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RECENT ADVANCES in COMPUTATIONAL INTELLIGENCE, MAN-MACHINE SYSTEMS and CYBERNETICS

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Proceedings of the 8th WSEAS International Conference on COMPUTATIONAL INTELLIGENCE, MAN-MACHINE SYSTEMS and CYBERNETICS (CIMMACS '09)

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International Program Committee Members:

Preface

This year the 8th WSEAS International Conference on COMPUTATIONAL INTELLIGENCE, MAN-MACHINE SYSTEMS and CYBERNETICS (CIMMACS '09) was held at Puerto De La Cruz, Tenerife, Canary Islands, Spain, December 14-16, 2009. The conference remains faithful to its original idea of providing a platform to discuss computational intelligence, man-machine systems and cybernetics etc. with participants from all over the world, both from academia and from industry.

Its success is reflected in the papers received, with participants coming from several countries, allowing a real multinational multicultural exchange of experiences and ideas.

The accepted papers of this conference are published in this Book that will be indexed by ISI. Please, check it: www.worldses.org/indexes as well as in the CD-ROM Proceedings. They will be also available in the E-Library of the WSEAS. The best papers will be also promoted in many Journals for further evaluation.

A Conference such as this can only succeed as a team effort, so the Editors want to thank the International Scientific Committee and the Reviewers for their excellent work in reviewing the papers as well as their invaluable input and advice.

The Editors

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Plenary Lecture 1

Audio Interaction with Multimedia Information

Professor Mario Malcangi
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Abstract: Interacting with multimedia information stored in systems or on the web, points up several difficulties inherent in the signal nature of such information. These difficulties are especially evident when palmtop devices are used for such pur pose. Developing and integrating a set of algorithms designed for extracting audio information is a primary step toward providing user-friendly access to multimedia information and the developing of powerful communication interfaces. Audio has several advantages over other communication media. These include: hands-free operation; unattended interaction; simple, cheap devices for capture and playback; etc.
A set of algorithms and processes for extracting semantic and syntactic information from audio signals, including voice, has been defined. The extracted information is used to access information in multimedia databases, as well as to index them. More extensive higher-level information need to be extracted from the audio signal, such as audio-source identification (speaker identification) and genre in musical audio. A primary task involve transforming audio to symbols (e.g. music transformed into score, speech transformed into text) and transcribing symbols to audio (e.g. score transformed into musical audio, text transformed into speech). The purpose is to search for and access any kind of multimedia information by means of audio.
To attain these results, digital audio processing, digital speech processing and soft-computing methods need to be integrated.

Brief Biography of the Speaker:
M. Malcangi graduated in Computer Engineering from the Politecnico di Milano in 1981. His research is in the areas of speech processing and digital audio processing. He teaches Digital Signal Processing and Digital Audio Processing at the Universita degli Studi di Milano. He has published several papers on topics in digital audio and speech processing. His current research efforts focus primarily on applying soft-computing methodologies (neural networks and fuzzy logic) to speech synthesis, speech recognition, and speaker identification, where deeply embedded systems are the platform that supports the application processing.

Plenary Lecture 2

Developing Mathematical Techniques for Clustering Fuzzy Relational Data

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Abstract: Fuzzy clustering methods using objective functions and solving optimization problems for clustering object data have been very developed, and some of them with a great success as the fuzzy c-means families or hybrid clustering models. Even so, we will focus our attention in fuzzy cluster analysis for relational data which presents a more algebraic structure because generally deals with concepts as decomposition of matrices, fuzzy proximity relations or transitive closures.

One of the most applied fuzzy clustering methods for relational data is the single linkage, which coincides with the transitive closure by the t-norm of the minimum. This method establishes very suitable mathematical properties but sometimes presents inappropriate results, keeping all the objects separated or merging all the objects in only a cluster. Some authors have surpassed these difficulties, improving the results, using the transitive closure by another t-norm, but, unfortunately, appearing other inadequate properties.

