Modelling Contextual Meta-Knowledge in Temporal Model Based Diagnosis

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Abstract. Applying Model Based Diagnosis (MBD) techniques in medical domains reveals the need to use deep causal knowledge modelling frameworks as well as temporal management techniques to capture the dynamic component of disease evolution (with the latter being very important in other domains). Despite the intense research activity in the field of Temporal MBD, there are three issues that have not been analysed in depth: (a) modelling complex interaction of contextual information, (b) evaluation of hypotheses possibility degrees and (c) the structure of explanations. Our aim is to present a general framework for Temporal MBD which approaches these problems and to demonstrate the suitability of the Fuzzy Temporal Constraints Networks formalism ($FTCN$) for representing the domain temporal dimension.

1 Introduction

Since the beginnings of AI, the design of intelligent systems for medical diagnosis has been one of the most prolific areas. Recent, research in this area has paid increasing attention to the use of deep causal models, especially if they are considered as integrated in Model Based Diagnosis (MBD) techniques, which have proved their efficiency in the design of intelligent diagnosis systems [13, 17].

The use of MBD techniques in medical domains reveals the importance of temporal component modelling to capture the dynamics of the systems under analysis [7, 14]. However, the inclusion of temporal representation techniques in MBD has increased the complexity of the diagnosis process. Different formalisms have been proposed for representing time in MBD, ranging from totally qualitative approaches [12], based in Allen's interval logic [1], to totally quantitative approaches [8, 16]. A serious attempt to provide a general framework for temporal MBD can be found in [3, 6], which present a general characterization of temporal MBD at knowledge level.

Despite the intense research activity in this area, there are three questions that have still not been deeply analyzed: (a) the interaction between contextual knowledge, that is, knowledge that plays the role of premises instead of consequences of some hypothesis, (b) evaluation of hypotheses possibility degrees, and (c) the structure of the explanation provided. In most MBD proposals, contextual knowledge is integrated in deep causal models as observations (inputs to diagnostic process) [3, 6]. However, there are situations in which modelling context knowledge in this way makes the design of a diagnostic system more complex. Although different ways for evaluating hypotheses possibility degrees have been proposed (see for example [18]), they results, in practice, inefficient in domains with a high number of observations per disease. Therefore, our aim is to present of a general framework for Temporal MBD which solves the problems previously posed and to demonstrate the suitability of Fuzzy Temporal Constraints Network framework ($FTCN$) [2, 15] for temporal dimension representation.

The structure of the paper is as follows: the underlying temporal framework is laid out, in a concise manner, in section 2. In section 3, the temporal behavioral model is presented. The elements that constitute the inputs for temporal MBD are introduced in section 4. The structure conforming the solution as well as the definition of temporal diagnosis explanation is described in section 5. In section 6, we sketch the process for building a diagnostic explanation. Section 7 illustrates how the hypotheses possibility degree is evaluated. Finally, we provide conclusions and future works.

2 Temporal Framework

In our proposal for Temporal MBD, the temporal dimension is modelled by means of the so-called *Fuzzy Temporal Constraint Network* ($FTCN$) formalism [2, 15]. A $FTCN$ is a pair $\mathcal{N} = \langle \mathcal{T}, \mathcal{L} \rangle$ 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 normalised and unimodal possibility distribution $\pi_{L_{ij}}$, 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 possible 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 normalised.

3 Temporal Behavioral Model

In this proposal, we opt for a Temporal Behavior 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 in a *Diagnostic Fuzzy Temporal Patterns Knowledge Base* ($DFTPKB$). Apart from the abnormal behavioral model, TBM includes knowledge about how the context affects the temporal behavioral model, referred to as *Contextual Meta-knowledge base* (CXT). Hence, $TBM = \langle DFTPKB, CXT \rangle$.

