Fuzzy Constraint Satisfaction Approach for Landmark Recognition in Mobile Robotics *

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This work deals with landmark recognition in mobile robotics, using a new model based on Constraint Satisfaction Problems (CSP): the Multivariable Fuzzy Temporal Profile model (MFTP). A representation supported by CSPs makes it possible to capture a morphological description of the patterns that landmarks give rise to on sensor readings. Its representation, based on Fuzzy Set Theory, allows the imprecision and uncertainty that are characteristic of the problem to be handled. The work places special emphasis on those aspects that are resolved by means of this approach: the ability to model semantically rich landmarks, the simplicity of its description, and the high computational efficiency of the proposed detection algorithms. Finally, a validation of the model in the detection of various landmarks over ultrasound (US) sensors is presented. In spite of these sensors being highly noisy and imprecise, the MFTP model successfully detects 95% of the landmarks on the reference wall.

Keywords: Landmark recognition, constraint satisfaction problems, data fusion, fuzzy sets, autonomous navigation

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1. Introduction

The autonomous navigation of a mobile robot requires having a representation of the environment in which the robot has to move. Obtaining a high quality representation is a complicated task [12,21,29]. On one hand, the sensors used to perceive an environment have a limited range, which forces the robot to move to build up a complete representation, introducing odometric errors into the measurements. On the other hand, these sensors usually have a high level of noise, which gives rise to an inadequate and even erroneous perception of the environment. Furthermore, the environment may have dynamic characteristics, and the robot must deal with its representation in real time.

This representation can be drawn up by identifying certain elements from the environment, referred to in the bibliography as landmarks or beacons. Any relevant object in the environment that can be recognized in a robust and reliable manner can be considered to be a landmark. A landmark-based representation of the environment incorporates an abstraction operation over the perceived information, allowing the representation to be simplified and structured; it projects the information in symbolic terms, which simplifies the resolution of high-level tasks, such as planning or communication with humans. In the bibliography, two types of landmarks can be distinguished: on one hand, some authors define landmarks with a low semantic content, but which are easily identifiable (e.g., flat surfaces, edges, cylinders, etc [7,15,27,28,33]), while others use landmarks with a greater semantic content, but which are more difficult to identify (e.g., doors, corners, corridors, etc. [2,14,16,18,26]). In general, the latter are the most useful, as their higher semantic content aids in defining and reasoning about the topological structure of the environment. Another factor to be taken into consideration for evaluating the usefulness of a landmark is whether it is common to a large number of environments, since the more environments have this landmark the more general the navigation system upon which it is based will be. In indoor environments, corridors, which contain information that is essential for navigation, and doors, which connect the different places of the environment, are probably the most useful landmarks, as besides bearing valuable topological information, they are common to almost all indoor environments. Doors have an additional characteristic that makes them even more interesting: in the majority of indoor environments they are the most common landmark, and thus can be very helpful for localizing mobile robots. For example, a short trajectory in a given corridor may be sufficient for door-based localization, while corridor-based localization may require the robot to travel a considerable distance through a number of corridors.

The bibliography shows the use of different types of sensors for landmark detection: sonar, laser [20,32], and video camera [5,9]. The most frequently-used sensors in mobile robotics are sonar belts [4,10], where each sensor measures the distance to an obstacle in the environment. The widespread use of these sensors is due principally to their low cost, simplicity and low energy consumption; nevertheless, their measurements are greatly affected by noise, and are highly imprecise, which severely hampers their use in recognition tasks. It is possible to obtain more precise measurements of the environment, with less noise, using laser sensors; the downside is their high cost, which makes them unadvisable if a low-cost robot is aimed for, and their high energy consumption, which can severely curtail the robot's autonomy. Video cameras allow large quantities of information to be extracted from the environment, but making use of all this information implies a high computational load.

In this work we use the Multivariable Fuzzy Temporal Profile model (MFTP), a new model that is based on the Constraint Satisfaction Problem (CSP) formalism [8], and on the Fuzzy Set Theory [35], to detect landmarks over the sensors of mobile robots. We have applied this model to the recognition of landmarks over sonar sensors, to show the model's capability of handling noisy signals. The MFTP model makes it possible to describe the patterns produced by landmarks on the sensor signals, and to project them into a computable representation, which is used to identify the pattern, and thus the landmark, over the sensor readings. We have developed a tool that permits the description and validation of the pattern over the sensor readings, and a software application that works as a client of the robot, enabling real-time identification of landmarks.

This paper is structured as follows: in the next section the problem of sonar landmark detection is described, and the most relevant approaches from the bibliography are appraised. Section 3 explains the MFTP model, the matching process and how MFTP is capable of modelling patterns corresponding to different landmarks that are common in indoor environments. Section 4 shows the experimental results obtained for the Nomad 200 and Pioneer AT robots in different environments, and these results are discussed in section 5. Finally, in section 6 the most relevant conclusions of this work are presented, along with its possible future extension.

2. US based landmark-detection: related work

The operation of US sensors is based on the measurement of the time elapsed from the emission of a sound pulse, of a range of frequencies, until its reflection off objects ahead of the sensor is detected [19]. Based on the speed of sound, the distance to the reflecting objects can be calculated. These sensors are inexpensive, simple to install, relatively precise, light, and energy efficient. Nevertheless, they do have limitations, the most important possibly being their low angular resolution, since the pulses are emitted forming a conical beam of approximately 10^o. Moreover, very smooth surfaces or highly oblique angles of incidence may give rise to specular reflections and hinder the detection of the object. On occasion, the reflected beam collides with another new object, giving rise to a distance that is greater than the true one. An additional problem is *crosstalking*: a beam emitted by one sensor may be received by another one. This can be minimized by following certain sensor trigger patterns.

All these problems result in sonar readings having high levels of noise and imprecision, the result of which is that there are few successful works in the literature where they have been applied to landmark detection. Achieving good detection is even harder when landmarks produce non-distinctive patterns over sensors, such as door frames, as these patterns can be distorted or falsified by the noise and imprecision of the readings. This has resulted in more expensive and complex, but also more precise, sensorial devices (e.g., laser [20] or vision [9]) being preferred in the literature to locate doors, and other landmarks which produce subtle patterns.

One approach to overcoming the limitations of imprecision and noise in US sensors is to construct sensors with various emitters and receivers [1,6,13,25,31]. In order to do so, they measure the changes over time in the echoes received by the different receivers, and on the basis of this information it is determined which type of landmark is returning the US. The main drawbacks for these types of sensors are that they are more complex than standard ones (which simply measure the time of flight of the US pulse) and, as far as the authors are aware, their lack of commercial use. In any case these sensors have only been used successfully in the detection of three simple types of landmarks: flat surfaces, corners and edges.

The detection of doors, one of the most important landmarks in indoor environments, is much harder when the system aims to distinguish between open and closed doors. For example, in [9] a sonar sensor is employed for locating open doors, whilst a vision system is used for detecting closed ones, due to the lack of salient characteristics in the patterns produced by the latter over US sensors.

In [16] an expert system is built that attempts to reproduce the *modus operandi* of a set of humans locating doors visually over US signals. Detecting each new landmark requires studying how humans solve the problem, as well as finding and implementing a different *ad hoc* detection procedure. In this article a single test case is shown, where 9 out of 10 doors are correctly detected, but no real validation is provided.

