MFTP: a model to represent hierarchies of abstraction defined over multiple parameters.

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Abstract. In this work we present the Multivariable Fuzzy Temporal Profile model (MFTP), which enables expert knowledge on the behaviour of a physical system to be projected into a computable description. This description can be used to identify a signal pattern over a set of parameters representing the temporal evolution of the system.

The MFTP model, which is based on Constraint Satisfaction Problems (CSP) and on Fuzzy Logic theory, makes an explicit representation of an abstraction hierarchy with which to integrate findings over multiple parameters. This representation makes it possible to supply detailed explanations of the information obtained from the system, and to develop efficient pattern recognition procedures.

Keywords: Temporal abstraction, temporal reasoning, pattern recognition, constraint satisfaction problems, fuzzy sets.

1 Introduction

In recent years human experts in the field of patient supervision have seen how new, sophisticated electronic measuring devices, along with advances in communication technologies, have supplied them with ever more exhaustive and detailed information on the systems that they have to oversee. This increase in the amount of information available is advantageous if it can be suitably assimilated by the human expert; otherwise, the task of supervision becomes increasingly complicated [9]. This may even lead to more errors being made, and the decision-maker may opt to reject information leading him outside the domain of his competence.

Systems that require continuous operation, and which involve reasoning on temporal information, are especially affected by this problem, as the continuous flow of information can easily overload the decision-maker. The control of industrial processes, perception in mobile robotics and patient supervision are domains that are particularly affected by this problem. The agents in control of these systems would benefit from having mechanisms supplying them with information of greater temporal granularity and semantic content, on the basis of low-level information from the system. Thus the decision-maker would be freed of a large part of the burden of interpreting information and could concentrate on the task of reasoning on its behaviour.

In this work we present a solution for the explicit representation of knowledge. Here we give a significant role to the representation and handling of vagueness and imprecision. In the bibliography there are a number of proposals that tackle the problem following the same approach. Cheung *et al*. [3] and Konstantinov *et al*. [7] develop two models that allow the qualitative description of the temporal evolution of a pattern based fundamentally on the signs of the slope and curvature of the signal.

Calvelo *et al*. [4] present a model that is capable of representing multivariable patterns. The patterns are defined on the basis of several primitives (rises, falls, stationary) which are combined among themselves by means of a series of operators (meets, overlaps, during, equals, etc.). These primitives necessarily need to be evaluated over maximal intervals: users cannot specify the temporal extension of the primitives (rises *for one minute*).

The use of fuzzy sets in the representation of trends lends additional versatility to the models. Drakopoulos *et al*. [5] present a pattern recognition model in which each pattern is represented by a class. Each class is characterized by a set of measurements made over the temporal evolution of a series of parameters, for which a fuzzy value is defined. This fuzzy value, represented by a trapezoidal possibility distribution, indicates the degree of compatibility between the measurement and the pattern.

Steimann *et al*. [12] develop a model that enables the description of trends over the temporal evolution of a single parameter based on the concept of fuzzy trajectory. Although somewhat awkwardly, the model can be extended to modelling a complex profile as a succession of trends. Lowe *et al*. [8] extend the previous model to allow the detection of multivariable patterns. Nevertheless, its weak point is still the modelling of profiles of more than one trend.

In this work we present the MFTP model, which enables expert knowledge of a system to be projected into a computable model. In short, a MFTP is defined on the basis of a set of points of special significance for the expert. These points are defined over the evolution of the set of parameters of the system, along with a fuzzy representation of the tolerance allowed for the evolution of each parameter between them. Furthermore, with the model it is also possible to define a set of relations that jointly restrict the evolution of more than one parameter, giving rise to a multivariable pattern. By means of the recursive definition of the model it is possible to represent information abstracted from the signal in a hierarchy of representational levels.

The work is laid out in the following manner: in the next section we offer a series of preliminary definitions, in order to then go on to explain the MFTP model in section three. Section four deals with the matching algorithms of the MFTP; we then go on to see how, taking advantage of the modularity of the model and the peculiarities of the domain, we obtain an algorithm that can be run in real time. In section five we briefly comment on the possible applications of this

Figure 1. Three stages in the detection of a double-door pattern on an US signal from a mobile signal from a mobile robot: 1) localize sharp rises; 2) correlate them in the same parameter; and 3) associate events from 2) in different parameters.

model, and finally, in section 6, we give the conclusions of this work and comment on future lines of research.

