A model to perform knowledge-based temporal abstraction over multiple signals

A. Otero[*1], P. Félix[1], C.V. Regueiro[2], M. Rodríguez[1] and S. Barro[1].

[1]Dpto. de Electrónica e Computación Universidade de Santiago de Compostela.
Santiago de Compostela 15782, Spain.

[2]Dpto. Electrónica de Sistemas, Universidade de A Coruña, Coruña 15071, Spain.

[*]Corresponding author's email: elabra@usc.es

Abstract

In this paper we propose the Multivariable Fuzzy Temporal Profile model (MFTP), which enables the projection of expert knowledge on a physical system over a computable description. This description may be used to perform automatic abstraction on a set of parameters that represent the temporal evolution of the system. This model is based on the constraint satisfaction problem (CSP) formalism, which enables an explicit representation of the knowledge, and on fuzzy set theory, from which it inherits the ability to model the imprecision and uncertainty that are characteristic of human knowledge vagueness.

We also present an application of the MFTP model to the recognition of landmarks in mobile robotics, specifically to the detection of doors on ultrasound sensor signals from a Nomad 200 robot.

1 Introduction

The proliferation of new and more sophisticated electronic measuring devices, together with improvements in communication processes, enable the development of tasks, such as supervision, in a more reliable and precise manner, by placing exhaustive and ever more complete information at the disposal of the decision-making process. Nevertheless, the enormous quantity of data to be handled considerably increases the difficulty of this process [7], which frequently leads to problems in the assimilation of input data, and thus, lead to errors [8]. In many cases the solution involves rejecting those data that situate the decision-maker outside the domain of his/her competence.

The control of industrial processes, robotics, and patient supervision are domains that are especially affected by this problem; they require a continuous operation in which representation and reasoning about time is a fundamental key in the solution of problems.

This leads to the necessity of having mechanisms for the automation of abstraction processes; mechanisms that have to supply information of greater granularity and higher semantic content [12]. Thus, the decision-maker off-loads a good proportion of the data-interpretation processes, facilitating the quickest and most suitable performance possible.

The aim of the present work is to show a model, MFTP, based on knowledge representation, that makes it possible to perform abstraction over the behaviour of a physical system on the basis of a set of sampled parameters. This model allows the automatic generation of information that is organized into a hierarchy of levels of abstraction, taking as a starting point the set of sampled parameters that represent the temporal evolution of the system.

2 Temporal framework

We consider time as being projected on a one-dimensional discrete axis $\tau = \{t_0, t_1, ..., t_i, ...\}$. Thus given an i belonging to the set of natural numbers $\mathbb{N}$, t_i represents a *precise* instant. We assume that t_0 represents the temporal origin, before which the existence of any fact is not relevant for the problem under consideration. We consider a total order relation between them, in such a way that for every $i \in \mathbb{N}$, $t_{i+1} - t_i = \Delta t$, where Δt is a constant. Δt is the minimum step of the temporal axis.

3 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 and convex fuzzy subset of $\mathbb{R}$. A fuzzy set A with membership function μ_A is *normal* if and only if $\exists\ v \in \mathbb{R}$, $\mu_A(v) = 1$. A is said to be *convex* if and only if $\forall v, v', v'' \in \mathbb{R}$, $v' \in [v, v'']$, $\mu_A(v') \geq$ min $\mu_A(v), \mu_A(v'')\}$.

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. By means of π_A we define a fuzzy subset A of $\mathbb{R}$, which contains the possible values of A, being A a disjoint subset, in the sense that its elements represent mutually excluding alternatives for A.

We introduce the concept of **fuzzy increment** with the aim of representing quantities, such as the difference between two numbers, fuzzy or not. An increment D is represented by a normal and convex possibility distribution π_D, defined over $\mathbb{R}$. Given a pair of fuzzy numbers (A,B) the increment between A and B is given, following Zadeh's extension principle [16], by D such that:

$$\pi_D(i) = \max_{i=t-s} \min\{\pi_A(t), \pi_B(s)\}$$

We define **fuzzy interval** by means of initial and final fuzzy numbers, and its extension, which is a fuzzy increment and which represents the difference between the end-values of the interval. By $I_{(A,E,D)}$ we denote the interval that is delimited by the values A and E, with a distance between them of D. In order for an interval to have sense, it must start before it can finish. For this reason we assume that the support of D has to be included in the set of positive numbers; i.e., $\forall i \in \mathbb{R}$, $i \leq 0$, $\pi_D(i) = 0$. In this manner, although the distributions of A and E overlap, the constraint on the length of the interval will reject any assignment to A of a value equal to or bigger than E.