We have developed another general procedure in order to try to avoid these difficulties, integrating in a homogeneous methodology the three main steps that are compulsory for clustering, namely: to define the similarity between objects, how to relate the similarity between objects and between clusters, and, finally, the own clustering method. Many fuzzy similarity indexes are defined applying crisp properties. Defining the similarity without this requirement we can also establish the theoretical mathematical bases for ensure that the corresponding index of similarity defines a proximity relation, showing that is essential for this purpose the algebraic structure of the t-norm. Defining the clusters as elements of the same referential space where belong the data we are able to implement an algorithm, based only on the fuzzy cardinality of the fuzzy subsets that describe the objects, which shows promising results.

Brief Biography of the Speaker:
Narcis Clara is Associate Professor of the Department of Computing and Applied Mathematics of the Higher Polytechnic School at the University of Girona. He is graduated in Mathematics for the University of Barcelona and he received the Ph. D. degree from the University of Girona. His research experience and interests are diverse and essentially cover the theory of fuzzy connectives, fuzzy additive generators of t-norms, fuzzy similarity measures, fuzzy clustering and complex systems. He is member of the Differential Equations, Modelling and Applications research group although he usually cooperates with other research groups for dealing with uncertainty in Economics and Management, and Chemical Engineering. He has participated in several projects mainly for developing new mathematical techniques for classification and prediction of environmental and economic variables based on fuzzy systems and neural networks. In collaboration with the Laboratory of Chemical and Environmental Engineering he has developed techniques of soft computing for predicting the quality of water at the effluent of a wastewater treatment plant. He has contributed in many subsidized university projects; papers published in edited books, peer-reviewed journals and international conference proceedings, and have served as a reviewer of International Conferences.

Alignment of Visual Maps in Multirobot FastSLAM

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Abstract: This paper focusses on the study of the Map Alignment problem in a multirobot SLAM context. The map fusion problem can be tackled in two stages: map alignment and map merging. The alignment stage consists in obtaining the tranformation between the reference systems of the robots. Then, in the map merging stage, the maps built by different robots can be fused into a single one. In this paper, we concentrate on the alignment stage. Particularly, we have a team of robots, each one building its own local map independently. At some point, the fusion of the maps may be required. In this case, these maps must be aligned. We therefore evaluate a set of aligning methods. These methods establish correspondences between each pair of maps and compute an initial estimate of the alignment. Finally, we apply the least squares minimization to obtain a more accurate solution. Each robot extracts distinctive 3D points from the environment with a stereo camera. Then, the robots use these observations as landmarks to build their maps while simultaneously localize themselves. The SLAM problem is solved using the FastSLAM algorithm. The movements of the robots occur only in 2D plane, so although the maps are 3D landmark-based, the alignment takes place only in 2D.

Key–Words: Multirobot visual SLAM, Map alignment, visual landmarks.

1 Introduction

The capability of building a map of the environment while localizing itself in this map is essential for a robot to be autonomous. This problem is known as *Simultaneous Localization and Mapping* (SLAM) and has received a great attention in the last years [14]. The basis of the SLAM problem is that the robot builds its map of the environment and simultaneously localizes itself in this map. The existent SLAM algorithms share this idea but differ in the methods used to solve this problem. In this paper the SLAM algorithm is based on FastSLAM [16]. This algorithm uses a particle set which represents the uncertainty of the robot's pose whereas each particle has its own associated map.

The problem of SLAM can be solved by a single robot, but this task will be performed more efficiently if there is a team of robots which construct cooperatively a map of the environment. This approach is denoted as multi-robot SLAM [12, 13]. In some approaches, the estimate of the trajectories and map building is performed jointly [7, 10]. In this case, the initial relative position of the robots should be known, which is something that may not be possible in practice. We concentrate on other solutions in which each robot builds its own map independently [23]. In these approaches, a set of local maps is maintained until the fusion of these maps is required. When using this approach, new observations should only be compared to a limited number of landmarks in the local map. Additionally, the construction of the local maps can be performed even if the relative positions of the robots are unknown.

We use a team of Pioneer-P3AT robots, provided with a laser sensor and a STH-MDCS2 stereo head form Videre Design. When using cameras as sensors, a higher amount of information from the environment is obtained. Moreover, the 3D coordinates of the points from the scene can be provided when using stereo cameras. This approach is denoted as visual SLAM [21].