2 A practical example

Figure 1 shows an example of a real pattern in the domain of mobile robotics. Mobile robots must extract information from the landmarks of the environment via their sensors. These landmarks often give rise to characteristic patterns [11]; the one shown in Fig. 1 corresponds to a double door.

Double doors produce two sharp rises, each of them perceived in around a second, in the ultrasound sensor signal pointing to 45^o with respect to the forward direction of the robot. The initial one is produced by the first doorframe, and the second by the joint of the two panels of the door. A temporal relation must hold between these rises, which guarantees compatibility with a double-door pattern. If this temporal relation holds, a higher-level finding is identified. This in turn must be related to another identical, but temporally displaced finding of the signal from another US sensor in order to confirm the appearance of a double-door pattern (see Fig. 1).

With this pattern we show how the MFTP model can describe not only the pattern, but also its implicit abstraction hierarchy. The model emphasizes two important properties of abstraction: modularity and efficiency. Modularity in the sense that a certain pattern may form part (sub-pattern) of the definition of different patterns. Regarding efficiency, we will show how the abstraction hierarchy can be exploited to outperform the matching of a pattern as a whole.

3 Previous definitions

We consider time as being projected onto a one-dimensional discrete axis $\tau = \{t_0, t_1, ..., t_i, ...\}$, where t_i, $i \in \mathbb{N}$, is a *precise* instant. t_0 represents the temporal origin, before which the existence of any fact is not relevant for the problem under consideration. For every $i \in \mathbb{N}$, $t_{i+1} - t_i = \Delta t$, where Δt is the minimum step of the temporal axis.

Given as the 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. By means of π_A we define a fuzzy number A as a fuzzy subset 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. The fuzzy increment between a pair of fuzzy numbers A and B is given, following Zadeh's extension principle [14], by $D = A \ominus B$ such $\pi_{D=A\ominus B}(i) = \max\limits_{i=t-s} \min\{\pi_A(t), \pi_B(s)\}$.

4 Signal abstraction

The ultimate aim of the MFTP model is to identify the occurrence of the pattern $\mathcal{M}$, described by a human expert, over the temporal evolution of the physical system $\mathcal{S}$, automatically generating information that is organized into a hierarchy of abstraction levels. The system $\mathcal{S}$ is characterized by a set of parameters $\mathcal{P} = \{\mathcal{P}^1, ..., \mathcal{P}^m\}$. $\mathcal{P}$ is obtained by means of an acquisition and sampling process, such that $\mathcal{P}^j = \{(v^j_{[1]}, t^j_{[1]}), ..., (v^j_{[k]}, t^j_{[k]}), ...\}$.

The MFTP model is an extension of the FTP model [6], which enables the description of a finding as a morphology described over 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. Often the appearance of a finding over a single parameter, which on its own may be not a major determinant, may well be of interest if it appears to be related with other findings on other parameters which also do not seem to be definitive when taken on their own.

The MFTP model dealt with in this work enables human experts to project their knowledge into a hierarchy of abstraction levels. This hierarchy is captured explicitly by the model, and enables it organize the information that is generated in the same manner as a human expert, to offer detailed explanations as to how the items of raw information have been combined to generate information with a higher level of abstraction, and to allow more modular and efficient matching to be carried out. In addition, knowledge acquisition becomes more ergonomic, as no predefined organization of the description information is forced, rather it is adapted to that of the expert.

The MFTP model is based on the formalism of Constraint Satisfaction Problems (CSP), and on the fuzzy set theory. An MFTP is made up by a set of points of special significance for the expert, which are defined over the temporal evolution of the system, and a set of constraints which limit the evolution of the parameters between them. The points of special significance, which we call significant points, are composed by a pair of variables, one represents the magnitude of the point and the other its instant of occurrence. The constraints are represented as possibility distributions that limit the values that can take the variables of the significant points.

