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Rao-Blackwellized Particle Filters Multi Robot SLAM with Unknown Initial Correspondences and Limited Communication

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Abstract— **Multi robot systems are envisioned to play an important role in many robotic applications. A main prerequisite for a team deployed in a wide unknown area is the capability of autonomously navigate, exploiting the information acquired through the on-line estimation of both robot poses and surrounding environment model, according to Simultaneous Localization And Mapping (SLAM) framework. As team coordination is improved, distributed techniques for filtering are required in order to enhance autonomous exploration and large scale SLAM increasing both efficiency and robustness of operation. Although Rao-Blackwellized Particle Filters (RBPF) have been demonstrated to be an effective solution to the problem of single robot SLAM, few extensions to teams of robots exist, and these approaches are characterized by strict assumptions on both communication bandwidth and prior knowledge on relative poses of the teammates. In the present paper we address the problem of multi robot SLAM in the case of limited communication and unknown relative initial poses. Starting from the well established single robot RBPF-SLAM, we propose a simple technique which jointly estimates SLAM posterior of the robots by fusing the prioceptive and the eteroceptive information acquired by each teammate. The approach intrinsically reduces the amount of data to be exchanged among the robots, while taking into account the uncertainty in relative pose measurements. Moreover it can be naturally extended to different communication technologies (bluetooth, RFId, wifi, etc.) regardless their sensing range. The proposed approach is validated through experimental test.**

I. INTRODUCTION

Mobile robots systems have been involved in many applications including museum guide robots, surveillance, planetary exploration, search and rescue [1]. In order to successfully accomplish such tasks, the robots are required to jointly estimate their position and a map model while traveling in an unknown environment. For this reason, the development and application of Simultaneous Localization And Mapping (SLAM) have attracted large attention over the last decade. While the maturity of SLAM in single robot scenarios is recognized in many recent works [2], [3], [4], a big research challenge is to extend these approaches to multi robot scenarios in order to enhance autonomous exploration and large scale SLAM. Although improving efficiency, accuracy and robustness of operation, multi robot systems introduce several sources of complexity requiring a bigger effort in designing probabilistic filters for the estimation of the SLAM posterior of different robots by fusing the prioceptive and the eteroceptive information acquired by each teammate. Compared to a single robot scenario, several challenges arise, including: 1) distributed posterior estimation from the available data, gathered by different robots; 2) the influence of limited bandwidth and sensing range, connected to the use of unreliable wireless communication channels; 3) team coordination and need of shared world representation; 4) complexity and memory requirements in dependence of the number of robots and map size; 5) intrinsically dynamic environment. Several techniques for the estimation of SLAM posterior of a team of robots have been proposed in order to fuse local maps and information from individual robots into integrated and shared world representations (further details can be found in Section II). One crucial point lies in the assumption about the knowledge of the robots initial relative locations. If the *initial correspondence* of robots locations is assumed to be known, the problem easily extends from single robot SLAM techniques [5], [6]. However, if the relative initial locations are not known, a consistent integration is challenging. In addition, *centralized* solutions, in which all the information are transferred to a central node, that performs computation over the whole team posterior, are often unlikely since wireless channels are sensitive to failures and communication among teammates can be quickly saturated by the large amount of information gathered. As a consequence *distributed* approaches are required, relaxing the strong assumption that the whole team has to remain inside the communication range of the central node. Distributed estimation allows the robots to build their own world representation using only local information and the data gathered by the teammates. Although the computation remains local, the outcome of the estimation over the map model should be as shared as possible in order to enhance team coordination. As an example, task allocation can be performed to improve cooperative exploration, and it can be accomplished by a central unit which assigns the tasks to individuals or managed in a decentralized fashion, but in both cases it requires a shared representation. Finally the technique used to solve SLAM is required to be *scalable* (in terms of memory and complexity) and *robust* to dynamic environments, since the team travels in the same scenario and each robot should build a consistent map although facing the teammates that represent moving obstacles.

