J Intell Manuf (2010) 21:145–153
DOI 10.1007/s10845-008-0171-8

Temporal-based medical diagnoses using a Fuzzy Temporal Reasoning System

Silvana Badaloni · Marco Falda

Received: 9 August 2008 / Accepted: 15 August 2008 / Published online: 8 November 2008

Abstract We apply the Fuzzy Temporal Constraint System we have developed to the case of SARS (Severe Acute Respiratory Syndrome). The idea is to characterize the temporal evolution of the symptoms of this ill-known disease by modelling patients' data in a Fuzzy Temporal Constraint Network. We discuss how the system is able to manage both fuzzy qualitative and metric constraints allowing to represent in a flexible manner the symptoms of different patients. In this way it is possible to deduce characteristic periods of an ill-known disease such as SARS was. A new user interface is included into the architecture of the System.

Keywords Temporal reasoning · Fuzzy constraints

Introduction

In the identification of ill-known diseases, the temporal evolution of the symptoms is one of the most important aspects. Very often information about a new disease is imprecise and vague, due to the fact that the disease itself is hardly recognized by studying the symptoms of the patients.

In general, as medical data and processes are dependent on time and are affected by vagueness and uncertainty, it is difficult to model them by means of purely mathematical and analytical methods. The fuzzy-set based approaches can be regarded as the most suitable ones to deal with imprecise medical data especially when epidemiological studies cannot be developed due to the lack of statistical data. These approaches allow one the ease of expression offered by symbolic models avoiding the unwieldiness of analytical alternatives, bridging the gap between the discrete world of reasoning and the continuity of reality (Steimann 2001; Abbod et al. 2001). Two worth noting examples are the application of Possibilistic Temporal Reasoning based on Fuzzy Temporal Constraint for the diagnosis of Brucellosis (Godo and Vila 2005) and the approach proposed in Wainer and Sandri (1999) to solve the problem of poisonous mushrooms intoxication.

Dealing with the design of temporal reasoning systems, another important point concerns the development of interfaces allowing the user to describe, for example in the medical domain, the temporal knowledge about the evolution of a disease in terms of constraints; in this case there may be the need to express a wide range of temporal references for the description of the symptoms (Augusto 2005). Moreover, the management of vague input is particularly important when information is told from human memory, as in the case of patients reports about symptoms, since human perception of time elapsing may be frequently imprecise (Barro et al. 1994). Human reasoning about uncertainty is often poorly coherent, while an automated system endowed with an appropriate user interface could guarantee a homogeneous treatment of vague data. This should help the work of the physician who often has to interpret the description of a patient or to identify the appearing of a new disease detecting its typical patterns.

This paper deals with an application of a temporal model based on the Fuzzy Temporal Constraint Networks paradigm (Dubois et al. 1996; Godo and Vila 2005). Temporal information coming from the domain may be both qualitative such as "the interval I_1 with fever precedes the interval I_2 with cough" or metric such as "fever lasts one day" or mixed such as "symptom m_2 follows symptom m_1 and starts at 8pm".

S. Badaloni · M. Falda (✉)
Department of Information Engineering, University of Padova, via Gradenigo 6, Padova 35131, Italy
e-mail: marco.falda@unipd.it

S. Badaloni
e-mail: silvana.badaloni@unipd.it

To cope with different types of fuzzy temporal information, the Fuzzy Temporal Reasoning System (FTR System) (Badaloni et al. 2004) has been developed by integrating the IA^{fuz} approach (Badaloni and Giacomin 2006), that is an extension of Allen's Interval Algebra (Allen 1983), with the representation of metric temporal information. This system has been applied to different domains, for example Satellite Scheduling (Badaloni et al. 2007b).

We consider a set of medical data concerning the temporal evolution of symptoms of different patients affected by an unknown or ill-known disease (presumably Severe Acute Respiratory Syndrome - SARS) (Poutanen et al. 2003) and we represent them as a temporal scheduling problem. Once modelled such data in the fuzzy constraint temporal network, we propose a method based on the application of our FTR System for abstracting general temporal features characterizing the disease, if they exist (namely the incubation period). The modelling of SARS disease was considered in a previous paper (Badaloni and Falda 2006b); here we enhance the interaction with the user. To this aim we propose a new architecture for the FTR System including a user interface, focusing our attention on the translation of fuzzy metric temporal constraints into a special language able to model all the trapezoidal possibility distribution shapes managed by FTR.

Section "Qualitative and metric constraints" describes our approach to integrate temporal information in presence of vagueness and uncertainty in the FTR System, section "Design of the interface" introduces the architecture proposed, section "Application to medical diagnoses" defines the medical problem under study (SARS), and reports the considered temporal data showing how the problem can be modeled.

