Proceedings Book

40th International Symposium on Robotics

Edited by:

Luis Basañez - Raúl Suárez - Jan Rosell

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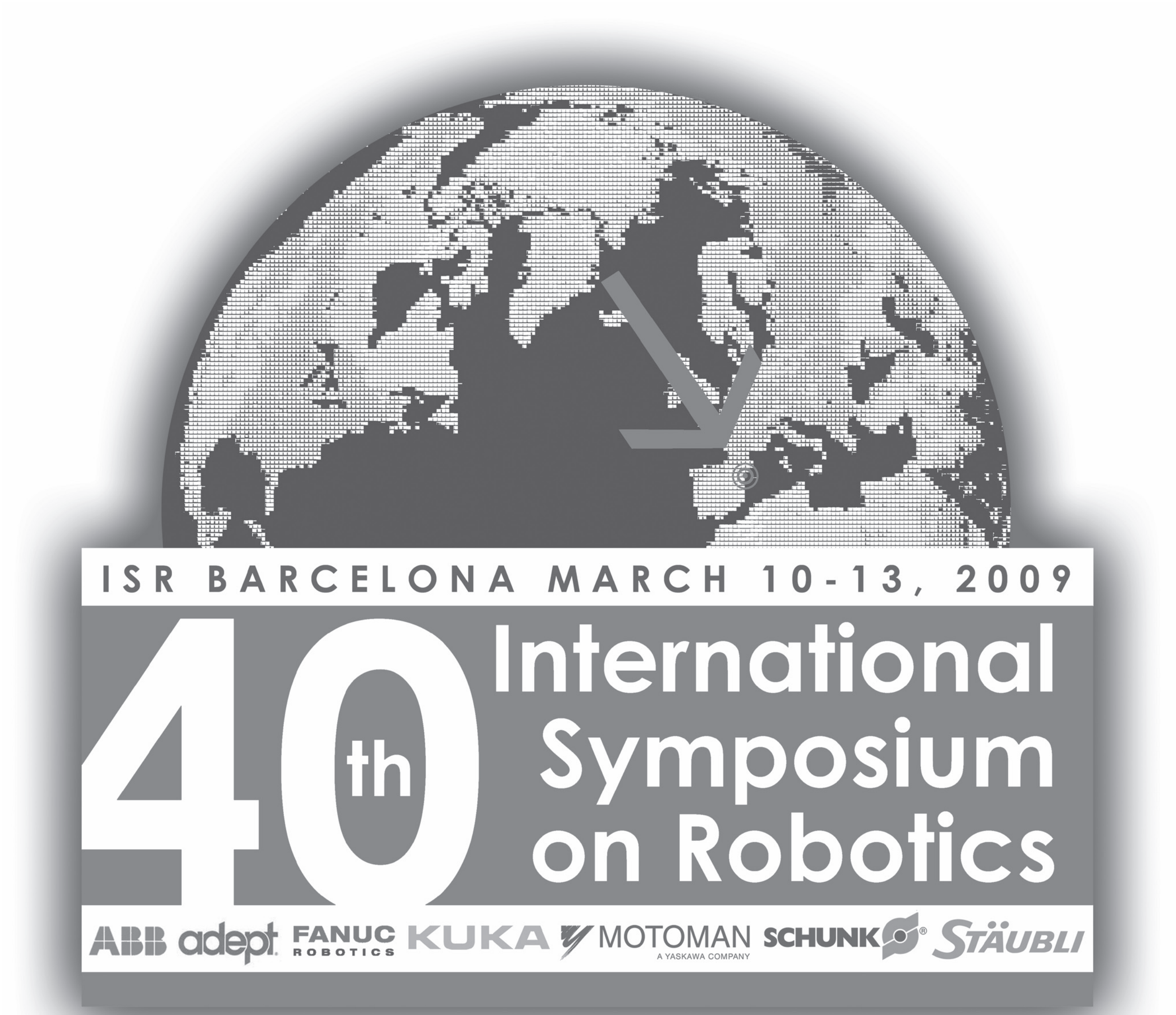

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Foreword

Since the first International Symposium on Industrial Robots (ISIR) held in Chicago in 1970, Robotics has experienced an important evolution and has extended its field from the industrial manufacturing operations to different kind of services useful to the well-being of humans and equipment like domestic tasks, entertainment, handicap assistance, inspection and maintenance, surgery and therapy, and public relations, among many others. This is the reason for the change of the symposium title that becomes, from 1998, International Symposium on Robotics (ISR).