In [18] fuzzy temporal rules are used to identify patterns over the temporal evolution of the US sensor signals. Fuzzy rule-based pattern description is not intuitive, and it does not allow a clear separation between the knowledge base employed and the detection algorithms that use this knowledge. This means that adding landmarks to the system requires implementing new matching algorithms, which is not the case with our proposal. In this work a validation of the proposal is presented, the results of which are improved upon in the present study.

Landmarks, extracted from US signals, are used in [33] to localize a mobile robot. Candidate landmarks are extracted by means of triangulation, and a voting scheme selects the best of them. This method only finds point landmarks (vertical edges), such as door-frames, that cannot be integrated into higher abstraction level landmarks, such as doors, and is more oriented to detecting landmarks which produce strong patterns over sonar signals in non-symmetrical environments, such as furniture in rooms.

In [26] the authors build a set of templates for several landmarks, and employ them to search for landmarks over US sensors. The templates are built under the assumption that sonar sensors will provide a precise outline of the landmark, and they depend both on the type of landmark, and on the orientation from which it is observed. This approach cannot be applied to door frames, as they have concave surfaces and, as the authors state, their method cannot be applied due to the sonar reflections they produce.

Saphira [14], a commercial closed system, is able to detect doors employing US sensors, but only when they are located inside corridors; doors located on corners or in the intersection of corridors are outside its scope. The lack of documentation on the procedure employed for this commercial system for detecting doors, or its performance, precludes any comparison. Even so, in ours tests the use of our model has always given superior detection results.

3. Our approach for landmark detection: MFTP model

The different landmarks in an environment produce characteristic patterns over the temporal evolution of some of the robot's sensors. Some of these patterns may be easily described by knowing how the temporal evolution of the sensor will be affected by the landmark, and this description can be verified by the visual inspection of the sensor signals.

With the aim of clearly introducing the different concepts of the model, we use the door-detection

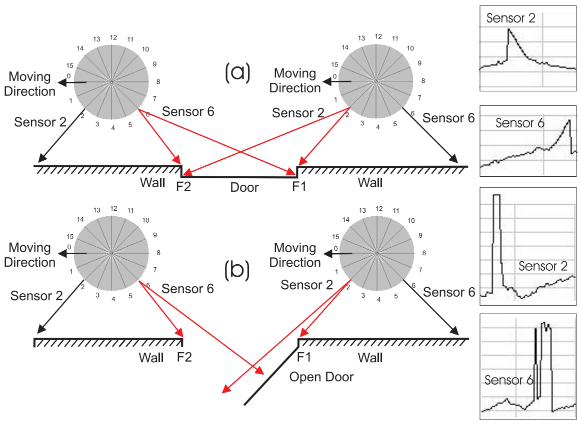

Fig. 1. Robot passing parallel a closed and open door, and their characteristic signal pattern on US signal.

problem. We now go on to analyze what happens to US readings when a mobile robot equipped with a belt of US sensors passes by a door. Before reaching the door, the signals of the sensors pointing to the wall 45^o forwards and backwards with respect to the displacement direction (sensors 2 and 6 in Fig. 1a) are approximately constant, as they measure the distance to the wall. Doors have flat, smooth surfaces which reflect the USs, thus when the sensor pointing 45^o forwards is directed at a closed door, the US beam does not reflect off it, rather off the furthest side of the door frame (F2). This phenomenon produces a sharp rise in this sensor (sensor 2 in Fig. 1a). If the door is open no object reflects the beam back to the US, which also gives rise to a sharp increase in the signal of this sensor (Fig. 1b).

Later on the sensor pointing 45^o backwards is the one that is directed at the door, and the beam reflects off the first door-frame (F1). As long as the robot moves away from this frame the sensor value increases gradually, until this sensor once again is pointed at the wall; at this juncture there is a pronounced fall in the sensor value (Fig. 1a). The same fall occurs if the door is open, due to the reflection of the US beam on the wall beyond the door (Fig. 1b).

With the Multivariable Fuzzy Temporal Profile model (MFTP) it is possible to identify a pattern $\mathcal{M}$, described by a human being, over the temporal evolution of a set of parameters $\mathcal{P} = \{\mathcal{P}^1, ..., \mathcal{P}^n\}$. In the landmark detection problem, each of the parameters $\mathcal{P}^j$ corresponds with a robot sensor reading, $\mathcal{P}^j = \{v^j_{[m]},\ m \in \mathbb{N}\}$, $t^j_{[m]}$ being the time instant corresponding to the sample m. The pattern $\mathcal{M}$ consists of a series of findings and relations between them; each one of these findings can in turn be represented by another MFTP that acts as a sub-MFTP of the main pattern.

The MFTP model is based on the formalism of *Constraint Satisfaction Problems* (CSP) [30], and on the *Fuzzy Set Theory* [34]. The CSP formalism supplies a support for pattern representation, as well as for the development of recognition algorithms. Using the Fuzzy Set Theory enables it to adequately model and handle the imprecision and uncertainty that are characteristic of the problem.

The MFTP model [23] extends the Fuzzy Temporal Profile model (FTP) [11], the latter allowing findings described as a particular morphology over the temporal evolution of a single parameter to be represented and recognized. The fact of being able to relate the occurrence of different findings amongst parameters is of great importance: a sharp increase in the readings of a sensor may be brought about by many causes (noise, a column, a turn by the robot itself, etc.). We will see how the integration of information from a number of sensors makes it possible to eliminate the high number of false positives that could be expected of the detection of such a simple pattern over such a noisy signal.

3.1. Fuzzy concepts

Given as discourse universe the set of real numbers $\mathbb{R}$, a **fuzzy number** A is a normal ($\exists\ v \in \mathbb{R}$, $\mu_A(v) = 1$) and convex ($\forall v, v', v'' \in \mathbb{R}$, $v' \in [v, v'']$, $\mu_A(v') \geq \min\ \mu_A(v), \mu_A(v'')\}$) fuzzy subset of $\mathbb{R}$. We obtain a fuzzy number A from a flexible constraint given by a possibility distribution π_A, which defines a mapping from $\mathbb{R}$, to the real interval $[0, 1]$. Given a precise number $v \in \mathbb{R}$, $\pi_A(v) \in [0, 1]$ represents the possibility of A being precisely v. Although the validity of MFTP model is not restricted to a specific representation of possibility distributions, in practice it will suffice to work with a trapezoidal representation $A = (\alpha, \beta, \gamma, \delta)$, where $[\beta, \gamma]$ represents the *core*, $core(A) = \{v \in \mathbb{R} | \pi_A(v) = 1\}$, and $]\alpha, \delta[$ represents the *support*, $supp(A) = \{v \in \mathbb{R} | \pi_A(v) > 0\}$ (See Fig. 2).

We introduce the concept of **fuzzy increment** with the aim of representing quantities, such as the difference between two numbers, fuzzy or not.

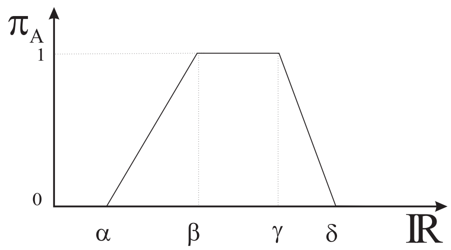

Fig. 2. Trapezoidal possibility distribution.