As witness of the attention paid by the robotic community to the mentioned challenges, there is a large literature in the field of multi robot SLAM, which ranges from the application of Extended Kalman Filter (EKF) [7] to Sparse

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Extended Information Filters [8], manifold representations [9] and Rao-Blackwellized Particle Filters (RBPF) [10]. Although the last technique is probably the most used for estimating metric maps in single robot scenarios, few authors tried to extend this approach to the multi robot posterior estimation. In such a case the high dimensionality of the state in the estimation process and the intrinsically centralized structure of the filter prevents efficient solutions unless ad-hoc techniques are applied.

We propose an approach to multi robot SLAM based on RBPF, for a realistic setting in which the relative initial positions of the robots are unknown and mild assumptions on wireless communication are considered. Our approach even applies to the case in which short range communication technologies (bluetooth, RFId, etc.) are employed. According to [7], when a rendezvous occurs, the teammates exchange information, and each robot applies coordinate transformation in order to have the external data expressed in its own reference frame. Then Rao-Blackwellized Particle Filters perform estimation over received data, taking into account the uncertainty in relative measurements during rendezvous.

In the following section we provide an overview of the state-of-the-art approaches to multi robot SLAM. In Section III our approach to RBPF-SLAM is described in deep and clarified through practical examples. Then in Section IV we present results from a real test. Conclusions are drawn in Section V.

II. RELATED WORK

Multi robot SLAM is an active research field and many efforts were devoted in finding suitable filtering techniques able to deal with a team of robots performing cooperative exploration in unknown environments. As mentioned above, the problem imposes harder constraints than single robot SLAM, so many authors proposed ad-hoc extensions of the bayesian framework to adapt it to distributed multi agent estimation. In order to face the challenge of integrating the information collected by different robots in a consistent representation, early research works proposed the use of the *Extended Kalman Filter* (EKF) [7], [11], [12], to jointly estimate robots and landmarks posterior included in an augmented state space. In [7], multi robot SLAM problem is addressed, relaxing the hypothesis of known initial correspondence. When two robots sense each other in the communication range, relative distance and bearing measurements are evaluated in order to compute the mutual transformation between reference frames which allows to align the respective independent maps into a single representation. Since the EKF involves a complexity which grows quadratically in the state space dimension, Thrun [8] formulated the landmark-based multi robot SLAM using the *Sparse Extended Information Filter* (SEIF), which constitutes an efficient solution of the SLAM problem in the information space. SEIF represents the posterior by a sparse Gaussian Markov random field (GMRF) parameterizing the multivariate distribution through the information vector and the information matrix. Taking advantages from the structure of the filter, SEIF approach can be performed in a distributed manner, overcoming the non easily decomposable structure of the EKF. As metric maps are characterized by higher resolution and allow finer planning and exploration, many authors proposed to overcome the less detailed topological representation, by exploiting the idea of sub-map approach in order to build a graph-like topological map, in which vertices represent local metric maps and edges describe relative positions of adjacent local maps. These algorithms are shown to be extendable to the multi robot SLAM [13]. Unfortunately, when the number of features in the environment increases, the computation cost becomes unsustainable.

Another representation of map merging problems is based on grid maps and feature matching. In a recent work [14], Carpin borrowed some concepts from image processing, applying line detection algorithms and Hough transform to the original metric map. Fox *et al.* [2] proposed an algorithm for estimating relative position of pairs of robots when they are in communication range. One robot uses an adaptive particle filters to estimate its position in the other robot's partial map and, in order to check whether and how two robots partial maps are overlapped, they construct a hidden Markov model that predicts observations of a robot out of the partial map. For the purpose of avoiding false map merging, the two robots actively estimate their location and arrange to meet at one rendezvous point. If they fail to meet, the map fusion hypothesis is rejected, otherwise, the maps are integrated into a consistent representation. Exploiting the crucial importance of loop closing and data association in SLAM, Howard [9] proposed a manifold map structure that facilitates data association and loop closure detection without risking map consistency. The advantage of this methodology is that it postpones the time of data association decisions until the robots have high confidence. In [9], this basic approach is applied to multi robot SLAM by adopting maximum-likelihood estimation algorithm [15] for the manifold representation. Because of the centralized processing, the communication issue should be carefully considered, and many drawbacks arise reducing the potential number of teammates in the system.

