_{1:t}, Bel^j_{1:t}, R_m, R_b, T) \quad (5)$$

where θ is a binary variable indicating the sharing mode with 0: *measurement-sharing* or 1: *belief-sharing*, $Bel^i_{1:t}$ and $Bel^j_{1:t}$ the current beliefs of the i^{th} robot and the j^{th} robot, R_m the loss rate for sharing measurements and R_b for sharing beliefs, T the time period within which we tried to determine the sharing mode, and f the function evaluating the performance in accuracy. Note that both R_m and R_b are needed as measurements and beliefs are of different sizes, so their loss rates could be different under the same communication load.

Through f, the algorithm selects the sharing mode by optimizing the estimation accuracy. However, for practical online algorithms, the exact performance in accuracy cannot be determined before actual measurements are fetched. Therefore, we instead reduce estimating f to estimating U_z and U_b in a probabilistic manner, which determine the *expected uncertainty reduction* by measurement-sharing and belief-sharing respectively:

$$f(\theta; Bel^i_{1:t}, Bel^j_{1:t}, R_m, R_b, T) \sim \begin{cases} U_z(Bel^i_{1:t}, Bel^j_{1:t}, R_m, T), & \text{if } \theta = 0 \\ U_b(Bel^i_{1:t}, Bel^j_{1:t}, R_b, T), & \text{if } \theta = 1 \end{cases} \tag{6}$$

In other words, we decide the sharing mode that maximizes the expected uncertainty reduction as the estimate with smaller uncertainty is more likely to be accurate as long as the noise models are statistically correct.

Now our goal is to take the packet loss effects into account in evaluating U_z and U_b. Regarding U_z, based on the common practice that measurements are assumed without cross correlations and are processed independently in measurement-based MR-SLAT, we firstly generate the *expected pseudo measurements* according to the expected time of receiving one new measurement, which can be estimated from the loss rate R_m, the performance of the front-end feature extraction modules, and the scene setting. For instance, assuming that in average 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 pseudo measurements, without loss of generality we assume that the objects in the current state are equally-likely to be observed. Based on the generated pseudo measurements, the expected uncertainty reduction through sharing measurements considering the packet loss effects can be estimated following the standard measurement-based MR-SLAT procedure.

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

$$U_b(Bel^i_{1:t}, Bel^j_{1:t}, R_b, T) = \sum_{t=1}^{T} (R_b)^{T-t}(1 - R_b) I_b(t; Bel^i_{1:t}, Bel^j_{1:t}, T) \tag{7}$$

where I_b is the function estimating the expected 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 pseudo expected measurements, and then following the belief-based MR-SLAT procedure, the expected uncertainty reduction considering the loss rate can be estimated.

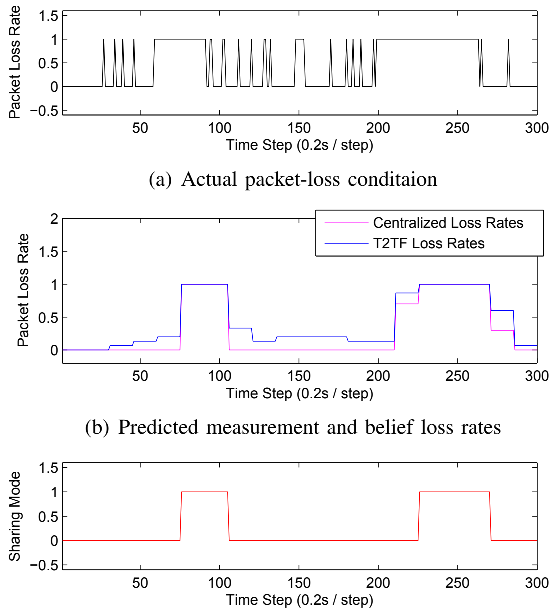
Based on the estimation process of expected uncertainty reduction between two robots, the sharing mode of the i^{th} robot is decided by comparing the summations of the estimated expected uncertainty reductions to all the other teammate robots with measurement-sharing and belief-sharing respectively:

$$\theta_i = \arg\max_{\theta} \sum_{j, j \neq i} f(\theta; Bel^i_{1:t}, Bel^j_{1:t}, R_m, R_b, T) \tag{8}$$

In the case with two nodes, our proposed decision module resorts to the optimal solution in the probabilistic point of view. However, Equation 8 only resorts to an approximate solution as the information shared among the other robots are neglected. The reason of this information ignorance is due to the observation that to estimate that information, the algorithm has to enumerate all possible sharing-modes of all the robots, which would result in an algorithm with exponentially-growing complexity that can be inapplicable in practice. However, our experiments demonstrate that by Equation 8 the proposed decision module provides satisfactory results, based on which ComAd MR-SLAT outperforms measurement-based and belief-based MR-SLAT under different communication conditions.