Qualitative and metric constraints

Our integration model (Badaloni et al. 2004) is able to deal with qualitative and metric fuzzy constraints: let's describe these components.

Qualitative constraints

The most common approach to reason with qualitative temporal information is the Allen's Interval Algebra (Allen 1983); in this algebra each constraint is a binary relation between a pair of intervals, represented by a disjunction of *a atomic relations*:

$$I_1\ (rel_1, \ldots, rel_m)\ I_2$$

Each rel_i is one of the 13 mutually exclusive atomic relations that may exist between two intervals (such as *equal*, *before*, *meets* etc.).

Allen's Interval Algebra has been extended in Badaloni and Giacomin (2006) with the Possibility Theory (Dubois et al. 1996) by assigning to every atomic relation rel_i a degree α_i, which indicates the *preference degree* of the corresponding assignment among the others

$$I_1 R I_2 \text{ with } R = (rel_1[\alpha_1], \ldots, rel_{13}[\alpha_{13}])$$

where α_i is the preference degree of rel_i ($i = 1, \ldots, 13$); preferences are defined in the interval [0, 1]. An example of an IA^{fuz} constraint is

$$I_1(b[0.5], m[1.0], eq[0.3])I_2$$

The classic approach is re-obtained if we take the set {0, 1} instead of the interval [0, 1].

Intervals are interpreted as ordered pairs $(x, y) : x \leq y$ of $\Re^2$, and soft constraints between them as fuzzy subsets of $\Re^2 \times \Re^2$ in such a way that the pairs of intervals that are in relation rel_k have membership degree α_k.

If temporal entities are points, the Point Algebra (Vilain et al. 1989) and its fuzzy extension (Badaloni and Giacomin 2006) can be used; in this algebra the set of the atomic relations is $\{<, =, >\}$, and it is possible to assign a preference degree to each atomic relation as in the case of IA^{fuz}, obtaining a fuzzy point algebra (in the following simply PA^{fuz}). For example, given two temporal points P_1 and P_2 a PA^{fuz} relation could be written as

$$P_1\{< [0.5], = [1.0], > [0.3]\}P_2$$

representing the fact that we prefer that P_1 happens when P_2 happens, but it could also be acceptable that P_1 precedes P_2 or P_1 follows P_2. As shown in Dubois et al. (1996), preference degrees can be interpreted as possibility degrees or uncertainty among the atomic relations involved.

For the classical case in which temporal information is not affected by uncertainty and vagueness, a Qualitative Algebra QA that includes all the combinations that can occur between temporal points and intervals has been defined in Meiri (1996). It contains the Point Algebra PA, the Interval Algebra IA and the Point–Interval algebra PI, referring to point–point, interval–interval and point–interval relations. In order to build the fuzzy Qualitative Algebra QA^{fuz}, we have considered the corresponding fuzzy extensions PA^{fuz}, IA^{fuz} (Badaloni and Giacomin 2006) and PI^{fuz} (Badaloni et al. 2004).

Metric constraints

As far as temporal metric information is concerned, traditional temporal constraint satisfaction problems (TCSPs) (Dechter et al. 1991) have been extended to the fuzzy case by several authors (Barro et al. 1994; Godo and Vila 2005; Keravnou 2002). In most cases trapezoidal distributions have been used, since they are enough expressive and do not require expensive computations. We adopt generalized trapezoidal distributions: each trapezoid is represented by a 4-tuple of values describing its four characteristic points plus a degree of consistency α_i denoting its height.

$$T_k = \ll a_k, b_k, c_k, d_k \gg [\alpha_k]$$

with $a_k, b_k \in \Re \cup \{-\infty\}$, $c_k, d_k \in \Re \cup \{+\infty\}$, $\alpha_k \in (0, 1]$, $\ll$ is either (or [and $\gg$ is either) or].

The points b_k and c_k determine the interval of those temporal values which are more plausible, whereas a_k and d_k determine the interval out of which the values are absolutely impossible. The effective translation of $\ll$ and $\gg$ is not completely arbitrary, but it is constrained by rules that lead to build well-formed trapezoids (Badaloni et al. 2004).

In this way the usual trapezoids can be modeled, but they can be further generalized by combining the previous rules; for example to represent the sentence "before *d*" we can use the trapezoid $(-\infty, -\infty, c_i, d_i)[\alpha_i]$ which is more precise than $(-\infty, -\infty, d_i, d_i][\alpha_i]$ = "not after *d*". We can also model temporal events which are less prone to an easy natural language interpretation, as for instance a triangle that excludes the right extreme:

$$(a_i, a_i, a_i, d_i)[\alpha_i]$$

Using generalized trapezoids the expressiveness of the language for metric constraints is increased with respect to the work in Barro et al. (1994). In that work, where a language for the representation and the manipulation of temporal entities is proposed, only normalized trapezoids are considered. Besides, generalized trapezoids considered in this paper allow us to integrate qualitative constraints, as it will become clear in the following.

