A Fuzzy Constraint Satisfaction Approach for Landmark Recognition in Mobile Robotics

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Abstract

Landmark detection is essential for topological navigation, and many type of sensors have been used for this task. Ultrasound (US) sensors are one of the most common in mobile robots, but their readings include a high degree of imprecision and noise, which makes it hard obtain reliable detections with them. In this work, we apply a model, based on fuzzy constraint satisfaction problems (FCSP), for detecting doors over US sensors in mobile robots. Experimental results using a Nomad 200 mobile robot show 91% of doors correctly detected, which supports the reliability and robustness of the proposed methodology.

1 Introduction

Landmarks are fundamental for topological navigation in mobile robots, both for representing the environment with landmark-based maps and for locating the robot [3]. Although the advantages of topological navigation are undeniable, its performance critically depends on the correct identification of the different landmarks that make the environment map up. Any relevant object in the environment that may be recognized in a reliable way can be labelled as a landmark. Nevertheless, the most interesting and useful landmarks are those that are also helpful for defining the topological structure of the environment, such as doors and corridors in indoor environments.

Different sensors have been used in robotics, but the most frequently used are rings of US sensors [3, 5], where each sensor measures the distance to an obstacle in the environment. The wide use of these sensors is mainly due to their low cost, simplicity and low energy consumption. Their principal drawbacks are noise and uncertainty in the measurements, so they seldom are used for landmark detection.

In this work we apply the Multivariable Fuzzy Temporal Profile model (MFTP), a model based on the constraint satisfaction problem (CSP) formalism, and on fuzzy set theory, to detect topological landmarks, over mobile robot's sensors. We will center our work in the detection of doors, as they connect the different places in indoor environments, information essential for route planning. They are the most important indoor landmarks.

This paper is structured as follows. In the next section the problem associated to door detection using US is described, and a discussion on the most relevant approaches to door detection with ultrasound sensors is addressed. Section 3 is devoted to describe the MFTP model, and the next section the matching procedure. Section 4 shows and discusses the experimental results obtained with a Nomad 200 mobile robot in an indoor environment. Finally, section 6 presents the most relevant conclusions of this work and its future extensions.

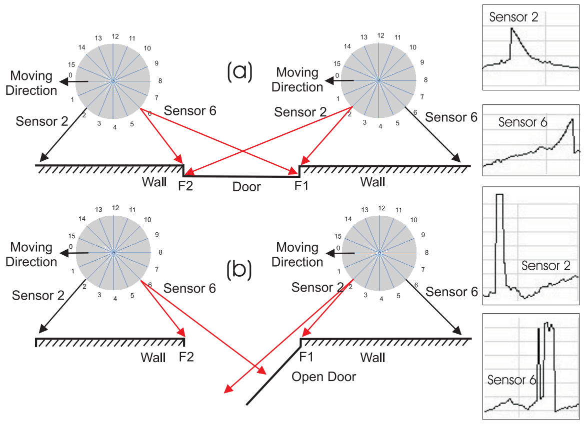

Figure 1: Robot passing parallel a closed, and open door, and their characteristic US signal pattern.

2 US based door-detection

The different landmarks in the environment of a mobile robot often give rise to characteristic patterns over the signals from the robot's sensors. Due to sensor noise and the robot's movements, these patterns usually vary significantly from one occurrence to another; nevertheless, they are normally reproducible and can be visually identified on the signal.

One of these reproducible patterns arises on the robot's US signal when it passes parallel to a door. Let us analyze this pattern for the case of a Nomad 200 robot, equipped with a ring of 16 US sensors. Before reaching the door, the signals from sensors 2 and 6 (Fig. 1a) are relatively constant, as they measure the distance to the wall. The doors have flat, smooth surfaces which reflect the USs, thus when sensor 2 is directed at the closed door the US waves do not reflect off the door, rather off the opposite door frame (F2). This phenomenon produces a sharp rise in the sonar signal 2 (Fig. 1a). If the door is open no object reflects the US, which also gives rise to a sharp increase in the signal of this sensor (Fig. 1b). Later on it is sensor 6 that is directed at the door and the waves reflect off the first door-frame (F1). While the robot moves away from this frame the sensor value increases gradually, until sensor 6 once again is pointed at the wall; at this juncture there is a pronounced fall (Fig. 1a). The same occurs if the door is open (Fig. 1b).