Finally in [10] Rao-Blackwellized Particle Filters is applied to a multi robot scenario. This work is interesting for the description of the fundamental difference between known and unknown initial pose of the robots. Howard [10], after detailing his solution to the former case, focuses the attention on the latter, proposing to augment the state space with other robots trajectories. When two robots meet at occasional rendezvous, a new instance of the filter is started and each robot continues to update its filter using its own information and the data transferred by the teammate using wireless. Although this work is strictly related to the proposed approach, some limitations reduce its effectiveness. Howard neglected the noise on relative measurements and assumed for his approach a stable wireless connection that allows the robots to exchange every command and measurement from sensors. A careful study of this technique reveals that the approach is substantially centralized and each robot uses a fixed particle set size to perform estimation over an augmented state space, although this has a large impact on the consistency of the map as we underlined in our previous work [16].

III. Multi Robot RBPF-SLAM

We consider the case in which a team of K robots, each one equipped with laser scanner, pan-tilt camera and odometric pose estimation, travels in an unknown indoor scenario, with the primary aim of building a consistent metric representation of the environment. This representation should be as shared as possible in order to enhance team coordination and allow active rendezvous and loop closing procedures. Moreover we assume that each robot has local knowledge of the surrounding environment (given by laser and camera) and can communicate with the teammates within a maximum distance r. We use a metric representation since the team is assumed to work in a highly symmetric environment in which it is tricky to solve the correspondence problem of a landmark-based representation if no ad hoc artificial landmarks are added.

A. Approach Overview

The approach we propose is an efficient extension of RBPF single robot SLAM. Before and after each rendezvous the robots of the team perform their estimation using FastSLAM, following the path drawn by [17] and [18]. When a rendezvous occurs, a simple procedure allows to fuse the information in an effective and distributed fashion. This procedure can be summarized in three phases:

– *Data exchange*: robot i receives, from the met teammate, the data acquired from the last meeting (or from the beginning if it is the first meeting between the two robots) to the rendezvous instant; in order to minimize the data to be exchanged the robot j communicates only the preprocessed information containing the laser stabilized odometry and the corresponding laser scanner measurements.

– *Reference frame transformation*: from the information communicated and from relative pose measurements the data received is suitably roto-translated in robot reference frame.

– *Estimation on virtual data*: once the data is roto-translated, it is included in the sensor buffer, as if it was due to laser and odometric measurements. RBPF estimate SLAM posteriors from received data, using suitable process models with the corresponding uncertainty. Finally, after the filtering of received data is complete, the particles restart from their poses before the meeting, and continue the estimation process, according to grid-based FastSLAM.

The approach is detailed in the following subsections.

B. Team Setup and FastSLAM

The robots start from unknown initial poses (relative position of each robot is unknown too) and they begin to acquire information from the surrounding environment and from the prioceptive sensors. While traveling, each robot collects trajectories and map hypotheses estimated through RBPF-SLAM. Since the map probability can be computed analytically given the robot path, it is possible to factorize the joint probability through Rao-Blackwellization [19]:

$$p(x_{1:t_i}, m_i \mid z_{1:t_i}, u_{0:t_i-1}) = p(m \mid x_{1:t_i}, z_{1:t_i}) \cdot p(x_{1:t_i} \mid z_{1:t_i}, u_{0:t_i-1}) \quad (1)$$

In (1) the state includes the robot trajectory $x_{1:t_i} = x_1, x_2, \ldots, x_{t_i}$ and the map m_i, both estimated from the measurements $z_{1:t_i} = z_1, z_2, \ldots, z_{t_i}$ and the commands $u_{0:t_i-1} = u_0, u_1, \ldots, u_{t_i-1}$. The previous equation provides the basis for single robot grid-based FastSLAM: the particle filter is applied to the problem of estimating potential trajectories and a map hypothesis is associated to each sample. Before the first rendezvous, the robot i estimates $p(x_{1:t_i}, m_i \mid d_{1:t_i})$ that is the belief of the robot (from the beginning to the current time step) given the information acquired $d_{1:t_i} = \{z_{1:t_i}, u_{0:t_i-1}\}$. Following the framework of Howard, we build SLAM posterior using *stabilized laser odometry* [10]. Stabilized laser odometry increases the accuracy of odometric pose estimation and it is useful to reduce the number of measurements processed, discarding, for example, scans acquired when the robot does not move.