When the discourse universe is time the concept of fuzzy number serves to represent *fuzzy instant*, the concept of fuzzy increment serves to represent the *fuzzy temporal extension* between two fuzzy instants, and lastly the fuzzy interval serves to represent *fuzzy temporal intervals*. Together they will be the entities with which we will model the time in our model.

4 The MFTP Model

The Multivariable Fuzzy Temporal Profile model (MFTP) enables the identification, over the temporal evolution of a set of parameters, a pattern $\mathcal{M}$ of special significance, described by a human expert, which consists of the appearance of a set of morphologies over each parameter and relations between them.

The MFTP model is an extension of the FTP model [4], 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, which is outside the scope of the FTP model, 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. In this sense, the temporal disposition of a set of findings plays an important role in those tasks related with the interpretation problem. It is reasonable to expect a temporal abstraction tool to be able to handle this knowledge in the representation of a system's evolution. This is the most significant step carried out by the MFTP model with respect to its predecessor, the FTP model.

Both FTP and MFTP models will be the tools that enable us to structure the representation of the system information into different levels of abstraction, with the MFTP realizing the identification of those findings defined by the composition or association of other findings.

The MFTP model is based on the formalism of Constraint Satisfaction Problems (CSP) [14], and on the fuzzy set theory. 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 the different parameters.

The ultimate aim of the model is to identify the occurrence of the pattern $\mathcal{M}$ over the evolution of the physical system $\mathcal{S}$, automatically generating information organized in a hierarchy of levels of abstraction. The system is 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 $\mathcal{P}^j = \{(v^j_{[1]}, t^j_{[1]}), ..., (v^j_{[m]}, t^j_{[m]}), ...\}$. We suppose that over $\mathcal{P}$ we have defined an MFTP $\mathcal{M}$, and by $\mathcal{N}^j$ we denote a FTP that is described over the parameter $\mathcal{P}^j$. For a clearer explanation of the model, we suppose that over each parameter only one FTP is defined.

4.1 The FTP Model

The aim of the Fuzzy Temporal Profile (FTP) model 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 $(v^j_{[m]}, t^j_{[m]}) \in \mathcal{P}^j$.*

By $\mathcal{A}^j_i$ we denote the assignment of precise values from the evolution $\mathcal{P}^j$ to the variables of X^j_i; i.e., $\mathcal{A}^j_i =$

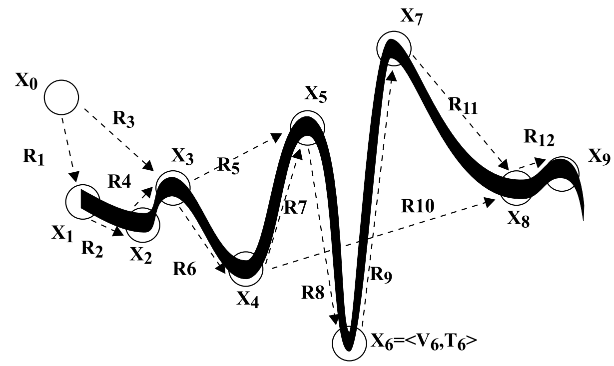

Figure 1. Graph corresponding to a FTP.

$(v^j_{[m]}, t^j_{[m]})$ means that $V^j_i = v^j_{[m]}$ and $T^j_i = t^j_{[m]}$. A general fuzzy constraint is defined between a set of significant points, providing a computable support to soft descriptions of the form of a signal.

Definition 2 *A **fuzzy constraint** $\mathcal{R}$ between a set of significant points $X^j_0, X^j_1, ..., X^j_g$ is defined by means of a fuzzy relation $C = C(X^j_0, X^j_1, ..., X^j_g)$. C is defined by means of a membership function μ_C, which associate a degree of satisfaction of $\mathcal{R}$ to each assignment of precise values to the significant points $X^j_0, X^j_1, ..., X^j_g$.*

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 to capture a good number of features.

A constraint $L^j_{i_1 i_2}$ is defined by means of a normal, convex possibility distribution $\mu_C(X^j_{i_1}, X^j_{i_2}) = \pi^{L^j}_{i_1 i_2}(l)$ where $\pi^{L^j}_{i_1 i_2}(l)$ represents the possibility of the temporal duration between $T^j_{i_1}$ and $T^j_{i_2}$ taking the precise value l. By definition $\pi_{L^j_{i_1 i_1}}(x) = 0, \forall x \neq 0$, and $\pi_{L^j_{i_1 i_1}}(0) = 1$. In the domain of linguistic variables, these constraints may also correspond to the assignment of a linguistic description q_i, from within the set $\mathcal{L} = \{q_1, q_2, ..., q_z\}$ of qualitative descriptions of values from the respective discourse universe. Using the constraints $L^j_{i_1 i_2}$ we can model temporal relations between significant points, described by means of expressions such as "approximately a quarter of an hour later". In [5], Félix *et al.* propose a language that allows fuzzy constraints between significant points to be generated by applying arithmetic operators to linguistic expressions.