2.1 Related work

Sonar sensor-based door detection is a complex task, especially when the system aims to detect both open and closed doors. Usually systems described in the literature avoid the uncertainty and errors associated to ultrasound sensors by using more precise (and expensive) sensorial mechanisms, such as laser or vision. There are also a number of hybrid solutions [4], where an ultrasound sensor is employed for locating open doors, whilst a vision system is used for detecting closed doors.

There are a small number of papers on sonar-based detection of doors. To the best of our knowledge, the detection of closed doors with ultrasound sensors has only been tackled in [8]. Here an expert system attempts to simulate human behaviour when visually locating doors. The main drawbacks of the system are its non-intuitive implementation, its difficulty to be generalized to other landmarks, and the lack of a complete validation.

Landmarks, extracted from sonar signals, are used in [12] to locate the robot. Candidate landmarks are extracted by means of triangulation, and a voting scheme selects the best of them. Only point landmarks (vertical edges as door-frames) that cannot be integrated into higher abstraction level landmarks (such as doors) are found using this method. Other two methods of landmark detection based on US sensors are presented in [1]. To detect them the robot must rotate its tower and remain stationary. On the other hand, the authors aim to detect plane surfaces, open and closed corners and cylinders, but not doors.

There also is a commercial closed system, Saphira [7], which is able to detect doors employing sonar sensors, but only when they are located inside corridors. The lack of documentation on the procedure employed for this commercial system for detecting doors or its performance precludes any comparison.

3 Our approach for door detection: MFTP model

The Multivariable Fuzzy Temporal Profile model (MFTP) enables the identification, over the temporal evolution of a set of parameters, of a pattern $\mathcal{M}$ of special significance, described by a human expert. The pattern $\mathcal{M}$ consists of the appearance of a set of morphologies over each parameter and relations between them. $\mathcal{M}$ is defined over the evolution of the physical system $\mathcal{S}$, characterized by a set of parameters $\mathcal{P} = \{\mathcal{P}^1, ..., \mathcal{P}^n\}$. $\mathcal{P}$ is obtained by means of an acquisition and sampling process, such that $\mathcal{P}^j = \{(v^j_{[1]}, t^j_{[1]}), ..., (v^j_{[m]}, t^j_{[m]}), ...\}$.

The MFTP model is an extension of the FTP model [6], which enables the description of a special finding as the temporal evolution of a single physical parameter. The fact of being able to relate the occurrence of different findings amongst parameters is of great importance, since in most cases the appearance of a finding over a single parameter, which may be not a major determinant isolated, may well be of interest if it appears related with other findings on other parameters which also do not seem to be definitive taken on their own.

The MFTP model is based on the formalism of *Constraint Satisfaction Problems* (CSP) [11], and on the *fuzzy set theory [13].* An MFTP is represented by means of a network of fuzzy constraints between a set of significant points that are defined over the evolution of different parameters.

3.1 Prior definitions

In this section we introduce some basic fuzzy notions, upon which the MFTP model is based.

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.

We introduce the concept of **fuzzy increment** with the aim of representing quantities, such as the difference between two numbers, fuzzy or not. The fuzzy increment between a pair of fuzzy numbers A and B is given, following Zadeh's extension principle [13], by D such that: $\pi_D(i) = \max_{i=s-t} \min\{\pi_A(t), \pi_B(s)\}$.

3.2 The FTP Model

The aim of the Fuzzy Temporal Profile (FTP) model [6] is to represent and reason about the evolution of a profile, relative to a single physical parameter $\mathcal{P}^j$, which takes real values in time. The model projects a fuzzy description of the temporal evolution of the parameter onto a *fuzzy constraint* network between a set of *significant points.*

Definition 1 *We define* ***significant point*** *on a physical parameter $\mathcal{P}^j$, X^j_i, as the pair formed by a variable from the domain V^j_i and a temporal variable T^j_i. A significant point $X^j_i = < V^j_i, T^j_i >$ represents an unknown value V^j_i for the physical parameter $\mathcal{P}^j$ at an unknown temporal instant T^j_i. In the absence of constraints the variables V^j_i and T^j_i may take any precise value $v^j_{[m]}$ and $t^j_{[m]}$, respectively, where $(v^j_{[m]}, t^j_{[m]}) \in \mathcal{P}^j$.*

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

Definition 2 *A* ***fuzzy constraint*** *$\mathcal{R}$ between a set of significant points $X^j_1, X^j_2, ..., X^j_g$ is defined by means of a fuzzy relation $C = C(X^j_1, X^j_2, ..., X^j_g)$. 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 $X^j_1, X^j_2, ..., X^j_g$.*

