CF-IDC: a Robust Robot's Self-Localization in Dynamic Environments using Curvature Information

P. Núñez, R. Vázquez-Martín, A. Bandera, and F. Sandoval, *Member, IEEE*

***Abstract*— This paper describes a complete laser-based approach for self-localization of mobile robots. The presented algorithm is a novel variant of the classic *Iterative Dual Correspondence* Method (IDC). Our scan matching method improves results of this popular algorithm in dynamic environments, due to the changed elements between two consecutive scans acquired by the robot are detected and removed of the matching process. To do that, the curvature information of each element of the environment is used. The proposed scan matching algorithm consists of three stages. Firstly, the whole raw data laser is segmented into groups of consecutive range readings using a distance-based criterion and the adaptive curvature function for each group is computed. Then, this set of curvature functions is matched to the set of curvature functions associated to the previously acquired laser scan. Finally, IDC algorithm is applied only considering those scan points which belong to the set of matched curvature functions. Thus, the system is outstanding in terms of robustly, accuracy and computation time. The implemented algorithm is evaluated and compared to the classic IDC scan matching approaches. Experimental results show that the new variant of the popular IDC algorithm performs well as it adjusts in a good way to changing environments.**

***Index Terms*— scan matching, adaptive curvature function, mobile robotics.**

I. Introduction

One of the key functions in autonomous mobile robot is to keep track of its pose - position and orientation - while moving. To achieve this relative localization and to reduce the increasing error from the use of dead reckoning, it is common that the robot carries external sensors, like a 2D laser range finders, to perceive the environment. Two consecutive scan data taken from different locations and time instants can be matched and then, it is possible to update the position estimate according to the matching results. It can be noted that the aim is not directly to build an accurate map, but rather to ensure a stable and fast localization, regardless of the robot's speed and without any restrictions of the covered distance [9]. Thus, scan matching techniques estimate the robot's displacement between two time instants by directly comparing the perceived scans.

The main differences between the existing scan matching algorithms is the use or not of features extracted from the raw data [1]. In fact, it is possible to categorize scan matching approaches based on their association method, such as *feature to feature*, *point to feature* and *point to point*. Feature to feature approaches have as common basis a first step where they interpret laser scans in order to acquire a set of unequivocal features of the environment which will be matched in a second step. Usually natural landmarks are the most common of features used in these algorithms. Amongst them, line segments [3], [2], corners or range extrema [9] have been used for finding the best estimate of the robot's motion. The main disadvantages of these scan matching methods is the dependence on the existence of features in the environment.

In point to feature methods, points of a scan are matched to scene features. The most popular of these type of approaches was developed by Cox [4]. This algorithm matched points with lines of a priori known map. In order to use it in scan matching algorithm where the robot's working environment is unknown, Gutmann et al. [3] matched points of the scan to lines extracted from the reference scan. Obviously, similar to features to features methods previously described, a correct operation of this algorithm depends on the existence of geometrical entities in the environment.

Finally, several authors have been developed point to point algorithms to perform in any type of scenario (structured or unstructured), directly dealing with raw data. One interesting approach was developed by Pfister et al. [5] where authors considered models of expected sensor uncertainty, and then they computed the appropriate weighting for each measurement so as to optimally estimate the displacement. Recently Diosi et al. [1] described a new point to point approach where Polar coordinates for the scan range reading is used. They named this method as *Polar scan matching* (PSM), and the point association was calculated by simply matching points with the same bearing. However, the most of classic scan matching techniques are based on an iterative process, where in each iteration the system estimates the displacement that better explains the overlap between two consecutive scans. In the work of Besl and Mac Kay [11], authors introduced the *iterative closest point* (ICP) algorithm, where each point of the current scan is matched with the point of the reference scan which smallest Euclidean distance. In order to improve convergence problem of this algorithm related with robot's rotation, Lu and Milios [12] developed an *iterative matching range point* (IMRP), where now each point of the current scan is corresponded with the point of the reference scan which has the matching range from the origin. These same authors proposed the popular *iterative dual correspondence* (IDC), which use a combination of both ICP and IMRP approaches

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P. Núñez is with Dept. Tecnología de los Computadores y las Comunicaciones, Universidad de Extremadura, Spain (e-mail: pmnt@uma.es)

Rest of authors are with the Grupo de Ingeniería y Sistemas Integrados, Dept. Tecnología Electrónica, Universidad de Málaga, 29071-Málaga, Spain.

