A Fuzzy Approach to Temporal Model-Based Diagnosis for Intensive Care Units

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Abstract.
In the Intensive Care Unit (ICU) domain, temporal evolution of diseases and patients' contextual information are critical pieces of knowledge that must be considered in the design of a diagnosis task. The uncertainty inherent in the description of temporal information associated to diseases requires a temporal representation and reasoning framework. This temporal framework has to be flexible enough to facilitate its integration in a behavioral model. This paper proposes a Temporal Behavioral Model (TBM) that makes this integration possible and permits the specification of contextual information (that may modify the TBM). A diagnosis process is also proposed. This process uses temporal model based techniques and Fuzzy Temporal Constraints Networks (FTCN) as the underlying temporal framework. Some heuristics, which affect not only the temporal reasoning dimension but also the causal, have been designed in order to compute solutions efficiently.

1 INTRODUCTION

Physicians at intensive care units (ICUs) have to deal with an overwhelming amount of data provided not only by on-line monitoring but also collected from patients' records (e.g., laboratory results), which are, in most cases, collected manually at different time instants. In order to provide efficient decision support systems and medical research tools in the ICU domain, it is necessary to integrate and analyse the information provided from these different sources. These tools are focused on the analysis of patient's evolution over time. This kind of analysis may provide valuable information for making decisions about patient treatments and for improving clinical guidelines.

A good analysis of patient evolutions lies in an efficient diagnosis process. The use of deep causal models together with model-based diagnosis techniques has proved its efficiency in the development of intelligent diagnosis systems [17]. Moreover, the ICUs domain reveals the importance of the temporal component modelling in capturing the temporal information associated to patient evolution [13]. However, the inclusion of temporal representation techniques in MBD has increased the complexity of the diagnosis process. Different formalisms have been proposed to represent time in MBD, ranging from totally qualitative approaches [11], based on Allen's interval logic [1], to totally quantitative approaches [9, 15, 16]. A serious attempt to provide a general framework for temporal MDB can be found in [3, 8], which presents a general characterization of temporal MDB at knowledge level.

Our goal, therefore, is to present a general framework for Temporal MDB, along the lines of [3] but using an algebraic approach based on Fuzzy Temporal Constraints Network framework ($FCTN$) for temporal dimension representation.

The structure of the paper is as follows: the underlying temporal framework is described in a concise manner in section 2. Section 3 presents the temporal behavioral model. The elements that constitute the inputs and outputs of the algorithm are introduced in section 4. The diagnosis process is analysed in section 5. Section 6 shows some experimental results provided by a performance analysis. Finally, we provide conclusions and future works.

2 TEMPORAL FRAMEWORK

In some proposals for Temporal MBD, the temporal dimension is modelled by means of the so-called *Fuzzy Temporal Constraint Network* ($FTCN$) formalism [14]. A $FTCN$ is a pair $\mathcal{N} =< \mathcal{T}, \mathcal{L} >$ consisting of a finite set of temporal variables, $\mathcal{T} = \{T_0, T_1, ..., T_n\}$, and a finite set of binary temporal constraints, $\mathcal{L} = \{L_{ij},\ 0 \leq i, j \leq n\}$ defined on the variables of $\mathcal{T}$. A $FTCN$ can be represented by means of a directed constraint graph, where nodes represent temporal variables and arcs represent binary temporal constraints.

Each binary constraint L_{ij} on two temporal variables T_i and T_j is defined by means of a convex possibility distribution $\pi_{L_{ij}}$ ($\pi(v') \geq min\{\pi(v), \pi(v')\}; v \leq v' \leq v''$), whose discourse universe is $\mathbb{Z}$, and which restricts the possible values of the time elapsed between both temporal variables. In the absence of other constraints, the assignments $T_i = t_i$ and $T_j = t_j$ are possible if $\pi_{L_{ij}}(t_j - t_i) > 0$ is satisfied.