One remaining issue is that in practical online applications, the communication conditions, i.e. loss rates for sharing measurements and beliefs, are unknown at the time when making the sharing mode decisions. In our implementation, the sharing mode is decided for every 3 second-long window based on the communication condition predicted statistically by the condition in the previous window.

Fig. 2 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 loss rate of sharing measurements is less than or equal to the loss rate of sharing beliefs by simple duplicated transmission under the same communication bandwidth. Our mode decision module behaves as expected: 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. Based on the decided sharing



(a) Actual packet-loss conditaion

(b) Predicted measurement and belief loss rates

(c) Decided sharing modes

Fig. 2. The result of the developed mode decision for two nodes in a 300-frame sequence

modes, the scheme of our hybrid measurement and belief sharing algorithm is introduced in the next section.

B. Hybrid Measurement and Belief Sharing

This section describes our hybrid 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.

1) Information Sender's View: When the i^{th} robot is in the measurement-sharing mode, the robot simply sends the new fetched 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:

$$Bel^i_{T_1:t} \sim Pr(X^i_t | U^i_{T_1:t}, Z^i_{T_1:t}), \text{ for } T_1 \le t \le T_2 \tag{9}$$

The beliefs, $Bel^i_{T_1:t}$ for $T_1 \le t \le T_2$, 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.

2) Information Receiver's View: Each robot always maintains a state, $Bel^M_{1:t}$, which integrates the odometry data and measurements of the robot itself and those in the measurement-sharing mode:

$$\begin{aligned} &Bel^M_{1:t} \sim \\ &\quad Pr(X_t | \{U^i_{1:t}, Z^i_{1:t}, \forall i \in M\}, \{U^j_{1:T_j}, Z^i_{1:T_j}, \forall j \notin M\}), \\ &\quad M = \{i | \theta_i = 0\} \end{aligned} \tag{10}$$

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 $Bel^M_{1:t}$ with the other beliefs received from the robots in belief-sharing mode:

$$Bel_{1:t} \sim BM(Bel^M_{1:t}, \{Bel^j_{T_j:t} | \forall j \notin M\}) \tag{11}$$

For preventing the information reuse problem, the merged global state $Bel_{1:t}$ would not be replaced or fed back to $Bel^M_{1:t}$ to keep $Bel^M_{1:t}$ 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 $Bel^j_{T_j:T3}$ into $Bel^M_{1:t}$ to make sure that its odometry data and measurements contained in $Bel^j_{T_j:T3}$ are not lost.

V. EXPERIMENTAL EVALUATION

In order to verify the effectiveness of the proposed hybrid algorithm, ComAd MR-SLAT is evaluated under different packet loss rates and different bursty loss lengths.

A. 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. The motion and sensor models follow the parameters we applied in practical RoboCup competitions [8]. In addition, 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.

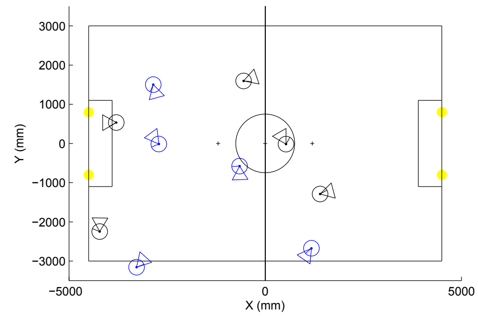


Fig. 3. Setting of the multi-robot scene for evaluation. Following the motion models and sensor models used in practical RoboCup scenes, e.g. odometry noises, feature extraction noises, detection recall rates, various packet loss rates and bursty loss lengths are simulated. Blue circles denote robots that can communicate with each other, and black circles denote the moving objects.

B. Five-vs.-Five with Homogeneous Communication

This experiment simulates a five-vs.-five scenario as shown in Fig. 3. 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 are assumed, which simulates the case in which communication is realized through one centralized device such as the WiFi device used in practical RoboCup competitions.