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for resolving the self-localization problem.

On the other hand, most of these scan matching methods have been designed for situations in which the environment is static during the measurement process. Therefore, dynamic items (e.g, persons or objects moving around the robot) can lead to serious mistakes in the estimation of the errors in pose estimation. The most of the environments in which robot works are subject to significant changes, and thus all these methods are inefficient in the estimate robot's pose. Recently, significant modifications have been included in these algorithms that improve their results in such scenarios. Thus, in the work of Bengtsson et al. [10] authors describes two new algorithms which are variants of the classic scan matching approaches: IDC-S (IDC-Sector) and Cox-S (Cox-Sector). Basically, these algorithms divide the current scan into N fixed sectors, and each sector is matched separately with the reference scan, removing sectors which error values larger than a defined threshold.

This paper proposes a novel variant of the IDC approach which can deal with dynamic, structured or unstructured environments (CF-IDC algorithm). This method follows a similar idea of Bengtsson et al's approach. In spite of calculating a whole point to point matching, only a sectorized scan matching is applied. The proposed method does not use fixed sectors as in the Bengtsson et al's case, but they are defined using a two-step segmentation described in next sections, and more concretely, sectors are characterized by their associated curvature functions. The paper is organized as follows: Section II is a brief description of classic point to point IDC algorithm. Section III details the proposed CF-IDC method. Section IV shows some experimental results and the comparative studio, finally, conclusions and future work are presented in Section V.

II. Classic IDC Scan Matching algorithm

Let $p_t = (x_t, y_t, \theta_t)^T$ the t-th pose of the robot, where (x_t, y_t) are the co-ordinates in the XY horizontal-frontal plane, and θ_t is the orientation with respect to the vertical axis Z. Scan matching approaches estimate the relative displacement of the robot between two different time instants by comparing consecutive scans provided by a laser range finder (see Fig. 1). This relative displacement, $\Delta p = (\Delta x, \Delta y, \Delta\theta)^T$, can be used to update the robot's pose. Thus, given a pose and estimated relative shift Δp, the updated pose p_{t+1} is calculated as:

$$\begin{pmatrix} x_{t+1} \\ y_{t+1} \\ \theta_{t+1} \end{pmatrix} = \begin{pmatrix} x_t \\ y_t \\ \theta_t \end{pmatrix} + \begin{pmatrix} cos\theta_t & sin\theta_t & 0 \\ -sin\theta_t & cos\theta_t & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \Delta x \\ \Delta y \\ \Delta\theta \end{pmatrix} \tag{1}$$

In robotic field, scan data are typically in the form $\{(r,\phi)_{i|i=1\ldots N_R}\}$, on which $(r,\phi)_i$ are the polar co-ordinates of the i-th range reading (ρ_i is the measured distance of an obstacle to the sensor rotating axis at direction ϕ_i) and N_R is the number of range readings. Fig. 1 illustrates the basic geometry of the scan matching problem.

The proposed algorithm have been thought for working in changing environment using a modified version of the Iterative Dual Correspondence (IDC) algorithm [12]. It is demonstrate that IDC scan matching algorithm is an efficient method to estimate the robot motion between two consecutive time instants. However, main drawbacks in this method is related to bad associations (very common in dynamic environment, where new objects appear in the environment and modify its position).