Let's show a more significant example and consider the following sentence:

> "The third molars *usually* appear between the ages of 16 and 24"

By setting the "origin of time" on the birth of a person and assuming a time granularity of years, we can model this sentence as

$$T : \{(16, 24, +\infty, +\infty)[0.7]\}$$

In Fig. 1 its graphical representation is shown.

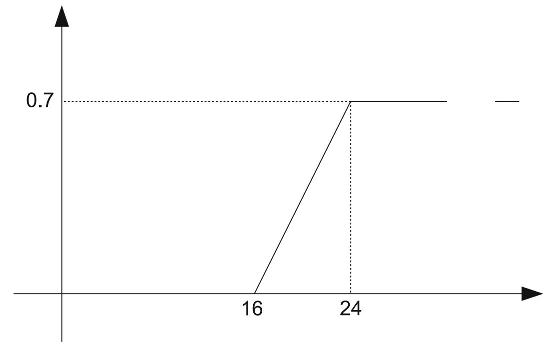


Fig. 1 Example of trapezoidal possibility distribution

The RTF solver

Following the idea proposed in Meiri (1996) for classical temporal constraints, we have designed a solver that can manage temporal networks where nodes can represent both points and intervals, and where edges are accordingly labeled by qualitative and quantitative fuzzy temporal constraints. A more detailed description of our approach can be found in Badaloni et al. (2004). Fuzzy qualitative constraints and fuzzy metric constraints have been integrated together in a single framework defining two transformation functions $QUAN^{fuz}$ and $QUAL^{fuz}$ that allow switching from the qualitative to the metric plane and vice versa. In the conversion from the metric to the qualitative plane any metric constraint that represents a positive distance between temporal events is transformed into the "before" qualitative constraint, any constraint that represents a negative distance is transformed in the "after" qualitative constraint; null metric distances correspond to "equals" qualitative constraint. It is not difficult to see that in this way a lot of information is lost. On the other hand, nothing is lost in the inverse conversion, in fact each atomic PA relation is transformed into a semi-axis or a point (see also (Meiri 1996) for details). For this reason, when the constraints to be represented are of different nature, the operations between qualitative and metric constraints are made, as far as possible, in the metric plane, in order to loose as less information as possible. There is a case however where it is not possible to remain in the metric plane; this happens when the composition operation involves a qualitative relation between a point and an interval. In this case it is necessary to transform the metric operand and to operate in the qualitative plane. Once the operations have been extended to the fuzzy case (Badaloni et al. 2004), usual algorithms to solve CSPs can be easily generalized; local consistency has been expressed as the degree of satisfaction which denotes the acceptability of an assignment with respect to the soft constraints involved in the relative sub-network. According to Dubois et al. (1996), this degree of satisfaction corresponds to the least satisfied constraint. Path-Consistency and Branch & Bound algorithms have been generalized to the fuzzy case adding some relevant refinements that improve their efficiency. Path-consistency allows to prune significantly the search space while having a polynomial computing time.

The constraint solver has been implemented in ANSI C++ and can be compiled in several Operating Systems; it has a console interface and reads constraint networks coded in XML format according to a specific XML Schema.

This interface is fast, simple and portable in several Operating Systems, but it is not user-friendly; for this reason we have developed an easier interface for specifying fuzzy constraints, focusing our attention on fuzzy metric constraints, since they are more complex than fuzzy qualitative constraints.

Design of the interface

Knowledge layers

The main purpose of the user interface is ease the input of the constraints, but it has two further advantages: first, it can guarantee coherence in the formalization of the fuzzy constraints, second, it can interpret the results computed by the constraint solver.

Qualitative temporal constraints have an interpretation that is easy to figure out by people, because they have been introduced in the context of Natural Language Processing (Allen 1983); therefore they can be directly presented to the users. Temporal metric constraints are instead far less intuitive and their expressiveness could be poorly exploited if they had to be translated into trapezoidal possibility distributions.

In order to keep the interface simple and precise, we limit the set of temporal sentences that the user can express, rather than trying to interpret all the possible (syntactically correct) sentences expressed in an unrestricted Natural Language.

The architecture of the interface, that stays between the user and the constraint solver, is composed by two levels: as shown in Fig. 2:

1. the "Knowledge Base Management";
2. the "User Interface Language".