In order to describe the behaviour of a parameter, a set of constraints limiting the fuzzy temporal duration, fuzzy increment and fuzzy slope between a set of significant points seems

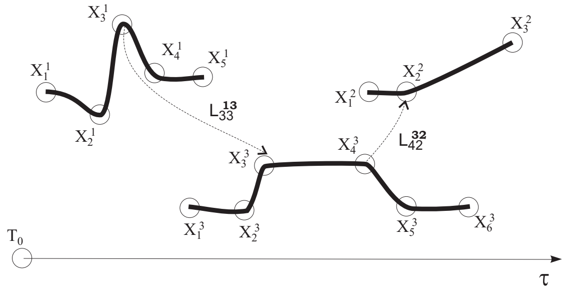

Figure 2: The hypergraph associated to MFTP made up of three morphologies over three different signals.

to capture a good number of features. So we have defined a constraint $L^j_{i_1 i_2}$, by means a fuzzy temporal increment, which constrains the domain of the variables $T^j_{i_1}$and $T^j_{i_2}$; a constraint $D^j_{i_1 i_2}$, by means a fuzzy increment, which constrains the domain of the variables $V^j_{i_1}$and $V^j_{i_2}$; and a constraint $M^j_{i_1 i_2}$, by means a fuzzy number, which constrains the domain of the variables $V^j_{i_1}$, $V^j_{i_2}$, $T^j_{i_1}$and $T^j_{i_2}$

Definition 3 *A* ***Fuzzy Temporal Profile*** $\mathcal{N}^j = \{X^j, \mathcal{R}^j\}$ *is defined as a finite set of significant points* $X^j = \{X^j_1, X^j_2, ..., X^j_{n^j}\}$ *and a finite set of constraints* $\mathcal{R}^j = \{\mathcal{R}^j_1, ..., \mathcal{R}^j_{f^j}\}$ *between them.*

3.3 The MFTP Model

The MFTP model is an extension of the FTP model which allows constraints between significant points that are defined over different parameters. Most common constraints between significant points defined over different parameters limit the fuzzy temporal duration and fuzzy increment. So we have defined a constraint $L^{j_1 j_2}_{i_1 i_2}$, which constrains the domain of the variables $T^{j_1}_{i_1}$ and $T^{j_2}_{i_2}$; and a constraint $D^{j_1 j_2}_{i_1 i_2}$, which constrains the domain of the variables $V^{j_1}_{i_1}$ and $V^{j_2}_{i_2}$.

Definition 4 *A Multivariable Fuzzy Temporal Profile* $\mathcal{M} = \{X^{\mathcal{M}}, R^{\mathcal{M}}\}$ *is defined as a finite set of significant points* $X^{\mathcal{M}} = \{X_1, X_2, ..., X_n\}$ *and a finite set of constraints* $R^{\mathcal{M}} = \{R_1, ..., R_f\}$ *between them.*

In this case fuzzy constraints limit the domains of significant points that can be defined over different parameters. A MFTP can be represented by a hypergraph in which nodes correspond to significant points, and arcs correspond to constraints. An example of a hypergraph associated to a MFTP is shown in Fig. 2.

4 Matching

The ultimate aim of the model is to identify the occurrence of the pattern $\mathcal{M}$ over the evolution of the physical system $\mathcal{S}$. Given that the MFTP model is based on the formalism of constraint networks, comparing a MFTP with $\mathcal{P}$ is formally equivalent to resolving a CSP [10], where the domains of the variable are determined by $\mathcal{S}$.

A solution to a MFTP $\mathcal{M}$ is a set of assignments $\mathcal{A} = \{A_1, A_2, ..., A_n\}$, where A_i is the assignation of precise values to the significant point $X^j_i \in X^{\mathcal{M}}$, i.e., $\mathcal{A}^j_i = (v^j_{[m]}, t^j_{[m]})$ means that $V^j_i = v^j_{[m]}$ and $T^j_i = t^j_{[m]}$, that satisfy the set of constraints $R^{\mathcal{M}}$ with a degree greater than zero. The degree of satisfaction of a solution $\mathcal{A}$ is given by:

$$\pi^{\mathcal{M}}(\mathcal{A}) = \min_{\mathcal{R}_k \in \mathcal{R}^{\mathcal{M}}} \{\pi^{\mathcal{R}_k}(\mathcal{A}^{\mathcal{R}_k})\}$$