Despite the high effort done in research and development, important aspects of robotics, both industrial and service, are still open challenges: better control performance, more and more efficient sensors and sensory systems, friendly and higher level programming, error recovery, real autonomy, efficient navigation, coordinated and networked robots, among others.

The following pages show a sample of these efforts made by the scientific and technical international community to respond to these challenges. More than fifty papers by experts from 11 countries have been selected by the International Programme Committee (IPC), made up of relevant persons from the academic and the industrial worlds. The scope of the papers ranges from robot modeling and control to human robot interaction, through topics like planning, robot vision and cognitive robotics.

The ISR has also become the annual mandatory meeting of industrial and applied oriented people involved in robotics and advanced automation. This fact is reflected in the significant number of papers dealing, for instance, with new robot applications, service robotics and aerial robots. In addition to the scientific-technical sessions, ISR'09 also offers to the participants several special sessions, not included in this book, dedicated to industrial sectors (aerospace, food), successful technology transfers, new and innovative products, and research strategies and funds opportunities in different geographic areas.

For the second time Barcelona, the great Mediterranean city, hosts the ISR (the first time was the 23rd ISIR in 1992). Now the ISR reaches the 40th symposium of the series and the Spanish Robotics Association (AER-ATP) has the honor and the privilege of organizing the event and to welcome the robotics community attending the ISR'09.

We hope that, in the nowadays difficult economic situation, the 40th ISR will contribute, at least in a modest way, to the progress of our society and the understanding of the people of different countries.

Luis Basañez
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Map Fusion of Visual Landmark-based Maps ⋆

M. Ballesta, O. Reinoso, A. Gil, L. Payá and M. Juliá *

* *Dept. of Industrial Systems Engineering, Miguel Hernandez University, Elche, Spain (e-mail: m.ballesta|o.reinoso|arturo.gil|lpaya|mjulia@umh.es).*

Abstract: In a multi-robot framework, each robot can build its own map independently. In this situation, the fusion of these local maps into a global one may be necessary. In this paper, we focus on the study of this problem, i.e., the Map Fusion problem. This task is performed in two different stages. First, the Map Alignment stage, in which the transformation between pairs of local maps is computed. Then, in the Map Merging stage, the data from each local map is fused into a unique map. Particularly, we use the RANSAC method in order to perform the alignment between maps. Then, in the map merging state, we propose a method that considers the uncertainty in the estimate of the maps. In these experiments, we use visual landmark-based maps, which have been built by the robots using the FastSLAM algorithm.

1. INTRODUCTION

Building maps is essential for robots in order to be considered as autonomous entities. For this reason, the problem of SLAM (Simultaneous Localization and Mapping) has received great attention. Some of the most common introductions to SLAM can be found in (Smith and Cheeseman [1990], Zunino and Christensen [2001]). The basis of the SLAM algorithms is that the robot builds its map of the environment and simultaneously localizes itself in this map. However, these algorithms differ in the way they solve this problem. So far, the most common solutions are based in one of these two approaches: the Extended Kalman Filter (EKF) or the Rao-Blackwellized particle filters (denoted with the general term FastSLAM). The EKF, introduced in (Smith and Cheeseman [1990]), estimates an augmented state vector including the robot's pose and the localization of the landmarks in the map. In general, this approach works well in environments with robust data association and there is a sparse set of landmarks, which are dispersed in the environment. A recent and also successful approach is the FastSLAM algorithm, which was introduced in (Montemerlo et al. [2002]). The most characteristic aspect of this algorithm is the use of a particle set which represents the uncertainty of the robot's pose whereas each particle has its own associated map. In this paper, the robots construct their maps using this approach. The main idea of the FastSLAM algorithm is to separate the two fundamental aspects of the SLAM problem: the estimate of the robot's pose and the estimate of the map. In this sense, the SLAM problem is divided in a localization problem and in several individual estimates of the landmarks. The solution to the SLAM problem is performed by means of a sampling and particle generation process, in which the particles whose current observations do not fit with their associated map are eliminated. The FastSLAM algorithm has proved to be robust to false data association and it is able to represent models of non-linear movements in a reliable way.