4.1 The FTP model

The aim of the Fuzzy Temporal Profile (FTP) model is to represent and reason on 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****, X^j_i, on a physical parameter $\mathcal{P}^j$ 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 vari-*

ables V_i^j and T_i^j may take any precise value $v^j_{[k]}$ and $t^j_{[k]}$, respectively, where $(v^j_{[k]}, t^j_{[k]}) \in \mathcal{P}^j$.

By $\mathcal{A}_i^j$ we denote the assignment of precise values from the evolution $\mathcal{P}^j$ to the variables of X_i^j; i.e., $\mathcal{A}_i^j = (v^j_{[k]}, t^j_{[k]})$ means that V_i^j = v_i^j = $v^j_{[k]}$ and T_i^j = t_i^j = $t^j_{[k]}$. We define a general fuzzy constraint between a set of significant points, providing a computable support to soft descriptions on the form of a signal.

Definition 2 *A **fuzzy constraint** $\mathcal{R}$ between a set of significant points $X^j_{i_1}, ..., X^j_{i_g}$ is defined by means of a fuzzy relation $C = C(X^j_{i_1}, ..., X^j_{i_g})$. 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 $X^j_{i_1}, ..., X^j_{i_g}$.*

In order to describe the behavior of a parameter, a set of constraints limiting the fuzzy temporal duration, fuzzy increment, and fuzzy slope between a pair of significant points seems to capture a good number of features. Hence we have defined a constraint $L^j_{i_1 i_2}$ by means of a normal and convex possibility distribution $\mu_C(X^j_{i_1}, X^j_{i_2}) = \pi^{L^j}_{i_1 i_2}(l)$ that limits the temporal extension between $t^j_{i_1}$ and $t^j_{i_2}$. Using the constraints $L^j_{i_1 i_2}$ we model a temporal relation between significant points described by means of expressions such us “each of them produced in *around a second*”.

A constraint $D^j_{i_1 i_2}$ is defined by means of a normal and convex possibility distribution $\mu_C(X^j_{i_1}, X^j_{i_2}) = \pi^{D^j}_{i_1 i_2}(d)$ that limits the fuzzy increment between $v^j_{i_1}$ and $v^j_{i_2}$. Using the constraints $D^j_{i_1 i_2}$ we model changes in the magnitude of a parameter such us “a sharp *rise* ”.

A constraint $M^j_{i_1 i_2}$ is defined by means of a normal, convex possibility distribution $\mu_C(X^j_{i_1}, X^j_{i_2}) = \pi^{M^j}_{i_1 i_2}(m)$, that limits the slope $((v^j_{i_2} - v^j_{i_1})/(t^j_{i_2} - t^j_{i_1}))$ between the points $X^j_{i_1}$ and $X^j_{i_2}$. Using the constraints $L^j_{i_1 i_2}$ we model linguistic descriptions of the type “a *sharp* rise”, where “sharp” is modelled by a high 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 $X^j = \{X_1^j, ..., X^j_{n^j}\}$ and a finite set of constraints $\mathcal{R}^j = \{\mathcal{R}_1^j, ..., \mathcal{R}_f^j, ...\}$ 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. FTP model also 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 Fig 2) by means of a membership function $\mu_{\mathcal{S}^j_{i_1 i_2}}(\mathcal{A}^j_{i_1}, \mathcal{A}^j_{i_2})$ [6].

4.2 The MFTP model

The MFTP model redefines the concept of general fuzzy constraint, allowing constraints to limit the values of a set of significant points belonging to different parameters, $C = C(X^{j_1}_{i_1}, ..., X^{j_k}_{i_g})$. We define the constraint dimensionality of $\mathcal{R}$, $\dim(\mathcal{R})$, as the number of different parameters over which the variables of C are evaluated.

Most common constraints between significant points defined over different parameters are constraints limiting the fuzzy temporal duration and fuzzy increment between a pair of significant points. Thus we have defined a constraint $L^{j_1 j_2}_{i_1 i_2}$ by means of a normal, convex possibility distribution $\mu_C(X^{j_1}_{i_1}, X^{j_2}_{i_2}) = \pi^{L^{j_1 j_2}}_{i_1 i_2}(l)$, that limits the temporal duration between $t^{j_1}_{i_1}$ and $t^{j_2}_{i_2}$. Using the constraints $L^{j_1 j_2}_{i_1 i_2}$ we model a temporal relation between different findings, such us “the rises over the signal from sensor A must *precede* rises over the signal from sensor B ”.