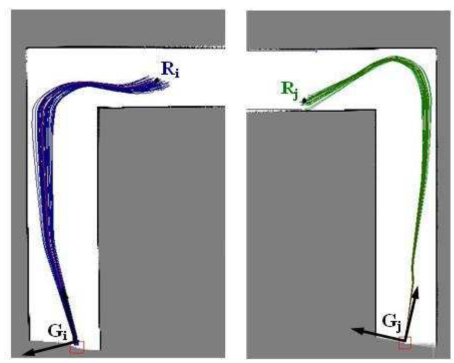

Fig. 1. Single robot FastSLAM before first rendezvous event. Each robot estimates both trajectory and map hypotheses in its own reference frame.

C. First Rendezvous and Data Exchange

It is worth noticing that we made no strict assumption on communication between robots nor on their synchronization. As a consequence each teammate has its own timer and a rendezvous episode should be denoted using the time stamp of each robot involved. Without loss of generality we assume that the rendezvous is between two robots at a time. When the first meeting between robot i and robot j occurs each one carries on its own information, respectively included in $p(x_{1:t_{ij,1}}, m_i \mid d_{1:t_{ij,1}})$ and $p(x_{1:t_{ji,1}}, m_j \mid d_{1:t_{ji,1}})$, and referred to different reference frames placed in the initial pose of each robot, respectively denoted as G_i and G_j. In the notation used $t_{ij,1}$ is the discrete time stamp of robot i (the former of the two indexes), at which it meets robot j for the first time (identified by the number after the comma).

At the first rendezvous each robot transfers its own piece of information, respectively contained in $d_{1:t_{ij,1}}$ and $d_{1:t_{ji,1}}$ to the other teammate, using, for example, wireless communication or other short range technologies (bluetooth, RFId etc.). This data can be figured out as a list of odometric poses with the corresponding laser scan. For the symmetry of the process and without loss of generality, in the following subsections we will limit our description to robot i.

D. Reference Frame Transformation

When robot i receives $d_{1:t_{ji,1}}$, in order to successfully include this piece of information in its posterior, it has to represent in G_i the poses contained in $d_{1:t_{ji,1}}$. In this context we assume that when the robots meet, they are able to measure their relative pose and the corresponding uncertainty using a pan-tilt camera associated to the laser (line of sight between the teammates is required). For each robot, the relative pose of the teammate can be obtained from the relative distance ρ_{ij} (given by the laser), the angle θ_{ij} at which robot i sees the robot j, and the angle θ_{ji}, at which robot j observes robot i (angular measurements can be easily performed by the cameras). From these measurements we can obtain the relative pose described by the vector $p_{R_iR_j} = [\rho_{ij}\cos\theta_{ij},\ \ \rho_{ij}\sin\theta_{ij},\ \ \pi + \theta_{ij} - \theta_{ji}]$, and compute the first-order approximation of the corresponding uncertainty, expressed by the covariance matrix $P_{p_{R_iR_j}} = [P_{mn}]$, with $m, n = 1, 2, 3,$ where:

$$P_{11} = \sigma^2_{\rho_{ij}}\cos^2\theta_{ij} + \rho^2_{ij}\sigma^2_{\theta_{ij}}\sin^2\theta_{ij} \tag{2a}$$

$$P_{12} = P_{21} = \frac{\sigma^2_{\rho_{ij}} - \rho^2_{ij}\sigma^2_{\theta_{ij}}}{2}\sin(2\theta_{ij}) \tag{2b}$$

$$P_{13} = P_{31} = -\rho_{ij}\sigma^2_{\theta_{ij}}\sin\theta_{ij} \tag{2c}$$

$$P_{22} = \sigma^2_{\rho_{ij}}\sin^2\theta_{ij} + \rho^2_{ij}\sigma^2_{\theta_{ij}}\cos^2\theta_{ij} \tag{2d}$$