We have performed our experiments with Pioneer-P3AT robots, provided with a STH-MDCS2 stereo head from Videre Design. Fig.1 shows one of these robots. The use of cameras can be explained since these devices are less expensive than other sensors, such as LASER, and offer a higher amount of information from the environment. This approach is denoted as visual SLAM (Valls Miro et al. [2006]). Besides, 3D information is provided when using stereo cameras. In this paper, the robots navigate through our building, in which the most common elements are doors, windows, posters on the walls, etc. The visual maps built by the robots are landmark-based. This kind of maps represent the localization of a set of distinctive points from the environment, referred to a coordinate system. Most visual SLAM approaches use landmark-based maps (Little et al. [2002], Gil et al. [2006]). Particularly, in this paper, the Harris Corner Detector (Harris and Stephens [1998]) is used to detect distinctive points from the environment. Then these points are described by a feature vector computed with U-SURF (Bay et al. [2006]). This combination detector-descriptor has been selected after performing a previous work (Ballesta et al. [2007], Martínez Mozos et al. [2007]). This feature extractor proved to be the most suitable under our requirements, i.e. repeatability and distinctiveness. The maps constructed by the robots using the FastSLAM algorithm consist of the 3D coordinates of the Harris points, the uncertainty in the estimate of these points and their associated descriptor.

The problem of SLAM can be performed by a single robot. However, in this paper, we focus on the multi-robot approach. The map building can be performed more efficiently if a team of robots cooperate in the solution of this task. The space is divided and the distances traversed

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by each robot will be reduced. Hence the map is finished in less time and the odometry errors are smaller.

In a multi-robot framework, the robots explore simultaneously the environment so that a suitable map can be built collaboratively. Regarding the estimate of the maps, two different categories can be established: solutions in which the robots construct together a unique map (Fenwick et al. [2002], Thrun [2001]) and solutions in which each robot constructs its own map independently (Stewart et al. [2003], Zhou and Roumeliotis [2006]). In the first case, the robots have a global notion of the unexplored areas, so the cooperative exploration can be improved. Furthermore, in the landmark-based case, a landmark can be updated by different robots. For this reason, the robots do not need to revisit an area in order to reduce the uncertainty in the estimate of the landmarks. However, this approach requires that the initial relative positions of the robots are known, which is something that is not always possible in practice. Due to this drawback, in this paper we focuss on other approach, i.e., the case in which each robot builds its map independently. One of the main advantages of using independent local maps, as explained in (Williams [2001]), is that the data association problem is improved. First, new observation should only be matched with a limited number of landmarks in the local maps. Next, when the local maps are fused into a global map a more robust association can be performed. In this case, the robots begin the navigation process having no knowledge about other robots' poses and observations.

In a multi-robot system, in which each robot constructs its own local map independently, the fusion of these maps into a global one may be necessary. This paper is focused on the Map Fusion problem. Particularly, we study the two stages of the Map Fusion problem: Map Alignment and Map Merging. Regarding the first one, we present a method to compute the transformation, if existent, between pairs of local maps. Then, we study the merging stage and fuse the aligned maps into a single one.

The paper is structured as follows. In Section 2 a brief description about the Map Fusion problem is presented. Then, Section 3 focuses on the Map Alignment step. It describes the RANSAC algorithm and the results obtained. Analogously, Section 4 presents the experiments performed in the map merging stage. Finally, in Section 5 the main conclusions are stated.

2. MAP FUSION

As mentioned before, the fusion of local maps is performed in two main steps. The first one consists in computing the transformation, if existent, between the local maps. This task is denoted as Map Alignment. Then, once the transformation between maps is known, the second step is to integrate the data of both maps in order to build a unique one. This second stage is called Map merging.

The Map alignment problem is solved by computing the transformation between the local maps, provided that it exists. In this way, the landmarks of both maps will be expressed in the same coordinate system. In order to solve this transformation, some approaches try to compute the relative poses of the robots. As soon as this measure is obtained, the alignment of the maps is immediate. In this sense, the easiest case can be seen in (Thrun [2001]), where the relative pose between robots is considered as known. However, a more difficult approach is presented in (Konolige et al. [2003], Zhou and Roumeliotis [2006]). In these strategies, a meeting point is arranged by the robots in order to share information of their maps and compute their relative poses. Nevertheless, more challenging will be the approaches in which the robots determinate whether any alignment exists or not without the need of a meeting point, but just sharing the information of their maps. Some authors present feature-based techniques in order to align maps (Se et al. [2005], Thrun and Liu [2004], Ko et al. [2003]). The basis of these techniques is to find matches between the local maps and then to obtain the transformation between them. In this paper, we propose a method in order to align landmark-based maps.