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$DFTKB$ is composed of a set *Diagnostic Fuzzy Temporal Patterns*, $DFTKB = \{DFTP_k\}$. Each $DFTP$ can be formally defined by the tuple $DFTP = \langle H, IM, IH, R^{dftp}, N\rangle$ where:

- H is the diagnostic hypothesis described by $DFTP$. Formally speaking, $H = \langle \hbar, t^H\rangle$, where $\hbar$ is the diagnostic concept associated to the hypothesis and t^H its corresponding temporal variable.
- $IM = \{im_k | k = 1, \ldots, n_{im}\}$, is the set of abnormal manifestations implied by the hypothesis $\hbar$. Implied manifestations can be formally defined by the tuple $im_k = (m_k, V_{m_k}, t_k^{im})$, where m_k represents the abnormal manifestations, V_{m_k} is the set of abnormal values associated to the manifestation and t_k its temporal variable.
- $IH = \{ih_k | k = 1, \ldots, n_{ih}\}$ is the set of hypotheses implied by $\hbar$ (in medical domains, ih_k is a disease caused by $\hbar$). Implied hypotheses can be formally described by the tuple $ih_k = (h_k, t_k^{ih})$, where h_k represents a hypothesis with t_k^{ih} as associated temporal variable.
- $R^{dftp} = \langle L^{dftp}, X^{dftp}\rangle$ is a consistent $FTCN$, where temporal variables in X^{dftp} are associated to H, IM and IH, $X^{dftp} = \{t^H, t_1^{im}, \cdots, t_{n_{im}}^{im}, t_1^{ih}, \cdots, t_{n_{ih}}^{ih}\}$ and the temporal constraints between them are defined in L^{dftp}, $L^{dftp} = C(t^H, t_1^{im}, \cdots, t_{n_{im}}^{im}, t_1^{ih}, \cdots, t_{n_{ih}}^{ih})$.
- $N : IM \cup IH \to [0, 1]$, is a function that defines the necessity degree associated to the causal relation between $\hbar$ and its implied manifestations and hypotheses, $N(mh_k) = N(\hbar \to mh_k)$ (where mh_k represents an implied manifestation or hypothesis). In medical domains, this function is analogous to the sensibility measure used in Evidence Based Medicine.

The main function of *Contextual Meta-Knowledge Base* is to modify $DFTPs$ definitions in order to adapt them to the contextual information. This interaction between TBM and contextual information is defined by means of a set of contexts rules, which can be formally defined in the following way:

$$DFTP \wedge cxt_0 \wedge \cdots \wedge cxt_n \wedge C(\tau_0, t_k^H, t_0^{cxt}, \cdots, t_n^{cxt}) \to \\ mf_0 \wedge \cdots \wedge mf_m \tag{1}$$

where:

- $DFTP$ is the diagnostic fuzzy temporal pattern on which context interaction is defined.
- $cxt_0, \cdots, cxt_n$ are conditions defined on contextual elements.
- $C(\tau_0, t^H, t_0^{cxt}, \cdots, t_n^{cxt})$ is the set of temporal constraints between temporal variables associated to $DFTP$ and $cxt_0, \cdots, cxt_n$
- $mf_0 \wedge \cdots \wedge mf_m$ are functions describing $DFTP$ modifications which adapt it to contextual information. These modifications can be accomplished by means of the following functions:
  - $modify\_values(DFTP, im_i, V_{m_i}^{new})$, substitutes the set of values which defines the abnormal manifestation im_i by the set $V_{m^i}^{new}$.
  - $modify\_necessity(DFTP, mh_i, N_i^{new})$, modifies the necessity degree associated to the implication $\hbar \to mh_i$. This function only affects the function N in $DFTP$ definition, updating it in the following way $N(mh_i) = N_i^{new}$.
  - $add\_implication(DFTP, mh_i^{new}, N_i^{new})$, adds an implied manifestation or hypothesis mh_i^{new} to $DFTP$ definition and assigns the necessity degree N_i^{new} to the corresponding causal relation, thus updating the N function in the following way $N(mh_i^{new}) = N_i^{new}$.
  - $remove\_implication(DFTP, mh_i)$, removes the implied manifestation or hypothesis mh_i from $DFTP$ definition.