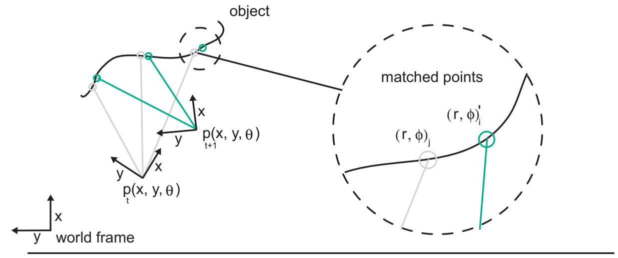

Fig. 1. Geometry of the scan matching problem. Relative robot's motion is estimated according to pairwise points of two consecutive scans.

The algorithm is based on an iterative process where it first computes the correspondence between two consecutive scans, and then it minimizes the distance error to compute the robot relative displacement, $\Delta p = (\Delta x, \Delta y, \Delta\theta)^T$. Thus, the basis of this algorithm is to find a corresponding point in the current scan for each reference scan point. In order to do that, each pairwise corresponding points must satisfy two rules, the closest point rule (basis of ICP) and the matching rule (basis of IMRP). The remaining points are then used in the matching process, and the algorithm finish when the least-squares errors sufficiently small. In the classic IDC algorithm, this least-squares errors was defined as

$$E(R_{\Delta\theta}, \Delta t) = \sum_{i=1}^{N_t} \left\| R_{\Delta\theta} P_i + \Delta t - P_i^{'} \right\|^2 \tag{2}$$

where $R_{\Delta\theta}$ is the rotation matrix, Δt is the translation matrix, P_i and $P_i^{'}$ are the pairwise points. Equations to obtain both $R_{\Delta\theta}$ and Δt are also described in the work of Lu et al. [12] (see this paper for more details).

IDC algorithm usually performs several iteration in the minimization of the square error defined in (2) due to the correct associations are unknown. Furthermore, matching may not always converge to the correct pose [1]. These problems are more common in changing environments and this is the reason because classic IDC is not a robust algorithm for working in dynamic scenarios.

III. CF-IDC algorithm

The aim of scan matching algorithm is to calculate an estimation of the robot's movement at each time instant. To do that, two consecutive scans are matched. The quality of this matching process is crucial for an accurate estimation. In fact, bad association between consecutive scans provokes a robot's pose error which is non-recoverable in the most of situations. Thus, a significant advance in these algorithms is the possibility of removing those outliers points which increasing the pose error. The approach described in this paper

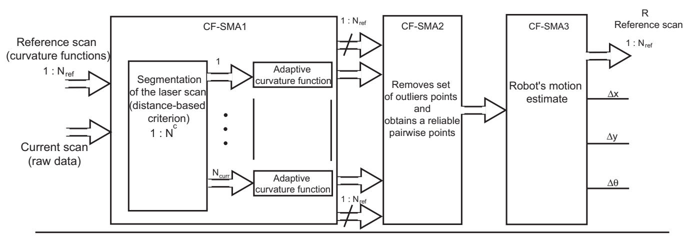

Fig. 2. Scan matching algorithm proposed in this chapter. Read the text for a complete description of the modules

follows this scheme, and the block diagram is illustrated in Fig. 2. As it noted, the proposed scan matching algorithm consists of three independent stages. Firstly, a segmentation step is applied to the whole raw data in order to divide the scan in a set of groups of consecutive range readings. In this same stage, curvature function is calculated for each scan segment. Next, a second stage removes outliers points using a two-steps algorithm which starts looking for pairwise curvature functions and after that, matches points of these corresponding functions. This step describes the kernel of the proposed scan matching method. Results of the previous step are used in a final stage where the robot motion is estimated. As only an accurate set of matched points is used, the approach obtains a reliable measure. Next, a brief description of the blocks diagram of Fig. 2, is provided.

