A tool for the analysis and synthesis of alarms in patient monitoring

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Abstract – *This work presents the Tool foR anAlyzing and disCovering PattErns (TRACE), which makes it possible to study the evolution of a patient by means of a set of monitoring parameters, and to generate alarms based on this study, in a simple and intuitive manner. These alarms have significant advantages over those currently available in the hospital setting. Underlying this tool is the Multivariable Fuzzy Temporal Profile model, which enables expert knowledge to be projected into a computable solution. On the basis of this knowledge TRACE permits the generation of pattern recognition software agents, which are capable of triggering an alarm in the presence of an expert-defined pattern, and which can be incorporated into intelligent patient supervision systems.*

Keywords: Patient supervision, pattern recognition, temporal abstraction, fuzzy sets, constraint satisfaction problems.

1 Introduction

Patient supervision requires medical staff to assimilate a large volume of information about patients: sex, age, anthropometric information, medical history, medicine administered, laboratory analyses carried out, and the physiological variables being monitored (heart and breathing rates, oxygen level, arterial pressure, ECG, ST segment deviation, etc.). It is this latter type of information, which is highly frequent in medical units, such as Intensive Care Units (ICU), that demands most attention of the medical staff, as it is continuously generated over time, and generally corresponds to physiopathological processes that require rapid response.

Signal alarms that incorporate commercial signal monitoring devices are rudimentary abstraction mechanisms that are triggered when the value of the signal being monitored leaves a set range that is considered normal. Due to their low specificity, these alarms give a large number of false positives, which are brought about principally by signal noise, and leads to physicians paying less attention to them [1]. There is a consensus of opinion in the medical profession as to the need for more sophisticated alarms, which should consider the imprecision and vagueness that are characteristic of medical knowledge [2], and/or fuse information arising from the evolution of one or more physiopathological parameters, and not only the current value of just one of them.

A number of proposals can be found in the bibliography [3, 4, 5, 6, 7] which have in common an explicit representation of knowledge based on a description made by a medical expert, and which address the vagueness and imprecision that are characteristic of this knowledge. Nevertheless, one aspect that is not generally dealt with in these proposals is the knowledge acquisition bottleneck problem [8]: the elicitation of knowledge is rarely sufficiently intuitive to be incorporated into medical routine, and the solutions proposed do not usually go beyond the proof of concept stage.

In this work we present the Tool foR anAlyzing and disCovering PattErns (TRACE). This tool seeks to overcome the knowledge acquisition bottleneck, enabling knowledge relative to alarms, defined over the temporal evolution of various parameters, to be visually and intuitively projected into a computable model: the Multivariable Fuzzy Temporal Profile model (MFTP) [9, 10]. The MFTP model is based on fuzzy logic, for capturing the vagueness and uncertainty that are characteristic of human knowledge, and on the Constraint Satisfaction Problem (CSP) [11] formalism, which enables it to manage the representation of experts' descriptions. Once this knowledge has been validated, TRACE encapsulates these alarms into agents, which carry out signal perception tasks in an intelligent patient supervision system.

Sections two, three and four of this work briefly expound upon the MFTP model. We then go on to describe a physiopathological complication, pulmonary embolism, which appears on a patient's monitored parameters, but which is not satisfactorily identified by the alarms currently available to physicians. In the following section this case is used as an example for describing TRACE, and section seven shows how the agents that are generated by this tool constitute a more efficient solution for the identification of this problem than the alarms that are currently available in clinical routine. In the final section conclusions are given, and future lines of work are mentioned.

2 Temporal framework

We consider time as being projected onto 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 irrelevant 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 Fuzzy fundamentals

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

A *fuzzy set* A in a discourse universe U is characterized by a membership function $\mu_A : U \rightarrow [0,1]$ which associates with each element $u \in U$ a real number in the interval $[0,1]$, which is called the degree of membership of u in A [12]. Given as the discourse universe the set of real numbers $\mathbb{R}$, a *fuzzy number* 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 C from a flexible constraint given by a possibility distribution π_C, which defines a mapping from $\mathbb{R}$ to the real interval $[0,1]$. Thus, given a precise number $v \in \mathbb{R}$, $\pi_C(v) \in [0,1]$ represents the possibility of C being precisely v.

In TRACE we employ a trapezoidal representation of π_C, in this way, $C = (\alpha, \beta, \gamma, \delta)$, $\alpha \leq \beta \leq \gamma \leq \delta$ (see Fig.1), where $[\beta, \gamma]$ represents the core, $core(C) = \{v \in \mathbb{R} |\ \pi_C(v) = 1\}$, and $]\alpha, \delta[$ represents the support, $supp(C) = \{v \in \mathbb{R} | \pi_C(v) > 0\}$.