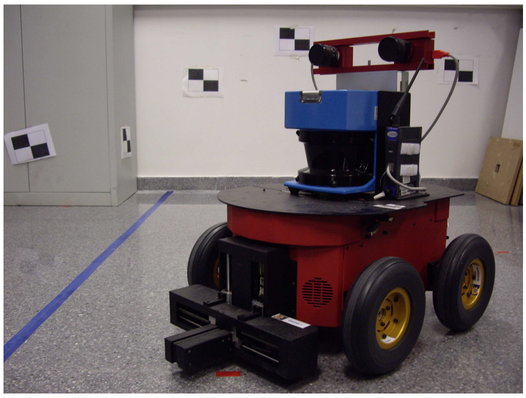


Fig. 1. Pioneer P3AT with a STH-MDCS2 stereo head.

The Map merging stage can be performed once the alignment has been solved. In (Fox [2005]), though, the combination of local maps is made using spatial constraints, which can be independent of the coordinate system in which the constraints are expressed. However, many other approaches compute the transformation between maps and determine correspondent parts of the maps before merging them. In (Thrun and Liu [2004]) they align the maps and then build a joint map establishing a correspondence list between both maps. In (Carpin et al. [2005]) they use occupancy maps and perform the map merging with a motion planing algorithm in which the local maps are rotated and translated until similar regions overlap. Then, in (Lakaemper et al. [2005]), they transform the scanning data into a map consisting of polylines and then establish correspondences between similar lines in order to merge these maps. It is noticeable that establishing a good set of correspondences between both maps will be decisive to merge these maps properly. In this paper we describe two methods to find good correspondences.

3. MAP ALIGNMENT

This section focuses on the computation of the transformation between pairs of local maps. In a recent work (Ballesta et al. [2008]), we compared the performance of several methods to compute the alignment between local maps.

These methods are suitable for this particular kind of maps, i.e., landmark-based. All these methods try to establish correspondences between the detected points in both maps by means of their descriptor similarity. Then, different techniques are used in order to compute the alignment. As a result of this previous work, the RANSAC algorithm showed the best results in terms of accuracy and regularity.

In the following subsection, the RANSAC algorithm is described.

3.1 RANSAC

This technique has been already applied to map alignment in (Se et al. [2005]). The steps of this algorithm are described below.

(1) First, a list of possible correspondences is obtained. Two points are considered as correspondences if the Euclidean distance between their descriptors is the minimum and it is below the threshold th_0. The coordinates $m = (x_i, y_i, z_i)$ are the landmarks of one of the maps, and $m' = (x'_i, y'_i, z'_i)$ their correspondences in the other map.
(2) In a second step, two pairs of correspondences are selected at random from the previous list. These pairs should satisfy the following geometric constraint:

$$A^2 + C^2 \approx B^2 + D^2 \quad (1)$$

where $A = (x'_i - x'_j)$, $B = (y'_i - y'_j)$, $C = (x_i - x_j)$ and $D = (y_i - y_j)$. The geometric constraint is satisfied if $|(A^2 + C^2) - (B^2 + D^2)| < th_1$. Then, two pairs of correspondences are used to compute the alignment parameters (t_x,t_y, θ) with the following equations:

$$t_x = x_i - x'_i \cos\theta - y'_i \sin\theta \quad (2)$$

$$t_y = y_i - y'_i \cos\theta + x'_i \sin\theta \quad (3)$$

$$\theta = \arctan \frac{BC - AD}{AC + BD} \quad (4)$$

(3) The third step consists in looking for possible correspondences that support the computed transformation (t_x,t_y, θ). The sets m and m' are aligned using this transformation. Then, if the Euclidean distance between pairs of correspondences is below the threshold th_2, this pair will be considered as a support. Finally, the second and third step are repeated M times. The final solution will be the one with the highest number of supports.

In our experiments, we have selected these values for the thresholds mentioned above: $th_0 = 2$, $th_1 = 2\ m$ and $th_2 = 0.2\ m$. Furthermore, a parameter $min = 20$ establishes the minimum number of supports in order to validate a solution and $M = 70$ is the number of times that steps 2 and 3 are repeated. These are considered as internal parameters of the algorithm and their values have been experimentally selected.

Once the alignment parameters (t_x,t_y, θ) have been computed, the maps can be aligned using the following transformation matrix:

$$T = \begin{pmatrix} \cos\theta & -\sin\theta & 0 & 0 \\ \sin\theta & \cos\theta & 0 & 0 \\ 0 & 0 & 1 & 0 \\ t_x & t_y & 0 & 1 \end{pmatrix} \quad (5)$$

3.2 Aligning experiments

In this section we present the results obtained with the RANSAC algorithm described in Section 3.1. Initially, the robots start from different initial positions and they have no knowledge about their relative position, so that they built their maps independently. At some point, the alignment of the maps may be required. In this sense we evaluate the performance of the RANSAC algorithm at different stages of the FastSLAM algorithm. At the beginning there is a sparse number of landmarks in the maps, and therefore the alignment is unlikely to be correctly computed. However, as the size of these maps increases, more correspondences between the maps will be found. In this situation, it is expected that the alignment is performed successfully.