- **CF-SMA1**. First step segments the current scan, C, into groups using a distance-based criterion and then computed the curvature function for each group (see Fig. 2). This curvature function is calculated using an estimator which adapts itself to the local surrounding of the studied range reading [7].
- **CF-SMA2**. Next, the set of curvature function is used to build a correlation matrix which measures the similarity between curvature function associated to current scan and previously acquired scan, denoted as reference scan, R. This matrix allows to select pairwise curvature functions and remove isolated groups which will not include in the robot's pose estimate. In order to perform this calculation in a fast and robust way, the approach implements a *Fast Fourier Transform* (FFT) algorithm which allows to compare curvature functions only using products. This step results in two subsets of corresponding points, $C' \subseteq C$ and $R' \subseteq R$, which permit to compute the pose shift as the optimal transformation mapping C' onto R'.
- **CF-SMA3**. Finally, the best local alignment between consecutive scans is obtained using this set of pairwise points. Here, classic IDC solution is employed for computing the optimal transformation, which improve its results due to dynamic elements of the environment have been discarded in the previous step. Once the pose shift is calculated, it can be used to update the robot's pose according to Eq. (1) and the process continues by saving the current scan as the new reference scan, $C \rightarrow R$

Next subsections present a detailed description of each stage.

A. FC-SMA1. Segmentation of the laser scan

The proposed scan matching approach is based on the matching of physical entities of the scene which are present in both scans. From this matching, it can be derived the search of pairwise points. Therefore, it will be necessary to obtain a complete description of the environment which allows to identify a set of distinguished entities. To obtain this description, the scan is firstly segmented using the adaptive breakpoint detector [6]. In this algorithm, two consecutive range readings belong to different segments if

$$||(r,\varphi)_i - (r,\varphi)_{i-1}|| > r_{i-1} \cdot \frac{\sin \Delta\varphi}{\sin(\lambda - \Delta\varphi)} + 3\sigma_r \qquad (3)$$

where $\Delta\varphi$ is the laser angular resolution, λ is an auxiliary constant parameter and σ_r the residual variance. In our experiment, the parameter values are $\sigma_r = 0.0005m$ and $\lambda = 10°$ [7].

Points which belong to the same segment are associated to one element of the environment. If each group of points is characterized by a curvature function, then the whole scan will be described by a set of N_c curvature functions, $C_{cf} = \{c_i | c_i \text{ is curvature function}, i = 1...N_c\}$. In our case, the curvature estimator is a modified version of the adaptive method described in [7]. With respect to the previous version, this new algorithm reduces the computational load by characterizing each range reading by an unique value (k_i). The method used to calculate the adaptive curvature function for each extracted segment consists of the following steps:

1) Calculation of the maximum length of laser scan presenting no discontinuities on the right side of the working range reading i, k_i. This is obtained as the largest value that satisfies

$$\sum_{j=1}^{k_i-1} d(j,j+1) - d(i,i+k_i) < U_k \qquad (4)$$

where $d(i,j)$ is the Euclidean distance from range reading i to range reading j, and U_k is a threshold value which allows the smoothing of the noise associated to the laser data acquisition. In our experiments, we have fixed this value to 1.0 as it provides satisfactory results for our laser rangefinder (SICK LMS200).

2) Estimation of the angle associated to each range reading i. This angle θ_i is equal to:

$$\theta_i = arctan\left(\frac{\sum_{j=1}^{k_i-1}(x_{j+1}-x_j)}{\sum_{j=1}^{k_i-1}(y_{j+1}-y_j)}\right) \qquad (5)$$

3) Calculation of the curvature index associated to each range reading i. This value can be calculated as:

$$\eta_i = \theta_{i+1} - \theta_i \qquad (6)$$

Fig. 3a illustrates this first segmentation step for a real scan of a structured environment. As it shown, six distinct segments