The first level deals with the normalization of temporal information, for example:

- the translation of expressions like "yesterday" or "3pm" (DiCesare et al. 1990);
- the location of the "origin of time";
- the definition of a criterion to fuzzyfy in a consistent way all vague temporal expressions;
- the temporal granularity connected to the domain;
- the decomposition of complex scenarios into atomic facts which can be individually associated to a time point or interval.

At the moment the "Knowledge Base Management" level has been studied but not yet developed.

The second level has the role of translating a set of temporal sentences into qualitative and metric constraints and, vice versa, qualitative relations and well-formed trapezoids, representing metric constraints, into a set of temporal sentences. It will be discussed in the following sub-section.

The user interface language

Now, we deal with the representation of temporal metric information for which the help of a user interface is more suitable.

In Natural Language there is a neat distinction between punctual and durative expressions (Engelberg 1999): the former have to be used to specify timepoints in which events happen (e.g. "at 5pm"), the latter to specify durations of events (e.g. "it lasted 5 min"). Notice that punctual/durative and relative/absolute notions are orthogonal concepts, the former being implicit in the nature of the action; in fact, we can express any of the following four possible combinations:

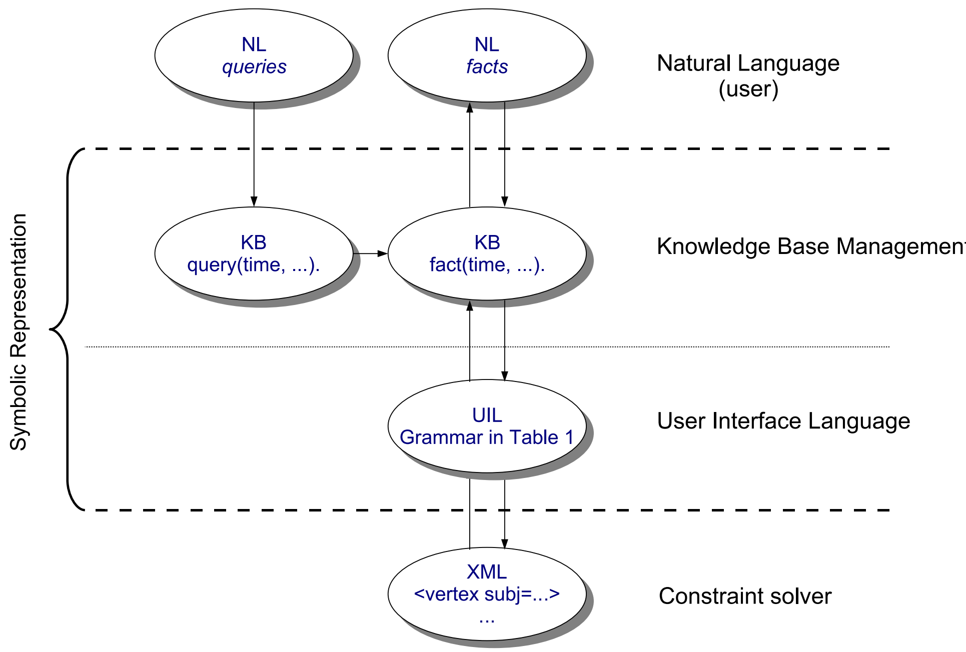
- punctual-absolute: "John will arrive at 12pm"
- punctual-relative: "John will arrive after about 2 hours w.r.t. Fred"
- durative-absolute: "The film will be more than about 2 hours long"
- durative-relative: "Film A lasts about 2 hours more than Film B"

The semantics of metric constraints described in section "Qualitative and metric constraints" refers to temporal distances between two events, thus expressing relative information, but if the "origin of time" is introduced then also absolute information can be specified. Our FTR System is able to represent the first three types of temporal information; the last type instead cannot be dealt using IA^{fuz} and a framework able to manage durations must be used, for example the INDU system (Pujari et al. 1999). In this system Allen's 13 interval relations are combined with relative durations of intervals expressed using PA; this leads to 25 atomic relations.

In Fig. 3 are reported the possible interpretations of the metric constraints. Cases a and b are dealt in a distinct way since they represent particular cases. In other cases trapezoids are decomposable in left and right parts which can be considered separately and interpreted as in Fig. 3. In Fig. 4 two examples of translations are reported.

We have defined the grammar generating the NL interpretations of Fig. 3. The set of the productions is reported in Table 1, where the symbol "::=" separates the head of the rules from their body, "|" delimits the mutually exclusive options delimited by "{ }", and "< >" indicates a non-terminal element; ϵ stands for a void terminal symbol.