The robots build landmark-based maps which consist of the 3D position of the Harris points [11] detected in the environment, an associated covariance matrix which represents the uncertainty in the estimate of these points and their corresponding U-SURF descriptor [3]. The selection of this feature extractor is the result of a previous work [15, 2, 9].

The intitial situation we consider is that there exists a team of robots which begin their navigation tasks independently and from different positions. The map building is done independently, since the robots have no initially knowledge about other robots' positions or observations. This is one of the major advantages of this approach, since the initial positions of the robots do not need to be estimated. At a specified moment, the fusion of the local maps into a global one may be required. We therefore study the map fusion problem [8]. We divide this problem into an alignment problem and a map merging problem. In this paper, we foccuss on the first one. The map alignment computes the transformation between local maps which have different reference systems. Particularly, we have performed a comparative evaluation of a set of aligning methods which are suitable for landmark-based maps. Even though the maps have 3D landmarks, the motion of the robots is performed in a 2D plane. For this reason, the result of the alignment is a 2D transformation. It is also notable, that the solution given by this aligning methods is only an estimate of the alingment. We therefore use the least squares minimization to obtain the real estimate.

2 Map Alignment

The map alignment problem tackles the computation of the transformation between local maps so that they can be expressed in the same reference system.

In this situation, most approaches try to find the relative position of the robots. In this sense, the easiest case can be seen in [20], where the relative position of the robots is supposed to be known. Nevertheless, more difficult approaches are [13] and [23]. In these cases, the robots try to establish a meeting point in order to measure their relative positions.

In this paper, we focuss on finding these relative positions without the need of meeting at some point; on the contrary, the robots would share information of their maps in order to find the alignment between them. Our work is based on some previous approaches in which maps are aligned by means of landmark-based techniques. Particulary, we focuss on the alignment of visual maps consisting of 3D landmarks. We consider that the origin of the reference system is located in the starting point of the robot.

In the following, we present a set of aligning methods that are evaluated in order to find the most suitable one using this kind of maps (Section 3). In Section 4, the results of the comparative evaluation can be observed. These experiments are carried out using two local maps built by two different robots. Finally, in Section 5 we propose a method to solve the alignment problem when having more than two local maps.

3 Aligning Methods

The aligning methods presented in this section compute the transformation between two local maps. This transformation consists on three alignment parameters: translation in x and y (t_x and t_y) and rotation (θ). In order to do this, these methods establish first a list of correspondent landmarks between the maps. Although the landmarks are 3D (x,y,z), the alignment is performed in 2D, because the robots move in a 2D plane (x,y). Nevertheless, the third component of the landmarks (z) is also compared when establishing correspondences.

It is noticeable that these methods obtain only a first estimate of the aligning parameters. The set of correspondences and this estimate are used as the input of a *least squares minimization* that eliminates outliers and obtains the final solution [17].

In the following, we describe briefly the aligning methods that we compare.

3.1 RANSAC (Random Sample Consensus)

This technique has been already applied to map alignment in [19]. First a list of correspondences (m,m') is obtained comparing two maps. The association is performed by means of the Euclidean distance between the descriptors of the landmarks. Then, two pairs of correspondences ($[(x_i, y_i, z_i)$,$(x'_i, y'_i, z'_i)]$ and $[(x_j, y_j, z_j), (x'_j, y'_j, z'_j)]$) are selected at random from the previous list. These pairs should satisfy the following geometric constraint [19]:

$$|(A^2 + B^2) - (C^2 + D^2)| < th \qquad (1)$$

where $A = (x'_i - x'_j)$, $B = (y'_i - y'_j)$, $C = (x_i - x_j)$ and $D = (y_i - y_j)$. And th a threshold, which is established experimentally. The two pairs of correspondences are used to compute the alignment parameters (t_x, t_y, θ) with the following equations:

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

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

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

The third step consists in looking for possible correspondences that support the solution obtained (t_x, t_y, θ).