Where $\mathcal{A}^{\mathcal{R}_k}$ is the projection of $\mathcal{A}$ over the set of significant points involved in $\mathcal{R}_k$, and $\pi^{\mathcal{R}_k}(\mathcal{A}^{\mathcal{R}_k})$ is the degree of satisfaction of the constraint $\mathcal{R}_k \in \mathcal{R}^{\mathcal{M}}$ for the assignment of precise values given by $\mathcal{A}$. $\pi^{\mathcal{M}}(\mathcal{A})$ represents the degree of similarity between a fragment of the evolution of $\mathcal{S}$ with the MFTP $\mathcal{M}$.

We have conceived an assignment procedure based on a search tree [9], as our aim is to discard futile assignments following an ordered method. Despite this, matching an MFTP is, in the general case, an NP-complete problem.

The implementation currently available of the matching algorithms based on the MFTP model divides the process into two stages. In the first stage occurrences of each FTP $\mathcal{N}^j$ are searched for over its corresponding evolution $\mathcal{P}^j$, thus obtaining a history of the occurrences of each $\mathcal{N}^j$. The history of $\mathcal{N}^j$ occurrences is used for a second matching algorithm which searches for occurrences of the FTPs that satisfy the constraints that the expert has described between significant points belonging to different parameters. The result of this matching stage is a history of the occurrences of the pattern $\mathcal{M}$. Both search procedures are performed by a nFC0 Forward Checking algorithm [2], achieving a real time performance for the door detection task.

The matching algorithm of the MFTP algorithm have been implemented in the Tool foR anAlyzing and disCovering pattErns (TRACE)[9]. This tool allows the graphic projection of a pattern in a MFTP, and the automatic identification of the pattern described over a set of signals. As a result of the matching over each parameter the tool colours in those signal fragments that have shown compatibility with each of the FTPs that make up the MFTP, and in the upper half of the tool appear icons that represent occurrences of the global patterns (doors in this case).

5 Experimental results

In order to validate the pattern for door detection over US sensors we have carried out a number of experiments in the setting of Fig. 3. We have attempted to make them as representative as possible of the different situations in which the Nomad 200 robot can operate: the robot's speed differs from one register to the others, and the base and tower have been aligned and unaligned. With regard to doors, some were closed, while other were either open or ajar.

In all the experiments carried out the displacement of the robot was effected under a "wall-following" behaviour, following both left- and right-hand outlines. This behaviour keeps the robot closer to the wall being followed than to the wall on the opposite side. Given that the angular precision of the US sensors is superior over shorter distances, this behaviour results in superior detection of the doors in the outline that the robot is follow-

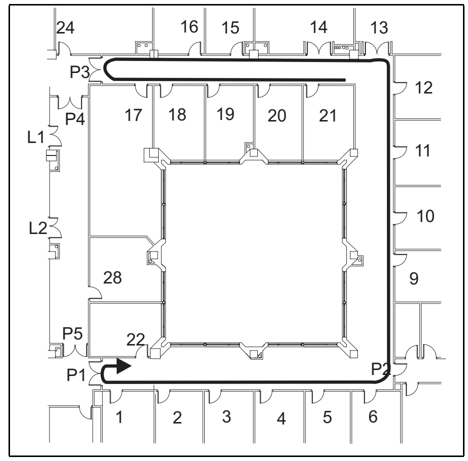

Figure 3: Environment in which experiments were carried out, showing the trajectory with base and tower aligned.

ing. Nevertheless, the detection of the doors on the wall not being followed is much worse due to the greater distance between the sensor and the opposite wall.

The knowledge base employed in the tests included in the present work consists of a sharp increase over the sensor aimed 45^o in a forward direction, followed by a sharp decrease in the sensor aimed 45^o towards the rear (see Fig. 1). The values of the sharp increase and decrease must be, at least, approximately equal to the breadth of the door. In order to take the imprecision of the ultrasound sensors into account, the value employed in both cases was *greater than approximately 40 cm*.

US sensor 2 starts pointing to the door around 1.10 m. before it, and US sensor 6 stops pointing around 1.10 m. after; the width of the simple doors is a little more than 1 m, while double's is near 2 m. When the robot perceives a door, its wall-following behavior performs two corrections in the trajectory: one just before the door, and the other after it. These corrections cause the robot to slow down. Given the 3-4 m length path that the robot must traverse and the different average speeds of the robot passing along the door we came up with the temporal distance between both events: *from approximately 20 seconds until approximately 2 minutes*.