For example, in an intensive care unit (ICU) it is very common to increase patient's blood pressure (when it is excessively low) by means of the corresponding therapy. If, in this context, a rise in blood pressure is detected, it is not to be considered as an abnormal manifestation, since the rise is expected. Therefore, in order to select $DFTPs$ in this context, the abnormal manifestation *high blood pressure* should be removed from $DFTPs$ definition (if this manifestation is present) by means of the $remove\_implication$ function. This approach for modelling context interaction allows more complex relations between TBM and context to be modelled than those described in classical temporal MBD models [6, 3]

Once contextual meta-knowledge is applied to a given $DFTP$, it is referred to as *Contextualized* $DFTP$. This contextualization implies modifications in $DFTP$ definition (if any) by means of any of the modifying functions and the determinations of its temporal localization, which is needed to test the temporal constraints stated in the antecedents of contextual meta-knowledge rules (expression 1). In the rest of the paper, when the term $DFTP$ is used, it should be considered as a reference to a contextualized $DFTP$.

4 Diagnostic Process Inputs

The temporal diagnosis model, described in this work, like classical diagnosis models, requires as inputs, the set of observations to be explained, contextual information and temporal information. The evaluation of the hypothesis possibility requires the definition of a possibility measure over the observations set. Therefore, the input for our temporal diagnosis model is composed of:

- The set of observations to be explained $EVT = \{evt_i | i = 1, \cdots, n_{obs}\}$, given as a set of events, $EVT = EVT^+ \cup EVT^-$, where EVT^- contains abnormal events and EVT^+ normal ones. Each event can be defined by the tuple $evt_i = (m_i, v_{evt_i}, t_i^{evt})$, where m_i stands for the corresponding manifestation, v_{evt_i} represent the values associated to the event, and t_i^{evt} is the temporal variable associated. For example, a precordial intense pain can be defined by the events $(pain, precordial, t_a)$ and $(pain, intense, t_a)$.
- $\Pi_{evt} : EVT \to [0, 1]$ is a function indicating the possibility degree associated to events in EVT.
- The set of contextual observation $CXT_{evt} = \{cxt_i | i = 1, \cdots, n_{cxt}\}$, given as a set of contextual events. Each contextual event can be defined by the tuple $cxt_i = (c_i, v_{cxt_i}, t_i^{cxt})$, where c_i is a contextual observable which can be a concept belonging to the patient's clinical record (such as sex, age, clinical antecedents,..) or therapies applied, v_{cxt_i} is the value associated to the contextual observable (for example, male, 72, smoker,..) and t_i^{cxt} is the temporal variable associated.
- $R^{input} = \langle X^{input}, L^{input}\rangle$ is a consistent $FTCN$, where temporal variables in X^{input} are associated to events in $EVT \cup CXT_{obs}$, and their corresponding temporal constraints are defined in L^{input}.

Elements introduced in this section and section 3 can be included in the definition of **Fuzzy Temporal Diagnosis Problem**:

Definition 1 *Given a Temporal Behavioral Model* $TBM = \langle DFTPKB, CXT \rangle$*, a set of events* $EVT = EVT^{+} \cup EVT^{-}$*, a set of contextual events* CXT_{evt}*, and a consistent* $FTCN$ R^{input}*, a* ***Fuzzy Temporal Diagnosis Problem*** *can be defined as the tuple* $FTDP = \langle TBM, EVT, CXT_{evt}, R^{input}, \Pi \rangle$*, with* Π *defining the minimum possibility degree for hypotheses in diagnosis explanation to be accepted.*

The possibility degree threshold Π allows those hypotheses which are not sufficiently supported by observed behavior to be pruned from the explanation generated. Hence, the main goal of a $FTDP$ is to find a set of hypotheses (represented by its respective $DFTP$) which covers all the observations. A formal definition of diagnosis explanation will be given, in section 5.