$$P_{23} = P_{32} = \rho_{ij}\sigma^2_{\theta_{ij}}\cos\theta_{ij} \tag{2e}$$

$$P_{33} = \sigma^2_{\theta_{ij}} + \sigma^2_{\theta_{ji}} \tag{2f}$$

From the knowledge of the relative pose and the final robots' poses, respectively $[x_i, y_i, \theta_i]$ and $[x_j, y_j, \theta_j]$, it is possible to compute the vector describing the relative pose between G_i and G_j, according to [7] and [11]:

$$T_{G_iG_j} = [T_1, T_2, T_3]^T \tag{3}$$

where,

$$\begin{aligned} T_1 &= x_i + \rho_{ij}\cos(\theta_i + \theta_{ij}) \\ &\quad -(y_j\sin(\theta_{ij} - \theta_{ji}) - x_j\cos(\theta_{ij} - \theta_{ji})) \\ T_2 &= y_i + \rho_{ij}\sin(\theta_i + \theta_{ij}) \\ &\quad +(x_j\sin(\theta_{ij} - \theta_{ji}) + y_j\cos(\theta_{ij} - \theta_{ji})) \\ T_3 &= \pi + \theta_i + \theta_{ij} - \theta_{ji} - \theta_j \end{aligned}$$

The first two components of the vector correspond to the translation to be applied in order to express the poses of robot j in G_i, whereas the last component provides the rotation angle. The above described transformation is clarified in Fig. 2, which enlightens the reference frames involved in the transformation. It is worth noticing that the angle θ_{ji} and the final odometric pose of robot j in G_j should be previously communicated by robot j itself. If ρ_{ji} is also communicated, although not strictly necessary, it can be averaged with ρ_{ij} allowing, under the hypothesis of independent Gaussian noise, to reduce the variance of distance measurement to $\sigma^2_{\rho_{ij}}\sigma^2_{\rho_{ji}}/(\sigma^2_{\rho_{ij}} + \sigma^2_{\rho_{ji}})$.

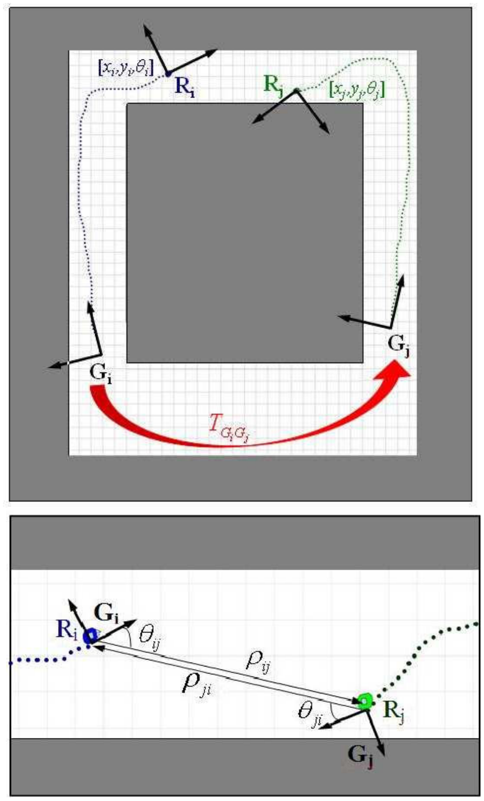

Fig. 2. When a rendezvous event occurs each robot knows its final pose (respectively $[x_i, y_i, \theta_i]$ and $[x_j, y_j, \theta_j]$) expressed in G_i and G_j and is able to measure the relative pose of the teammate. It is possible to attach a reference frame to the final position of each robot in order to understand how the overall transformation is the composition of the roto-translation between the represented reference frames.

Once the stabilized odometry of robot j is roto-translated into the reference frame of robot i, the latter has all the necessary information to evaluate SLAM posterior including received data.

Remark 1: The data received was preprocessed by robot j, which refined odometry through laser stabilization [10]. Such a preliminary computation reduces the number of recorded poses, since outliers or successive poses in which the robot was stationary are discarded. This fact further shrinks the communication overhead.