A constraint $D^j_{i_1 i_2}$ is defined by means of a normal, convex possibility distribution $\mu_C(X^j_{i_1}, X^j_{i_2}) = \pi^{D^j}_{i_1 i_2}(d)$ where $\pi^{D^j}_{i_1 i_2}(d)$ represents the possibility of the fuzzy increment between $V^j_{i_1}$ and $V^j_{i_2}$ taking the precise value d. By definition $\pi_{D^j_{i_1 i_1}}(x) = 0 \; \forall x \neq 0$, and $\pi_{L^j_{i_1 i_1}}(0) = 1$. Using the constraints $D^j_{i_1 i_2}$ we can model linguistic descriptions such as "a slight rise", which describe changes in the magnitude of the physical parameters between significant points.

The significant point $X^j_0 = < V^j_0, T^j_0 >$ represents the origin of times and values. We suppose that any fact which happens before T^j_0 is not relevant for the problem under consideration. This significant point will allow us to convert unary descriptions over the absolute temporal instant, or magnitude, of a significant point ("A little after 5:00 ...") into binary constraints between this significant point and X^j_0.

A constraint $M^j_{i_1 i_2}$ is defined by means of a normal, convex possibility distribution $\mu_C(X^j_{i_1}, X^j_{i_2}) = \pi^{M^j}_{i_1 i_2}(m)$, where $\pi^{M^j}_{i_1 i_2}(m)$ represents the possibility of the slope between the points $X^j_{i_1}$ and $X^j_{i_2}$ taking the precise value m. By definition $M^j_{i_1 i_1}$ is the universal constraint π_u. Using the constraints $M^j_{i_1 i_2}$ we model linguistic descriptions of the type "the value rose gently", where "gently" is translated by a low slope value.

Definition 3 *A **Fuzzy Temporal Profile** $\mathcal{N}^j = \{X^j, \mathcal{R}^j\}$ is defined as a finite set of significant points $X^j = \{X^j_0, X^j_1, ..., X^j_{n^j}\}$ and a finite set of constraints $\mathcal{R}^j = \{\mathcal{R}^j_1, ..., \mathcal{R}^j_{f^j}\}$ between them.*

A FTP can be represented by means of a hypergraph, in which the nodes correspond to significant points, and the arcs correspond to constraints (figure 1).

Furthermore, the FTP model enables us to restrict the evolution of a parameter $\mathcal{P}^j$ between each pair of significant points $X^j_{i_1}$ and $X^j_{i_2}$ (see figure 2) by means of a membership function $\mu_{\mathcal{S}^j_{i_1 i_2}}(\mathcal{A}^j_{i_1}, \mathcal{A}^j_{i_2})$ which allow us to model some descriptions of language, such as "the ultrasound signal raises slightly during the following 30 seconds" [5]. In the same line, an explanation of how to project on the model the use of fuzzy quantifiers, such as "throughout the last ten seconds the ultrasound signal has been higher than its mean value" is given in [2].

4.2 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.

We have placed special emphasis on the representation of the temporal disposition of the findings described in the pattern $\mathcal{M}$ of the system's evolution. Thus, amongst instants we represent those of convex point algebra [15], amongst intervals those defined by Allen [1], as well as relations amongst points and intervals, such as relations between the point and the beginning and ending points of the

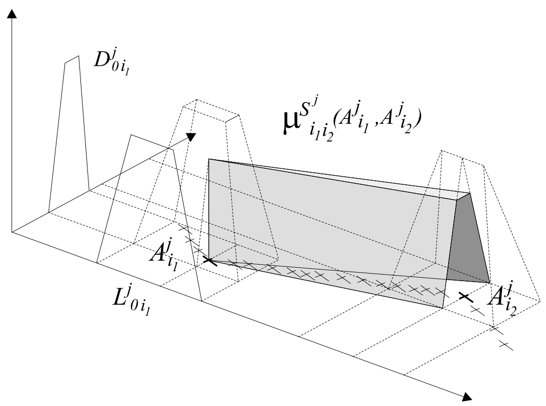

Figure 2. The semantics $S^j_{i_1 i_2}$ restricts the evolution of a parameter between two consecutive significant points. In the figure only the trajectories which fall into the fuzzy course described by $\mu^{S^j}_{i_1 i_2}(A^j_{i_1}, A^j_{i_2})$ are allowed by the semantic constraint.