An n-tuple $S = (t_1, ..., t_n) \in \tau^n$ is a *σ-possible solution* of a $FTCN$ network $\mathcal{N}$ if $\pi^{S_\mathcal{N}} = \sigma$, where $\pi^{S_\mathcal{N}} = \min\{\pi_{L_{ij}}(t_j - t_i),\ 0 \leq i, j \leq n\}$. The possibility distribution $\pi^{S_\mathcal{N}}$ defines the fuzzy set $S_\mathcal{N}$ of the σ-possible solutions of the network, with $\sigma \geq 0$. A $FTCN$ network $\mathcal{N}$ is *consistent* if and only if $S_\mathcal{N}$ is greater than a previously established threshold α, where $\alpha \in [0, 1]$, with $\alpha = 1$ being equivalent to the crisp case. The value of α is conditioned by the context and is set up arbitrarily by the user.

This model has been implemented and extended in FuzzyTIME [4], a general purpose temporal reasoner that provides high level language and reasonings capabilities on fuzzy temporal constraints between temporal variables which can represent intervals or time instants.

3 TEMPORAL BEHAVIORAL MODEL

In this proposal, we opt for a Temporal Behavioral Model, TBM, an abnormal behavioral model in which only the causal and temporal relations between hypotheses (diseases) and abnormal observations caused by them are represented. These relations are defined

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by *Diagnostic Fuzzy Temporal Patterns* ($DFTPs$). Apart from the abnormal behavioral model, a $DFTP$ includes knowledge about how the context affects the temporal behavioral model, referred to as *Contextual Meta-knowledge* (CTX). Hence, $TBM = \{DFTP_k\}$. Each $DFTP$ can be formally defined by the tuple $DFTP = \langle H, IM, IH, R^{dftp}, CTX\rangle$ where:

- H is the diagnostic hypothesis described by $DFTP$.
- $IM = \{im_k | k = 1, \dots, n_{im}\}$, is the set of abnormal manifestations implied by the hypothesis H.
- $IH = \{ih_k | k = 1, \dots, n_{ih}\}$ is the set of hypotheses implied by H (in medical domains, ih_k is a disease caused by H).
- $R^{dftp} = \langle \mathcal{T}^{dftp}, \mathcal{L}^{dftp}\rangle$ is a consistent $FTCN$, where temporal variables in $\mathcal{T}^{dftp}$ are associated to H, IM and IH, $\mathcal{T}^{dftp} = \{t^H, t_1^{im}, \cdots, t_{n_{im}}^{im}, t_1^{ih}, \cdots, t_{n_{ih}}^{ih}\}$ and the temporal constraints between them are defined in $\mathcal{L}^{dftp}$, where $\mathcal{L}^{dftp} = C(t^H, t_1^{im}, \cdots, t_{n_{im}}^{im}, t_1^{ih}, \cdots, t_{n_{ih}}^{ih})$. Furthermore, only those constraints defined by the expert are instantiated, and a subsequent process computes the minimal network of constraints between all temporal variables.
- $CTX = \{CTX_i\}$ is the set of temporal contexts. A context describes how the $DFTP$ definition is modified when a context factor occurs (temporal or atemporal concepts). Formally $CTX_i = \langle AC_i, TC_i, R_i^{ct}, MF_i\rangle$ where:
  - AC_i is the set of possible atemporal concepts described in the context (e.g. patient age, smoker).
  - TC_i is the set of possible temporal concepts described in the context (e.g. a drug was given at a certain time).
  - R_i^{ct} is a FTCN that includes constraints in the hypothesis H with the temporal concepts TC_i
  - $MF_i = \{mf_1, ..., mf_m\}$ is the set of modification functions (mf_i) that describes the DFTP modifications. These functions create, delete and modify elements of the IM, IH sets, and the R^{dftp} network.