Remark 2: If a wireless communication is active in the considered scenario, the robots can exchange information also in the time interval between two meetings. In particular the robots can share their current poses, which are fundamental to plan active rendezvous, once the robots know the transformation between their reference frame. Notice that rendezvous remains crucial, since the odometric information transferred between the robots gradually derives, whereas when meeting occurs, pose constraints are added as clarified in the next subsection.

E. SLAM Posterior Estimation

The aim of the Rao-Blackwellized particle filters is the efficient estimation of SLAM posterior from noisy measurements. When dealing with multi robot scenarios, the filter should be applied in a proper way, in order to fuse in a coherent manner the information carried on by each robot involved in the rendezvous. Our approach stems from the observation that a rendezvous imposes an instantaneous constraint on relative poses of the two robots. This condition is similar to the constraint imposed by odometry at successive steps, that is described through a suitable process model in the filter.

In our approach, when robot i receives $d_{1:\ t_{ji,1}}$ from robot j, it includes these data in the filter from $d_{t_{ji,1}}$ (rendezvous pose) to d_1 (initial pose) as if they were acquired by its own sensors. In Fig. 3, the initial positions of robot i and j are S_1 and S_2, whereas points F_1 and F_2 are their rendezvous poses respectively. Therefore, the procedure corresponds to attach the inverted odometric data (from F_2 to S_2) to the initial odometric data carried on by robot i (from S_1 to F_1). This piece of information can be used as input to RBPF, that extract the SLAM posterior from the rough data. When applying the prediction step from the last pose of i (F_1) to the final pose of j (F_2), a proper *prediction model* must be considered. While in traditional FastSLAM this probabilistic model stems from the *odometry motion model*, in such a step, it derives from the relative measurement $p_{R_i R_j}$ and its uncertainty ($P_{p_{R_i R_j}}$). The *update model* remains unaltered since measurements are still given by the laser. After this step the filtering process continues using the motion model since the poses from F_2 back to S_2 are linked by odometric constraints. When RBPF end the estimation over the path of robot j, each particle restarts from its previous pose at time $t_{ij,1}$ and all particle poses are predicted one step later to S_3. Hence the robot continues the estimation through RBPF-SLAM, applied to its own measurements, until the exploration process ends at a generic point F_3. During the estimation over the external data, the robot i processes the information of the other robot as if it was traveling backward following the trajectory of the robot j. The surplus of information $d_{1:t_{ji,1}}$ represents a kind of virtual movement, since the robot i acquires measurements on the environment and on the odometric poses of robot j that were not obtained physically from its own sensors but were observed and communicated by another robot. After the rendezvous, robot i posterior $p(x_{1:t_{ij,1}}, m_i \mid d_{1:t_{ij,1}}, d_{1:t_{ji,1}})$ includes the data of robot j and both the map and the trajectories are updated accordingly. Finally we must observe that the approach is effective since the estimation process is remarkably faster than the acquisition of new measurements. As a consequence the information carried on by the other robot are quickly included in the posterior, preserving the on-line nature of the estimation process. Details on latencies are reported in Section IV.

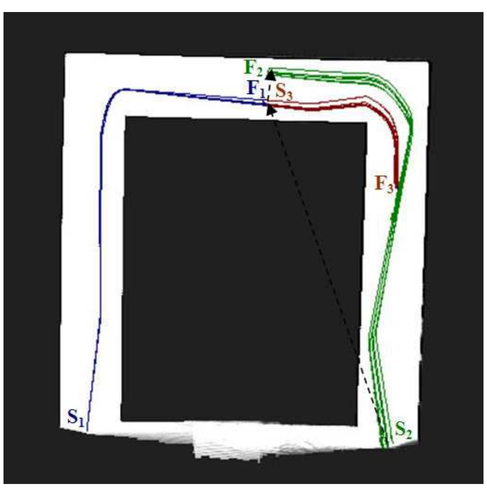

Fig. 3. Multi robot RBPF-SLAM. After rendezvous the overall map and trajectory hypotheses include the information acquired by both robots involved in the meeting.