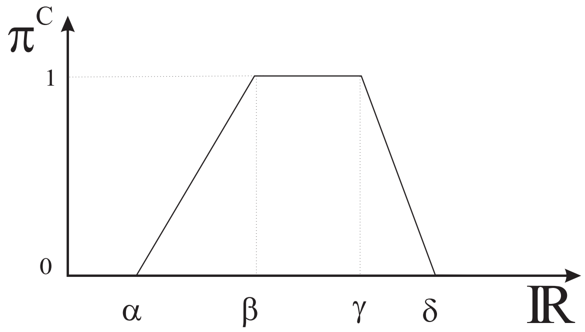

Fig. 1: Example of a trapezoidal possibility distribution.

4 The MFTP model

Patient monitoring supplies a set of parameters $\mathcal{P} = \{P^1, ..., P^n\}$, each one of which is obtained by a signal sampling process, in the form of a temporal series $P^j = \{(v^j_{[m]}, t^j_{[m]}) |\ m \in \mathbb{N}\}$.

The MFTP model is an extension of the FTP model [9], a previous model for the representation and recognition of morphologies on the evolution of a parameter P^j, allowing the relation of the appearance of a set of morphologies over different parameters. The ability 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 determining factor on its own, may well be of interest if it appears related with other findings on other parameters which also seem to be not significant on their own.

The MFTP model projects a fuzzy description of the temporal evolution of the system onto a fuzzy constraint network between a set of points taken over the temporal evolution of the system that are called significant points.

Definition 1 *We define a* ***significant point*** X^j_i *associated with a parameter* P^j*, as the pair* $X^j_i =< V^j_i, T^j_i >$ *formed by a variable of the domain* V^j_i *and a temporal variable* T^j_i.

In the absence of any constraints, the variables V^j_i and T^j_i may take any precise value $v^j_{[m]}$ and $t^j_{[m]}$, respectively.

Definition 2 *We define a* ***fuzzy constraint*** $\mathcal{R}$ *between a set of significant points* $X^{j_1}_1, ..., X^{j_g}_g$ *by means of a fuzzy relation* $C = C(X^{j_1}_1, ..., X^{j_g}_g)$. 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* $X^{j_1}_1, ..., X^{j_g}_g$.

In principle, nothing restricts the form of the constraints that belong to the description of a MFTP. Nevertheless, experience has shown that it is possible to capture a large number of nuances from the temporal evolution of a parameter by using the following constraints between pairs of significant points X^j_i and X^j_k: a constraint D^j_{ik} on the *increase* in value between the pair of points $(V^j_k - V^j_i)$; a constraint L^j_{ik} on the *temporal extension* between the points $(T^j_k - T^j_i)$; and a constraint M^j_{ik} on the *slope* of the line that joins these points $((V^j_k - V^j_i)/(T^j_k - T^j_i))$.

Between significant points belonging to different parameters the most common constraints are temporal distance $L^{j_1 j_2}_{i_{j_1} k_{j_2}}$, and the difference in value $D^{j_1 j_2}_{i_{j_1} k_{j_2}}$ between pairs of significant points. Each of these constraints is given by a fuzzy number, which is represented in TRACE by means of a trapezoidal possibility distribution.

Until now, in applications employing the MFTP model, constraints of a descriptive nature, such as those presented here, have been the most common and useful. Nevertheless, in other application domains where there are mathematical models of the system, such as the control of chemical processes, we believe that constraints originated from these models will play a more important role.

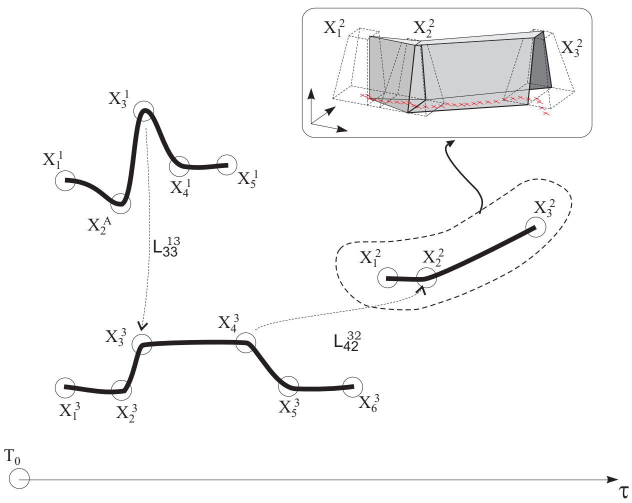

Fig. 2: Hypergraph associated with a MFTP made up of three morphologies over different signals. Nodes represent significant points and arcs fuzzy constraints.