Our experiments have been performed with maps built independently by means of the FastSLAM algorithm, using real observations from the environment. The FastSLAM algorithm is performed in several iterations according to the number of movements made by the robots. In our experiments, k is an index that denotes the iteration order. Figure 2 presents the results of the alignment performed by RANSAC in the different iterations of the FastSLAM algorithm. In all these cases, the alignment is performed using the most probable particle of the FastSLAM algorithm. Particularly, the error in the estimate of the alignment parameters (t_x, t_y and θ) is represented in y-axis. The error in t_x and t_y is expressed in meters and the error of θ in radians. The k-iteration of the FastSLAM algorithm is shown in the x-axis. The error in the estimate of the alignment parameters is computed as the Euclidean Distance between each parameter and a relative measure, denoted as *Ground Truth*. This measure has been obtained after calibrating the relative position of the robots being at their respective initial positions. These initial positions are the origin of the local reference frame of each robot. In the figure, it can be observed that the error in the t_x and θ parameters is always below 0.2 m or rad respectively. On the other hand, it can be deduced that the estimate of the t_y parameter is the most critical. This phenomenon is due to the fact that the robot moves forward along the y-direction most of time so that the uncertainty when observing features in this direction may be higher. Anyway, the results obtained with RANSAC are considerably accurate and therefore it is a suitable algorithm for this kind of maps.

Figure 3 shows a 2D view of an alignment performed with RANSAC. The maps illustrated in this figure are 3D landmark-based. Figure 3(a) presents the local maps (map_1 and map_2) referred to the relative reference frame of each robot, which is located in their origin. Both maps have some common landmarks which have been found by the RANSAC algorithm. In this figure, some correspondent points are indicated. Then, the aligning parameters t_x, t_y and θ are computed with RANSAC. The result is presented in Figure 3(b), where both maps have been

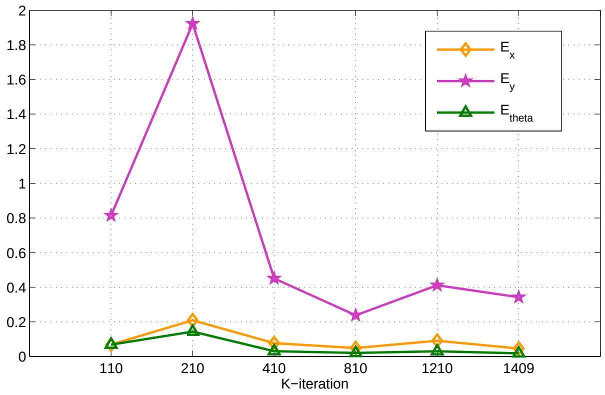


Fig. 2. Error values in the alignment parameters obtained with the RANSAC algorithm.

aligned. These maps have been obtained after performing the FastSLAM algorithm completely. The dimension of these maps is 35×10 meters approximately and their size is $map_1 = 263$ landmarks and $map_2 = 364$ landmarks.