F. Following Rendezvous Events

The procedure described in the previous subsection can be easily generalized to an arbitrary number of meetings. After the first rendezvous, each new encounter with the previously met robot corresponds to a loop closing event, adding constraints that are introduced in the filter through a resampling phase that selects the trajectories that best describe all the information acquired. Moreover, including virtual measurements from other robots, loop closure can occur also if the robot revisits places traveled by the met teammates. In the k-th rendezvous, the robots do not transfer the data $d_{1:\ t_{ji,k}}$ but only the piece of information from the last meeting to the current time stamp, i.e., $d_{t_{ji,k-1}:\ t_{ji,k}}$. This is not only a necessity dictated by the limited bandwidth, but derives from structural properties of the filtering process. If the same data is included twice in the RBPF, the filter interprets this information as the robot traveled twice in a place that was really visited only once. As a consequence resampling phases occur although no useful information for resampling is added. Based on this consideration our method allows to preserve filter consistency and at the same time it takes advantage of the small amount of data exchanged during rendezvous.

We conclude this section observing that when more than two robots intervene in the estimation process the procedure described above remains unchanged. The only aspect to be carefully considered is the imposition of the constraints given by the odometry, measurements and rendezvous events. In our implementation we preferred each robot to provide only the information acquired through its own sensors, regardless past meetings with other teammates. In this fashion we preserve the simplicity of implementation making the proposed technique an effective extension of grid-based FastSLAM.

The proposed approach is validated and discussed in the following Section, in which experimental results are discussed.

IV. Test and Discussion

In this Section we report the results of the implementation of our approach in a real scenario. We considered the case in which two robots travel inside an office-like environment cooperatively building a map. Experiments were performed in the corridors and labs of Politecnico di Torino, over an area of approximatively 200 m^2. The test scenario is challenging since it was performed in an environment with many non reflective surfaces in presence of people traversing corridors. The used mobile robots (Fig. 4) are ActivMedia Pioneers P3-DX equipped with a laser range sensor SICK LMS200, a pan tilt camera and odometry pose estimation. Moreover a visual marker is attached to each teammate, and this marker is endowed with a bar code useful to distinguish the robots. RBPF-SLAM, performed by each robot, was implemented applying *adaptive resampling technique*, proposed by Stachniss *et al.* [20], and *stabilized laser odometry*, further detailed in [10]. The map estimated by robot 1 and the corresponding estimated trajectory (including the pieces of data received from robot 2) are shown in Fig. 5. The reader is referred to the same figure for the following description.

Fig. 4. Robots P3-DX used for real test. A bar code marker is used to distinguish the robots.

The team is firstly deployed in different locations, respectively labeled with S_1 and S_2. The robots cover the first piece of trajectory till they arrive in positions I_1 and I_2, where the first rendezvous occurs. Once the robots meet, they measure the relative poses and exchange data using a wireless communication (based on a client/server architecture). Robot 1 includes in its posterior the external information related to the path S_2 - I_2 and then continues its route, traveling in loop (A) and applying FastSLAM. In the meanwhile robot 2 explores the lab (B) and arrives in position F_2. Robot 1 visits room (C) and, once arrived in F_1, it finally meets robot 2 for the second time. The data received from robot 2 allows robot 1 to complete its map, reducing the time required for exploration and enhancing loop closing. The dual procedure is applied to robot 2, producing a similar map.

Remark 3: the approach is distributed and for the random nature of the RBPF-SLAM, the maps built by each teammate are not exactly equal. On the other hand, the maps only differ by few cells, preserving the structure of the scenario. As a consequence our approach allows to build a shared representation which can be used for team coordination.