Theoretical descriptions of diseases are clearly shown in medical manuals, however those descriptions are deeply conditioned by the present situation of each particular patient. Temporal contexts are therefore important aspects of diagnosis. The presence or absence of manifestations can be explained by a given disease, but this could change depending on patient contextual conditions. These conditions affect existing manifestations, but they also could justify new symptoms not gathered in the original $DFTP$. Other possible representations of TBM are possible. However, the representation of context knowledge and the behavior in medical environments is easily represented by the model previously proposed in this work.

As an **example**, we present a (simplified) description of the acute myocardial infarction (AIM) according to the TBM presented: The AIM (Root Hypothesis: (AIM, t_1)) is manifested by a *precordial pain*, and *moderate values of the ST levels* (implied manifestations: (pain, location,precordial,t_2), (ST-level, intensity, moderate,t_3)), the second one *more or less two minutes after* the infarction (temporal constraint: t_3 APPROX 2 MINS AFTER t_1). The AIM could also produce a *mixed shock syndrome* (implied hypothesis: (Mixed-Shock-Syndrome, t_4)).

4 DIAGNOSIS ALGORITHM INPUTS AND OUTPUTS

In order to provide a solution, the diagnosis process requires as inputs (apart from the TBM) the patient's observations ($EVT^- = \{evt_i | i = 1, ..., n_{obs}\}$), the contextual observables ($CTX_{obs} = \{ctx_i | i = 1, .., n_{ctx}\}$), and a consistent temporal network (R^{input}), whose temporal variables are associated to elements in EVT^- and CTX. In most cases, these temporal variables are specified as absolute time instants, which makes the reasoning process more efficient.

In our proposal, the diagnostic process output (i. e., the explanation provided) is composed not only of a set of abducibles, such as in [3, 11], but by all the elements that conform the final instantiated causal network (physiopathological and ethiological diagnosis, in medical domains). This kind of diagnosis explanation is necessary from the point of view of decision support system development. Therefore, the diagnosis algorithm output can be formally defined as the tuple $EXP = \langle CN_{exp}, R^{exp}, DFTP_{exp}, BL_{exp}, AB_{exp}\rangle$ where:

- CN_{exp} represents a directed graph describing the final causal network, where nodes represent observables and hypotheses in the final explanation.
- R^{exp} is a $FTCN$ where the temporal variables are associated to the CN_{exp} nodes.
- $DFTP_{exp}$ is the set of contextualized DFTP selected for explanation.
- BL_{exp} represents the binding list. It is a set of links between the hypothesis nodes of the causal network and their corresponding temporal patterns definitions.
- $AB \subset DFTP_{exp}$ is the set of abducibles generated by the diagnosis process.

In MBD, different interpretations of temporal diagnosis explanation have been proposed. On the one hand, there is totally consistency-based diagnosis [10, 12], in which the explanation provided should be consistent with all observations. On the other hand, there is totally abduction-based diagnosis [7, 13], in which the explanation should logically entail all the observations.

The same considerations can be made for temporal dimension. In [3], a generic knowledge level model for temporal MDB is proposed in which the definition of explanation has been parameterized. This parameterization allows the definition of explanation to be moved on the continuous line defined between totally consistent diagnosis and totally abductive diagnosis. In our proposal we opt for an intermediate model in which an abductive component is applied to abnormal events EVT^-, and components consistency is applied for the temporal dimension. This intermediate interpretation of diagnosis explanation can be formally stated as follows:

Definition 1 ***(Temporal Diagnosis)****. Given a Temporal Diagnostic Problem* $TDP =< TBM, EVT, CTX_{evt}, R^{input} >$, $EXP =< CN_{exp}, R^{exp}, DFTP_{exp}, BL, AB >$ *is a possible explanation for* TDP *iff:*

1. $DFTP_{exp} \bigcup CTX_{evt} \bigcup CTX \models EVT^-$,
2. $R^{input} \bigcup R^{exp}$ *is consistent.*

5 THE DIAGNOSIS PROCESS

The diagnosis process in this work is described by an algorithm based on the TBM described in Section 3. The following assumptions have been made:

Multiple cardinality solution. Several hypotheses may be found in a solution, which represent alternative or complementary solutions. Furthermore, different instances of the same hypothesis (the same hypothesis located at different time instants) are possible in a solution. However, all hypotheses should be consistent with the context information.