Definition 3 *We define a* ***Multivariable Fuzzy Temporal Profile*** *(MFTP)* $\mathcal{M} = \{W^{\mathcal{M}}, X^{\mathcal{M}}, R^{\mathcal{M}}\}$ *as a finite set of MFTPs* $W^{\mathcal{M}} = \{\mathcal{M}_1^{\mathcal{M}}, ..., \mathcal{M}_s^{\mathcal{M}}\}$*, a finite set of significant points* $X^{\mathcal{M}} = \{X_1^j, ..., X_n^k\}$ *and a finite set of constraints* $R^{\mathcal{M}} = \{R_1, ..., R_f\}$ *amongst the points of* $W^{\mathcal{M}}$ *and* $X^{\mathcal{M}}$*.*

This definition allows the explicit representation of a system with multiple levels of abstraction. Usually, a sub-MFTP forms part of the MFTP in which it is contained by means of its significant end points, which delimit the temporal interval of occurrence. An MFTP can be represented with a hypergraph, in which the nodes correspond with significant points, and the arcs with constraints (see Fig. 2).

MFTP model also enables us to restrict the evolution of a parameter $\mathcal{P}^j$ between each pair of significant points $X_{i_1}^j$ and $X_{i_2}^j$ (see Fig. 2) by means of a membership function $\mu_{\mathcal{S}^j_{i_1 i_2}}(\mathcal{A}_{i_1}^j, \mathcal{A}_{i_2}^j)$ [13]. This fuzzy constraint models different forms of evolution of the parameter between the pair of significant points $\mathcal{A}_{i_1}^j$ and $\mathcal{A}_{i_2}^j$.

4.1 Matching

As the MFTP model is based on the CSP formalism, to identify the $\mathcal{P}$ is formally equivalent to find one or more solutions to $\mathcal{M}$ over the domain determined by $\mathcal{P}$.

We denote by $X^{\mathcal{M}*}$, the set of all the significant points which either belong to the MFTP $\mathcal{M}$ or to any of its sub-MFTPs:

$$\begin{aligned} X^{\mathcal{M}*} &= X^{\mathcal{M}} \cup X^{\mathcal{M}_1^{\mathcal{M}}*} \cup X^{\mathcal{M}_2^{\mathcal{M}}*} \cup ... X^{\mathcal{M}_s^{\mathcal{M}}*} \\ &= \{X_1^1, ..., X_{n^1}^1, ..., X_1^m, ..., X_{n^m}^m\}, \end{aligned}$$

where $X^{\mathcal{M}_h^{\mathcal{M}}*}$ is the set of significant points that belong to the sub-MFTP $\mathcal{M}_h^{\mathcal{M}} \in W^{\mathcal{M}}$, or to any of its sub-MFTPs.

Definition 4 *We define a* ***solution*** *of* $\mathcal{M}$ *as a set of assignations* $\mathcal{A} = \{A_1^1, ..., A_{n^1}^1, ..., A_1^m, ..., A_{n^m}^m\}$*, where* $\mathcal{A}_{n^k}^k = (v_{[m]}^k, t_{[m]}^k) \in P^k$*, 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:*

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

Where $\mathcal{A}^{\mathcal{M}_h^{\mathcal{M}}}$ is the projection of $\mathcal{A}$ over the set of significant points 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 compositional scheme of abstraction defined in the pattern $\mathcal{M}$ guides the search of solutions that satisfy the equation (1). Performing the matching in as many abstraction levels as there are in the problem makes it possible to construct complete histories of events of interest at each level of abstraction. Besides, in this way it is possible to give detailed explanations to the human operator as how has been possible to synthesize high level information from raw data; 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.

In the lowest level of abstraction there is the raw data of the system, $\mathcal{P}$, and in the highest the global pattern $\mathcal{M}$. The search for solutions starts with those MFTPs that do not contain any sub- MFTPs: $\mathcal{M}_o = \{W^{\mathcal{M}_o}, X^{\mathcal{M}_o}, R^{\mathcal{M}_o}\}$, where $W^{\mathcal{M}_o} = \emptyset$, due to which the Equation (1) is simplified to:

$$\pi^{\mathcal{M}_o}(\mathcal{A}^o) = \min_{\mathcal{R}_k \in \mathcal{R}^{\mathcal{M}_o}} \{\pi^{\mathcal{R}_k}(\mathcal{A}^{\mathcal{R}_k})\} \quad (2)$$

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 assignations taken directly over $\mathcal{P}$ or assignations arising from the solutions found for some $\mathcal{M}_h^{\mathcal{M}}$.

To implement the matching algorithms of the MFTP model we have based on forward checking (FC), the backtracking algorithm with the most suitable behavior [14]. FC can be extended to non-binary constraint problems in six different ways: nFC0, nFC1, nFC2, nFC3, nFC4 and nFC5 algorithms [15]. Each of them maintains a different level of consistency between the past variables and the future ones.

The nFC0 algorithm is the one which forces the lesser level of consistency, but it has been shown that it employs less CPU time than other nFCx algorithms in CSP whose graph is not dense. Experience has shown us that graphs associated with MFTPs are usually not dense, which converts this algorithm in the most suitable algorithm for most part of real MFTPs. nFC0 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. This ensures that there will always be at least one value in the domain of the variable that follows according to the assignment order that is compatible with the current assignment.