The pattern described makes it possible to

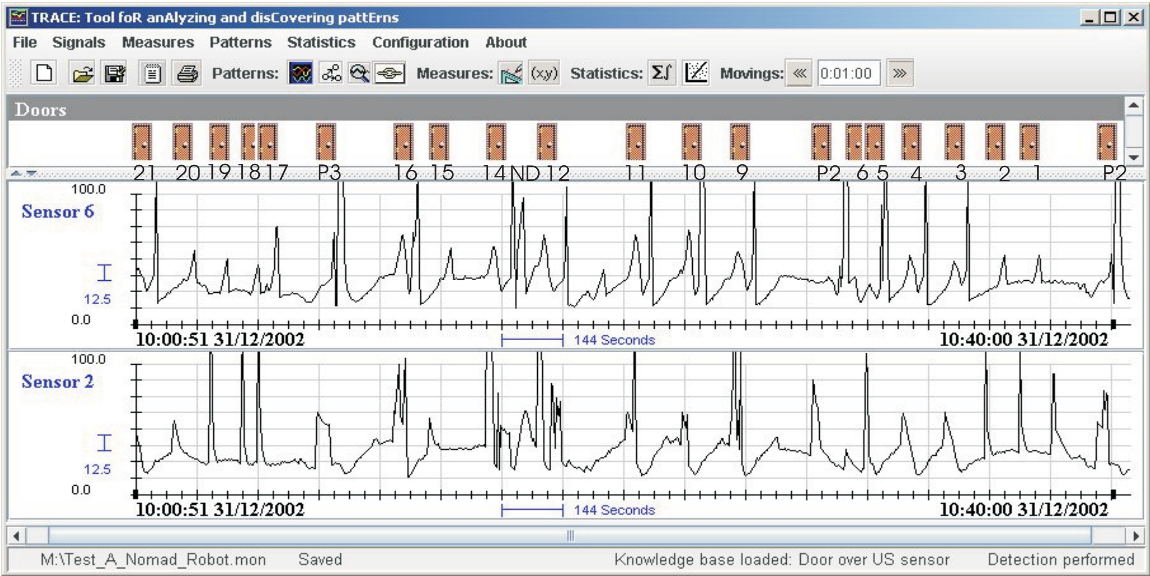

Figure 4: Doors detected in the trajectory shown in Fig. 3, visualized in the TRACE.

identify both open and closed doors. Moreover, those doors that are in the opposite outline produce on sensors 10 and 14 a pattern that is similar to the one given on sensors 2 and 6 by the doors in the outline being followed, which allows the doors to be located simultaneously in both outlines.

By way of example, we now go on to comment on the results obtained in two of the experiments carried out.

5.1 Trajectory with base and tower aligned

In this experiment the base and tower were maintained aligned throughout the trajectory. The robot followed the path shown in Fig. 3 guided by a "left-hand wall-following" behaviour. Fig. 4 shows the result of the door-detection, visualized in the PDAT. We have labelled each of the icons with the number of the corresponding door in the map giving in Fig. 3. If the detection turned out to be a false positive, the icon is labelled as "FP", and non-detected doors as "ND".

This trajectory corresponds with Test A from tables 1 and 2. The door lost in the outline being followed is due to the fact that the turn being effected by the robot at that instant excessively distorts the signal, cancelling out the

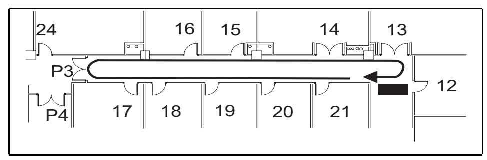

Figure 5: Trajectory with base and tower unaligned

sharp decrease pattern. In the opposite outline the high number of false positives is due to both the greater distance to the wall and the presence of a glass wall in the corridor between doors 1 and 6. The changes in material in this glass wall, from glass to metal, give rise to increases and drops in the sensor signals, which are often taken as doors.