Parsimonious covering based diagnosis. The proposed algorithm explains the abnormal event set EVT^{-}_{new} through parsimonious covering. New hypotheses are included in the final explanation if and only if events cannot be explained by the hypotheses already instantiated. Of course, the solutions provided do not contradict either temporal or atemporal contextual concepts.

Acceptable efficiency of the process. Despite the fact that the algorithm presents an exponential time execution, the algorithm includes some heuristics (subsumption and temporal shifting) to improve efficiency. Experimental results,as we will see in Section 6, point to an acceptable time response.

5.1 Subsumption

The aim of the subsumption process is to avoid an excessive proliferation of temporally nearby hypotheses. Thus, before creating a new instantiated pattern to explain a given event evt_i, the subsumption process tries to include it in one of the already instantiated patterns, particularly those patterns in $DFTP_{exp}$ which match with the patterns in TBM and which explain evt_i.

In order to subsume a given evt_i, with $dftp_k = evoke(evt_i)$, in $DFTP \in DFTP_{exp}$, the subsumption process checks if the temporal constraints defined in $dftp_k$ in which evt_i takes part are consistent with the temporal constraints of R^{exp} (the temporal constraint network of the solution). In other words, the event evt_i is included in the solution and all temporal constraints related to this event in $dftp_k$ are added to R^{exp}. After that, if R^{exp} is temporally consistent (that is, if the consistency degree is greater than the previous established threshold), the event evt_i is subsumed. Furthermore, this event is explained by the hypothesis of $dftp_k$ that already explains other events of the solution. This process is carried out by a temporal query to the temporal reasoner using local propagation of the fuzzy constraints, similar to the technique defined in [2].

Figure 1 shows how evt_3 is subsumed in $DFTP$. Thus, on the right-hand side, the causal network of the pattern is represented, where evt_3 is a cause of H_1. On the left-hand side a part of the temporal constraint network of the solution is represented. Hence, the new temporal constraints on the network can be observed, due to the temporal variable associated to evt_3.

The diagnosis algorithm tries to subsume an event in a pattern when contextualization is not possible. We consider that contextualization is a process of characterizing a pattern for a given event in a given context. Therefore, there is no sense in associating this event within an existing pattern of the solution, because is is always assumed that any solution that can be framed in a context is better than any other that can not.

However, subsumption usefulness refers to the time execution factor. The subsumption process slows down the growth of instantiated hypotheses, which is exponential. Subsumption allows events to be explained by instantiated hypotheses of the solution, avoiding temporal nearby instances of hypotheses.

5.2 Temporal Shifting

When subsumption is not possible, is a new pattern instantiation enough?. The answer is no. When a given event cannot be subsumed, it is due to temporal inconsistencies in the instantiated pattern, $DFTP$. However, $DFTP$ could possibly explain the new event if temporal conditions were different.

Thus, we therefore propose including a new instance of the same pattern and associating the event to it. If we reconsider the failed subsumption, we will notice that only a few of the associated events subsumed into it do not allow the new subsumption. According to this, some of these events (already subsumed) can be subsumed by the new instance of the pattern. In conclusion, a temporal shifting process will produce two instances of the same pattern (at different time instants), whose hypotheses explain at least one different event and, perhaps, some common events.

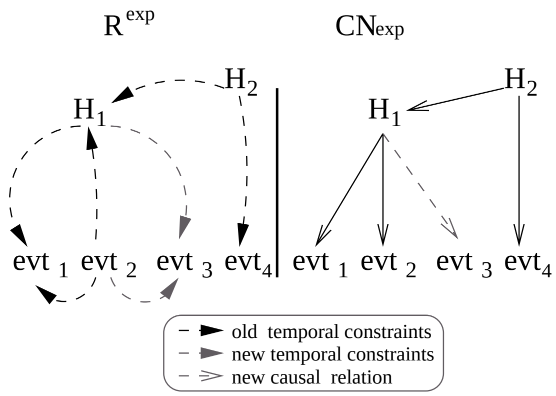

Figure 1. Subsunction.