The fuzzy increment between pair of fuzzy numbers A and B is given, following Zadeh's extension principle [34], by D such:

$$\pi_D(i) = \underset{i=t-s}{maxmin}\{\pi_A(t), \pi_B(s)\}$$

3.2. The MFTP Model

A MFTP [23] is made up of a set of especially relevant points, defined over the temporal evolution of the sensors readings, and a set of flexible constraints delimiting the evolution that is expected in the presence of a landmark. These constraints are represented by fuzzy numbers, allowing a pattern to be modelled as a flexible set of possible evolutions of the parameters.

Definition 1 *We define* **significant point** *on a parameter* $\mathcal{P}^j$*,* $X_i^j =< V_i^j, T_i^j >$*, as the pair formed by a variable from the domain* V_i^j *and a temporal variable* T_i^j*. In the absence of constraints the variables* V_i^j *and* T_i^j *may take any precise value* $v_{[m]}^j$ *and* $t_{[m]}^j$*, respectively.*

We denote by $\mathcal{A}_i^j =< v_i^j, t_i^j >$ the assignment of precise values to the significant point X_i^j, i.e., it means that $V_i^j = v_i^j = v_{[m]}^j$ and $T_i^j = t_i^j = t_{[m]}^j$.

A general fuzzy constraint is defined between a set of significant points, providing a computable support to soft descriptions about the evolution of a parameter.

Definition 2 *A* **fuzzy constraint** $\mathcal{R}$ *between a set of significant points* $X_{i_f}^{j_1}, ..., X_{i_g}^{j_k}$ *is defined by means of a fuzzy relation* $C = C(X_{i_f}^{j_1}, ..., X_{i_g}^{j_k})$*.* C *is defined by means of a membership function* μ_C*, which associates a degree of satisfaction of* $\mathcal{R}$ *to each assignment of precise values to the significant points* $X_{i_f}^{j_1}, ..., X_{i_g}^{j_k}$*.*

With the aim of making a compact but sufficiently expressive description of a signal pattern, we use a reduced set of constraints, which carry out a fuzzy linear approximation to the desired pattern. In order to do so we define three types of fuzzy constraints between each pair of significant points, which limit: the duration between points, the increase in value between them, and the slope of the imaginary straight line that joins them.

Fuzzy duration. We define a constraint $L_{i_1 i_2}^{j_1 j_2}$ between significant points $X_{i_1}^{j_1}$ and $X_{i_2}^{j_2}$ on parameters $\mathcal{P}^{j_1}$ and $\mathcal{P}^{j_2}$ ($L_{i_1 i_2}^j$ if j_1=j_2=j), by means of a normal, convex possibility distribution $\mu_{C=L_{i_1 i_2}^{j_1 j_2}}(X_{i_1}^{j_1}, X_{i_2}^{j_2}) = \pi_{i_1 i_2}^{L^{j_1 j_2}}(h)$, that limits the temporal extension between these two significant points. The assignments $T_{i_1}^{j_1} = t_{i_1}^{j_1}$ and $T_{i_2}^{j_2} = t_{i_2}^{j_2}$ are possible if $\pi_{i_1 i_2}^{L^{j_1 j_2}}(t_{i_2}^{j_2} - t_{i_1}^{j_1}) > 0$. In Fig 3 the constraint L_{12}^2 allows the linguistic description "a little after" to be modelled.

Fuzzy increase. We also define a constraint $D_{i_1 i_2}^{j_1 j_2}$ between significant points $X_{i_1}^{j_1}$ and $X_{i_2}^{j_2}$ on commensurable parameters $\mathcal{P}^{j_1}$ and $\mathcal{P}^{j_2}$ ($D_{i_1 i_2}^j$ if j_1=j_2=j), by means of a normal, convex possibility distribution $\mu_{C=D_{i_1 i_2}^{j_1 j_2}}(X_{i_1}^{j_1}, X_{i_2}^{j_2}) = \pi_{i_1 i_2}^{D^{j_1 j_2}}(d)$, that limits the fuzzy increment between these significant points. The assignments $V_{i_1}^{j_1} = v_{i_1}^{j_1}$ and $V_{i_2}^{j_2} = v_{i_2}^{j_2}$ are possible if $\pi_{i_1 i_2}^{D^{j_1 j_2}}(v_{i_2}^{j_2} - v_{i_1}^{j_1}) > 0$. In Fig 3 the constraint D_{12}^2 allows modelling the linguistic description "increase on the sensor's reading".

Fuzzy slope. For significant points $X_{i_1}^j$ and $X_{i_2}^j$ corresponding the same parameter $\mathcal{P}^j$, it is useful to define a constraint $M_{i_1 i_2}^j$, by means of a normal, convex possibility distribution $\mu_{C=M_{i_1 i_2}^j}(X_{i_1}^j, X_{i_2}^j) = \pi_{i_1 i_2}^{M^j}(m)$, that limits the slope of the line between these points. The assignments $V_{i_1}^j = v_{i_1}^j$, $V_{i_2}^j = v_{i_2}^j$, $T_{i_1}^j = t_{i_1}^j$ and $T_{i_2}^j = t_{i_2}^j$ are possible if $\pi_{i_1 i_2}^{M^j}((v_{i_2}^j - v_{i_1}^j)/(t_{i_2}^j - t_{i_1}^j)) > 0$. In Fig 3 the constraint M_{12}^2 models the linguistic description "sharpness in the increase of the sensor's readings", where "sharpness" is modelled by a high slope value.

Definition 3 *We define a* **Multivariable Fuzzy Temporal Profile** *(MFTP)* $\mathcal{M} =< W^{\mathcal{M}}, X^{\mathcal{M}}, R^{\mathcal{M}} >$ *as a finite set of MFTPs* $W^{\mathcal{M}} = \{\mathcal{M}_1^{\mathcal{M}}, ..., \mathcal{M}_s^{\mathcal{M}}\}$*, a finite set of significant points* $X^{\mathcal{M}} = \{X_{i_1}^{j_1}, X_{i_2}^{j_1}, ..., X_{i_{n_{j_1}}}^{j_1}, X_{i_1}^{j_2}, ...\}$ *and a finite set of fuzzy con-*

straints $R^{\mathcal{M}} = \{R_1, ..., R_z\}$ *amongst the points of* $W^{\mathcal{M}}$ *and* $X^{\mathcal{M}}$.

The recursive structure of the MFTP model is based on the manner in which humans carry out abstraction operations, by integrating multiple items of information at different levels: often a finding is defined as a complex pattern that arises from the aggregation of a set of findings over different parameters. Each of these findings may also be a pattern. At the same time, any finding may form part of different patterns describing more complex findings. The structure described by a certain pattern can be interpreted as an expression that may be formed by a set of non terminal symbols (each one of the MFTPs $\mathcal{M} =< W^{\mathcal{M}}, X^{\mathcal{M}}, R^{\mathcal{M}} >$, where $W^{\mathcal{M}} \neq \varnothing$) and a set of terminal symbols (each one of the MFTPs $\mathcal{M} =< W^{\mathcal{M}}, X^{\mathcal{M}}, R^{\mathcal{M}} >$, where $W^{\mathcal{M}} = \varnothing$). Terminal symbols correspond to findings defined as a set of significant points and a set of constraints between them. The aggregation of findings is carried out by means of new constraints that link the different findings by means of their significant points.