5 Diagnosis Explanation

In obtaining a solution for $FTDP$, we are interested not only in a set of abducibles that explains the observations, as [12, 3], but in the causal network composed of all the elements considered in building the explanation: events, manifestations and hypotheses (implied or not), as well as temporal relations between these elements. Hence, in our model, a diagnosis explanation is defined as the tuple $EXP = \langle CN_{exp}, R^{exp}, DFTP_{exp}, BL_{exp}, AB_{exp} \rangle$, where:

- $CN_{exp} = \langle N, A, \Pi_{cn}, N_{cn} \rangle$ is a graph representing a causal network where:
  - N is the set of nodes, in which each node is defined by the tuple $\langle n_i, t_i^{cn} \rangle$, where n_i is the node associated to either a manifestation or hypothesis, and t_i^{cn} its corresponding temporal variable.
  - A is the set of arcs in which each arc is defined by the tuple $\langle n_j, n_k \rangle$, with n_j y n_k being the arc source and target respectively.
  - $\Pi_{cn} : N \rightarrow [0, 1]$, is the function that defines the possibility degree of the hypotheses associated to the nodes in CN. If a node $n_i \in N$ is associated to an event evt_k, then $\Pi_{cn}(n_i) = \Pi_{obs}(evt_k)$.
  - $N_{cn} : A \rightarrow [0, 1]$, is the function that indicates the necessity degree of causal arcs in CN, information defined in $DFTPs$ through function N
- $R^{exp} = \langle L^{exp}, X^{exp} \rangle$ is a $FTCN$ where X^{exp} is the set of temporal variables associated to nodes in CN, and L^{exp} is the set of temporal constraints between those temporal variables.
- $DFTP_{exp}$ is the set of contextualized $DFTP$ selected for explanation.
- BL is a set of links between the hypotheses included in the causal network and their corresponding temporal patterns. Therefore $BL = \{\langle n_i, DFTP_i \rangle | n_i \in N \ \wedge \ DFTP_i \in DFTP_{exp}\}$.
- AB is the set of abducibles generated by the diagnosis process. Obviously, $AB \subset DFTP_{exp}$

In MBD, different interpretations of temporal diagnosis explanation have been proposed, ranging from totally consistency-based diagnosis [11, 13] to totally abduction-based diagnosis [5, 14]. The same considerations can be made for the temporal dimension. Brusoni et al. [3] present a generic knowledge level model for temporal MBD in which the definition of explanation has been parameterized. This parameterization allows the definition of explanation to be moved along the continuous line defined between totally consistent diagnosis and totally abductive diagnosis. Following this proposal, we opt for an intermediate model in which an abductive component is applied to abnormal events EVT^{-}, and the consistency component is applied for both normal events EVT^{+} and temporal dimension. This intermediate interpretation of diagnosis explanation can be formally stated as follows:

Definition 2 ***(Fuzzy Temporal Diagnosis)****. Given a Fuzzy Temporal Diagnostic Problem* $FTDP = \langle TBM, EVT, CXT_{evt}, R^{input}, \Pi \rangle$*,* $EXP = \langle CN_{exp}, R^{exp}, DFTP_{exp}, BL, AB \rangle$ *is a possible explanation for* $FTDP$ *iff:*

1. $DFTP_{exp} \bigcup CXT_{evt} \bigcup CXT \models EVT^{-}$,
2. $DFTP_{exp} \bigwedge EVT^{+} = \emptyset$.
3. $R^{input} \bigcup R^{exp}$ *is consistent.*
4. $\forall DFTP_i \in DFTP_{exp}, \Pi_{cn}(DFTP_i) \geq \Pi$

In other words, the explanation generated must: (1) logically entail the abnormal observations taking into account the contextual knowledge, (2) be consistent with the normal observations and (3) with the temporal information observed, and (4) the hypotheses possibility degree must be higher than a previous established threshold. This definition of temporal diagnosis imposes some requirements on the design of the diagnostic process in the sense that two sequential processes are necessary. The first process must abductively build the explanation taking into account temporal information (in order to fulfill condition (1)) and the second process must check hypothesis consistency and its possibility degree (condition (2)). A CommonKADS Knowledge Model of a diagnosis task which meets the previous requirements can be found in [16].