The use of fuzzy logic, besides allowing MFTP model to represent the vagueness and imprecision of human knowledge, also increases the robustness of the matching process. It is specially remarkable the benefits obtained from the use of fuzzy quantifiers [16], which allow to deal with signal noise within MFTP model, without preprocessing the signals with filtering algorithms.

In the knowledge acquisition phase we prefer to keep as close as possible to the expert's representation of the pattern. Experts are settle down to deal with noisy signals without filtering, and this is the way we usually work with TRACE. However TRACE does include tools to perform statistical filtering over the signals, which can be employed to filter false positives.

A different issue is the application of MFTP matching algorithms in a real-time patient supervision system. Despite the signal processing could be carried out without filtering, false positives can slow down the matching process, by

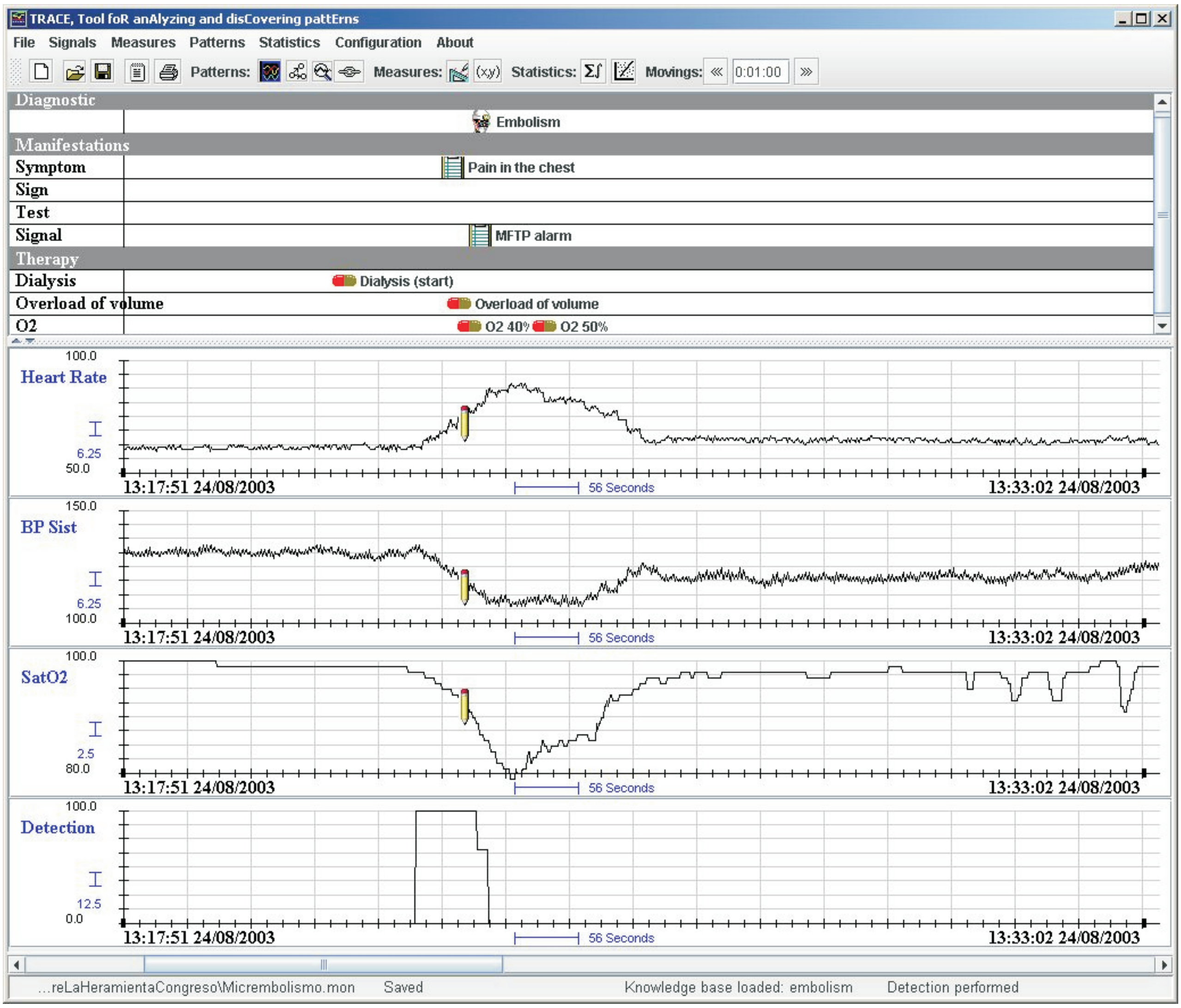

Fig. 3: TRACE showing the detection of a pulmonary embolism. In the upper part of the window icons represent manually acquired data, classified in diagnostic, manifestations and therapy. Below these are the parameters of the register, and the degree of compatibility between the pattern and the register.

forcing the matching algorithm to backtrack many times before discovering a dead-end. Thus filtering algorithms will be considered for the real-time application of the matching algorithms.