In Figure 2, the temporal shifting of H_1 ($\overline{H}_1$) is represented when the evt_3 is explained. On the right-hand side, the causal network is represented. There, H_1 hypothesis can explain evt_3 when the hypothesis is shifted. On the left-hand side the temporal constraint network (R^{exp}) is represented. Note that a temporal constraint inhibits the subsumption of evt_3 in H_1. Due to this, H_1 is temporally shifted ($\overline{H}_1$). This new instance of the hypothesis does explain evt_3. Moreover, evt_2 could also be subsumed in $\overline{H}_1$.

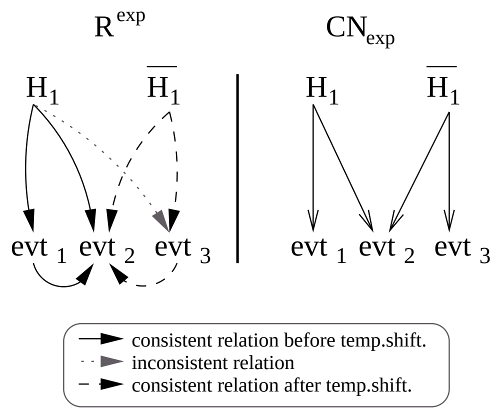

Figure 2. Temporal Shifting.

The temporal shifting process is used when subsumption is not possible. However, this process reduces the algorithm's efficiency because of the large amount of calculi for temporal consistence checking, in spite of the local propagation process. Furthermore, this process could imply new subsumptions. In our opinion, this problem could be partially reduced using some heuristics, which determine whether the hypothesis must be shifted or not. In this work, we suggest the application of this shifting technique only with the latest temporal instance of the pattern ($last(D)$, line 10 of Algorithm 1).

This heuristic increases the probability of finding at least one hypothesis that can explain the event. Moreover, it avoids the combinatorial explosion of explaining the hypothesis, because a single temporal shifted hypothesis per event is guaranteed. We are currently considering working with temporal intervals which provide a higher level of abstraction. The use of intervals shows us how to associate a concrete persistence to a $DFTP$. The definition of hypotheses persistence will allow the aggregation of nearby temporal hypotheses, e.g. describing temporal influence interval on pattern instances. In this case, it could be possible to aggregate those temporally shifted hypotheses allocated in the same influence interval, so that a single hypothesis substitutes all of them.

5.3 The Diagnosis Algorithm

Once the selected event is explained and removed from EVT_{new} (initially $EVT_{new} = EVT^{-}$), its explaining hypothesis (hypotheses) will be a new event to be explained, and therefore will be included in EVT_{new}. The algorithm finishes when it is not possible to find a higher level hypothesis, abducibles of the solution, that can explain any of the EVT_{new} events. The diagnosis process can be described, as follows:

1. An event e is selected from EVT_{new}. The event e is possibly associated to an evidence or a hypothesis.

2. The algorithm searches ($evoke()$, line 5) all possible patterns D from TDM that can explain event e.

3.Finally, the algorithm tries to include each pattern of D found in the solution as follows: 1)The algorithm considers temporal and atemporal concepts from the context information input (CTX_{obs}), then the algorithm tries to contextualize ($contextualized()$, line 7) the pattern. 2)If contextualization is not possible, the diagnosis process tries to subsume ($subsume()$, line 9) the event in any of the already instantiated patterns that exist in the partial solution (see Section 5.1). 3)When subsumption is not possible either, the temporal shifting process (see Section 5.2) is applied ($temporal\_shifting()$, line 12). Due to the computational cost of this procedure, this process must fulfil some heuristic conditions like that proposed in section 5.2. 4)If non previous actions are possible, the diagnosis process will generate an instance of the new pattern in the solution (generate_new(), line 17).