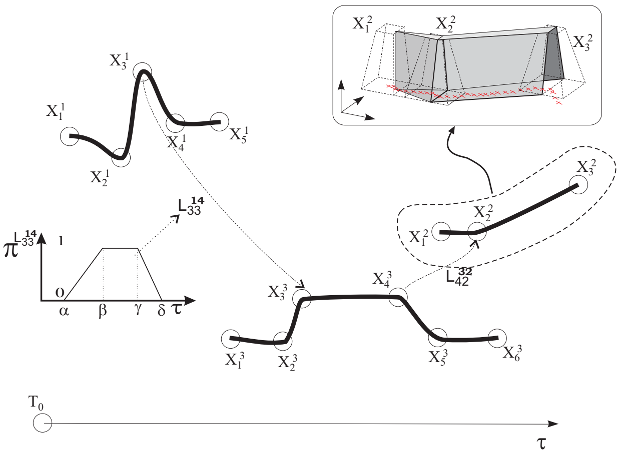

Figure 2. The hypergraph associated to an MFTP made up of three morphologies over three different signals.

A constraint $D^{j_1 j_2}_{i_1 i_2}$ by means of a normal, convex possibility distribution $\mu_C(X^{j_1}_{i_1}, X^{j_2}_{i_2}) = \pi^{D^{j_1 j_2}}_{i_1 i_2}(d)$, that limits the fuzzy increment between $v^{j_1}_{i_1}$ and $v^{j_2}_{i_2}$. Using the constraints $D^{j_1 j_2}_{i_1 i_2}$ we model linguistic descriptions such us “*small difference* between the magnitudes of both parameters ”.

Definition 4 *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 $X^{\mathcal{M}} = \{X^{j_1}_{i_1}, X^{j_1}_{i_2}, ..., X^{j_k}_{i_v}, X^{j_k}_{i_{v+1}}, ...\}$ and a finite set of constraints $R^{\mathcal{M}} = \{R_1, ..., R_f, ...\}$ amongst the points of $W^{\mathcal{M}}$ and $X^{\mathcal{M}}$.*

Normally, a sub-MFTP $\mathcal{M}_h^{\mathcal{M}}$ belongs to a MFTP $\mathcal{M}$, where it is contained by means of the significant end points, which delimit the temporal interval of occurrence of $\mathcal{M}_h^{\mathcal{M}}$. The constraints $R_i \in R^{\mathcal{M}}$ may be defined between significant points that belong to $X^{\mathcal{M}}$, between significant points that belong to the set of sub-MFTPs $W^{\mathcal{M}}$ or between both types of significant points.

The recursive nature of the MFTP model follows the manner in which humans describe patterns: a finding is usually defined as a complex pattern of findings, and a set of relations between them. Normally each sub-MFTP represents a finding that belongs to the global pattern, and the constraints $R^{\mathcal{M}}$ model the set of relations that the findings must satisfy in order to give rise to the global pattern. The recursive nature of the model explains the fact that each of the findings may in turn be a pattern. It is also this recursive nature that makes it possible to organize knowledge into different levels of abstraction.

An MFTP can be represented by a hypergraph in which nodes correspond to significant points, and arcs correspond to constraints. Fig. 2 shows a hypergraph representing a MFTP.

5 Pattern detection

Given that the MFTP model is based on the formalism of constraint networks, comparing a MFTP with $\mathcal{P}$, is formally equivalent to solving a CSP [1], where the domains of the variables are defined by the acquired information $\mathcal{P}$.

Definition 5 *We define a* **solution** *of $\mathcal{M}$ as a set of assignments $\mathcal{A} = \{A_1^1, ..., A_{n^1}^1, ..., A_1^m, ..., A_{n^m}^m\}$ 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:*

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

Where $\mathcal{A}^{\mathcal{M}_h^{\mathcal{M}}}$ is the projection of $\mathcal{A}$ over the set of significant points that belong to $\mathcal{M}_h^{\mathcal{M}}$, 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 $\pi^{M_h^{\mathcal{M}}}$ is the degree of satisfaction of the finding $\mathcal{M}_h^{\mathcal{M}}$. $\pi^{\mathcal{M}}(\mathcal{A})$ represents the degree of similarity between a fragment of the evolution $\mathcal{P}$ with the pattern of findings $\mathcal{M}$.