Fig. 2 Knowledge layers



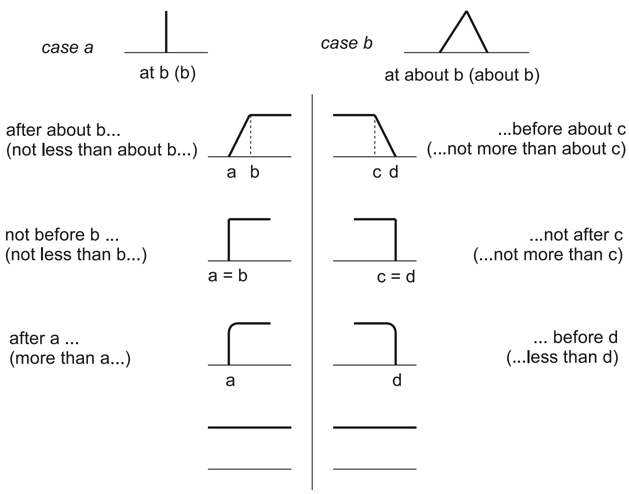


Fig. 3 Natural Language interpretation of metric constraints (in parentheses the durative expressions)

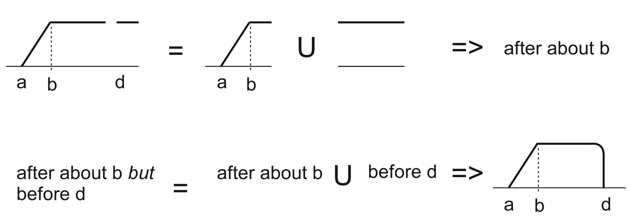


Fig. 4 NL interpretation of a fuzzy metric constraint and vice versa

Application to medical diagnoses

The SARS case

SARS is a kind of pneumonia spread from Far East in 2003; in that period it was not well understood, in particular the temporal evolution of its symptoms. One of the first papers written in that period (Poutanen et al. 2003) was about the cases in Toronto and studied also the dynamics of SARS. We will take into account only four patients of ten (Patients 1, 2, 7 and 8), because they are better described from the temporal point of view. In this study the scenario has been simplified, but it is sufficient to show the flexibility of the constraints that can be used to model a problem; the system can be applied to tens of patients thus outperforming a human analysis in terms of coherence and consistency.

The starting point is the natural language description reported in (Poutanen et al. 2003).

> The Toronto index case(Patient 1) and her husband traveled to Hong Kong to visit relatives from February 13 through February 23, 2003. They returned to their apartment in Toronto on February 23, 2003. Patient 1, a 78-year-old woman, had fever, anorexia, myalgias, a sore throat, and mild nonproductive cough two days after returning home. Two days later, she noted the development of increasing cough with dyspnea. She died three days later, on March 5, at home, nine days after the onset of her illness.
>
> The index patient's 43-year-old son (Patient 2), had fever and diaphoresis on February 27. Within approximately five days he became afebrile, but concurrently, a nonproductive cough, chest pain, and dyspnea developed. Because of persistent symptoms, 4 days later he was assessed at a hospital and noted to have a fever (temperature, 39.8°C) and an oxygen saturation of 82% while breathing room air. Despite intensive physiological support, multiorgan dysfunction syndrome developed, and he died on March 13,

Table 1 Grammar for the language of metric constraints

$< S >$	::=	$\{< ABS > \mid < REL >\}$
$< ABS >$	::=	$\{< ONE\_T_A > \mid < TWO\_T_A >\}$
$< ONE\_T_A >$	::=	$\{< BA_1 > \mid < BA_2 > \mid < AT >\}$ number
$< BA_1 >$	::=	$\{< B\_NEG > \mid < A\_POS > \mid < A\_APPROX >\}$
$< B\_NEG >$	::=	$not < B\_POS >$
$< A\_POS >$	::=	$after$
$< A\_APPROX >$	::=	$< A\_POS > about$
$< BA_2 >$	::=	$\{< A\_NEG > \mid < B\_POS > \mid < B\_APPROX >\}$
$< A\_NEG >$	::=	$not < A\_POS >$
$< B\_POS >$	::=	$before$
$< B\_APPROX >$	::=	$< B\_POS > about$
$< AT >$	::=	$\{< AT\_POS > \mid < AT\_APPROX >\}$
$< AT\_POS >$	::=	$\{at \mid on\}$
$< AT\_APPROX >$	::=	$< AT\_POS > about$
$< TWO\_T_A >$	::=	$< BA_1 >$ number but $< BA_2 >$ number
$< REL >$	::=	$\{< ONE\_T_R > \mid < TWO\_T_R >\}$
$< ONE\_T_R >$	::=	$\{< ML_1 > \mid < ML_2 > \mid < IN >\}$ number
$< ML_1 >$	::=	$\{< LT\_NEG > \mid < MT\_POS > \mid < MT\_APPROX >\}$
$< LT\_NEG >$	::=	$not < LT\_POS >$
$< MT\_POS >$	::=	$more\ than$
$< MT\_APPROX >$	::=	$< MT\_POS > about$
$< ML_2 >$	::=	$\{< MT\_NEG > \mid < LT\_POS > \mid < LT\_APPROX >\}$
$< MT\_NEG >$	::=	$not < MT\_POS >$
$< LT\_POS >$	::=	$less\ than$
$< LT\_APPROX >$	::=	$< LT\_POS > about$
$< IN >$	::=	$\{< IN\_POS > \mid < IN\_APPROX >\}$
$< IN\_POS >$	::=	ϵ
$< IN\_APPROX >$	::=	$< IN\_POS > about$
$< TWO\_T_R >$	::=	$< ML_1 >$ number but $< ML_2 >$ number