Definition 3 is designed to make the model as general as possible. Nevertheless, in a good number of applications, door detection among them, a pattern to be detected is defined by a specific temporal layout between the findings, and each one of these findings is defined as a particular morphology of the evolution of a parameter. Thus a pattern of findings is given by a MFTP $\mathcal{M} =< W^{\mathcal{M}}, \varnothing, R^{\mathcal{M}} >$ where each finding $\mathcal{M}_h^{\mathcal{M}} \in W^{\mathcal{M}}$ is defined over a single parameter, and takes the form $\mathcal{M}_h^{\mathcal{M}} =< \varnothing, X^{\mathcal{M}_h^{\mathcal{M}}}, R^{\mathcal{M}_h^{\mathcal{M}}} >$.

A MFTP can be represented by a hypergraph in which nodes correspond to significant points, and arcs correspond to constraints. Figure 3 shows the hypergraph of the MFTP used to recognize doors. This graph agrees geometrically with the morphology of the profile that it represents, which makes it a visual metaphor that helps in pattern editing. Thus, along with the MFTP model, the Tool foR anAlising and disCovering pattErns (TRACE) has been developed [24]. This is graphical tool for visually editing patterns. TRACE incorporates a set of utilities for handling the model's fuzzy constraints, aiding in the landmark definition task.

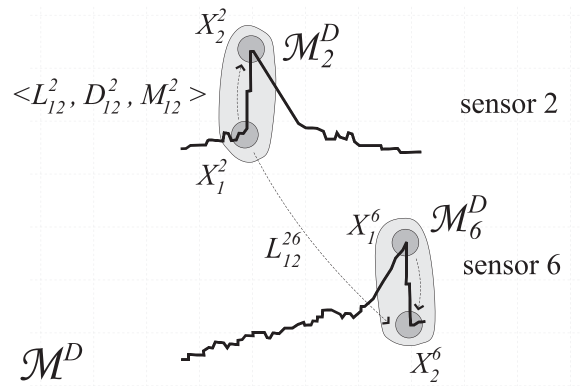

Fig. 3. Graph corresponding to the pattern that models a generic door, regardless of whether it is open or closed, drawn over a real occurrence of a door pattern.

3.3. Landmark recognition

The ultimate aim of the MFTP model in its application to landmark recognition is to identify the occurrence of a landmark $\mathcal{M}$ over the evolution of the sensor readings $\mathcal{P}$ of the robot. From the CSP formalism, the recognition task is formally equivalent to the search for solutions $\mathcal{M}$ in $\mathcal{P}$.

Definition 4 *We define a* **solution** *of* $\mathcal{M}$ *as a set of assignments* $\mathcal{A} = \{A_1^1, ..., A_{n^1}^1, ..., A_1^m, ..., A_{n^m}^m\}$ *to all the significant points of* $\mathcal{M}$ *that satisfies the set of constraints that make up* $\mathcal{M}$*, with a degree greater than zero. The degree of satisfaction of a solution* $\mathcal{A}$ *is given by:*

$$\pi^{\mathcal{M}}(\mathcal{A}) = min\{\min_{\mathcal{M}_h^{\mathcal{M}} \in \mathcal{W}^{\mathcal{M}}}\{\pi^{\mathcal{M}_h^{\mathcal{M}}}(\mathcal{A}^{\mathcal{M}_h^{\mathcal{M}}})\}, \min_{\mathcal{R}_k \in \mathcal{R}^{\mathcal{M}}}\{\pi^{\mathcal{R}_k}(\mathcal{A}^{\mathcal{R}_k})\}\}, \quad (1)$$

where $\mathcal{A}^{\mathcal{M}_h^{\mathcal{M}}}$ is the projection of $\mathcal{A}$ over the set of significant points involved in $\mathcal{M}_h^{\mathcal{M}}$, and $\mathcal{A}^{\mathcal{R}_k}$ is the projection of $\mathcal{A}$ over the set of significant points involved in $\mathcal{R}_k$. $\pi^{\mathcal{R}_k}$ is the degree of satisfaction of $\mathcal{R}_k \in \mathcal{R}^{\mathcal{M}}$ and $\pi^{\mathcal{M}_h^{\mathcal{M}}}$ is the degree of satisfaction of $\mathcal{M}_h^{\mathcal{M}} \in W^{\mathcal{M}}$. $\pi^{\mathcal{M}}(\mathcal{A})$ represents the degree of similarity between a fragment of the evolution $\mathcal{P}$ with the landmark described by $\mathcal{M}$.

We have conceived a search tree-based assignment procedure with the aim of discarding futile assignments by following an ordered method. The search for solutions is performed by Forward Checking algorithm [3]. This algorithm maintains arc consistency between those constraints that involve the current variable and one future variable each time that a value is assigned to a variable. In this way there will always be at least one value in the domain of the following variable that is compatible with the current assignment. This search algorithm is the most suitable backtracking algorithm for our problem [22].

The recognition procedure that has been developed orders the search following the bottom-up tree structure of the MFTP. Firstly solutions are sought for those MFTPs that contain no sub-MFTPs: those that directly model a morphology over one of the parameters. This allows a history of occurrences for each sub-MFTP to be obtained. Amongst these occurrences, we then search for the one that best satisfies the constraints that permit this sub-MFTP to be integrated into the MFTP that contains it. And this is repeated until $\mathcal{M}$ is found, following the expression 1.

The door pattern represented in Figure 2 is a very simple example of modelling by means of an MFTP $\mathcal{M}_D$ containing two sub-MFTPs: $\mathcal{M}^D =< \{\mathcal{M}_2^D, \mathcal{M}_6^D\}, \varnothing, L_{12}^{26} >$, where $\mathcal{M}_2^D$ represents a sharp increase in sensor 2, and $\mathcal{M}_6^D$ represents a sharp decrease in sensor 6. $\mathcal{M}_2^D$ can be easily described by $\mathcal{M}_2^D =< \varnothing, \{X_1^2, X_2^2\}, \{L_{12}^2, D_{12}^2, M_{12}^2\} >$. In a similar manner, $\mathcal{M}_6^D$ can be described by $\mathcal{M}_6^D =< \varnothing, \{X_1^6, X_2^6\}, \{L_{12}^6, D_{12}^6, M_{12}^6\} >$. Matching is carried out in two stages: first of all, $\mathcal{M}_2^D$ and $\mathcal{M}_6^D$ are detected over signal readings acquired on sensors 2 and 6, respectively. The expression for $\mathcal{M}_2^D$, where $\mathcal{A}^{\mathcal{M}_2^D} = (A_1^2, A_2^2)$, is written below, and an analogue expression applies for $\mathcal{M}_6^D$:

$$\pi^{\mathcal{M}_2^D}(\mathcal{A}^{\mathcal{M}_2^D}) = min\{\pi^{L_{12}^2}(t_2^2 - t_1^2),$$
$$, \pi^{D_{12}^2}(v_2^2 - v_1^2)), \pi^{M_{12}^2}((v_2^2 - v_1^2)/(t_2^2 - t_1^2))\} \quad (2)$$

where each one of the assignments A_i^2 (respectively, A_i^6) comes from the readings of the US sensor 2 (respectively, sensor 6).