4. MAP MERGING

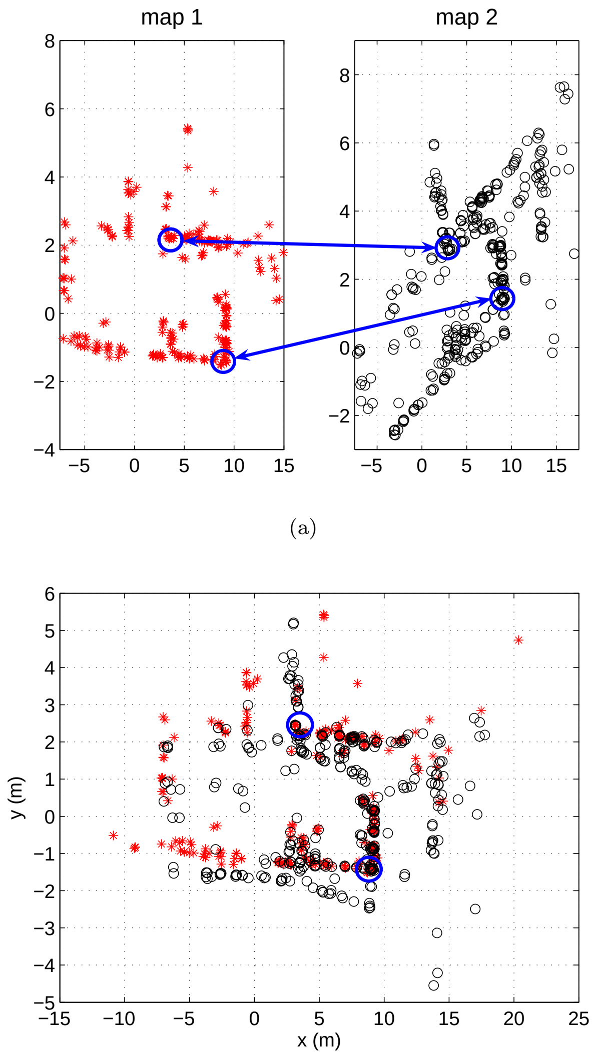
Once the alignment between two local maps has been computed, the next step is to fuse this data in order to construct a unique map. In this sense, it is important to consider the uncertainty in the estimate of the landmarks performed by each robot independently. The data to be merged is the part that the local maps have in common and that satisfies the alignment computed previously. Particularly, the data we should merge consists of the 3D coordinates of the landmarks (x, y, z), their corresponding uncertainty, which is a 3×3 covariance matrix, and the descriptor associated to each landmark. Due to the nature of this data (3D variables having uncertainty), we have considered that the most suitable method in order to solve this problem is a *Multivariable Stationary Kalman Filter*. The following formulation has been used to merge the landmarks of map_1 and map_2 (Fig.3):

$$Kalman\ gain: \quad K_{\{i\}} = cov_{1\{i\}} \cdot (cov_{1\{i\}} + cov_{2\{i\}})^{-1} \quad (6)$$

$$Global\ coord.: \quad C_{G\{i\}} = C_{1\{i\}} + K_{\{i\}} \cdot (C_{1\{i\}} - C_{2\{i\}}) \quad (7)$$

$$Global\ uncertainty: \quad cov_{G\{i\}} = (I - K_{\{i\}}) \cdot C_{1\{i\}} \quad (8)$$

where i is an index ($i \in \{1, N\}$) that denotes each matched landmark. N is the total number of matched landmarks between both maps (1 and 2).The G subindex denotes the data of the global map (map_G) and the 1 and 2 subindexes belong to the data of map_1 and map_2 respectively. Consequently, $C_G\{i\}$ indicates the 3D coordinates of landmark i in the global map. This landmark is the result of matching and merging a common landmark between both local maps, map_1 and map_2. C_2 denotes the 3D coordinates of map_2 expressed in the map_1's reference system (i.e. after the alignment process). Finally, $cov_{G/1/2}$ are the 3×3 covariance matrices, which represent the uncertainty in



(a)

(b)

Fig. 3. Map alignment (2D view). Fig. 3(a) shows the local maps before the alignment. Fig. 3(b) shows the same maps after the alignment.

the location of the landmarks in map_G, map_1 and map_2 respectively.

Additionally, each landmark belonging to map_1 or map_2 has its own associated descriptor. When we match a common landmark between these local maps, and then merge it, the descriptor in the global map will be the mean between the descriptors in the local maps.

4.1 Merging experiments

After estimating the alignment parameters t_x, t_y and θ, the fusion of the maps can be performed. The only requirement is to find the set of landmarks that are common in both maps. The total number of common landmarks is what we have denoted as N in Section 4. The resulting map_G is the union between map_1 and map_2, having been merged the N common landmarks of these maps. The rest of landmarks that belong exclusively to each map remain in their original form. In order to compute the set of common landmarks, we have test the two different methods that are described in the following.

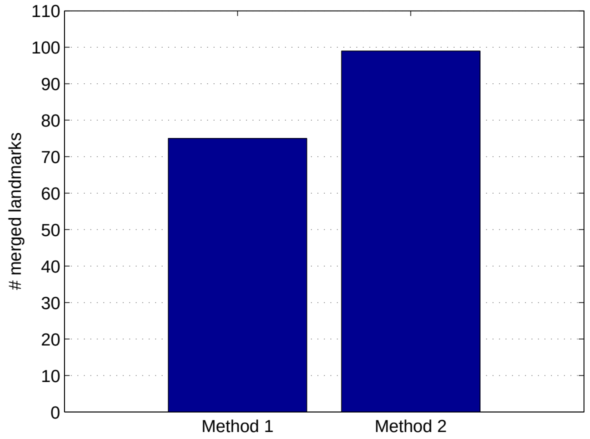


Fig. 4. Number of common landmarks between map_1 and map_2.