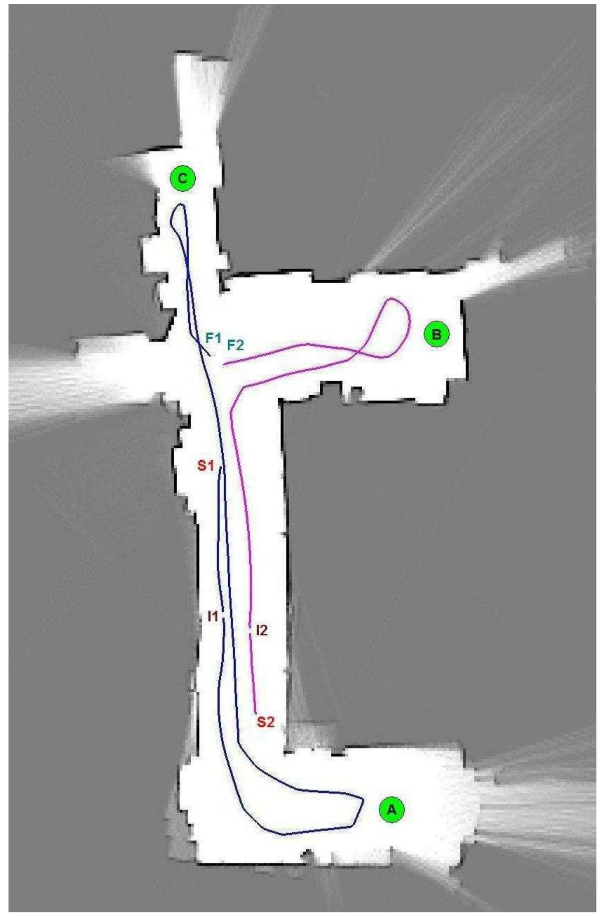

Fig. 5. Map estimated through RBPF multi robot SLAM during experimental test at Politecnico di Torino.

Fig. 6 shows the length of the sensor data queue that should be processed at each time step. The x-axis of the figure corresponds to physical time. Notice that the two peaks, that coincide with the instants in which external data are received from the other teammates, are quickly reduced by the RBPF. This observation allows us to conclude that, after a short latency, the estimation process comes back to its on-line nature. The maximum delay observed, using a common laptop, was 36 s.

V. Conclusion

The present paper proposes an efficient extension of RBPF-SLAM to multi robot scenarios. Although Rao-Blackwellized Particle Filters (RBPF) have been demonstrated to be an effective solution to the problem of single robot SLAM, few extensions to teams of robots exist, and these approaches are characterized by strict assumptions on both communication bandwidth and prior knowledge on relative poses of the teammates. We relaxed the assumptions of related works, addressing the problem of multi robot SLAM in the case of limited communication and unknown relative

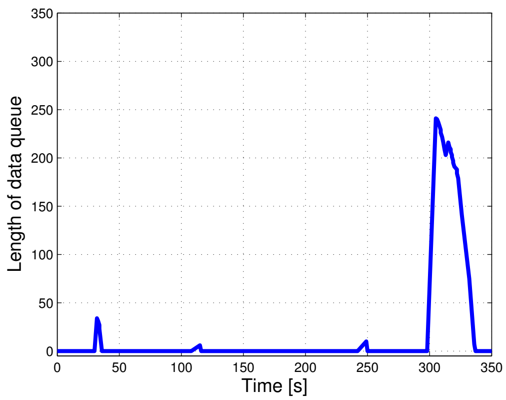

Fig. 6. Length of the sensor data queue that should be processed at each time step of the real test. The peaks correspond to rendezvous events in which external data is added to the queue.

initial poses. Our approach allows to jointly estimates SLAM posterior of the robots by fusing the prioceptive and the eteroceptive information exchanged among teammates. RBPF multi robot SLAM involves the communication of a small amount of data, while taking into account the uncertainty in relative pose measurements. Moreover it can be naturally extended to different communication technologies (bluetooth, RFId, wifi, etc.) regardless their sensing range. Before and after each rendezvous the robots of the team perform their estimation using FastSLAM. When a rendezvous occurs, a simple procedure allows to enhance information fusion in an effective and distributed fashion. This procedure can be summarized in the three phases, respectively called *data exchange*, *reference frame transformation* and *estimation on virtual data*. When the filtering of received data is complete, the particles restart from their poses before the meeting, and continue the estimation process, according to grid-based FastSLAM. After the first encounter the robots share similar (i.e., not exactly equal) representations of the map, up to a known roto-translation. Moreover the knowledge of the transformation between the reference frame of the teammates, allows to plan active rendezvous improving map consistency. The solution is shown to be an efficient and robust solution to multi robot SLAM and it is further validated through real test.

VI. ACKNOWLEDGMENTS

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