6 Building the Explanation

Let us suppose that the diagnosis task has built part of a diagnosis explantation which has been stored in $EXP = \langle CN_{exp}, R^{exp}, DFTP_{exp}, BL_{exp}, AB_{exp} \rangle$. Suppose that, at this stage, the diagnosis task has to explain a new abnormal event $evt = (m, v_{evt}, t^{evt_i})$, which can be explained by $\overline{DFTP} = \langle H, IM, IH, R^{dftp}, N \rangle$ by means of the implied manifestation $\overline{im} = (\overline{m}, V_{\overline{m}}, t^{\overline{im}})$ [2].

In order to avoid a broad spread of temporally close hypotheses in the final explanation, the diagnosis task first tries to subsume new events in some already instantiated hypothesis in EXP. Therefore, a *parsimonious hypotheses instantiation* is applied [16]. Let us suppose that a pattern explaining evt exists in EXP and let this pattern be $\overline{DFTP}$. This implies that:

- An event, associated to the hypothesis represented by $\overline{DFTP}$, must have been previously generated and the corresponding node $n^{\hbar}$ must have been inserted in CN_{exp}.
- A set of nodes associated to some events, $\{evt_1, evt_2, \ldots, evt_n\}$, should exist in CN_{exp}. Suppose that these events are explained by $\overline{DFTP}$ by means of the implied manifestations $\{im_1, im_2, \ldots, im_n\} \in IM$. Of course, arcs between $\overline{DFTP}$ and $\{evt_1, evt_2, \ldots, evt_n\}$ are also present in CN_{exp}.
- t^{H} (associated to $\hbar$) and t^{evt_i} (associated to events evt_i) must exist in R^{exp}. Constraints between these temporal variables, and between them and the origin of time τ_0 must also exist (constraints are propagated throughout R^{exp}).

At this point, the diagnosis task must check if evt can be subsumed in $\overline{DFTP}$. This process consists of determining the consistency of R_{expe} after inserting the constraints specified in $\overline{DFTP}$. That is:

[2] $m = \overline{m}$ y $v_{evt} \in V_{\overline{m}}$

1. The constraints $C(t^{\overline{im}}, t^{im_i})$ $(i = 1, \cdots, n)$ and $C(t^H, t^{\overline{im}})$ can be determined from the $\overline{DFTP}$ definition.
2. As the previous constraints must be satisfied between t^{evt} and t^{evt_i} and between t^{evt} and t^H, the following constraints must be inserted in R^{exp}:

$$(t^{evt}\ C(t^{\overline{im}}, t^{im_1})\ t^{im_1}) \wedge (t^{evt}\ C(t^{\overline{im}}, t^{im_2})\ t^{im_2}) \wedge \ldots \wedge \\ \wedge (t^{evt}\ C(t^{\overline{im}}, t^{im_n})\ t^{im_n}) \wedge (t^H\ C(t^H, t^{\overline{im}})\ t^{evt} \quad (2)$$

3. If R^{exp} is consistent after inserting (and propagating) the constraints defined in expression 2, evt can be subsumed in $\overline{DFTP}$ and CN_{exp} must be accordingly updated.