5.2 Trajectory with base and tower unaligned

In this experiment the robot follows the trajectory shown in Fig. 5, guided by a "left-hand wall-following" behaviour, the robot's base and tower are not aligned. For this reason we have to reorganize the sensors in order to select, at each instant, the signal from the sensor whose direction is closest to the desired one (45^o to the right and to the left, forwards and backwards). This adds a degree of distortion to the signal, as can be seen in

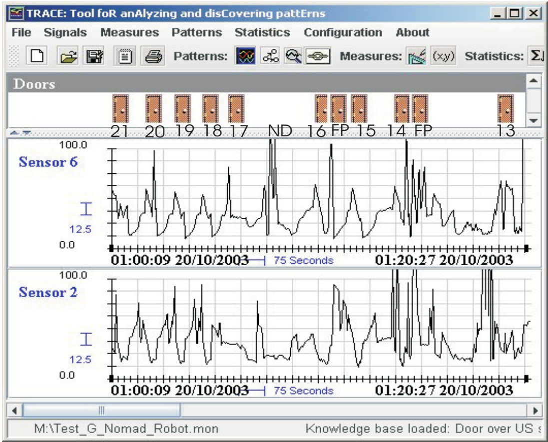

Figure 6: Door detection in the trajectory shown in figure 5.

Fig. 6, which significantly hinders detection. Obtaining satisfactory door-detection under these conditions would release other sensors, as laser and video camera, to be employed in other tasks.

Fig. 6 shows the result of the detection on the trajectory in Fig. 5, which corresponds with Test G in tables 1 and 2. Once again the turns are responsible for door loss, and, on this occasion, they are also the principal source of false positives, possibly due to the trajectory being a short one, with two 180^o turns.

5.3 Results of the validation

In total seven different tests were carried out. The results of the detections of the close and opposite outlines are shown in two different tables: table 1 and 2, respectively. In the outline followed by the robot 94% of the doors are detected, on average, with 12% being false positives. In the opposite outline there is a detection rate of 86%, but with 53% being false positives. As was to be expected, detection is significantly better for the outline being followed by the robot than for the opposite one, due to the loss of angular resolution in the US sensors with the increase in distance.

The robot's velocity did not appear to appreciable affect the quality of detection: e.g., trajectory E was carried out at the robot's maximum velocity, 40 cm/second, and the results obtained are similar to the other tests. We don't expect the robot's speed to be a problem, as far as the firing frequency of the US sonar is able to scale with the robot's speed. Non-alignment of the base and the tower did have an appreciable effect: trajectories F and G were carried out without the base and tower being aligned, and the detection results are noticeably inferior.

Table 1: Door detection during a wall-following task: reference wall.

Test	TD	DD	CD	FP	%CD	%FP
A	22	21	21	0	95	0
B	19	19	19	0	100	0
C	10	10	10	1	100	10
D	23	29	21	7	91	24
E	13	14	12	2	92	14
F	10	11	9	2	90	18
G	10	11	9	2	90	18
Total	107	115	101	14	94	12

TD: Total Doors; DD: Detected Doors; CD: Correct Detections; FP: False Positives

Table 2: Door detection during a wall-following task: opposite wall

Test	TD	DD	CD	FP	%CD	%FP
A	11	19	11	8	100	42
B	11	17	8	9	73	53
C	2	12	2	10	100	83
D	12	25	11	14	91	56
E	11	15	9	6	82	40
F	9	17	6	11	67	64
G	9	15	8	6	89	40
Total	65	120	56	64	86	53

TD: Total Doors; DD: Detected Doors; CD: Correct Detections; FP: False Positives

6 Conclusions

Doors are landmarks critical for topological navigation in mobile robotics as they show the structure of indoor environments and point out regions that can be reached by the robot.

In spite of their importance, only a small number of works deal with their detection based on US sensors, perhaps the most frequently used sensors in mobile robotics, mostly due to the high level of noise and uncertainty in the measures they provide.

The MFTP model allows a direct representation of the knowledge involved in the pattern of doors over robot's US sensors, and their detection in real time. In spite of being a very simple and common-sense characterization of the pattern, the percentage of correctly detected doors is very high (91%) when distance from the robot to the wall is within the usual values (e.g., when executing a wall-following behaviour). For greater distances the number of false positives noticeably increases. This is due to the limited precision of ultrasound sensors over greater distances. For such cases, other sensors (laser, vision) are more suitable.

Other applications of our MFTP-based detection method are currently being developed, such as the detection of other types of landmarks (e.g. corridors, open and closed corners and columns), with encouraging preliminary results. A further problem which remains to be solved is the precise location of the detected landmarks with respect to the robot, mainly for including the detection process into a map building task.

Acknowledgements

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