5 Clinical Example

We show the functioning of TRACE applied to the monitoring of pulmonary embolism in a bed-ridden patient, which is a frequent clinical complication that is under-diagnosed in situations where symptoms are light, and may be a precursor in life-threatening clinical situations. The early detection of a compatible monitoring pattern may help to endorse the high degree of suspicion that its clinical diagnosis requires of the physician. At the level of the physiopathological signals that are habitually monitored in an Intensive Care Unit, the mere concurrence of arterial desaturation of oxygen with increased heart-rate and a relative fall in systolic blood pressure, is a monitoring pattern that is compatible with this diagnosis.

On their own, heart rate, oxygen level and blood pressure are physiological signals that are subject to continual variations; hence setting alarm thresholds for them requires looking for a compromise between sensitivity and specificity for abnormality, so that the medical staff should not be overloaded with false positives. When these thresholds are not sufficiently sensitive to detect certain deviations from normality of physiopathological interest, such as pulmonary embolism, where more subtle deviations than the alarm threshold permits may be relevant, this shortfall must be made up through continuous supervision by the medical staff.

The medical staff's work-load would be significanlty reduced if a monitoring system based on a temporal pattern of knowledge, constructed over the joint basis of these three physiological parameters, were available to them. Reducing the number of false positives in the alarms that are detected, and narrowing down the threshold criteria for each individual parameter, would make it possible to detect situations without serious clinical consequences, but which, nevertheless, with a good degree of probability, represent physiological states that need to be assessed by the physician.

6 TRACE

TRACE is an implementation of the MFTP model [10] which makes it possible to project a description of those behaviors over the signal that are of physiopathological interest into a computable representation, and to identify them over a patient's signal register. At the same time, TRACE incorporates a set of utilities that make it an efficient tool for analyzing medical signals for discovering patterns: it can be used in clinical investigation, and also as a clinical knowledge acquisition interface. These features make TRACE a valid tool for studying, describing and validating intelligent alarms in patient monitoring.

We have opted for a Java-based implementation of TRACE due to its portability, which facilitates its application in an environment with such heterogenous equipment as hospitals. This tool is part of a line of research into the intelligent supervision of patients in Intensive Coronary Care Units, in the setting of which a clinical information system that supplies ubiquitous access to information generated on the patient is being developed [17, 18]. Information arising from the monitoring of patients is stored in MIT-BIH format records, and these registers constitute the input to TRACE.

Moreover, TRACE supplies forms for the collection of manually acquired parameters (such as body temperature or non-invasive blood pressure readings) or data arising from clinical analysis, which are fed in by auxiliary staff. Finally, with the aim of interacting with commercial signal analysis tools, it also enables the user to work with data in text format, which this type of tool usually produces and uses.

In order to accurately interpret the set of parameters arising from the monitoring of patients we must also take into consideration their clinical history: age, sex and habits, as well as the symptoms, signs, tests carried out, drugs that have been administered, etc. TRACE allows this information to be gathered along with each parameter register, and all this is visualized on the temporal axis divided into three groups: *diagnoses*, *treatments* and *events* (See Fig. 3), the final one in turn being divided into *symptoms*, *signs*, *tests* and *signals*.

This information is annotated textually, with its temporal location either being introduced in text format, or indicated on the temporal axis with the mouse, and establish the context in which the register of signals must be interpreted. During the research phase this context allows patterns to be described in the most specific manner possible, and the patient's state can be related with the evolution of the parameters arising from the monitoring.

This information can easily be represented by means of fuzzy temporal constraint network-based model, and can subsequently be used to interpret the patient's general state [19]. In the tool, the presence of an annotation is shown by an icon, and the information contained therein can be treated (see Fig 4). A number of these icons can be seen in the upper part of the window in Fig. 3.

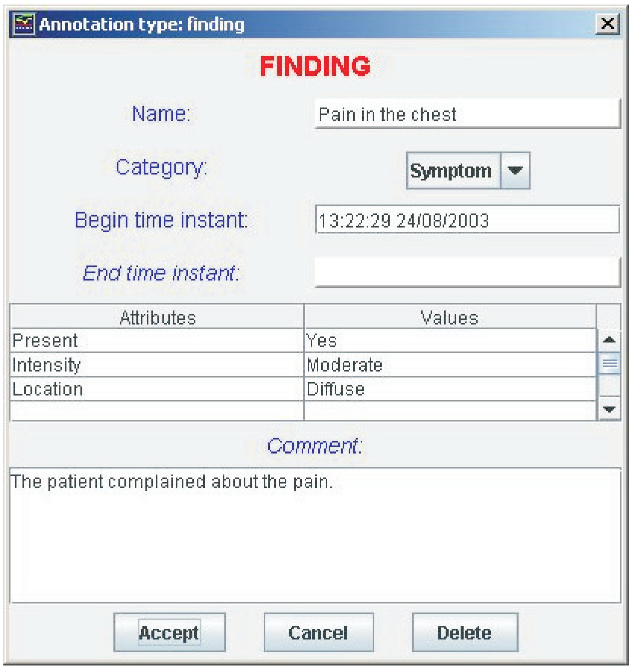

Fig. 4: This window allows the events, represented by icons on the top of the main window of TRACE to be edited (see Fig. 3).