The search for solutions that satisfy the equation (1) is carried out following the compositional scheme of abstraction defined in the pattern $\mathcal{M}$. The lowest level of abstraction has the raw data of the system, $\mathcal{P}$, and the highest the global pattern $\mathcal{M}$. The search for solutions starts with those MFTPs that, containing part of $\mathcal{M}$, do not in turn contain any MFTPs: $\mathcal{M}_o = \{\cdot, X_o^{\mathcal{M}}, R_o^{\mathcal{M}}\}$, due to which the equation (1) is simplified to:

$$\pi^{\mathcal{M}_o}(\mathcal{A}^o) = \underset{\mathcal{R}_k \in \mathcal{R}^{\mathcal{M}_o}}{min} \{\pi^{\mathcal{R}_k}(\mathcal{A}^{\mathcal{R}_k})\} \tag{2}$$

The computational complexity of the search for these solutions is $O(e^{n_o})$, where n_o is the number of significant points of $\mathcal{M}_o$. The solution for each MFTP defines a vector of assignments that constitute the domain of the possible assignments in the next level of abstraction up.

The degree of satisfaction for the solutions of $\mathcal{M}$ is calculated on the basis of the degrees of satisfaction for the solutions of the findings that are assembled (first term of the equation 1), and the degree of satisfaction for the set of constraints $R^{\mathcal{M}}$ (second term of the equation (1)). The projection $\mathcal{A}^{\mathcal{R}_k}$ can now be made up of assignments taken over $\mathcal{P}$ or assignments arising from the solutions found for some $M_h^{\mathcal{M}}$. When A_i^j, taken from a solution $\mathcal{A}^{\mathcal{M}_h^{\mathcal{M}}}$ of $M_h^{\mathcal{M}}$, is assigned to a significant point $X_i^j \in M_h^{\mathcal{M}}$, the values taken from $\mathcal{A}^{\mathcal{M}_h^{\mathcal{M}}}$ have to be assigned to all the significant points $X_{i'}^{j'} \in X^{M_h^{\mathcal{M}}}$. Similarly, if any assignment of these significant points needs to be retracted, as it has resulted in a search error, all the assignments taken from $\mathcal{A}'$ must be retracted. The complexity of the matching process is $O(e^{n+m})$, where n is the number of significant points of $X^{\mathcal{M}}$ and m the number of findings assembled.

5.1 The algorithm employed for the matching

The matching algorithms of the MFTP model are based on forward checking (FC), the backtracking algorithm with the most suitable behavior [13]. In [1], Bessiere demonstrates that the extension of FC to non-binary constraint problems can be achieved in six different ways: nFC0, nFC1, nFC2, nFC3, nFC4 and nFC5 algorithms. Each of these algorithms maintains a higher level of consistency between the variables which have been assigned a value and the variables which remain without value (past variables and future variables): nFC0 forcing the lowest level of consistency and nFC5 the highest.

We have chosen the nFC0 algorithm because, as has been shown in [1], it employs less CPU time than other nFCx algorithms in problems in which the graph is not dense. Habitual descriptions of patterns in both patient supervision and mobile robotics are projected onto sparse graphs. 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 that is compatible with the current assignment in the domain of the variable that follows according to the assignment order.

Moreover, heuristics can be used to speed up matching, such as initially matching less common pattern events (high value, sharp peak, etc.), or to obtain the best dynamic order of assigning values to variables, as in the Bessier's heuristics "dom+reg" [2]

5.2 A common particular case

Our experience in medical and robotic domains has shown us that there is a hierarchy of abstraction that is by far the most common. Normally when experts search for the global pattern over $\mathcal{P}$, they initially look for a series of morphologies that are defined over each parameter $\mathcal{P}^j$. Afterwards they verify whether these morphologies appear together in the global pattern. In this case, the abstraction hierarchy has three distinct levels: raw data, history of morphological events over each parameter, and occurrences of the global pattern.