If evt cannot be subsumed in $\overline{DFTP}$, a new instance of $\overline{DFTP}$ must be created and inserted in EXP (figure 1):

1. Nodes representing $\hbar$ and evt, and an arc between them are inserted in CN_{EXP}. The rest of the structures in EXP are also updated to reflect this new situation.
2. Temporal information in R^{exp} is also updated by inserting the temporal variable associated to $\hbar$, t^H, and the constraint between t^H and $t^{\overline{im}}$:

$$t^H\ C(t^H, t^{\overline{im}})\ t^{evt} \quad (3)$$

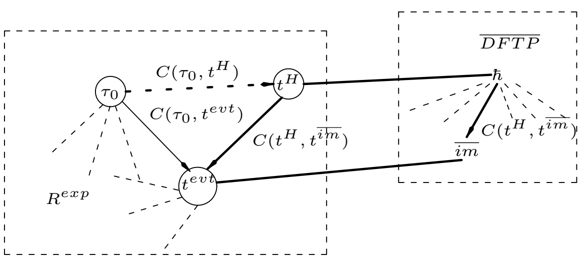

Figure 1. $DFTP$ instantiation effects in R^{exp}

An important advantage of $FTCN$ framework is that, after inserting the temporal constraint specified in expression 3 , the constraint propagation algorithm will infer the constraint $C(\tau_0, t^H)$ (thick dotted line in figure 1). This constraint allow us to determine the temporal location of the $\overline{DFTP}$.

7 Hypotheses Possibility Degree

Evaluation hypotheses possibility degree makes hypothesis ranking and ruling out (according to a previously established threshold) possible. This evaluation can be accomplished by means of the Dubois and Prade Possibility Theory Modus Tollens [10], which can be stated as follows:

$$\begin{array}{ll} N(\hbar_i \rightarrow mh_j) \geq a & \Pi(\hbar_i \rightarrow mh_j) \geq A \\ N(mh_j) \leq b & \Pi(mh_j) \leq B \\ \hline N(\hbar_i) \leq max(v(A \leq b), b)) & \Pi(\hbar_i) \leq max(1-a, B) \end{array}$$

where $v(cond)$ is the boolean truth function, $\hbar_i$ is $DFTP$ main hypothesis, and mh_j is an implied manifestation or hypothesis belonging to $DFTP$. In our proposal, given $DFTP = \langle H, IM, IH, R^{dftp}, N\rangle$, a represents the necessity degree of causal implication $\hbar \rightarrow mh_j$, and can be obtained from function N in $DFTP$, $N(\hbar \rightarrow mh_j) = N(mh_j)$. A represents the causal implication possibility degree and is always 1 since its necessity is different from 0. B represents the possibility degree associated to an implied hypothesis or manifestation. In the case of manifestations, $B = \Pi_{obs}(evt_k)$. As we are interested in determining hypotheses possibility degree, there is no need to evaluate hypotheses necessity degree, therefore b is not necessary. However, there are several sources that contribute to hypotheses possibility degree, their implied manifestations and hypotheses, so we need to combine them. For this purpose, the different sources are considered as independent and an upper bound will be used for the values of a, A, b and B. The previous assumptions allow us to apply the Dubois and Prade [10] evidence combinations expressions, which can be stated as follows:

$$N(\hbar) = \max_k(N_k);\ \Pi(\hbar) = \min_k(\Pi_k) \quad (4)$$

Expressions (4) allows us to calculate hypothesis possibility degree when several implied manifestations and hypotheses are considered.

Definition 3 *Given a $DFTP = \langle H, IM, IH, R^{dftp}, N\rangle$, a set of implied manifestations $IM' = \{im_k\}$ with $IM' \subset IM$, associated to the events evt_k^{im}, and a set of implied hypotheses $IH' = \{ih_l\}$ with $IH' \subset IH$ with possibility degree $\Pi_{ih}(ih_l)$, the possibility degree of the hypothesis represented by $DFTP$, written $\Pi(\hbar)$, can be calculated by the expression:*

$$\Pi(\hbar) = min(\Pi_{im}(\hbar), \Pi_{ih}(\hbar)) \quad (5)$$

Where $\Pi_{im}(\hbar)$ is the component of the possibility degree of $\hbar$ provided by implied manifestations, and can be calculated using the following the expression:

$$\Pi_{im}(\hbar) = \max_{im_k \in IM'}(1 - N(im_k), \Pi_{obs}(evt_k)) \quad (6)$$

with evt_k being the event associated to im_k.