Function COVER (TBM, EVT^{-}, CTX_{obs}, R^{input}) **return** EXP
1 : subsumed = FALSE
2 : EVT_{new} = EVT^{-}
3 : **while** $EVT_{new} \neq \varnothing$ **do**
4 : **for each** $evti \in EVT_{new}$ **do**
5 : D = evoke(evt_i)
6 : **for each** $dftp_i \in D$ **do**
7 : **if not** contextualized($dftp_i, evt_i, EXP$) **then**
8 : **if** $dftp_i \in DFTP_{exp}$ **then**
9 : **if(not** $subsume(evt_i, dftp_i, EXP)$ **and**
10: **not** subsumed **and** last(D) = $dftp_i$ **)then**
11: subsumed = TRUE
12: $dftp_{new}$ = temporal_shifting($evt_i, dftp_i, EXP$)
13: evt_h = associateevent($dftp_{new}$)
14: EVT_{new} = $EVT_{new} \cup \{evt_h\}$
15: **endif**
16: **else**
17: $dftp_{new}$ = generate_new($evt_i, dftp_i, EXP$)
18: evt_h = associate_event ($dftp_{new}$)
19: $EVT_{new} = EVT_{new} \cup \{evt_h\}$
20: **endif**
21: **endif**
22: **endfor**
23: $EVT_{new} = EVT_{new} \setminus \{evt_i\}$
24: **endfor**
25: **endwhile**
endFunction

Algorithm 1: Parsimonious covering algorithm.

6 PERFORMANCE ANALYSIS.

In this work, we have focused our analysis on time execution factors, trying to find the most relevant variables that influence the performance of the diagnosis process. The objective of this analysis is to ascertain the influence of different parameters of the input space on the overall performance. The following factors are considered:

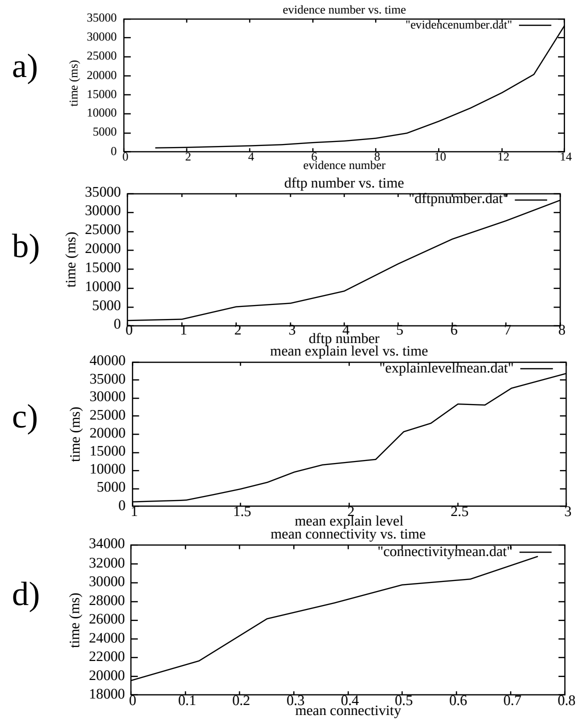

Figure 3. Experimental results of the algorithm. Prototype: Java. Proc:AMDAthlonXP Freq:1.53GHz RAM:256MB