3.2 SVD (Singular Value Decomposition)

One of the applications of the Singular Value Decomposition (SVD) is the registration of $3D$ point sets [1, 18]. First, a list of correspondences (m,m')

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is obtained as explained in Section 3.1. In addition, the geometric constraint of Equation 1 is evaluated. Given this list of possible correspondences, our aim is to minimize the following expression:

$$\|Tm - m'\| \tag{5}$$

where m are the landmarks of one of the maps and m' their correspondences in the other map. On the other hand, T is the transformation matrix between both coordinate systems (Equation 6).

$$T = \begin{pmatrix} \cos\theta & \sin\theta & 0 & t_x \\ -\sin\theta & \cos\theta & 0 & t_y \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{6}$$

3.3 ICP (Iterative Closest Point)

The Iterative Closest Point (ICP) technique was introduced in [4, 22] and applied to the task of point registration. The ICP algorithm consits of two steps that are iterated. First, given an initial estimate T_0, a set of correspondences (m, m') is computed, so that it supports the initial parameters T_0. T_0 is the transformation matrix between both maps and is computed with Equations (2),(3) and (4). Then, the previous set of correspondences is used to update the transformation T. The new T_{x+1} will minimize the expression: $\|T_{x+1} \cdot m' - m\|$. The algorithm stops when the set of correspondences does not change in the first step, and therefore T_{x+1} is equal to T in the second step.

3.4 ImpICP (Improved Iterative Closest Point)

The improved ICP (ImpICP) method is a modification of the ICP algorithm presented in Section 3.3, which has been implemented *ad hoc*. This new version is motivated by the importance of obtaining a precise initial estimation of the transformation parameters T_0. The accuracy of the results obtained is highly dependent on the goodness of this initial estimate. For that reason, in this new version of the ICP algorithm, we have increased the probability of obtaining a desirable result. Particularly, we obtain three different initial estimates instead of only one. This is performed by selecting three different pairs of correspondences each case in the second step of the RANSAC algorithm (Section 3.1), leading to three initial estimates. For each initial estimate, the algorithm runs as in Section 3.3. Finally, the solution selected is the transformation that is supported by a highest number of correspondences.

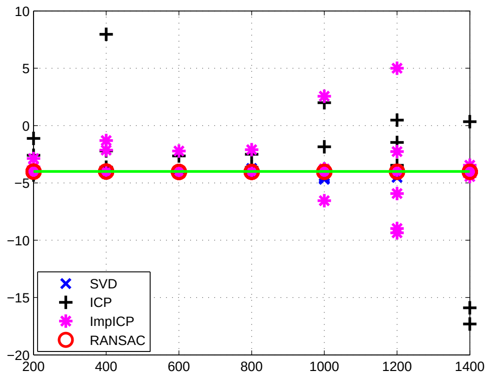

Figure 1: Results component t_x

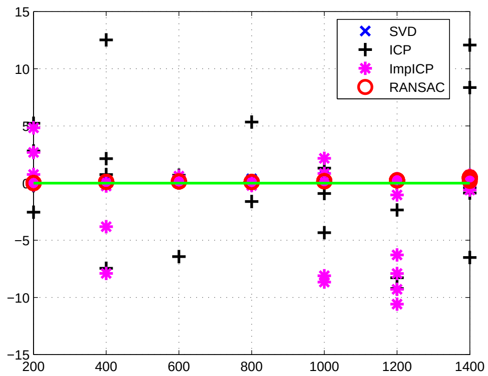

Figure 2: Results component t_y

4 Evaluation of the aligning methods

In this section, we present a comparative evaluation of the aligning methods presented in Section 3. We consider the situation in which two robots begin the mapping task independently, starting at different positions. Each robot build its map with the FastSLAM algorithm using a set of $M = 100$ particles.

Particularly, we want to evaluate the behavior of the aligning methods at different steps of the mapping process. At the beginning, the maps built by each robot have sparse landmarks resulting in a extremely reduced number of correspondences between both maps. As a consequence, the alignment of these maps will surely fail. However, this situation improves as the size of both maps increases in such a way that there are more coincident landmarks between both maps. In this second situation, the map alignment is expected to be performed successfully.

In order to carry out our experiments, the most probable map of each robot is used to compute the transformation between both maps. The alignment is done in several iterations of the FastSLAM algorithm.