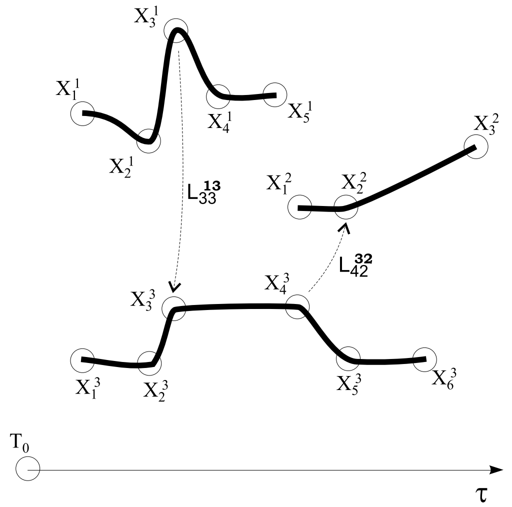

Figure 3. The hypergraph associated to MFTP made up of three morphologies over three different signals.

interval. Moreover, a representation based on fuzzy sets enables the model to capture the imprecision that is present in quantitative relations between temporal events, which is found in expressions such as "approximately five minutes later".

We previously define the constraint dimensionality of R, $\dim(R)$, as being the number of different parameters over which the variables of C are evaluated. Trivially for all $R^j_k \in R^j$ it holds that $\dim(R^j_k) = 1$.

As has been done for the FTP model, we now go on to define an extensible set of constraints that are habitual in expert's descriptions.

Definition 4 *A constraint $L^{j_1 j_2}_{i_1 i_2}$ is defined by means of a normal, convex possibility distribution $\mu_C(X^{j_1}_{i_1}, X^{j_2}_{i_2}) = \pi^{L^{j_1 j_2}}_{i_1 i_2}(h)$ with $j_1 \neq j_2$, where $\pi^{Lj_1 j_2}_{i_1 i_2}(h)$ represents the possibility that the fuzzy increment between $T^{j_1}_{i_1}$ and $T^{j_2}_{i_2}$ is precisely h. $L^{j_1 j_2}_{i_1 i_2}$ constrains the temporal duration between significant points defined over different parameters.*

Using the constraints $L^{j_1 j_2}_{i_1 i_2}$ we can model linguistic descriptions of the type "ultrasound signal 15 goes back to approximately the initial value a little before ultrasound signal 11 starts to rise".

Definition 5 *A constraint $D^{j_1 j_2}_{i_1 i_2}$ is defined by means of a normal, convex possibility distribution $\mu_C(X^{j_1}_{i_1}, X^{j_2}_{i_2}) = \pi^{D^{j_1 j_2}}_{i_1 i_2}(d)$ with $j_1 \neq j_2$, where $\pi^{D^{j_1 j_2}}_{i_1 i_2}(d)$ represents the possibility that the fuzzy increment between $V^{j_1}_{i_1}$ and $V^{j_2}_{i_2}$ is precisely d. $D^{j_1 j_2}_{i_1 i_2}$ constrains the increment in the magnitude between significant points defined over different parameters.*

Using the constraints $D^{j_1 j_2}_{i_1 i_2}$ we can model linguistic descriptions of the type "the value in sensor 15 before starting to rise is approximately equal to the value in sensor 11 before starting to rise".

Definition 6 *A Multivariable Fuzzy Temporal Profile $M = \{X^{\mathcal{M}}, R^{\mathcal{M}}\}$ is defined as a finite set of significant points $X^{\mathcal{M}} = \{X_0, X_1, ..., X_n\}$ and a finite set of constraints $R^{\mathcal{M}} = \{R_0, R_1, ..., R_f\}$ between them.*

A MFTP M can be decomposed into a set of FTPs $N^{\mathcal{M}} = \{N^1, N^2, ..., N^m\}$ and a set of constraints $R^{\mathcal{M}^*} = \{R_k \in R^{\mathcal{M}} : \dim(R_k) > 1\}$. This decomposition groups the significant points of $\mathcal{M}$ into sets belonging to the same FTP: $X^{\mathcal{M}} = \{X^1_0, ...X^1_{n^1}, ..., X^m_0, ...X^m_{n^m}\}$, where X^j_i is the i significant point of N^j. We consider, with no loss in generality, that the time origin of all the FTP belonging to a MFTP is the same: $T^1_0 = T^2_0 = ... = T^m_0$.

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 figure 3. The constraints that we can find between the different parameters may be descriptive, acquired by using linguistic descriptions [5] or by means of some type of graphical tool [9], or they may come from mathematical models of the system.