The matching algorithm searches the sensor signals for sets of assignments that are compatible with the constraints of $\mathcal{M}_2^D$: $\{\mathcal{A}_1^{\mathcal{M}_2^D}, ..., \mathcal{A}_p^{\mathcal{M}_2^D}, ...\}$, and $\mathcal{M}_6^D$: $\{\mathcal{A}_1^{\mathcal{M}_6^D}, ..., \mathcal{A}_q^{\mathcal{M}_6^D}, ...\}$. In the following stage $\mathcal{M}^D$ is searched for over the sets of previous assignments, the constraints that limit both sets being checked, in this case L_{12}^{26}:

$$\pi^{\mathcal{M}^D}(\mathcal{A}) = min\{\pi^{\mathcal{M}_2^D}(\mathcal{A}_p^{\mathcal{M}_2^D}), \pi^{\mathcal{M}_6^D}(\mathcal{A}_q^{\mathcal{M}_6^D}),$$
$$\pi^{L_{12}^{26}}(t_2^6 - t_1^2)\} \quad (3)$$

where $\mathcal{A}_p^{\mathcal{M}_2^D} \subset \mathcal{A}$ and $\mathcal{A}_q^{\mathcal{M}_6^D} \subset \mathcal{A}$.

The recursive structure of the representation improves the efficiency of the recognition task, since when we break the pattern down, we are effectively dividing the original problem into simpler problems. If we also add certain heuristics to the recognition [22], such as the initial search for the most salient features of the different patterns, highly satisfactory results can be obtained, as will be seen in the results section.

The solutions obtained by 3 are filtered by a simple rule that checks whether the different door patterns found overlap each other (they correspond to a single door) or not (they correspond to different doors).

The landmark recognition algorithms have been implemented in TRACE (See Fig. 6). TRACE makes it possible to validate described patterns, and to adjust the parameters of the matching procedures to optimize its running; e.g., the degree of compatibility over which a landmark is considered to be correctly identified must be indicated. As a result of the execution of the recognition algorithms over the readings of each sensor, the tool colours in those signal fragments that show a degree of compatibility with the corresponding finding, and makes a set of icons representing the occurrences of the landmark appear (doors in Fig. 6).

Patterns defined with TRACE are stored in XML format. Using TRACE, adding or modifying a landmark is simply a case of editing, employing an intuitive graphical user interface, a file in this format. In the MFTP model, the knowledge and the recognition algorithms are kept apart, which significantly simplifies its practical use, as no knowledge of its implementation is required.

3.4. More on doors and other landmarks

The pattern described by means of the MFTP model makes it possible to identify both open and closed doors. Moreover, those doors that are in the opposite outline produce a similar pattern over sensors pointing 45^o forwards and backwards on this direction (sensors 10 and 14 in Fig. 1), which allows the doors to be located simultaneously in

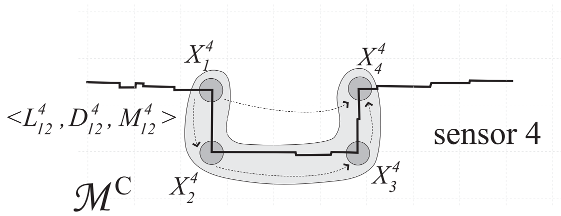

Fig. 4. The graph corresponding to the pattern that models a column, drawn over a real column pattern.

both outlines. It is also possible to define a distinctive pattern for open or closed doors, by simply integrating the behaviour of the sensor of the robot that is perpendicular to the wall (sensor 4 in Fig. 1) into the definition of the pattern, in order to verify whether the door sends back the ultrasound beam or not.

The manner in which the MFTP model is applied to door recognition is also applicable to the recognition of other landmarks of interest, such as corners, ends of corridors and columns (see Fig. 4), which are common to a large number of indoor environments. All these respond to a simple description over the signals captured by the sensors, and thus, can be represented by means of the MFTP model. In Section 4 a number of results relating to their detection are shown.

4. Experimental results

In order to validate our proposal we have carried out a series of tests on two different mobile robots: Nomad 200 and Pioneer AT. Both have a belt consisting of 16 US sensors which allows the application of the recognition pattern described in the previous section. The same pattern could be applied to any other machine with the same characteristics. All tests with the Nomad, and some of the tests with the Pioneer, were carried out in the environment shown in Fig. 5, in the Department of Electronics and Computer Science of the University of Santiago de Compostela. In order to verify the generality of our proposal, some of the tests carried out with the Pioneer robot took place in two other different environments: the Science Faculty of the University of Santiago de Compostela, and the Department of Electronics and Systems of the University of A Coruña.

Four different types of landmarks were detected in the tests: doors, ends of corridors, corners and columns. In the experimental work special emphasis was placed on door detection, due to this landmark being difficult to detect, and of great relevance due to the topological information they contain. A software application acting as a client of the robot was implemented, in which the recognition algorithms were executed. The robot sends the sensor reading via a wireless network to the client, which in turn informs the robot about the landmarks detected. The computational load of the algorithms does allow them to be integrated into the robot itself, but this manner was more beneficial for carrying out the experimental studies and the validation of both the patterns defined and the algorithm.

All tests were carried out under a *wall following* behaviour [17]. This behaviour keeps the robot closer to the wall that is being followed than the opposite one, and is clearly beneficial for door detections, since the robot remains close to wall that it is following, and follows a path that is relatively parallel to it. In all other respects, our aim was for the test to be as representative as possible of the different situations in which a robot may operate: the robot's velocity differed from some tests to others, and in the particular case of the Nomad 200, its operation was considered with the turret set with the base, or in free movement, guided by a different behaviour from the base. With regard to door, some were closed, while some were open or ajar. Tests were also carried out with obstacles in the corridors and with people walking in them.

4.1. Door detection with the Nomad 200

A total of eight different tests were carried out with the Nomad robot in the environment shown in Fig 5. The results of the detection over the reference wall and over the opposite one are shown in Tables 1 and 2, respectively. Each of the tests corresponds to following a different trajectory through the passageways of the environment. Tests A-F were carried out with the turret fixed to the base of the robot, modifying the mean velocity of the robot, and the degree of openness of the different doors in the corridor, from completely closed to completely open. Tests G and H were carried out with the turret moving freely with respect to the base, which required the reordering of the

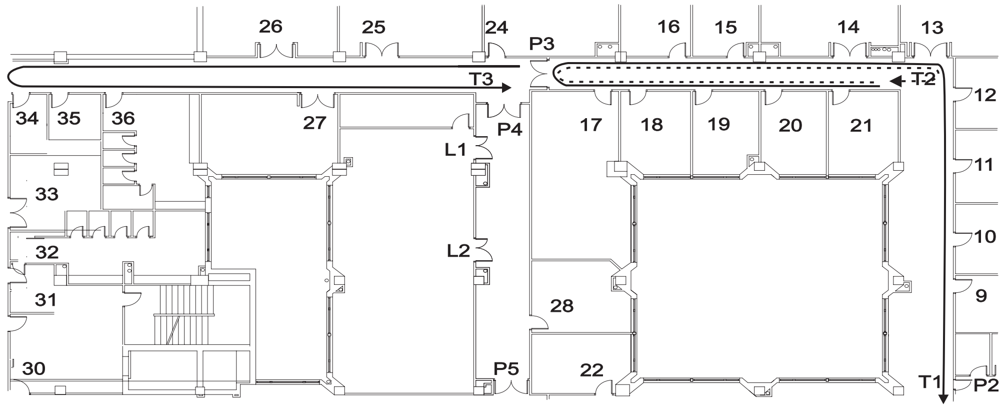

Fig. 5. Environment of the Department of Electronics and Computer Science of the University of Santiago de Compostela. A number of the trajectories followed by the robots are indicated. The other two environments have similar characteristics.

sensor readings in order to select the signal from the sensor closest to the direction of interest (45^o to the right and to the left, forwards and backwards) at each instant. By way of example, Figure 6 shows the result of the door detection from Test A, shown in Tables 1 and 2.