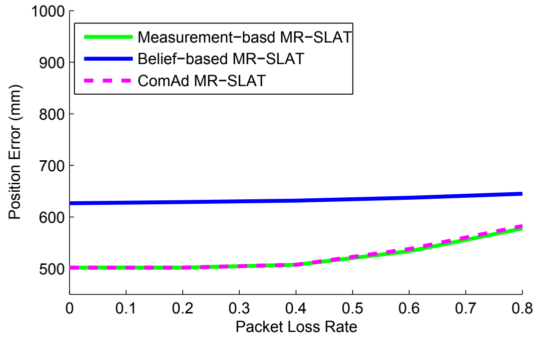
The performance of localization accuracy averaged from 80 Monte Carlo runs under different packet loss rates and bursty loss lengths is shown in Fig. 4. Firstly, regarding packet loss rates, it can be seen that the measurement-based MR-SLAT outperforms belief-based MR-SLAT when the packet loss rate is 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 bursty loss length 1, 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. 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 ComAd MR-SLAT successfully combines the advantages of measurement-based and belief-based MR-SLAT.

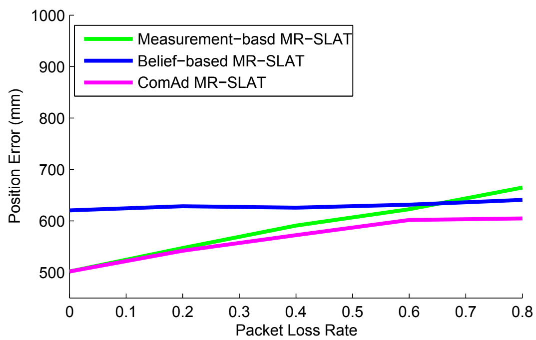
C. Heterogeneous Communication and Scalability

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. The results again demonstrate that the proposed ComAd MR-SLAT outperforms measurement-based and belief-based MR-SLAT, which verifies the effectiveness of ComAd MR-SLAT with heterogeneous communication links between robots. However, it can be observed that comparing to the homogeneous communication case, the performance of ComAd MR-SLAT is closer to the better one of measurement-based and 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.

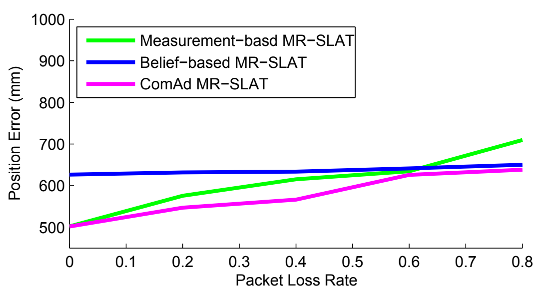
In addition, the scalability of ComAd MR-SLAT is also evaluated in a 10-vs.-10 scene as the setting illustrated in Fig. 6. The results are shown in Fig. 7. Due to the page limits of the paper, only the results of bursty lengths 1 and 40 are shown, but the results of other bursty lengths are similar. In this experiment, the proposed hybrid algorithm also works and based on the decided sharing-modes, ComAd MR-SLAT outperforms measurement-based and belief-based approaches.