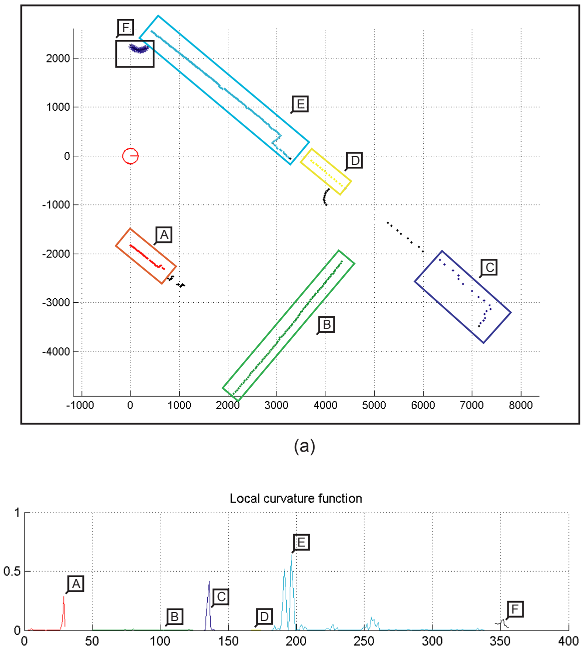

Fig. 3. CF-SMA1 description. a) The environment scan is segmented using the distance-based criterion; and b) Curvature functions of each segment are computed.

are defined in the figure. Isolated group of points are removed using by a constraint related to the size of each segment [7]. In Fig. 3b, the associated curvature functions associated to each scan segment in Fig. 3a are shown, where N_c in this case has a value of 6.

B. FC-SMA2. Comparison between consecutive scan: removing outliers

As it was aforementioned, the proposed approach is based on the idea that the tracking of physical entities of the scene can be carried out by matching the sets of curvature functions associated to two successively acquired scans. Thus, C_{cf} is compared to the set of curvature functions from reference scan, R_{cf}. If the number of groups in this reference scan is N_r, R_{cf} is defined as $R_{cf} = \{r_i | r_i \text{ is curvature function}, i = 1...N_r\}$. Then, in order to ensure the quality of the scan matching algorithm, the proposed approach divides the matching step in two stages. Firstly, the matching of curvature functions is obtained in a fast way using the Fourier domain. Next, those pairwise curvature functions constitute the set of matched points which are used to obtain the estimated displacement Δ_p, and remove isolated groups which will not include in the robot's pose estimate.

1) *Matching of curvature functions associated to laser scan*
Once the curvature functions associated to each group of the reference scan R and current scan C have been obtained (section II.A), a matching between both sets is performed to obtain a first estimation of the transformation that maps C onto R. This transformation will roughly correspond to the movement of the robot between these scans. To match these two sets of curvature functions, a matrix of possible matching pairs is built. The element $d_{i,j}$ of this matrix is defined by the similarity between two curvature functions. A fast way to measure the similarity of two curvature functions is working on the Fourier domain, where correlations are transformed into products [8]. In order to achieve this transformation in a low computational time, Fast Fourier Transform (FFTs) are used. It implies that the length of each curvature function must be previously normalized to a value of 2^n (e.g. 64, 128 or 256). Then, the correlation index or distance function, ρ_{ij}, is defined as

$$\rho_{ij} = max\left(IFFT\left[FFT[c_i] \cdot FFT[r_j]\right]\right) \qquad (7)$$

where IFFT is the Inverse Fast Fourier Transform, and $c_i \in C_{cf}$ and $r_j \in R_{cf}$. When all correlation indices have been calculated, the maximum value of this correlation matrix is found and the corresponding curvature functions of C and R are matched iff this value is higher than a previously defined threshold U_c. These value U_c is imposed to eliminate matched curvature function with a low value of correlation index. The described process is iteratively applied to obtain a set of pairwise curvature functions, $P_{cf} = \{p_k = (c_i, r_j)_k, c_i \in C_{cf},\ r_j \in R_{cf},\ k = 1...N_k\}$, where N_k is the number of matched curvature functions. Dynamic objects in the current scan are easily detected due to their associated curvature functions are not corresponding to another ones which define the reference scan.