Table 1

Door detection. Nomad robot: reference wall.

Test	T	D	CD	FP	%CD	%FP
A	16	15	15	0	94	0
B	17	19	17	2	100	11
C	17	20	17	3	100	15
D	22	24	20	4	91	16
E	11	12	10	2	91	17
F	11	12	9	3	82	25
G	10	11	9	2	90	18
H	10	11	9	2	90	18
Total	114	124	106	18	93	15

T: Total; D: Detected; CD: Correct Detections; FP: False Positives

Tables 3 and 4 show the results of door detection over the reference wall and on the opposite one, in diverse situations in which there were different obstacles in the environment, and in which people were allowed to walk freely. It should be mentioned that a smooth cardboard panel simulating a door was placed on one of the walls.. The tests carried out differed in the number and placement of obstacles, and in the number of people (up to ten) moving in the environment. The obstacles forced the robot to modify its behaviour, and on occasion, they were placed in order to hinder the correct perception of doors. By way of example, Figure 7 shows the results of door detection in Test D shown in Tables 7 and 4.

Table 2

Door detection. Nomad robot: opposite wall.

Test	T	D	CD	FP	%CD	%FP
A	11	12	10	2	91	17
B	18	20	15	5	83	25
C	18	20	16	4	89	20
D	18	17	14	3	78	18
E	11	11	8	3	73	27
F	11	10	8	2	73	20
G	9	12	6	6	67	50
H	9	12	8	4	89	33
Total	105	114	85	29	81	25

T: Total; D: Detected; CD: Correct Detections; FP: False Positives

4.1.1. Comments on the results

The results of the tests carried out are satisfactory. As was to be expected, detection in notably higher for the wall followed by the robot than in the opposite one, due to the loss of angular resolution in the US sensors resulting from the increase in distance. The principal cause of unsatisfactory recognition lies in the turns that the robot may make while in motion: the more erratic its behaviour, the worse the results of the door recognition algorithms are. However, when the robot follows a uniform trajectory, the results are excellent. On the other hand, the movement of the turret with regard to the base of the robot has a noticeable

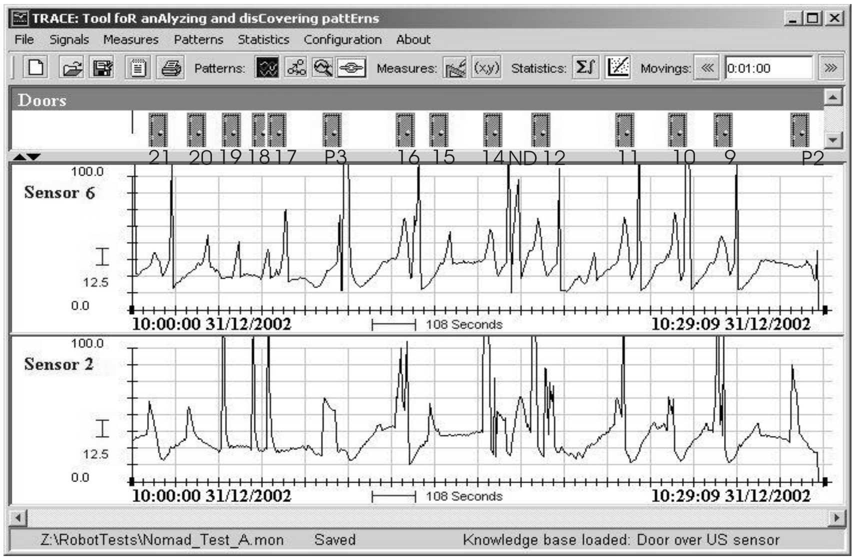

Fig. 6. The results of the detection while carrying out Test A on the following wall are shown. In the upper part, the doors detected are labelled. The undetected door (ND) was missed due to a sharp turn by the robot, resulting in a distorted signal reading.

Table 3

Door detection with obstacles. Nomad robot: reference wall.

Test	T	D	CD	FP	%CD	%FP
A	10	12	10	2	100	17
B	10	11	8	3	80	27
C	10	13	9	4	90	31
D	10	13	8	5	80	38
E	10	13	8	4	80	31
F	10	13	8	5	80	38
G	10	12	9	3	90	25
Total	70	87	60	26	87	30

T: Total; D: Detected; CD: Correct Detections; FP: False Positives

Table 4

Door detection with obstacles. Nomad robot: opposite wall.

Test	T	D	CD	FP	%CD	%FP
A	9	11	8	3	89	27
B	9	12	6	6	67	50
C	9	9	6	3	67	33
D	9	10	6	4	67	40
E	9	11	8	3	89	27
F	9	11	7	4	78	36
G	9	15	9	6	100	40
Total	63	79	50	29	79	37

T: Total; D: Detected; CD: Correct Detections; FP: False Positives

effect on the distortion of sensor readings; this especially limits the detection of the wall opposite the one being followed. The reason for this is to be found in the dynamic reordering of the sensors that is needed to extract the information necessary to detect the pattern. Furthermore, there is not always a sensor pointing in the desired direction, which means choosing the one that is closest, with the consequent distortion in the signal acquired.

The presence of obstacles hinders the obtention of satisfactory detection results, as the robot is forced to follow a winding route, amplifying the distortion in the sensor readings. Furthermore, some obstacles were placed in order to hinder the correct perception of doors, cancelling out their characteristic pattern. However, the movement of people did not significantly affect the results; even though they gave rise to distortion in the sensor readings, their rapid movement with respect to the robot did not hinder accurate recognition. The panel that was placed in order to simulate a door systematically gave rise to false positives. It should also be pointed out that the integration of information from various sensors has been fundamental for robust detection.

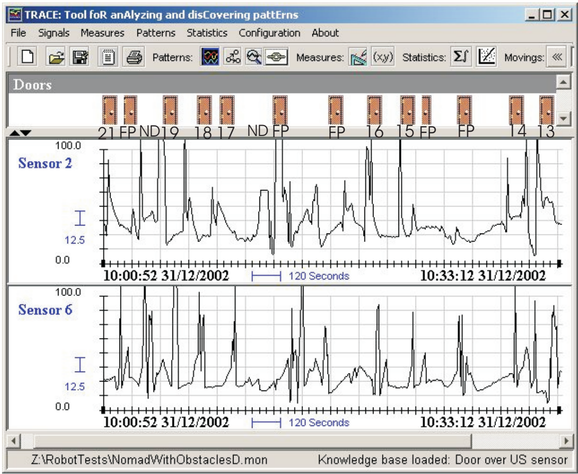

Fig. 7. Results of the detection during Test D from Table 5. In the upper section the doors detected are labelled; undetected doors are labelled ND, and false positives as FP.