Up until now, in applications carried out employing the MFTP model, constraints of a descriptive nature have been the most common and useful. Nevertheless, in other application domains where there are mathematical models of systems, such as process control, restrictions originated from these models will play a more important role. Thus, for example, the ideal gas encapsulated in a volume V, subjected to a pressure P and a temperature T verifies that $P \cdot V = K \cdot T$, where K is a constant. This physical knowledge could be modelled by means of a set of constraints $C(X^P_{i_P}, X^T_{i_T}, X^{\mathcal{V}}_{i_{\mathcal{V}}}) = V^P_{i_P} \cdot V^{\mathcal{V}}_{i_{\mathcal{V}}} - K \cdot V^T_{i_T}$ such that $\pi_C(x) = 0 \; \forall \; x \neq 0$, $\pi_C(0) = 1$, and $L^{PT}_{i_P i_T} = L^{T\mathcal{V}}_{i_T i_{\mathcal{V}}} = L^{\mathcal{V}P}_{i_{\mathcal{V}} i_P} = 0$, where $X^P_{i_P}$, $X^T_{i_T}$ and $X^{\mathcal{V}}_{i_{\mathcal{V}}}$ are significant points defined on the temporal evolution of the variables P, T and V, respectively.

5 Matching

The ultimate aim of the MFTP model is to identify a pattern that is described by an expert over a set of parameters P which describe the temporal evolution of a physical system S. Given that the MFTP model is based on the formalism of constraint networks, comparing a MFTP with P is formally equivalent to resolving a CSP [13], where the domains of the variable are determined by S.

A solution to a MFTP M is a set of assignments $A = \{A_0, A_1, ..., A_n\}$,where A_i is the assignations of precise values to the significant point $X_i \in X^{\mathcal{M}}$, that satisfy the set of constraints $R^{\mathcal{M}}$, with a degree greater than zero. The conjunctive combination of the fuzzy constraints of $\mathcal{M}$ is a fuzzy constraint given by the min operation. 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 could search for the MFTP as a whole, employing two levels of abstraction in the representation: the sampled signals, and the history of occurrences of M. Matching a MFTP as a whole may have a high computational complexity: the matching would be equivalent to solving a CSP with n variables, where n is the number of significant points which make up the MFTP.

Imitating human experts, we divide the matching into as many stages as the number of levels of abstraction given by the composition of findings. Typically, when the experts search for the global pattern over P they initially locate the morphologies over each parameter P^j, in order to check whether they give rise to the occurrence of a global pattern. In this case three levels of increasing abstraction are used: sampled signal, history of morphological events over each parameter, and multivariable pattern occurrences.

Following this approximation, in the first stage occurrences of each FTP N^j are searched for over its corresponding evolution P^j, thus obtaining a history of the occurrences of each N^j. The degree to which a set of assignments $A^j = \{A^j_1, ..., A^j_i\}$ satisfy the set of constraints of a FTP N^j is given by:

$$\pi^{\mathcal{N}^j}(A^j) = \min_{\mathcal{R}_k \in \mathcal{R}^j} \{\pi^{\mathcal{R}_k}(A^{\mathcal{R}_k})\} \tag{1}$$

Where $A^{\mathcal{R}_k}$ is the projection of A^j over the set of significant points involved in R_k, and $\pi^{\mathcal{R}_k}(A^{\mathcal{R}_k})$ is the degree of satisfaction of the constraint $R_k \in R^j$ for the assignment of precise values to the set of significant points of X^j involved in R_k

After this stage we must seek for sets of A^j which fulfil the set of constraints R^* of M, obtaining global solutions A for M. The degree of satisfaction of the global solution can be calculated on the basis of the degrees of compatibility of each FTP N^j with $A^j \in A$ by means of the following expression:

$$\pi^{\mathcal{M}}(\mathcal{A}) = \min \{\min_j \{\pi^{\mathcal{N}^j}(\mathcal{A}^j)\}, \min_{\mathcal{R}_k \in \mathcal{R}^{\mathcal{M}^*}} \{\pi^{\mathcal{R}_k}(\mathcal{A}^{\mathcal{R}_k})\}\} \tag{2}$$

Where $\mathcal{A}^{\mathcal{R}_k}$ is the projection of $\mathcal{A}$ over the set of significant points involved in $\mathcal{R}_k$.

Performing the matching in several stages decreases the complexity of this task. Looking for each morphology means performing the matching of the FTP; thus, in order to search for all the FTPs that make up the MFTP, we must solve m CSP, each with n^j variables. The complexity of the overall task is $O(e^{n^{j\max}})$, where $n^{j\max} = \max_j \{n^j\}$.