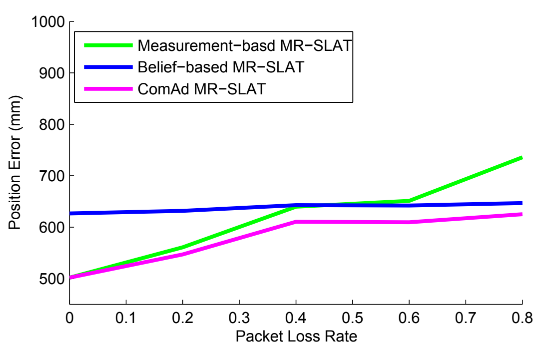
(a) Bursty loss length = 1



(b) Bursty loss length = 20

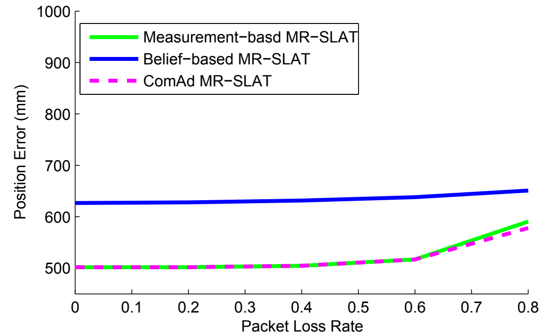


(c) Bursty loss length = 30

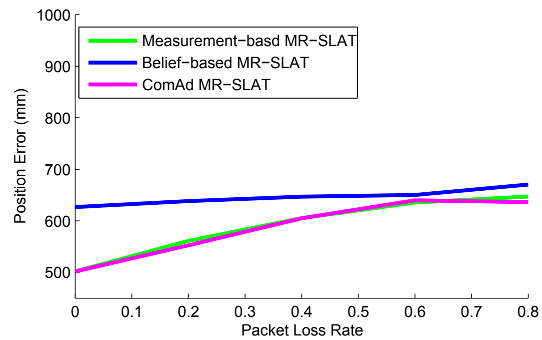


(d) Bursty loss length = 40

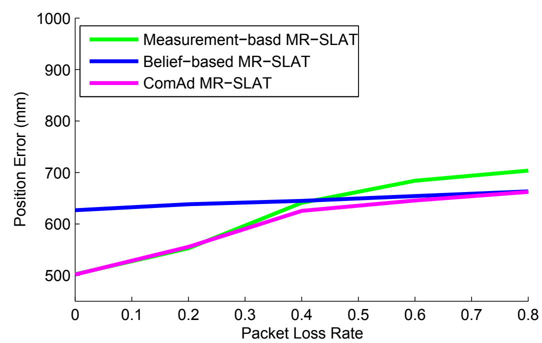
Fig. 4. Five-vs.-five with homogeneous communication. Comparison on the localization errors of measurement-based MR-SLAT, belief-based MR-SLAT, and the proposed ComAd MR-SLAT under different packet loss rates and different bursty loss length.



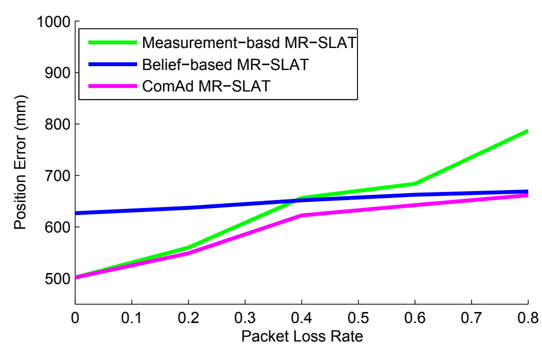
(a) Bursty loss length = 1



(b) Bursty loss length = 20



(c) Bursty loss length = 30



(d) Bursty loss length = 40

Fig. 5. 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.

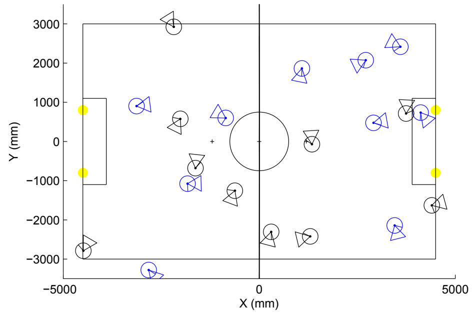
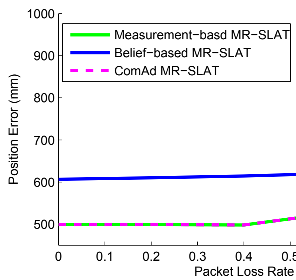
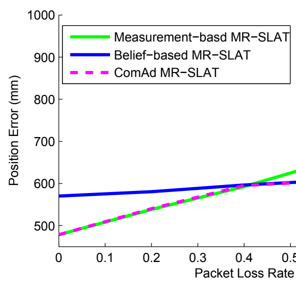


Fig. 6. Setting for scalability evaluation: Ten-vs.-ten with heterogeneous communication.



(a) Bursty loss length = 1



(b) Bursty loss length = 40

Fig. 7. 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 heterogenous communication conditions.

VI. Conclusions

In this paper, 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, a hybrid approach is developed to combine the advantages of both. By maximizing the expected uncertainty reduction, the sharing modes is decided considering the communication conditions online. Based on the decided sharing modes, the hybrid algorithm dynamically switches between measurement-sharing and belief-sharing without information loss or reuse. The proposed algorithm is evaluated in the RoboCup scenario. Following the models used in the practical RoboCup competitions, Monte Carlo runs with different packet loss rates and bursty lengths are simulated. In the experiments, the proposed ComAd MR-SLAT outperforms measurement-based MR-SLAT and belief-based MR-SLAT in localization accuracy. The experimental results demonstrate the effectiveness of the proposed algorithm and exhibit that ComAd MR-SLAT is robust under different communication conditions.