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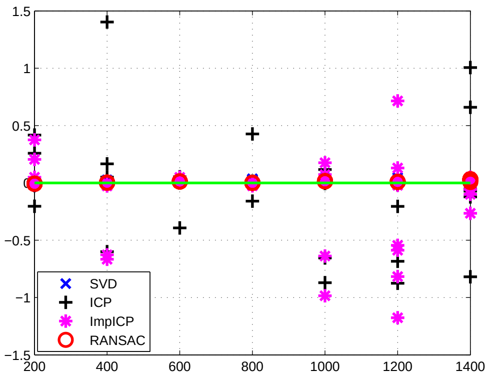

Figure 3: Results component θ

The most probable map is the map associated to the most probable particle of the filter at each particular moment. The aligning methods described above compute an estimate of alignment parameters t_x, t_y and θ, which is lately refined with a least square minimization.

Figures, 1, 2 and 3 show an example of the comparative evaluation performed. The x-axis represents the different k iterations of the Fast-SLAM algorithm at which the alignment is performed. In this case, we show values for $k = [200, 400, 600, 800, 1000, 1200, 1400]$. For each one of these k iterations, the alignment is performed by each method of Section 3, using the most probable map in each case. We have repeated the experiments 10 times, so that we obtain a set of values for each iteration. For reasons of clarity, we have presented the results of the alignment parameters separately. Figures 1, 2 and 3 represent the results obtained for t_x, t_y and θ respectively. In those figures, the ground truth is represented with a green line.

As we can deduce from the figures, RANSAC is the method that obtains the most accurate results, having also the lowest variance.

Figure 4 shows an example of the alignment stage with two local landmark-based maps: map1 and map2. These maps have been independently built by two robots and, at some point, the alignment transformation is computed. In this case, we show the result of aligning two maps with the solution given by RANSAC 3.1. This method compares map1 and map2, establish correspondences between them by the similarity of the descriptors and computes an initial estimate of the aligning parameters, which is improved by a least squares minimization. Fig. 4(c) shows the result of the alignment of map1 and map2. In this case, the landmarks of both maps are expressed in the same reference system. However, we still have two maps. For this reason, the next step, i.e., the map fusion, is necessary to obtain a global map.

5 Multirobot alignment

This section tackles the problem in which there are n robots ($n > 2$) whose maps should be aligned. In this case, the alignment should be consistent not only between pairs of maps but also globally. In order to deal with this situation, some constraints should be established [19].

First, given n maps ($n > 2$) and having each pair of them an overlapping part, the following constraint should be satisfied in the ideal case:

$$T_1 \cdot T_2 \cdot ... \cdot T_n = I \tag{7}$$

where I is a 3×3 identity matrix. Each T_i is the transformation matrix between map_i and map_{i+1} and corresponds to the matrix in Eq.6. The particular case of T_n refers to the transformation matrix between map_n and map_1. The constraint (7) leads to three expressions that should be minimized:

E1. $sin(\theta_1 + ... + \theta_n)$

E2. $t_{x1} + t_{x2}cos(\theta_1) + t_{y2}sin(\theta_1) + t_{x3}cos(\theta_1 + \theta_2) + t_{y3}sin(\theta_1 + \theta_2) + ... + t_{xn}cos(\theta_1 + ... + \theta_{n-1}) + t_{yn}sin(\theta_1 + ... + \theta_{n-1})$

E3. $t_{y1} + t_{x2}sin(\theta_1) + t_{y2}cos(\theta_1) - t_{x3}sin(\theta_1 + \theta_2) + t_{y3}cos(\theta_1 + \theta_2) + ... - t_{xn}sin(\theta_1 + ... + \theta_{n-1}) + t_{yn}cos(\theta_1 + ... + \theta_{n-1})$

Additionally, given a set of corresponding landmarks between map_i and map_{i+1}, and having been aligned the landmarks of map_{i+1} (m_j) into map_1's coordinate system with the transformation matrix T_i (see Equation 6), the following expression should be minimized:

$$m'_{j\{m(k)\}} - m_{i\{m(k)\}} \tag{8}$$

were $c(k)$ is the total number of correspondences between the k-pair of maps ($k \in \{1, n\}$). The number of equations that emerge from Equation 8 is $2c(1) + 2c(2) + ... + 2c(n)$. For instance, if we have $c(1)$ common landmarks between map_1 and map_2 and the transformation matrix between them is T_1, then for each common landmark we should minimize the following set of expressions:

Eδ. $x_2cos(\theta_1) + y_2sin(\theta_1) + t_{x1} - x_1$ with $\delta \in \{4, X + 4\}$

Eλ. $y_2cos(\theta_1) - x_2sin(\theta_1) + t_{y1} - y_1$ with $\lambda \in \{X + 5,\ 3X + 5\}$

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where $X = m(1) + m(2) + ... + m(n)$.