These patterns are projected onto a MFTP $\mathcal{M} = \{W^{\mathcal{M}}, \cdot, R^{\mathcal{M}}\}$, where $dim(R) > 1 \ \forall R \in R^{\mathcal{M}}$, and $\forall \mathcal{M}_h^{\mathcal{M}} \in W^{\mathcal{M}}$, $\mathcal{M}_h^{\mathcal{M}} = \{\cdot, X^h, R^h\}$. X^h is made up of all the significant points of $\mathcal{M}$ that are defined over a single parameter $\mathcal{P}^h$; similarly R^h contains all the constraints that only involve the set of significant points X^h.

The matching of these MFTPs is carried out in two stages: in the first we search for occurrences of each $\mathcal{M}_h^{\mathcal{M}}$ on the temporal evolution of their corresponding $\mathcal{P}^h$, thus obtaining a history of the occurrences of $\mathcal{M}_h^{\mathcal{M}}$. The degree to which the set of assignments $A^h = \{A_1^h, ..., A_{n^h}^h\}$ satisfies the constraints of $\mathcal{M}_h^{\mathcal{M}}$ is obtained by means of the equation 2. $\pi^{\mathcal{M}_h^{\mathcal{M}}}(A^{\mathcal{R}_k})$ represents the degree of similarity between $\mathcal{M}_h^{\mathcal{M}}$ and a fragment of the evolution of $\mathcal{P}^h$.

After this stage we search for sets of A^h that satisfy the set of constraints $R^{\mathcal{M}}$, obtaining global solutions $\mathcal{A}$ for $\mathcal{M}$. The degree of satisfaction of the global solution is calculated on the basis of the degrees of compatibility of each $\mathcal{M}_h^{\mathcal{M}}$ with $A^h \in \mathcal{A}$ and the degree of satisfaction of the constraints $R^{\mathcal{M}}$ using the Equation 1.

The global complexity of the process is $O(e^m + \sum\limits_{h=1}^{m} e^{n^h})$, where m is the number of sub-MFTPs and n^h the number of significant points of $\mathcal{M}_h^{\mathcal{M}}$. The matching of the MFTP as a whole has a complexity of $O(e^f)$, where $f = n + \sum\limits_{h=1}^{m} n^h$. Dividing the detection of a pattern into its subpatterns improves the efficiency, since $e^f >> (e^m + \sum\limits_{h=1}^{m} e^{n^h})$.

5.3 A highly efficient, non-optimal heuristics

In order to guarantee the completeness of the solution search algorithm we need to search for and store all possible solutions for all sub-MFTPs making up the global pattern, regardless of their degree of satisfaction. This is due to the fact that in a CSP, local solutions, even the optimal ones, need not form part of the global solution. To avoid an excessive computational load in this task we have developed a heuristics, by means of which it is not necessary to search for the solutions of each of the sub-MFTPs, rather a set of solutions that is

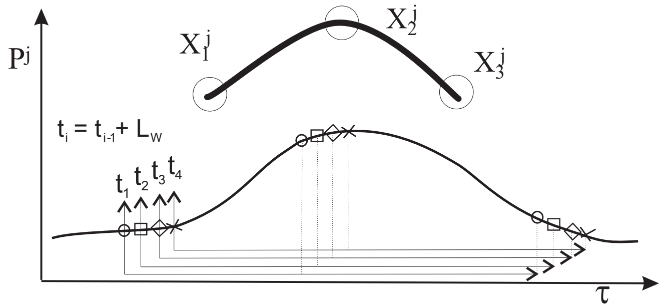

Figure 3. Using heuristics, we attempt to obtain a set of solutions for each finding that is spread out over its temporal extension. In this way we limit the number of solutions, hardly losing any information on the features of the finding.

as representative as possible for each finding, with the aim of finding a set of solutions that is a "sampling" of the occurrence of the finding (see Fig. 3). Although this heuristics is applicable to any abstraction hierarchy, for the sake of simplicity it is only explained here for the hierarchy of raw data, morphologies over each parameter, and global pattern.