Table 5

Door detection. Pioneer robot: reference wall.

Test	T	D	CD	FP	%CD	%FP
A	10	11	10	1	100	9
B	11	11	10	1	91	9
C	8	8	8	0	100	0
D	11	12	11	1	100	8
E	11	11	11	0	100	0
F	11	11	10	1	91	9
G	12	16	12	4	100	25
H	9	10	8	2	89	20
I	11	13	11	2	100	15
J	11	13	10	3	91	23
K	11	13	11	2	100	15
Total	116	129	112	17	97	13

T: Total; D: Detected; CD: Correct Detections; FP: False Positives

4.2. Door detection with the Pioneer

Due to its size and robustness, the Pioneer robot is easier to transport with guaranteed security, and it was used in a total of 11 tests in different environments. The results of the detection over the reference wall and over the opposite one are shown in Tables 5 and 6, respectively. Tests A-C correspond with the Department of Electronics and Computation, D-G with the Faculty of Sciences, and H-K with the Department of Electronics and Systems. Similarly as for the Nomad, the tests were carried out under a wide range of situations, considering that the Pioneer is single-bodied.

4.2.1. Comments on the results

Once again, the results of the tests carried out are satisfactory. Similarly as for the Nomad, the undetected doors and false positives are primarily due to turns made by the robot. Once again the detection is worse on the opposite wall, due to greater imprecision in the US sensors as the distance to the obstacle increases. On the other hand, there are no significant differences between the results of the detections in different environments, except in the experiments H-K, which give an increase in false positives. This is due to the fact that this environment contains a set of elements (radiators and plants) that act as obstacles and hinder the recognition of landmarks.

Table 6

Door detection. Pioneer robot: opposite wall.

Landmark	T	D	CD	FP	%CD	%FP
A	9	11	9	2	100	18
B	12	13	10	3	83	23
C	8	9	8	1	100	11
D	11	12	11	1	100	8
E	10	8	7	1	70	13
F	11	12	8	4	73	33
G	12	12	9	3	75	33
H	11	13	9	4	82	25
I	11	13	10	3	91	23
J	11	12	8	4	73	33
K	10	12	9	3	90	25
Total	116	128	98	29	84	23

T: Total; D: Detected; CD: Correct Detections; FP: False Positives

4.3. Other landmarks

In this section we give the results of the detection of corners, ends of corridors and columns. In the environments that we work with, these landmarks appear less frequently than doors, due to which we only give global results, and not for each individual test. The results of the detection with the Nomad are shown in Table 7, and with the Pioneer in Table 8. The corners and ends of passages of the Pioneer are from three different environments in which the tests were carried out, while the columns, and all the landmarks for the Nomad, are from the environment in Figure 5.

Table 7
Corner, Column and end of corridor detection. Nomad robot.

Landmark	T	D	CD	FP	%CD	%FP
Corner	9	8	8	0	89	0
End of corridor	10	9	9	0	90	0
Column	6	6	6	0	100	0

T: Total; D: Detected; CD: Correct Detections; FP: False Positives

Table 8
Corner, Column and end of corridor detection. Pioneer robot.

Landmark	T	D	CD	FP	%CD	%FP
Corner	5	5	5	0	100	0
End of corridor	16	16	15	1	94	6
Column	2	2	2	0	100	0

T: Total; D: Detected; CD: Correct Detections; FP: False Positives

In general it can be seen that there are hardly any false positives, due to these topological elements producing highly distinctive morphological patterns. The three undetected topological elements are due to the robot coming to a standstill or hesitating excessively when turning at a corner or end of corridor, which distorts the temporal evolution of the pattern, hindering its detection. Generally, it seems that errors in the detection of ends of corridors and corners are brought about by the excessive hesitation of the robot while it searches for a new wall to follow.

5. Discussion

Our proposal for landmark detection has been tested with two different robots in three distinct environments, always operating with wall following behaviour, under which the results obtained (95% correct detections and less than 15% false positives) are satisfactory on the wall followed by the robot; and although somewhat worse on the opposite wall (over 80% correct detections and less than 25% false positives), the increased imprecision of the problem enables us to be satisfied. When there are obstacles and people moving around in the environment the detection deteriorates in that they force the robot to deviate from a straight line. Although the detection rates (86% and 79% in the followed and opposite walls, respectively) are acceptable, there is an increase in false positives (30% for the wall followed and 37% for the opposite one).

As was to be expected, the global results obtained with the Nomad 200 are slightly poorer than those for the Pioneer. The reason is to be found in those tests carried out with the Nomad in which the turret was allowed to move freely with respect to the base of the robot, and the problems this gives rise to in the detection. In all other respects, the main determining factor in the detection stems from the turns the robot may make when in motion. The are no significant differences in the test regarding the environments tested or in changes in velocity during the trajectory.

It is common knowledge that false positives introduce an added difficulty into the handling of the information that enables us to represent an environment, since their use in localization tasks may place the robot in an erroneous position with respect to its own internal representation of the environment. In this sense, it is preferable to lose some of the characteristics or landmarks in the environment. The tests carried out show a slightly high number of false positives, which could be improved in various ways: through the fusion of additional sensorial information, by integrating pattern recognition over new sensors; and by means of including landmark recognition into a more complex task of drawing up a map of the environment. A task like this one allows the introduction of information-gathering and acquired information-reinforcement strategies.

One key perceptive problem is that of recognizing the same landmark from different perspectives. In this sense, for our method accurate perception depends on the robot operating under a wall-following or similar type of behaviour. Thus, if for example a robot is in a dynamic environment, operating with an *avoid mobile objects* type of behaviour, it is unlikely that our proposal would yield any valid results. In general, landmark recognition should be activated and deactivated according to the behaviour being followed by the robot.

In spite of the theoretical computational complexity of the MFTP model algorithms, the computational requirements of the procedures presented herein are low for patterns studied in real applications, and in particular for those studied in mobile robotics landmark recognition, where real-time performance has been achieved. By way of example, over a trajectory lasting approximately 30 minutes, door detection can be carried, on both walls, in under 5 seconds on a Pentium III running at 800 MHz. Regarding memory use, the knowledge base need only store a small number of trapezoidal possibility distributions; furthermore, the algorithm stores a small signal fragment, corresponding to the time that it takes the robot to find and go past the landmark. These low CPU and memory requirements make it possible to install our approach in low-cost robots with limited computational resources, which usually only have US and infrared sensors.

6. Conclusions and future work

In this work we supply a solution based on the Multivariable Fuzzy Temporal Profile model for landmark recognition in mobile robotics. This proposal places special emphasis on the handling of imprecision and uncertainty of information and on the fusion of information from multiple sensors. In particular, we have applied it to landmark detection using US sensors, due to their low cost, their habitual use in a large number of mobile robots, and due to the problems of imprecision caused by the measurements obtained. This does not preclude its application in other types of sensors; e.g. laser.

The tests carried out in the detection of doors, corners, columns and ends of corridors gave highly satisfactory results, both from the point of view of correct decisions, and of the performance of the algorithms developed. In this sense, the low computational requirements of the recognition algorithm allow it to be run in real time, and makes it appropriate for low-cost robots, with limited computational capacities.