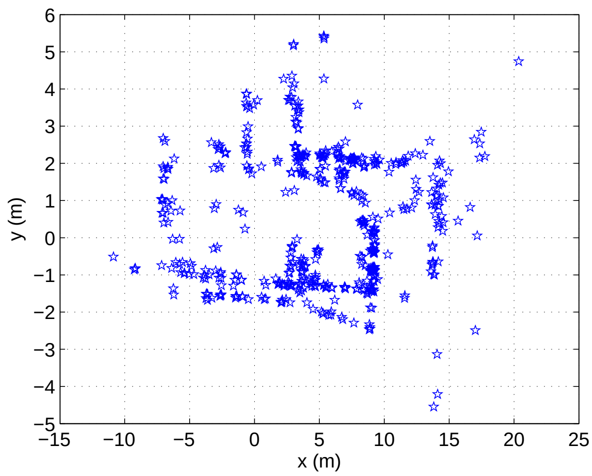


Fig. 5. 2D view of map_G. This map has been built after merging the data of map_1 and map_2 (Fig.3)

(1) *Method 1*. **Supports of the RANSAC algorithm**. One possibility is to consider the supports obtained with the RANSAC solution as the set of common landmarks. As described in Section 3.1, the supports are those correspondences between both maps that satisfy the alignment parameters. These points are geometrically close and also have a similar descriptor.

(2) *Method 2*. **New set of correspondences**. In this case, having the alignment parameters, the set of correspondences is obtained from the local map of each robot. The only similarity measure is the distance (in position) between pairs of correspondences. The Euclidean distance is used to compute this similarity.

In Figure 4, the results of the previous methods are shown. Particularly, for each method, the parameter N is presented, i.e., the number of common landmarks between both maps. *Method 2* is less restrictive and therefore it obtains a higher number of common landmarks, as can be deduced from the figure. Unfortunately, some of these correspondences may be wrong, since their descriptor

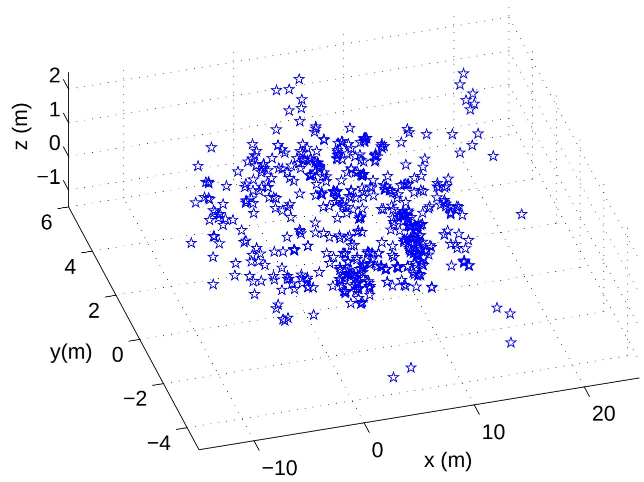


Fig. 6. 3D view of map_G. This map has been built after merging the data of map_1 and map_2 (Fig.3)

similarity has not been tested. For this reason, this method is not suitable for these experiments. As a consequence, we have performed our experiments using *Method 1*.

In Figures 5 and 6 the final result of a merged map is presented. Figure 5 presents the 2D view of the merged maps and in Figure 6 the fused map is shown in 3D. In this case, the z component of the landmarks varies from 0 to 2 m approximately, since these points have been extracted from the walls of our building. This fused map (map_G) is the result of merging the data from the maps of Fig. 3(a). For that reason, it is noticeable that Figure 5 is similar to Figure 3(a), with the difference that the maps in Figure 3(a) are only overlapped whereas in Figure 5 the maps have been merged. The non-common parts of each map are also represented.

5. CONCLUSIONS

The main purpose of this paper was to study the Map Fusion problem in a visual SLAM framework. The robots use the FastSLAM algorithm in order to build their maps by extracting distinctive features from the environment. These features consist of 3D points extracted by the Harris Corner Detector and described by U-SURF. In order to tackle the fusion of this kind of maps, we have divided the problem in two main stages: Map Alignment and Map Merging. In the first case, the RANSAC algorithm has been selected to compute the alignment between these landmark-based maps by matching common landmarks between them. This method has shown accurate results at different iterations of the FastSLAM algorithm, i.e., having different sizes of the overlapping area. Then, in the map merging step, two methods have been tested in order to establish a reliable set of correspondences between maps so that the fused map can be successfully obtained. The method used to merge these maps is based on a *Multivariable Stationary Kalman Filter*. This method considers the uncertainty in the estimate of the landmarks, which is different for each robot.