TRACE supplies two output files: on one hand, a set of patterns M_i that are constructed by means of the tool over the MFTP model. These patterns contain all the information that the patient supervision system needs to create a new agent that is capable of identifying the event of physiopathological interest described by the pattern. On the other hand, the context of supervision in which each one of the patterns of a given session occurred is stored. This defines a case-base upon which the objectivization of a given pattern is supported. In both cases, XML is the format chosen for representing information, in order to facilitate access to and processing of the information gathered in the information system.

6.1 Modelling signal findings

TRACE places at the disposal of the user a set of utilities and wizards for the modelling of patterns over signals corresponding to findings over each parameter. There are a number of options affecting the visualization of each of the parameters: modification of scale, sampling frequency or zoom. It also permits the calculation and storage of a number of descriptive statistics over the signals, which may be used as additional support for pattern definition or as an independent statistical tool, as well as calculating a correlation between parameters.

With regard to the modelling of profiles *per se*, the tool has a set of simple morphological templates (peaks, pulses, etc.) from among which the physician can choose the one that best describes the finding that he wishes to model (see Fig. 5) [20]. TRACE handles each morphological template and, generally, any pattern as a graph in which each arc is given by a set of constraints between significant points, which is visually represented by an arc with a padlock in the

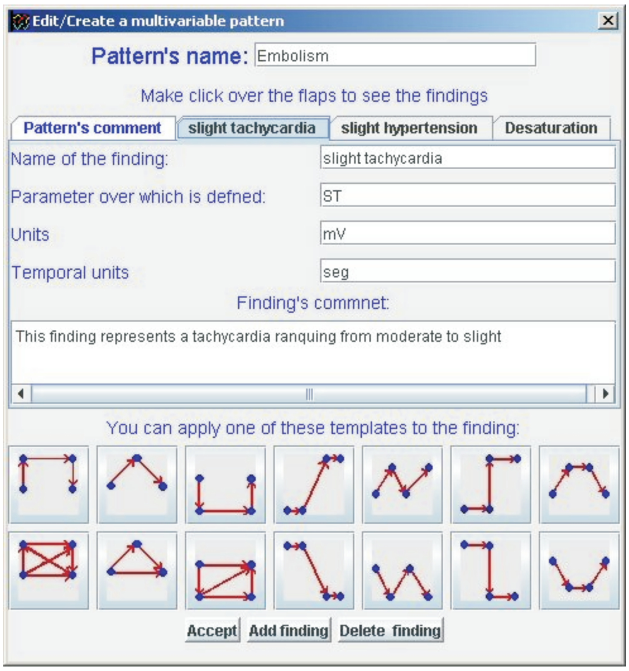

Fig. 5: This window allows the findings of the pattern to be added, deleted and edited. At the bottom we can see the morphological templates that can be applied to the findings.

middle. This padlock allows the constraints it represents to be edited.

These constraints are edited visually: each constraint is defined as a trapezoidal possibility distribution, and a simple graphic interface represents the outline of the pattern (see Fig. 7), and in the window of Fig. 6 all the constraints (size, temporal, slope and evolution) between the pair of significant points connected by the padlocked arc are shown. This window allows all the constraints between a pair of significant points to be edited either textually or visually with a mouse.

The most powerful utility, and the one that is most highly valued by the medical staff that have used the tool, is the wizard for the definition of morphologies over a parameter (see Fig. 8). This enables the expert to construct a characteristic evolution profile on the basis of the selection of a signal fragment in which a morphology of interest appears. The wizard enables the user to set the significant points over the selected fragment, and to define the fuzzy tolerance that is admissible between the trajectory of a compatible fragment and the prototype of the profile defined. This form of visual definition is highly intuitive, and is an effective form of dealing with the knowledge acquisition bottleneck.

6.2 Pattern of findings

The relations between findings identified over different parameters are fundamental for an accurate interpretation of the patient's state. A particular temporal arrangement between these findings may be the determining factor in identifying an abnormal situation, or in differentiating between different abnormal situations. TRACE allows these types of constraints to be defined in a simple visual manner as possibility distributions, using the same mechanism that was proposed for the modelling of findings.