2) *Removing outliers from the scans*
Each point of a curvature function has an associated Cartesian co-ordinate point, $m = (x, y)$. Thus, the set of pairwise curvature functions, P_{cf}, defines a set of N_t possible matched points, $M^t_{cf} = \{(m^c_i, m^r_j) |\ m^c_i,\ m^r_j \in \mathbb{R}^2,\ i = 1...N_t\ j = 1...N_t\ \}$. Rest of points are removed from the scan and they are not used in the robot's motion estimate, and thus, points associated to changing objects are eliminated. Therefore, points which take part in the classic IDC algorithm belong to the set M^t_{cf}, improving its results.

The robustness and accuracy of the proposed method is mainly provided on this matching of curvature function. Fig. 4 shows two consecutive scans and their associated curvature functions (current and reference scans has been drawn as red and blue color, respectively). Matched points and pairwise curvature functions are illustrated as distinct color boxes in both Figs. 4a-b, respectively. Black points in Fig. 4a represent isolated points which will be remove from the scan. In this particular case, the possible matched points, N_t is 325, and the the number of pairwise curvature functions, N_k, is 8.

C. CF-SMA3. Calculation of the relative translation and rotation

In the proposed method, iterations are reduced due to an improved matching process. Once outliers have been discarded,

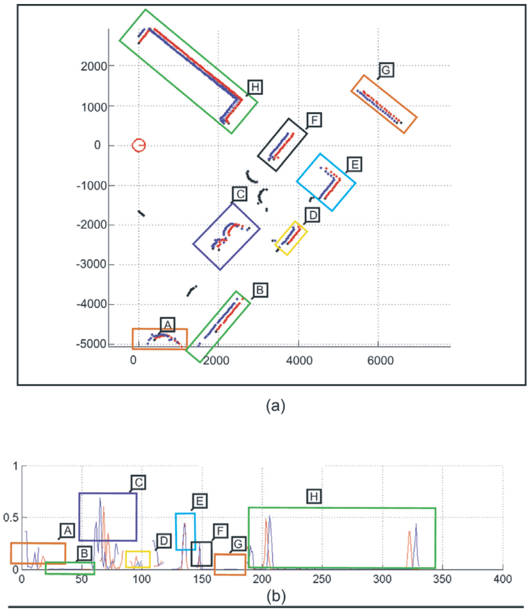

Fig. 4. a) Two consecutive laser scans and matched points ($N_t = 325$). Current scan: red. Reference scan: blue; and b) matching of curvature functions associated to scan a) ($N_k = 8$).

only the set of accurate pairwise points, M^t_{cf}, associated to the matched curvature functions, P_{cf}, is used in the classic IDC algorithm. Thus, as it was described in the Lu and Milius's work [12], an iterative process starts in order to minimize Eq. (2). In our case, IDC algorithm have been developed using Gutmann's implementation [3]. Here, the maximum number of iterations has been defined as 500 and the convergence of the algorithm was achieved when the error ratio was below 0.0001%.

IV. Experimental Results

The described scan matching algorithm has been tested in various real environments. Our Pioneer 2AT robot is equipped with a SICK Laser Measure System LMS200 and a Pentium III-1000 MHz. Experiments are focused on the evaluation of our method in terms of accuracy and processing time in dynamic environments.

A. Estimation of parameters

The proposed method requires choosing values for a set of parameters. The main parameters described in this paper are:

1) The parameters φ and λ used by the breakpoints detector.
2) The threshold value which determines the noise level tolerated by the adaptive curvature detector, U_k.
3) The minimum correlation index value to be considered as pairwise curvature functions, U_c.

As it was described in Section II.A, the process to obtain the values for φ and λ is based on the previous work of Borges and Aldon [6]. These values have been fixed to 0.005 meter and 10 degrees , respectively.

The threshold value U_k is used to eliminate spurious noise of the laser scan. In order to set it correctly, a set of real plane surfaces have been scanned at different distances from the robot. In these planar surfaces, the values must be fixed to do not detect any local peak. This simple experiment has provided us an U_k value equal to 1.0. This value has been used in all experiments described in this paper.

Similar experimental process has been used to obtain the value for U_c. This one is employed to improve the correlation process, thus pairwise curvature functions whose associated correlation index is lower than U_c = 0.4 are discarded. Thus, we ensure that dynamic objects are removing from the scan.