The proposal presented in this work allows the signal patterns that define each landmark to be handled easily, and supplies visual tools that make it simpler to edit them intuitively. It should be pointed out that these patterns are stored separately from the recognition algorithms, making it possible to re-use the latter when new patterns are incorporated.

On the other hand, the solution proposed supplies a set of landmarks with great semantic richness, and which are clearly useful in carrying out high-level tasks, such as map building, planning, or communication with humans. With regard to future work, we aim to define an environment representation model that naturally integrates the landmark recognition that has been proposed here.We are searching for a representation of the environment that handles imprecision in spatial relations between landmarks, and which can organize this representation into various levels of abstraction, according to the level of detail that is required for the execution of different tasks.

References

[1] B. Ayrulu and B. Barshan. Identification of target primitives with multiple decision-making sonars using belief functions. *International Journal of Robotics Research*, 17(6):598–623, 1998.

[2] B. Barshan, B. Ayrulu, and S. W. Utete. Neural network-based target differentiation using sonar for robotics applications. *IEEE Transactions on Robotics and Automation*, 16(4):435–442, 2000.

[3] C. Bessiere, P. Meseguer, E.C. Freuder, and J. Larrosa. On forward checking for non-binary constraint satisfaction. *Artificial Intelligence*, 141:205–224, 2002.

[4] J. Borenstein, B. Everett, and L. Feng. *Navigating Mobile Robots: Systems and Techniques*. AK Peters, 1996.

[5] G. Y. Chen and W. H. Tsai. An incremental-learning-by-navigation approach to vision-based autonomous land vehicle guidance in indoor environments using vertical line information and multiweighted generalized hough transform technique. *IEEE Transactions on Systems, Man and Cybernetics-Part B: Cybernetics*, 28(5):740–748, 1999.

[6] K. S. Chong and L. Kleeman. Feature-based mapping in real, large scale environments using an ultrasonic array. *International Journal of Robotics Research*, 18(1):3–9, 1999.

[7] J. de Lope and D. Maravall. Landmark recognition for autonomous navigation using odometric information and a network of perceptrons. In Springer-Verlag, editor, *Proc. of the 6th Intl. Work-conference on Artificial Nwural Networks, IWANN Intelligence 2085*, pages 451–458, 2001.

[8] R. Dechter. *Constraint Processing*. Morgan Kaufmann Publishers, 2003.

[9] G. Dedeoglu, M. J. Mataric, and G. S. Sukhatme. Incremental, on-line topological map building with a mobile robot. In *Proc of Mobile Robots XIV- SPIE99*, pages 129–139, 1999.

[10] H. R. Everett. *Sensors for Mobile Robots. Theory and Application*. AK Peters, 1995.

[11] P. Félix, S. Barro, and R. Marín. Fuzzy constraint networks for signal pattern recognition. *Artificial Intelligence*, 148:103–140, 2003.

[12] R. Greiner and R. Isukapalli. Learning to select useful landmarks. *IEEE Transactions on Systems, Man and Cybernetics-Part B: Cybernetics*, 26(3):437–449, 1996.

[13] L. Kleeman and R. Kuc. Mobile robot sonar for target localization and classification. *International Journal of Robotics Research*, 14(4):295–318, 1995.

[14] K. Konolige, K. Mayers, E. Ruspini, and A. Saffiotti. The saphira architecture: A design for autonomy. *Journal of Experimental and Theoretical Artificial Intelligence*, 9:215–235, 1997.

[15] S. Marsland, Nehmzow, and T. Duckett. Learning to select distinctive landmarks for mobile robot navigation. *Robotics and Autonomous Systems*, 37:241–260, 2001.

[16] M.R. Masliah and R.W. Albrecht. The mobile robot surrogate method for developing autonomy. *IEEE Transactions on Robotics and Automation*, 14(2):314–320, 1998.

[17] M. Mucientes, R. Iglesias, C. V. Regueiro, A. Bugarín, and S. Barro. A fuzzy temporal rule-based velocity controller for mobile robotics. *Fuzzy Sets and Systems*, 134:83–99, 2003.

[18] P. Carieña, C.V. Regueiro, A. Otero, A. J. Bugarín, and S. Barro. Landmark detection in mobile robotics using fuzzy temporal rules. *IEEE Transactions on Fuzzy Systems*, 12(4):423–435, 2004.

[19] U. Nehmzow. *Mobile Robotics: A Practical Introduction*. Springer, 2000.

[20] U. Nehmzow and C. Owen. Robot navigation in the real world: Experiments with Manchester's FortyTwo in unmodified, large environments. *Robotics and Autonomous Systems*, 33:223–242, 2000.

[21] G. Oriolo, G. Ulivi, and M. Venedittelli. Real-time map building and navigation for autonomous robots in unknown environments. *IEEE Transactions on Systems, Man and Cybernetics-Part B: Cybernetics*, 28(3):316–333, 1999.

[22] A. Otero, P. Félix, and S. Barro. MFTP: a model to represent hierarchies of abstraction defined over multiple parameters. In *ECAI Workshop on Spatial and Temporal Reasoning*, pages 95–100, 2004.

[23] A. Otero, P. Félix, C.V. Rodríguez, M. Rodríguez, and S. Barro. A model to perform knowledge based temporal abstraction. In *TIME ICTL-2003*, pages 128–136. IEEE Press, 2003.

[24] A. Otero, S. Barro P. Félix, and F. Palacios. A tool for the analysis and synthesis of alarms in patient monitoring. In *The 7th International Conference on Information Fusion*, pages 951–958, 2004.

[25] H. Peremans, K. Audenaert, and J. Van Campenhout. A high-resolution sensor based on tri-aural perception. *IEEE Transactions on Robotics and Automation*, 9(1):36–48, 1996.

[26] S. Rizzi, D. Maio, and M. Golfarelli. A hierarchical approach to sonar-based landmark detection in mobile robots. In *5th International Symposium on Intelligent Robotic Systems - SIRS97*, 1997.

[27] J. D. Tardos, J. Neira, P. M. Newman, and J. J. Leonard. Robust mapping and localization in indoor environments using sonar data. *International Journal of Robotics Research*, 21(4):311–330, 2002.

[28] S. Thrun. Bayesian landmark learning for mobile robot localization. *Machine Learning*, 33(1):41–76, 1998.

[29] S. Thrun. Learning metric-topological maps for indoor mobile robot navigation. *Artificial Intelligence*, 99(1):21–71, 1998.

[30] E. Tsang. *Foundations of Constraint Satisfaction*. Academic Press, 1993.

[31] S. W. Utete, B. Barshan, and B. Ayrulu. Voting as validation in robot programming. *International Journal of Robotics Research*, 18(4):401–413, 1999.

[32] G. Q. Wei and G. Hirzinger. Multisensory visual servoing by a neural network. *IEEE Transactions on Systems, Man and Cybernetics-Part B: Cybernetics*, 29(2):276–280, 1999.

[33] O. Wijk and H.I. Christensen. Localization and navigation of a mobile robot using natural landmarks extracted from sonar data. *Robotics and Autonomous Systems*, 31:31–42, 2000.

[34] L. A. Zadeh. The concept of a linguistic variable and its application to approximate reasoning. *Information Science*, 8:199–249, 1975.

[35] L.A. Zadeh. Fuzzy sets. *Information Sciences*, 8:338–353, 1965.