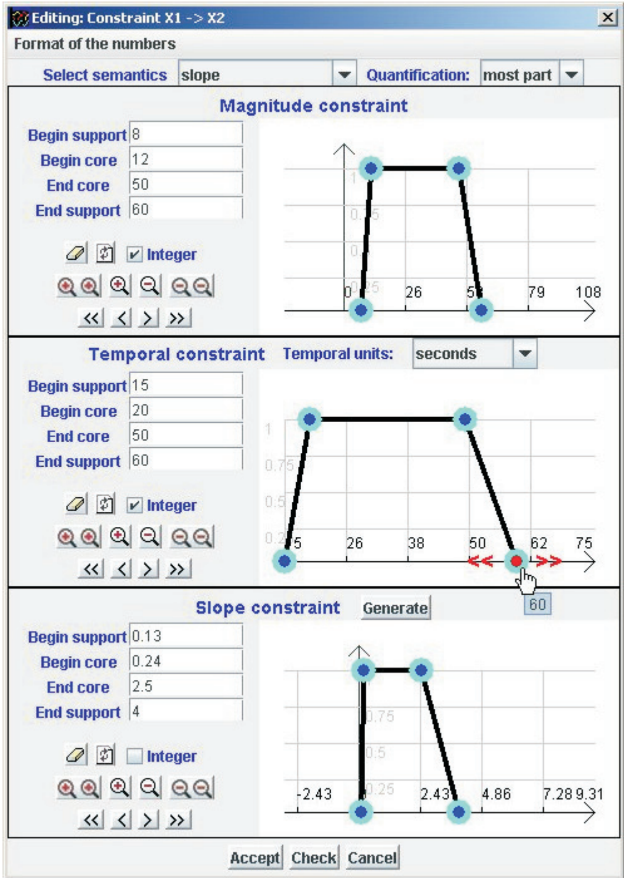

Fig. 6: From this window the constraints are edited, the values being inputted textually or with the mouse.

In order to generate the alarm for embolism we have to relate the three findings that make it up, so that they are approximately simultaneous. In order to do so we simply have to click on in the significant points between which we wish to introduce a new temporal constraint, and edit it in a window similar to the one in Fig. 6. In the same manner as for the constraints that define a finding, those that introduce relations between different findings are represented by an arc with a padlock, which allows it to be edited (see Fig. 7).

This concludes the definition of the knowledge base. Given that the tool is aimed at the development of pattern recognition agents, it is necessary to include a signal recognition stage, which will enable the refinement of the working database, and will allow the parameters of the recognition procedures to be adjusted, in order to optimize its implementation in clinical practice.

Once the detection has been carried out, the results of the detection of the morphological events are shown for each parameter in coded colours: red represents maximum compatibility, followed by orange, yellow, green and blue. Moreover, each execution of the recognition task generates a representation of the degree of compatibility of the global pattern, labelled *Detection* (see Fig. 3).

6.3 Pattern recognition agents

Signal pattern recognition adheres to the same structure followed in the definition of the MFTP model: a scheme

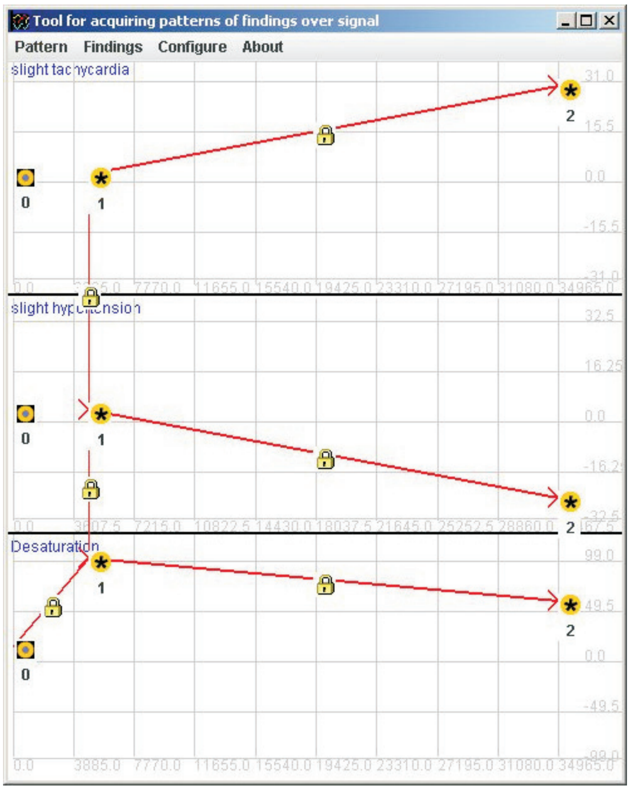

Fig. 7: Knowledge base of the pulmonary embolism visualized in TRACE. The dots represent significant points, and the arrows with a padlock in the middle represent fuzzy constraints.

of abstractions in which each level of events incorporates the events from a lower level, like pieces that slot together, through the addition of constraints between significant points.

The matching algorithms are completely separate from the knowledge that defines the patterns; this enables us to incorporate a new pattern detection agent (defined in an XML document) into the patient supervision system by simply sending the description of the pattern to the supervision system. This new agent, which is automatically generated by the system, triggers an alarm in the presence of the pattern in the monitoring system.