B. Experiments with Ground Truth

The first experiment consists on matching two consecutive scans acquired in the same robot's location ($p(x, y, \theta)$ = $(0, 0, 0)$), being the difference between one scan to another due to noise sensor and the presence of dynamic objects. Next, to the second scan is applied a random rotation and translation, where now $(x,\, y)$ position and orientation of the current scan was altered by average values 100 cm and $15°$ respectively, and variance σ_x = σ_y = 50 mm and σ_θ = 5 ° (see Fig. 5a). After applying each experiment 1000 times in this scenario, the final average error was limited to Δx= 20.29 mm, Δy = 28.16 mm and $\Delta\theta$ = 0.22° for the classic IDC algorithm and Δx= 12 mm, Δy = 22 mm and $\Delta\theta$ = 0.12° for the proposed method. The average number of iterations was 21 and 14, respectively. In this particular case, the average number of points N_t associated to the set of pairwise curvature functions was 245. Fig. 5b draws the convergence for each method and shows how our proposed method converges faster than classic IDC algorithm. Fig. 5c illustrates the evolution of the errors in our proposed method according to the number of the iteration.

C. Self-localization in dynamic environment

Given the settings and specifications described in section, we have teleoperated the robot into ISIS Group installation at the Andalusian Technology Park (Málaga). In this experiment, some people was walking around the robot, simulating a dynamic environment. Fig. 6 shows the results of the proposed approach. In Fig. 6a the resulting map of the scan matching algorithm is shown. There are not additional corrective algorithms in this experiment, and the results are obtained directly by the proposed method. It must be noted that dynamic objects are also represented in the figure (green points), but this information has been correctly discarded by the algorithm. Fig. 6b illustrates the trajectories calculated by the proposed and classic IDC methods. Table 1 compares the average time needed to calculate the trajectories from the dynamic environment described here. It can be appreciated that the proposed algorithm is computationally faster than IDC method due to the method has less iterations for the calculation of the relative displacement.

V. Conclusions and future works

This paper proposes a new variant of the classic *Iterative Dual Correspondence* scan matching algorithm to estimate

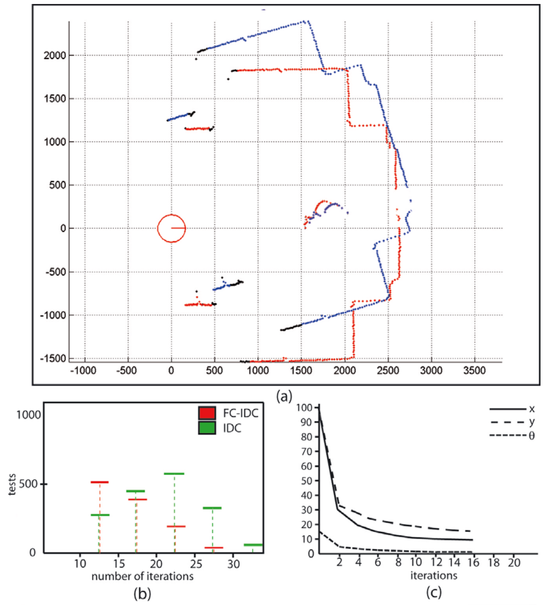

Fig. 5. a) Current and reference scans used for the first experiment; b) Convergence rate for classic IDC and proposed method; and c) Evolution of x, y and θ error.

TABLE I

TIME (S) NEEDED TO CALCULATE THE TRAJECTORIES FROM FIG. 6

Proposed Method	16.12
IDC	19.77

the robot planar displacement by matching two-dimensional range scans. The contribution is a previous step that removes isolated group of points associated to changing objects in the environment. To do that, the algorithm characterizes the whole scan using the curvature information which is invariant with respect to rotation and translation, and it can be fastly and efficiently computable. Then, a matching process is evaluated and points associated to dynamic objects are discarded. This increases the robustness of the method in real scenarios with respect to popular IDC algorithm. We have implemented and tested the technique in a real dynamic environments and results demonstrate that the described approach improves classic IDC algorithm in accuracy, robustness and convergence. Future works are focused on the implementation of a SLAM algorithm using the motion information estimate.