- **The Number of Input Events**. Far from reducing the number of conjectures, the increase of evidences, in medical domains increases their possible explanations. This is mainly due to the nature of clinical hypothesis, where the same evidence could be explained by several hypotheses. The increase of evidences requires more time to complete the whole explanation process and, therefore, the study considers only the time used to explain the first hypothesis of each evidence. As is shown in Figure 6.a, the execution time presents an exponential behavior of time, but this is expected if we consider that the time spent for checking temporal consistence (in temporal shifting and subsunctions) increases because of the growth of temporal variables and events at each iteration.
- **The Number of Patterns** required to find a solution (Figure 6.b). This parameter shows the influence of the number of $DFTPs$ considered in finding the solution, that is, how the depth of the causal network affects the process performance.
- **Mean Pattern Connectivity Degree** (K_m). Let us define connectivity (K) of a pattern ($DFTP$) in the TBM as follows:

$K_{DFTP} = |IH|$, that is, the number of implied hypotheses of patterns. Then K_m can be defined as:

$$K_m = \frac{\sum_{DFTP \in TBM} K_{DFTP}}{| \, TBM \, |} \tag{1}$$

- **Mean Pattern Explanation Degree** (E_m): Explanation degree (E) of a pattern ($DFTP$) in the TBM is defined as $E_{DFTP} = |IM| + |IH|$ with $IM \wedge IH \in DFTP$, that is, the number of causal links. The E_m is defined as:

$$E_m = \frac{\sum_{\forall DFTP \in TBM} E_{DFTP}}{| \, TBM \, |} \tag{2}$$

These last two factors, K_m and E_m, can be considered as a measure of the TBM complexity. E_m can be considered as an indication of the complexity in covering the initial observations (Figure 6.c) whereas K_m can be associated to the complexity in building CN_{exp} upwards from the first hypotheses to abducibles (Figure 6.d).

This work is focuses on the capacity of the presented model to represent causal and temporal knowledge, and the study of the performance analysis. Today, we are at the knowledge acquisition step, so a causal and temporal knowledge acquisition tool ($CATEKAT$) has been implemented for elaborating a complete TBM [5]. However, this step is not finished yet. Thus, the input data set used in this work has not been validated by the expert. In any case, we have taken into account that the complexity of causal and constraints network in the testing bench is similar to a small set of already validated patterns.

7 CONCLUSIONS AND FUTURE WORKS

This paper describes a general framework for temporal MDB which tackles the problems of modelling complex interaction between deep causal models and context knowledge and structure of explanations (solutions) provided. The proposed framework demonstrates the suitability of $FTCN$s for time management. Following the general framework proposed in [3], our proposal can be characterized in the following terms: (a) the temporal phenomenon described in this paper can be considered a temporal behavior one in which the consequences of the fact that the system is in a given state (normal or faulty) are observed after some time; (b) time is modelled by means of a metric time-ontology in which temporal information is represented by $FTCNs$ [4, 14]; and (c) with regard to the definition of the explanation chosen, we demand that the explanation provided logically entails all abnormal observations, and that its temporal information is consistent with the one observed. Therefore, we propose an abductive approach for observations and a totally consistent-based approach for temporal dimension.

The use of diagnostic temporal patterns proposed in this paper is similar to that defined in [9], but our proposal makes it possible to model causal relations between diagnostic patterns. Causal relations between diagnostic patters allow us to define a causal network of diagnostic patterns. Another difference lies in the temporal representation framework, since we use the Fuzzy Temporal Constraints Network formalism, while the diagnostic patterns defined in [9] make use of a quantitative interval based approach.

One of the main differences between our approach and Brusoni et al. [3] is related to the way that contextual knowledge is integrated in the model. In Brusioni's approach, contextual knowledge is defined as a set of maximal episodes that can be used in the antecedent of the logical formulae which conform the temporal behavioral model. In our model, contextual knowledge is defined as a set of logical formulae which includes knowledge about temporal relations between antecedents components, thus conforming a meta-knowledge base which defines how the context knowledge affects disease evolution definition. In our model, therefore, contextual information is orthogonal to temporal behavior.

Future works will focus on the integration of this model with a possibility theory based evaluation of hypothesis consistency (in order to provide a consistent explanation), and on the logical formulation in terms of temporal logic, like the one defined in [6].

8 Acknowledgement

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