After looking for occurrences of each FTP in order to complete the matching, we must look for the occurrences of each FTP that fulfil the set of constraints R^*. The complexity of this second task is $O(e^m)$, so the order of the overall complexity is $O(\max\{e^{n^{j\max}}, e^m\})$, while the complexity of solving a MFTP as a whole is $O(e^n)$ where $n = \sum_{i=1}^{m} n^i$.

The disadvantage of performing the matching with this approach is that we cannot be sure of finding the optimal solutions, as local optimal solutions do not have to be part of the optimal global solution.

It is possible to organize the information into more levels of abstraction, where each finding is built from a set of findings from a lower level; e.g., we could initially look for events that form part of a FTP, then look for the FTP over them, and finally we would look for occurrences of the whole MFTP.

If we wish to build up complete histories of the occurrence of events of interest at each level of abstraction, it is necessary to perform the matching in as many stages as there are levels of description in the problem. Besides, in this way it will be possible to give detailed explanations to the human operator as to how the lower-level information has been combined in order to generate higher-level information; and it is more suitable for agent-based implementation, where each agent can take charge of matching each finding, using the results from the previous agents.

5.1 The algorithm employed for the matching

We have conceived an assignment procedure based on a search tree, as our aim is to discard futile assignments following an ordered method. 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 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 degree to which a set of assignments $\mathcal{A}^j = \{\mathcal{A}^j_1, ..., \mathcal{A}^j_i\}$ satisfy the set of constraints of a FTP $\mathcal{N}^j$ is given by expression (1).

The degree of membership of the sample $(v^j_{[m]}, t^j_{[m]})$ of the evolution of P^j to an occurrence of the FTP N^j is given by the expression:

$$\pi^{\mathcal{N}^j}(v^j_{[m]}, t^j_{[m]}) = \max_{t^j_1 \leq t^j_{[m]} \leq t^j_{n^j}} \pi^{\mathcal{N}^j}(\mathcal{A}^j)$$

Where t^j_1, $t^j_{n^j}$ correspond to the samples assigned to the significant points X^j_1 and $X^j_{n^j}$ of N^j, the first and the last in temporal order.

Amongst the three major types of backtracking algorithms in the bibliography, simple backtracking (BT), backjumping (BJ) and forward checking (FC) [14], it is commonly accepted that the latter behaves better.

In [3] Bessiere shows that the extension of FC algorithms to non-binary constraint problems can be done in six different ways, and gives an algorithm for each extension: nFC0, nFC1, nFC2, nFC3, nFC4 and nFC5 algorithms. Each of these algorithms maintains a higher level of consistence between the variables which have been assigned a value and the variables which remain without value (past variables and future variables), nFC0 being the one which forces a lesser level of consistency and nFC5 the one which forces a stronger level of consistency.

We have chosen the nFC0 algorithm because, as has been shown in [3], it employs less CPU time than other nFCx algorithms (nFC1 till nFC5) in problems in which the graph is not dense. In dense CSPs the effort made in checking consistency is compensated by the greater pruning power of the other nFCx algorithms, these beating the nFC0 algorithm. At medium density problems all algorithms behave similar.

Graphs associated with both FTP and MFTP are not usually dense; furthermore experience has shown us that FTPs frequently have sequential topology (each significant point only has one constraint with its predecessor [4]), so the best algorithm, at least for a major part of real MFTP, is nFC0.

In the nFC0-type Forward Checking algorithm each time that a value is assigned to a variable arc consistency is maintained between those constraints that involve the current variable and one future variable. In this way there will always be at least one value that is compatible with the current assignment in the domain of the variable that follows according to the assignment order.

The history of $\mathcal{N}^j$ occurrences is used for a second matching algorithm, once again nFC0, which searches for occurrences of the FTPs that satisfy the constraints that the expert has described between significant points belonging to different parameters: i.e., those such that $\dim(\mathcal{R}) > 1$, where the result of this matching phase is a history of the occurrences of the pattern $\mathcal{M}$. The degree of compatibility of a solution $\mathcal{A}$ with a MFTP $\mathcal{M}$ that is calculated on the basis of the degrees of compatibility of each FTP $\mathcal{N}^j$ with $\mathcal{A}^j \in \mathcal{A}$ is given by the expression (2).

We must assign a degree of membership of the time instant t_i to an occurrence MFTP M. In order to be able to do this the expert must specify the temporal situation of the instant or interval of interest linked with this MFTP**,** which could be the assignment to the earliest and latest significant points to appear in the entire MFTP, but other options are also available.