References

[1] I. J. Cox and G. T. Wilfong, Eds., *Autonomous robot vehicles*. Springer-Verlag New York, Inc., 1990.

[2] J. Leonard and H. Durrant-Whyte, “Mobile robot localization by tracking geometric beacons,” *IEEE Transactions on Robotics and Automation*, vol. 7, no. 3, pp. 376–382, June 1991.

[3] D. Fox, W. Burgard, and S. Thrun, “Markov localization for mobile robots in dynamic environments,” *Journal of Artificial Intelligence Research*, vol. 11, pp. 391–427, 1999.

[4] D. Fox, W. Burgard, H. Kruppa, and S. Thrun, “A probabilistic approach to collaborative multi-robot localization,” *Autonomous Robots*, vol. 8, no. 3, pp. 325–344, 2000.

[5] S. Roumeliotis and G. Bekey, “Distributed multirobot localization,” *IEEE Transactions on Robotics and Automation*, vol. 18, no. 5, pp. 781–795, Oct. 2002.

[6] A. Howard, M. Matark, and G. Sukhatme, “Localization for mobile robot teams using maximum likelihood estimation,” in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2002, pp. 434–439.

[7] C.-C. Wang, C. Thorpe, S. Thrun, M. Hebert, and H. Durrant-Whyte, “Simultaneous localization, mapping and moving object tracking,” *The International Journal of Robotics Research*, vol. 26, no. 9, pp. 889–916, Sept. 2007.

[8] C.-H. Chang, S.-C. Wang, and C.-C. Wang, “Vision-based cooperative simultaneous localization and tracking,” in *IEEE International Conference on Robotics and Automation*, 2011, pp. 5191–5197.

[9] Y. Bar-Shalom and X.-R. Li, “Multitarget-multisensor tracking: principles and techniques,” *Storrs, CT: University of Connecticut*, 1995.

[10] S. Thrun and Y. Liu, “Multi-robot slam with sparse extended information filers,” in *Robotics Research*. Springer, 2005, pp. 254–266.

[11] E. D. Nerurkar, S. I. Roumeliotis, and A. Martinelli, “Distributed maximum a posteriori estimation for multi-robot cooperative localization,” in *IEEE International Conference on Robotics and Automation (ICRA)*, 2009, pp. 1402–1409.

[12] M. Aeberhard, S. Schlichtharle, N. Kaempchen, and T. Bertram, “Track-to-track fusion with asynchronous sensors using information matrix fusion for surround environment perception,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 13, no. 4, pp. 1717–1726, 2012.

[13] F. Govaers and W. Koch, “An exact solution to track-to-track-fusion at arbitrary communication rates,” *IEEE Transactions on Aerospace and Electronic Systems*, vol. 48, no. 3, pp. 2718–2729, 2012.

[14] A. Cunningham, V. Indelman, and F. Dellaert, “Ddf-sam 2.0: Consistent distributed smoothing and mapping,” in *IEEE International Conference on Robotics and Automation (ICRA)*, 2013.

[15] H. Chen, T. Kirubarajan, and Y. Bar-Shalom, “Performance limits of track-to-track fusion versus centralized estimation: theory and application [sensor fusion],” *IEEE Transactions on Aerospace and Electronic Systems*, vol. 39, no. 2, pp. 386–400, 2003.

[16] M. Yajnik, J. Kurose, and D. Towsley, “Packet loss correlation in the mbone multicast network,” in *Global Telecommunications Conference (GLOBECOM) Communications: The Key to Global Prosperity*, 1996, pp. 94–99.

[17] M. G. Rabbat and R. D. Nowak, “Decentralized source localization and tracking [wireless sensor networks],” in *IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, vol. 3, 2004, pp. iii–921.

[18] S. Matzka and R. Altendorfer, “A comparison of track-to-track fusion algorithms for automotive sensor fusion,” in *IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, 2008, pp. 189–194.

[19] X. Tian and Y. Bar-Shalom, “Sequential track-to-track fusion algorithm: exact solution and approximate implementation,” in *SPIE Defense and Security Symposium*. International Society for Optics and Photonics, 2008, pp. 696 910–696 910.