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An Extension to ICP Algorithm and its Application to the Scan Matching Problem

Armesto. Leopoldo*, Domenech, Luís**
Tornero, Josep*

**Control and Systems Engineering Department, Technical University of Valencia, Valencia 46022 Spain (Tel: +3496387007 (75796); (e-mail:leoaran@isa.upv.es;jtornero@isa.upv.es).*
***Design and Manufacturing Institute, Asociación de investigación en Diseño y Fabricación, Valencia 46022 Spain*

(e-mail:luidobal@posgrado.upv.es)

Abstract: This paper describes an extension of the well-known Iterative Closest Point (ICP) algorithm for solving problems such as Data Registration, Scan Matching, etc. In the standard ICP, the association uses the “closest point” rule, while, in the proposed extended ICP algorithm (eICP), N points are associated to any of the infinite points of a continuous curve defined by the other N points. This can be implemented by adding new degrees of freedom so the points can “freely” move on the continuous curve. Thus, we transform the original N to N correspondence problem of associating N points from one data set to N points of the other data set into a problem of associating N points with infinite possible points of the continuous curve. In addition to this, it is shown that the performance index to minimize in this new approach is independent from rotation and translation between the two scans, which avoids typical problems derived from the “closest point” rule. Moreover, this higher flexibility requires solving an N-dimensional optimization problem that doesn’t increases the computational cost with respect to the standard ICP, even for local or global search procedures. Furthermore, the convergence of the new algorithm can be improved by considering heuristic constrains such as preserving distances in the association process. In this sense, a constrained optimization solution that assumes preservation of distances between points (like a rigid mesh) is presented. This restriction transforms the N-dimensional optimization problem into a one-dimensional problem.

1. INTRODUCTION

Matching methods have been extensively studied in the past. There exist two different types of matching methods, where the main difference lies on the assumption of structured environments, i.e: environment with corners, lines, etc. or the assumption of a generic environment (non-structured).

In general, the structured matching techniques have proved to be very useful in indoor environments, where the structured assumption is perfectly granted. In such as situations, these techniques are faster and even could be more accurate than generic ones.

In general, structured matching techniques that consider this assumption perform a feature extraction step previous to the matching step. For instance, in SLAM techniques for Computer Vision it is very common to process corners, i.e.: with Harris Corner Detector (Harris & Stephens, 1988), and then match them by correlation in order to solve the SLAM problem, see i.e.: (Gemeiner. *et.al*., 2006), (Armesto, et. al., 2007), (Montiel, et. al., 2006).

Other approaches assume features that can be extracted from readings such points, lines or circles (Araujo and Aldon, 2004), (Chernov and Lesort, 2003), (Pfister and Roumeliotis, 2003). Several methods have been proposed to compute the pose of a mobile robot under such as conditions (Araujo and Aldon, 2002), (Betke and Gurvits, 1997), (Armesto, et. al., 2008), (Cohen and Koss, 1992), commonly known as triangulation, trilateration, etc.

On the other hand, there is a group of techniques that doesn't assume such as structured environment. In general, these techniques are based on an iterative process that estimates the relative pose that gets a better superposition.

Tools for these approaches are either probabilistic (Censi, 2006, Montesano, et. al. 2005) or geometric (Besl and McKay 1992), (Lu and Milios, 1997) and (Minguez and Montesano, 2006).

The main contribution of this paper is to take advantage of the continuous nature of the environment, that is, we assume that the environment is defined by a finite number of continuous elements and solve the Data Registration problem under such as assumption.

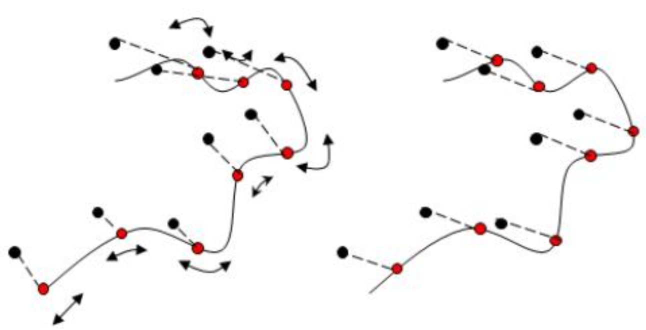

Fig. 1. The free movement of the points let us introduce mode DOF to obtain better estimations.