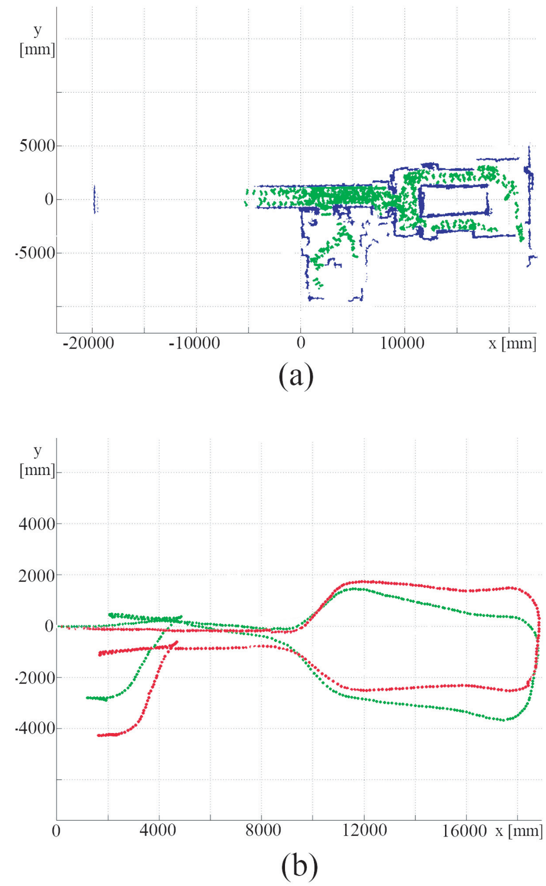

Fig. 6. Scan matching algorithms comparative. a) Resulting map obtained with the proposed algorithm (green points are autonomously removed by the proposed approach as they are considered to be part of dynamic items); and b) Trajectories computed by algorithms applied in this comparative studio. Red: proposed method, green: IDC algorithm. The environment is the ISIS group installation in the Andalusian Technology Park, in Málaga.

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VI. BIOGRAPHIES

Pedro Núñez was born in Spain in 1978. He received the title of Telecommunication Engineering from the University of Málaga, Spain, in 2003. In 2007 he joined the University of Extremadura as Assistant Professor in the Department of Tecnología de los Computadores y Comunicaciones. He is currently a research associate and Ph.D. Student at the University of Málaga. Past stay was with the Institute of System and Robotics (ISR, University of Coimbra, Portugal). His research interests include mobile robot localization and environment description.

Ricardo Vázquez-Martín was born in Spain in 1975. He received the M.S. degree in mechanical engineering from the University of Málaga, Spain (2002), majored in automation and electronics. After some years of working in companies related to industrial automation, in 2003 he returned to the University of Málaga to work as research assistant in the Electronic Technology Department. He is involved in his Ph.D., and his research interests include simultaneous localization and map building, feature extraction and software engineering.

Antonio Bandera was born in Spain in 1971. He received his title of Telecommunication Engineering and Ph.D. degree from the University of Málaga, Spain, in 1995 and 2000, respectively. During 1997 he worked in a research project under a grant by the spanish CYCIT. Since 1998 he has worked as Assistant Professor and Lecturer successively in the Department of Tecnología Electrónica of the University of Málaga. His research is focused on robotics and artificial vision.

Francisco Sandoval was born in Spain in 1947. He received the title of Telecommunication Engineering and Ph.D. degree from the Technical University of Madrid, Spain, in 1972 and 1980, respectively. In 1990 he joined the University of Málaga (UMA) as Full Professor in the Department of Electronic Technology (DTE). He is currently involved in autonomous systems and foveal vision, application of Artificial Neural Networks to Energy Management Systems, and in BroadBand and Multimedia Communication.