$\Pi_{ih}(\hbar)$ is the component of the possibility degree of $\hbar$ provided by an implied hypothesis, and can be calculated using the following expression:

$$\Pi_{ih}(DFTP) = \max_{ih_l \in IH'}(1 - N(ih_l), \Pi_{ih}(ih_l)) \quad (7)$$

As stated previously, this evaluation of hypothesis possibility could be included in an incremental abductive process for building the solution, as the one presented in [16].

8 Conclusions and Future Works

This paper describes a general framework for temporal MBD which tackles the problems of modelling complex interaction between deep causal models and context knowledge, and those of evaluation of hypotheses possibility degree and structure of explanations (solutions) provided. The framework proposed demonstrates the suitability of FTCNs for time management. Following the general framework proposed in [3] our proposal can be characterized in the followings 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 Fuzzy Temporal Constraints Networks [2, 15]; and (c) with regard to the definition of explanation chosen, we require that the explanation provided logically entails all abnormal observations and that is consistent with normal ones, and that its temporal information is consistent with that observed. Therefore, we propose an abductive/consistency-based 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 those defined in [8, 9], however 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 by linking them through their implied hypotheses. Another difference lies in the temporal representation framework, since we use the Fuzzy Temporal Constraints Network formalism proposed in [2, 15] while diagnostic patterns defined in [8] 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 in which 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 conforms 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, conforming a meta-knowledge base which defines how the context knowledge affects diseases evolution definition. Thus, in our model contextual information is orthogonal to temporal behavioral model, although both approaches can coexist in a given domain.

Wainer and Sandri [18] presented a temporal diagnostic model, which is also based on the FTCN formalism, which provides a framework for numerical evaluation of the hypothesis. However, its high computational complexity makes implementation inefficient, especially in domains where the number of observations per disease is high (as in the descriptions of diseases evolutions in an Intensive Care Unit). Another problem of the Wainer and Sandri approach stems from the difficulties that arise in integrating this approach in incremental abuductive algorithms, such as that presented in [16]. The framework presented in this paper solves the previous problems and makes use of medical domain knowledge (in terms of Evidence Based Medicine) for hypotheses evaluation.

In most temporal diagnostic models [8, 12, 18], solutions generated are composed of a set of abducibles inferred by the diagnostic process (according to the definition of explanation used) and the temporal information regarding the temporal location of the abducibles. This information is not sufficient when explanations generated by diagnostic process are intended to be used in a decision making process. It is in this case that complete information about the evolution of the system malfunction(s) (patient diseases in medical domains) is necessary. For this reason the output of our temporal diagnosis model is composed not only of a set of abducibles ($DFTPs$) and some information about their temporal location, but also of the causal relations between abducibles and between abducibles and observables. For this information to be complete, it is necessary to include information about the temporal relations between these elements (given as a global $FTCN$) and the abducibles possibility degree.

Future works can be considered from a theoretical and practical perspective. On the theoretical side, the definition of hypothesis neesd to be extended to include an attribute indicating its severity. Another theoretical extension includes the definition of the model presented here in logical terms using Fuzzy Temporal Constraint Logic ($FTCL$) [4], as underlying logical framework. On the practical side, a general temporal reasoner, which is based in $FTCN$ formalism, is being constructed. This temporal reasoner includes a grammar for defining temporal relations which will help us to reduce the semantic gap between the information acquired from experts and the information stored in the Temporal Behavioral Model. The integration of this temporal reasoner will facilitate the inclusion of a temporal abstraction process for clinical data. To this purpose, we are designing a framework for abductive temporal abstraction based on $FTCN$.

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