2003, 6 days after admission, and 15 days after becoming ill.

As a result of media attention, three additional cases of SARS were identified. The first case was in a previously healthy 37-year-old female family physician of Asian descent (Patient 7) who saw Patient 2 and his wife on March 6, when they were both symptomatic. Patient 7 had a severe headache on March 9, followed by fevers (temperatures of up to 40°C), myalgias, and malaise. Four days later, a nonproductive cough developed, and she was noted to have fever (temperature, 38.5°C) and tachypnea with an oxygen saturation of 100% on room air.

The second additional identified case was in a 76-year-old man of non-Asian descent (Patient 8). Patient 8 was assessed in the emergency department on March 7 for atrial fibrillation and observed overnight on a gurney separated by a cotton curtain 1 to 2 meters from Patient 2. Patient 8 was discharged home on March 8, and two days later he had fever (temperatures of up to 40°C), diaphoresis, and fatigue. Despite receiving broad-spectrum antibiotics, oseltamivir, intravenous ribavirin, and intensive support, he died on March 21, 5 days after admission and 12 days after the onset of his illness.

The four patients were suspected to have SARS because they lived in the same apartment in Toronto and the symptoms were similar to those reported in Hong Kong, where Patient 1 spent a week before returning home in Toronto.

Our aim is to characterize the incubation period, that is the period between the contagion and the first symptoms. To do this, we take into account the period during which the disease could have been got, the fever (as initial symptom), the cough, the contagion and the death:

- Patient 1
  - in travel from February 13 to February 23;
  - 2 days later, fever;
  - 2 days later, cough;
  - 3 days later, death.
- Patient 2
  - February 25, fever;
  - 5 days later, cough;
  - 4 days later, admitted to the hospital.
  - 4 days later, death.
- Patient 7
  - March 6, visits Patient 2;
  - March 9, fever;
  - 4 days later, cough.

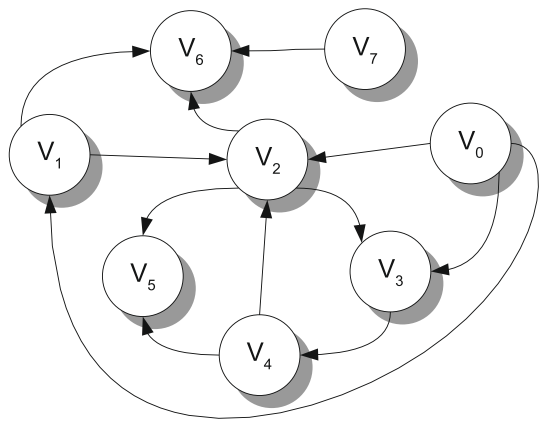


Fig. 5 Constraint Network example

- Patient 8
  - March 7, assessed in the emergency department near Patient 2;
  - March 8, discharged home;
  - 2 days later, fever;
  - 5 days later, death.

Temporal descriptions like these allow to build timetables for the four patients in exam (Figs. 6). Timetables have the aim to figure out a possible "origin of time" t_0 suitable for all the patients in the scenario to be described, in order to translate all the absolute time-points into relative distances to t_0; in fact metric constraints represent relative distances between temporal events, according to their semantics, and an "origin of time" is needed to express absolute constraints, as said in section "Design of the interface". Another purpose of the timetables is to transform all temporal expressions into multiples of uniform and conventional temporal units: in this problem the unit chosen is the "day".