So far, we have a non-linear system of $S = 3 + 2c(1) + 2c(2) + ... + 2c(n)$ constraints that we should minimize. In order to obtain the aligning parameters that minimize the previous S constraints, we use the MALTAB function **fsolve**. This iterative algorithm uses a subspace trust-region method which is based on the interior-reflective Newton method described in [5, 6]. The input for this algorithm is a initial estimate of the aligning parameters. This is obtained by the RANSAC algorithm of Sec.3.1 between each pair of maps, i.e., $map_1 - map_2$, $map_2 - map_3$, $map_3 - map_4$ and $map_4 - map_1$. This will be the starting point for the **fsolve** function to find a final solution.

6 Conclusion

In this paper we present an approach that tackles the multirobot SLAM problem. Particularly, we focus on the situation in which a team of robots build their own local maps of the environment. The main advantage of this approach is that the robots do not need to know other robots' positions, so that the map building can be performed independently. We concentrate on the map aligment stage, in which the transformation between different reference systems is computed.

In our experiments, the robots construct their maps by extracting Harris points from the environment. These points are characterized by a U-SURF descriptor in order to deal with the data association problem. Moreover, the FastSLAM algorithm is used to build the map. The maps thus built consist of the 3D coordinates of the landmarks, their corresponding uncertainty and an associated descriptor.

We evaluate a set of methods in order to find the most suitable for aligning this kind of maps. This methods establish correspondent landmaks based on the descriptor similayAs the results show, this method is RANSAC.

Acknowledgements: The research has been supported by the Spanish Ministry of Science and Innovation under pro jects DPI2004-07433- C02-01 and CICYT DPI2007-61197 and by the Generalitat Valenciana under grant BFPI/2007/096.

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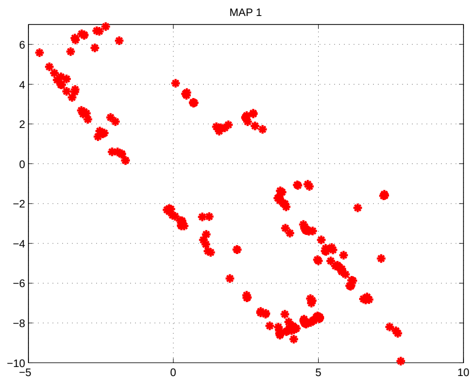
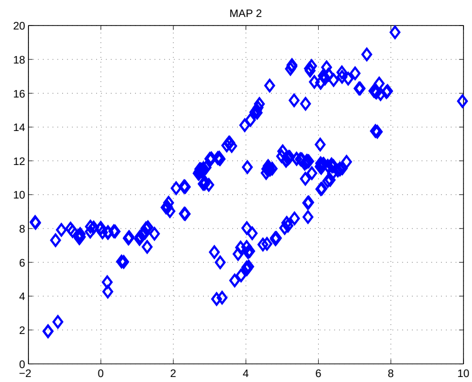
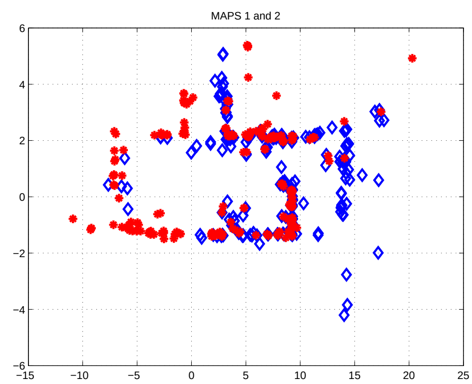


(a)



(b)



(c)

Figure 4: Map alignment (2D view). Fig. 4(a) shows the local map 1 before the alignment. Fig. 4(b) shows map 2. Fig. 4(c) show the same maps after the alignment.