Given the significant points $X^{j_1}_{i_1}$ and $X^{j_2}_{i_2}$, which the expert considers to be the end points of the interval (event if $X^{j_1}_{i_1} = X^{j_2}_{i_2}$) linked with this MFTP, the degree of membership of the time instant t_i to $\mathcal{M}$ is obtained by searching over P for the set of assignments A which maximizes the degree of satisfaction of the expression (2).

$$\pi^{\mathcal{M}}(t_i) = \max_{t^{j_1}_{i_1} \leq t_i \leq t^{j_2}_{i_2}} \{\pi^{\mathcal{M}}(A)\}$$

Where $t^{j_1}_{i_1}$ and $t^{j_2}_{i_2}$ correspond to the samples assigned to the significant points $X^{j_1}_{i_1}$ and $X^{j_2}_{i_2}$ respectively.

6 Practical Case

The MFTP model is currently being applied in two different domains: patient supervision and mobile robotics. Both domains may benefit from the automation of the abstraction process. In the former, amongst the numerous applications of the MFTP model, work is currently under way to construct alarms with a better specificity-sensitivity ratio than those presently available in the ICU domain. To improve this ratio the MFTP based alarms integrate information from several parameters, instead just from a single

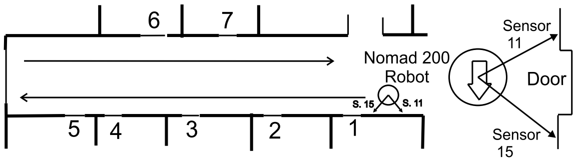

Figure 4. Diagram of the environment where the experiment described here was performed. The trajectory of the Nomad 200 robot and the doors along the route (marked with numbers) can be seen. Note the position of the ultrasound sensors used for door-detection with regard to the direction of the forward movement of the robot.

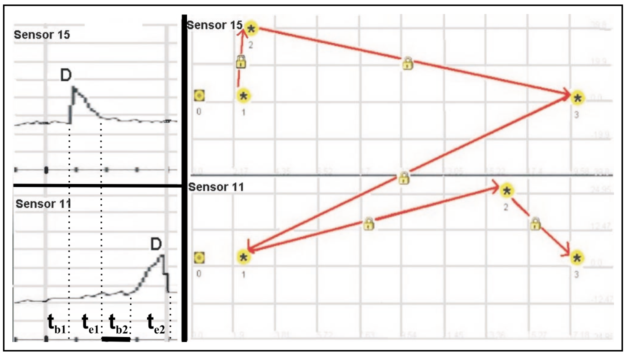

Figure 5. On the left is a signal fragment from ultrasound sensors 11 and 15, where morphologies corresponding to a door can be seen, marked on both signals with the letter D. We show the time interval of interest in the MFTP for door detection, the one limited by t_{e1} and t_{b2}. This interval allows the positioning of the door in the spatial dimension. On the right is the editting of the knowledge base used in the detection of the pattern shown on the left.

parameter, and the temporal evolution of them, instead of being triggered by only present data.

In the domain of mobile robotics the MFTP model can facilitate a knowledge-based interpretation from sensorial data and transformation into high-level information. One example of this application would be the detection of landmarks, fundamental for the basic task of navigation, and more specifically for the creation and updating of an internal map of the environment, and for locating the robot on this map.

Standing out amongst landmarks of an indoor environment are doors, as, besides serving as references, they establish connections between the different places of the environment, essential information for route-planning. Our objective is the detection of this type of landmark, using signals from ultrasound sensors.

These type of sensor supplies a signal with a high degree of noise, which rules out the application of techniques that do not tolerate imprecision well. On the other hand, the detection of the morphology corresponding to the finding of a door on one single sensor is not sufficiently reliable as many false positives appear, which makes the integration of information coming from other sensors essential, in order to increase the specificity of detection.

The Nomad 200 robot has a ring composed by 16 ultrasound sensors, placed each 22.5 degrees. We have chosen sensors 11 and 15 for the detection as these two sensors present a especially characteristic echo when the robot passes by a door, and is sufficient for a reliable detection. Sensor 15 is the first to pick up the door (figure 4), its signal showing a morphology consisting of a rapid rise followed by a gentler fall to approximately the initial value (figure 5). A little later sensor 11 picks up the door (figure 4), its signal showing a morphology which consists of a section of slow rise, followed by a sharp fall back down to approximately the initial value (figure 5).

Figure 5 shows the morphologies of the finding of a door over the sensors of the robot, and the editing of the MFTP that aims to model the finding using a Tool for the Automatic Acquisition and Recognition of Multivariable Patterns [9], which we have developed and which enables an expert to project their knowledge in a highly intuitive manner.