Modelling a disease

Four distinct networks have been built for each patient, starting from the previous data. In a preliminary phase the symptoms common to all patients have been identified by the physicians. There are seven significant points plus an interval V_6, represented in the network in Fig. 5; V_6 is the period during which the disease could be got and in the following will be called I.

The network vertices and are identical in each network:

- V_0: t_0, the "origin of time";
- V_1: begin of I;
- V_2: end of I;
- V_3: fever;
- V_4: cough;
- V_5: death;
- V_6: the contagion interval;
- V_7: contagion.

The "origin of time" has been set by the user (or by the "Knowledge Base Management" level) on February 23, that is the day in which Patient 1 returned home and infected her family (the days in the past are expressed as negative numbers). The end of period I coincides, respectively, with the death, the admission to hospital, the discharge to home and the one-day medical visit.

The constraints that refer to a patient have been modelled by the user interface, assuming an uncertainty of half a day:

- V_1: on about -10

  $V_0\{[-10.5, -10, -10, -9.5]\}V_1$

- V_0 is equal to V_2 (this is a qualitative constraint)

  $V_0\{=\}V_2$

- $V_3 - V_2$: not less than about 1 but not more than about 3

  $V_2\{(1, 1.5, 2.5, 3)\}V_3$

- $V_4 - V_3$: about 1 – 3 (indirect translation)

  $V_3\{(1, 1.5, 2.5, 3)\}V_4$

- $V_5 - V_4$: less than about 3

  $V_4\{(-\infty, -\infty, 3, 4)\}V_5$

All these constraints are metric and are described, as said before, using a trapezoidal possibility distribution that sets the maximal plausibility to the assignments in the core between b and c, and states as impossible the values outside the range (a, d).

Moreover, we need additional constraints in each patient's network to represent the following facts:

1. the contagion must be before the first symptom;
2. the I period is characterized by a begin and an end;
3. the contagion must be contained in period I:

$$V_7\{<\}V_3,\ V_6\{si\}V_1,\ V_6\{fi\}V_2,\ V_7\{d, s, f\}V_6$$

Notice that these are qualitative constraints having a degree of preference equal to 1, as here they are used only to link qualitative intervals with metric points. Another purpose of the "Knowledge Base Manager" level could be the homogeneous treatment of qualitative and metric constraints, in

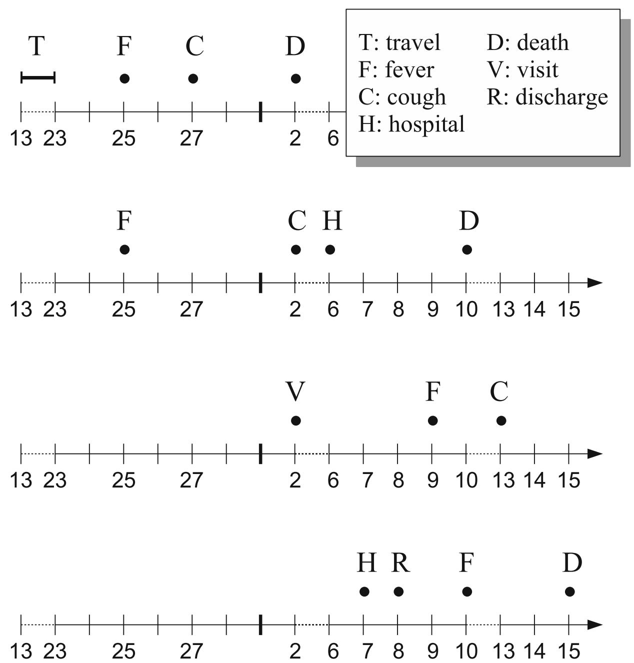


Fig. 6 Timelines for the patient's data

order to present the integration in terms of binary constraints based on Basic Temporal Relations (Schwalb and Vila 1998).

Solving the networks

From the minimal network we obtain the following incubation estimates in terms of constraints between the contagion V_7 and the fever V_3, being P_i the patients

- $P_1: V_3\{(-13.5, -12, -1, -1.0)\}V_7$
- $P_2: V_3\{(-4.5, -4.0, 0.0, 0.0]\}V_7$
- $P_7: V_3\{(-4.5, -3.5, -2.0, -1.0)\}V_7$
- $P_8: V_3\{(-5.0, -3.5, -1.5, -1.0)\}V_7$

The user interface translates the previous results as follows:

P_1: $V_7 - V_3$ not less than about 1 but not more than about 12;
P_2: $V_7 - V_3$ not less than 0 (i.e. "immediately after") but not more than about 4;
P_7: $V_7 - V_3$ not less than about 2 but not more than about 3.5 (or "about 2–3.5");
P_8: $V_7 - V_3$ not less than about 1.5 but not more than about 3.5 (or "about 1.5–3.5").