A temporal window is defined, the extension of which is greater than or equal to the maximum temporal duration of the sub-MFTP to be matched, in order to not lose any of the solutions. This duration is calculated in the MFTP's consistency analysis stage by means of the obtention of the minimum network.

By situating the temporal window at the beginning of the evolution of $\mathcal{P}^h$ we search for a single solution of the sub-MFTP within it; we then go on to repeatedly displace this window by a constant interval L_W, and search for a solution for each displacement (see Fig 3). The aim of this process is to obtain a set of solutions for each finding which, being spread out over the temporal evolution, capture a large quantity of the information pertaining to that occurrence of the finding. Due to the properties of continuity for real signals it is probable that, if the global pattern has occurred, some of the solutions obtained by means of this heuristics will satisfy the constraints that give rise to this global pattern.

L_W functions as a control parameter for the algorithm: for high values of L_W the algorithm needs less time to run, but less solutions for each occurrence are obtained, and there is a higher probability of occurrences of the global pattern being lost. For lower values the algorithm requires more time; nevertheless, it less likely that any global solution will be lost. The adjustment of this parameter depends on the dynamics of the system: for systems that develop slowly higher values can be used, whilst for systems that evolve rapidly low ones must be employed. The most accurate matching is obtained when $L_W = \Delta t$, where Δt is the sampling period.

Obviously, the use of this heuristics entails a non-complete matching. Nevertheless, its application in real problems, adapting the size of the temporal window L_W to the needs of the problem, has never resulted in the loss of occurrences of a pattern. On the other hand, coupled with the modular nature of MFTP, this heuristics makes it possible to fulfil the real-time requirements of the detection in all experiments carried out in the environments of robotics and patient supervision.

6 Applications of the MFTP model

The MFTP model is being applied in the domains of mobile robotics and patient monitoring in the setting of Intensive Care Units (ICU). In the former domain it is applied to landmark detection over signals from the sensors of mobile robots. A system for identifying doors, corners, ends of corridors and columns from ultrasound signals has been developed and validated [11]. The validation was carried out on two different robots (Nomad 200 and Pioneer AT) in three different environments. In spite of the noise and imprecision that are characteristic of these sensors, over 90% of all landmarks were detected.

In medicine the application of the MFTP model is twofold: on one hand it is used to generate intelligent alarms on the basis of the temporal evolution of various parameters arising from the monitoring of patients. On the other hand, is is used as a research tool for the discovery of new patterns, using for this TRACE (Tool foR anAlizng and disCovering pattErns [10]), a tool that makes it possible to graphically and intuitively define MFTPs and validate them over signal registers. The tool is currently being used in the Intensive Care Unit of the Hospital of Elche to further clinical knowledge. There are a number of lines of research that are under investigation in the setting of pattern discovery, such as the detection of anomalies in the disconnection of breathing apparatus, the detection of internal haemorrhages, studies of heart rate variability in patients suffering from hypersensitivity of the carotid sinus, amongst others.

7 Conclusions and future work

The MFTP's capability for explicitly capturing the hierarchy of abstraction levels that is inherent in an interpretation of a physical system along with its explicit representation of knowledge, markedly simplify the processes of capturing and checking knowledge. Furthermore, it allows detailed explanations to be made as to how information has been generated, thus improving expert's confidence in the results obtained.

The MFTP model can be used to generate high-level reports on the system and/or to lighten the computational load of intrinsically complex tasks, such as interpretation or diagnosis. In spite of the theoretically high constitutional complexity of the MFTP's matching algorithms, its modularity in detection along with the exploitation of the characteristics of the domain have enabled us to make an implementation of the algorithms that is capable of running in real time. Proof of this can be found in the applications implemented in the domains of mobile robotics and medicine, which are two setting with demanding real-time requirements.

With regard to future lines of work, we aim to construct a general abstraction framework in which fuzzy constraints will make it possible to integrate a number of abstraction techniques, not just the MFTP. The consistency of an MFTP is also an open question; the description of MFTP may be inconsistent, which means that there may not be a solution completely possible; hence the MFTP should be revised. It is also possible that even though the knowledge projected onto a MFTP is consistent, it can be further refined, and some constraints may be tightened, which would result in a more efficient matching process.

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