7 Clinical example revisited

The register shown in Fig 3 was obtained during the hemodialysis of a 39-year-old female patient with acute renal insufficiency secondary to severe necro-hemorrhagic pancreatitis. For this reason, the patient had previously undergone dialysis on a number of occasions. As can be seen in Fig. 3), immediately after starting dialysis, the patient rapidly showed symptoms of hypotension with increased heart rate and desaturation. The patient's condition improved subsequent to the administration of highly-concentrated oxygen (increased FiO2) and volume overload.

In a context in which, along with the alterations of the monitored parameters, we have to add the simultaneous appearance of thoracic pain of a pleuritic nature, the prior use

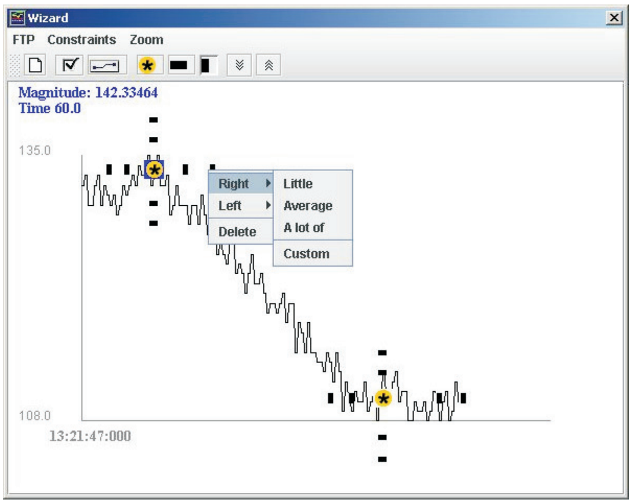

Fig. 8: Wizard for defining morphologies over a parameter. The black horizontal and vertical lines represent trapezoidal possibility distributions that show the temporal and magnitude deviation that is admissible for the trajectory of an evolution.

of a femoral catheter through which hemodialysis was carried out along with an electrocardiographic, radiographic and laboratory-compatible control, light to moderate pulmonary embolism was suspected, and subsequently diagnosed using imaging techniques.

¿From the point of view of the matter we are dealing with, it should be pointed out that the alarm generated by TRACE preceded the appearance of any threshold-generated alarm by one minute, being almost simultaneous with the intervention of the medical staff. This fact highlights the inadequacy of the alarms that are currently available in the ICU for monitoring this, and other pathologies. One minute may be of paramount importance in saving the lives of patients in situations such as the one described. In the case dealt with here, "gaining one minute" in the immediate administration of high concentrations of oxygen was undoubtedly of incalculable value.

Furthermore, the alarm also supplies previously interpreted presumptive diagnostic information, and as such, a predefined and automatic response which also aids in speeding up the physician response, as well as freeing him of a great deal of work, which Finally, besides the specific advantages that have already been mentioned in this work, we would emphasize that, in our opinion, this type of knowledge-based monitoring supplies completely new nuances in the application of medical knowledge to individual patients, even though it is still too early to pinpoint its relevance in health care, research and teaching. In the research field its application is the discovering of new findings, and relations between them and with other manifestations. In the teaching, the chance of formalize and represent graphically the knowledge involved in physiopathological patterns, learnt by veteran physicians, can be an inestimable aid to transmit this knowledge to novel physicians.

8 Conclusions and future work

Both the MFTP model and TRACE constitute a firm commitment towards supplying physicians with computer solutions that allow a simple and intuitive projection of the knowledge that they habitually use into a computable representation. This representation is used to generate a software agent, which is incorporated into an intelligent patient supervision system, allowing the triggering of an alarm based on the knowledge that the physician has projected over it.

The successful introduction of this new type of alarms requires clinical staff to be able to define alarms without the aid of a knowledge engineer; defining being understood as not only the elicitation of knowledge relative to the alarm, but also the generation of the agent charged with the task of its detection. The implication of knowledge engineer in any of the tasks will hinder the incorporation of the system into clinical practice, relegating it to the status of a research tool. Any work along these lines that is intended for use in clinical routine, must allow the physician to generate new alarms with levels of simplicity and transparency similar to that of modifying the thresholds of the alarms of a bed-side monitor.

To date, the clinical staff of the University Hospital of Elche have been satisfied with the use and possibilities offered by both the MFTP model and TRACE for research into signals from patient monitoring. Research is currently under way in studies of carotid hypersensitivity, internal hemorrhage, migraines, pulmonary embolism, etc.

The clinical staff have especially stressed the ergonomic nature of the tool, and how close the computational projection comes to expert intuition, facilitating all operations involved in knowledge acquisition, and increasing physicians' confidence in the results obtained.

The MFTP model makes it possible to integrate information from signal monitoring with the rest of the patient's information. This is achieved by means of a representation of temporal information based on fuzzy temporal constraint models, facilitating the development of information systems that avail themselves intensively of the temporal layout of stored events, which is of paramount importance in medicine for establishing suitable diagnoses. Our future work will be aimed at the development of an information system of these characteristics.

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