This echoes are produced by the doors frames. The point in which the ultrasound 15 comes back to the initial value is the point which allows us to locate the second frame of the door (see figure 5), because in this moment the sensor is really sizing the distance from the robot to the door frame, and not a distortion caused by the frame. In the same way the point where the ultrasound 11 starts raising sharply (see figure 5) is the point which allow us to locate the first door frame. Therefore, the last significant point of FTP which models the echo of a door over sensor 15, and the first significant point representing of the FTP representing the echo over the ultrasound 11 are the point which will define the begin and end of the finding of interest represented by our MFTP: a door.

Figure 6 shows the result of the matching, performed and visualized with the same tool. In the detection, 5 of the 7 existing doors were detected with a possibility of 1, and the other two with a possibility of approximately 0.7. In some cases the morphology corresponding to a door was detected on a single signal, although the integration of both sensors

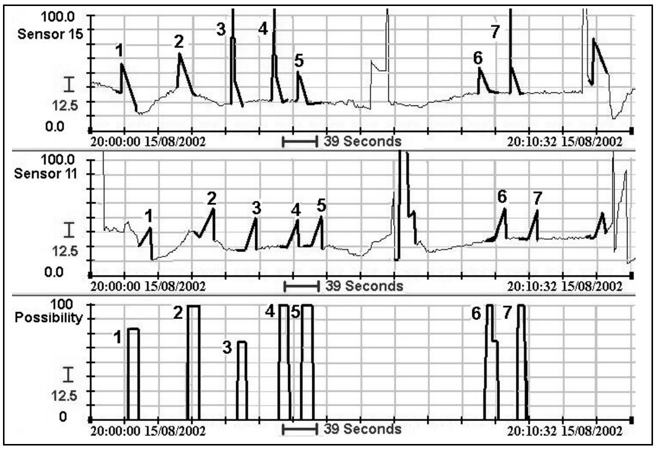

Figure 6. Detection of doors, of the map shown in the figure 4, employing ultrasound signals from the Nomad 200 robot. The numbers indicate to which of the figure 4 correspond each detection.

performed by MFTP model resulted in ruling out the finding (see sensor 11 between doors 5 and 6, for example).

In spite of the theoretically high complexity of the matching algorithms of the MFTP model, their application over problems of signal in the domains mentioned it is satisfactory. Thus, for example, less than 30 seconds were required to perform the detection shown in figure 6 on a Celeron™ processor at 466 MHz, whilst the robot took three minutes to cover the whole trajectory, due to which it is perfectly feasible to perform this detection in real time. On the other hand, further heuristic optimizations can be applied to the algorithms which can improve notoriously their performance; e.g., a filter based on particular values can be employed to locate the regions of the signal where a FTP may occur, avoiding scanning the whole signal.

Door-detection problem has also been tackled in [6], where an expert system (ES) is shown with this objective. The ES attempts to simulate the modus operandi of humans when they visually locate doors on the sonar signals. In this system a change in the morphology to be detected forces a redesigning of the ES, whilst the MFTP model requires an easy edition of constraints.

Another alternative for detecting doors could be to use occupancy grids [11], where door frames could be detected by using a sufficiently small cell-size. In practice this is not feasible, since this would force us to use a very high number of cells and the storage requirements and computational complexity of the algorithms used by occupancy grids are quadratic to the number of cells.

7 Conclusions and future work

In this paper we have presented a model, MFTP, that makes it possible to project an expert's knowledge onto a pattern of signals over a computable model, which is capable of automatically carrying out abstraction over a set of parameters that represent the temporal evolution of a physical system, by organizing information into a set of levels of increasing abstraction.

This abstracted information makes it possible to alleviate the computational load of intrinsically complex tasks such as those of interpretation or diagnosis. On the other hand, the use of CSP formalism and the theory of fuzzy sets enables the realization of an explicit representation of knowledge, simplifying the revision of the knowledge used as well as strengthening the expert's confidence in the results obtained.

We have also presented a practical application of the MFTP model: the detection of landmarks in mobile robotics. In the example given the high degree of reliability obtained in spite of signal noise should be noted, as well as the fact that this detection can be carried out in real time.

With regard to future projects, on a practical level, we aim to construct a module that permits the detection of further landmarks over ultrasound and laser sensor signals in mobile robots, and integrate it within an architecture able to carry out multiple tasks [10], such as navigation, map-drawing, location, etc.

On the theoretical level, we aim to construct a general framework for temporal abstraction in which a fuzzy-constraint-based network makes it possible to integrate multiple signal abstraction techniques, not only the ones based on the MFTP model.

On the other hand we must study the problem of the consistency of the MFTP; due to the redundancy of the descriptions of the expert the MFTP may be inconsistent, that means, there can not be a solution A that is completely possible, so we should ask the expert to revise the MFTP. It is also possible that despite the knowledge projected onto a MFTP is consistent can be further refined, and some constraints may be tightened, which will be translated into a more efficient matching process.

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