The temporal scheduling of P_1 symptoms are reported in Fig. 7, the period I is represented as a hatched rectangle and the incubation period as an interval between the begin of the period I and the onset of the first symptom. Schedulings for other patients are in Figs. 8, 9 and 10.

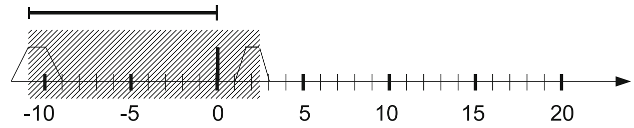


Fig. 7 Evolution in patient 1

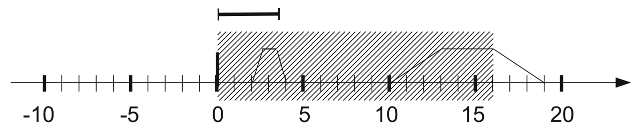


Fig. 8 Evolution in patient 2

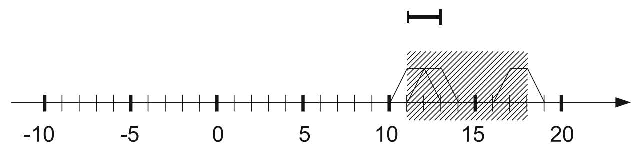


Fig. 9 Evolution in patient 7

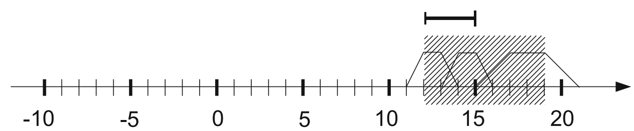


Fig. 10 Evolution in patient 8

The real incubation period is obtained, in our case, from the intersection of the estimated periods concerning the four patients and it is equal to about 2-4 days. In this case the deduction has been not too difficult, but in a more realistic scenario with a lot of temporal data to analyze an automated reasoning system could be very helpful for a physician that has to figure out the temporal evolution of the symptoms of a new disease; a step in this direction is the work in Falda (2007). Besides, a more robust technique should take into account the weight of data coming from different sources in order to reduce the influence of less common cases (possibly wrong).

The task of finding the minimal network is, in general $\mathcal{NP}$-complete. In our example constraints without disjunctions were enough to model the scenario, therefore in this particular case a polynomial Path-Consistency algorithm was sufficient. We are studying the complexity of QA^{fuz} in order to provide a more expressive set of qualitative constraints (Badaloni and Falda 2006a; Badaloni et al. 2007a), relying on well known results for the metric ones (Dechter 2003).

Conclusions

In (Badaloni and Falda 2005) we proposed a first application of our Fuzzy Temporal Reasoning System in the medical domain addressing the problem of recognizing an exanthematic disease starting from the approximated knowledge of the temporal sequence of its symptoms and from the imprecise data coming from a patient's description.

In the present paper we have considered the problem of the diagnosis from a different point of view. From a set of data concerning the temporal evolution of symptoms of different patients affected by an unknown or ill-known disease (presumably Severe Acute Respiratory Syndrome - SARS) (Poutanen et al. 2003) represented in a Fuzzy Constraint Temporal Network, it is possible to infer all the temporal relations between the significant symptoms of the disease. Thus, a characterization of the temporal durations of the most typical symptoms can be obtained.

This application can support the physician to obtain a better knowledge about ill-known diseases aiding him to deduce temporal evolution. Moreover, the user interface described in this paper allows the physician to specify and to interpret fuzzy temporal information.

As future work we intend to complete the work on the interface developing the "Knowledge Base Management" module. In order to make the system more useful a possible enhancement can be the management of constraint classes as proposed in (Falda 2007). Constraint classes allow for representing a set of temporal problems in a more compact way and share common subnetworks; therefore it will be possible to merge automatically the deduced durations in order to identify the most plausible one.

References

Abbod, M. F., von Keyserlingk, D. G., Linkens, D. A., & Mahfouf, M. (2001). Survey of utilization of Fuzzy Technology in Medicine and Healthcare. *Fuzzy Sets and Systems, 120*, 331–349.

Allen, J. F. (1983). Maintaining knowledge about Temporal Intervals. *Communications of the ACM, 26*(1), 832–843.

Augusto, J. C. (2005). *Temporal reasoning for decision support in medicine*.

Badaloni, S., & Falda, M. (2005). Discriminating exanthematic diseases from temporal patterns of patient symptoms. *Proceedings of the 10th Conference of Artificial Intelligence in Medicine (AIME 2005)* (pp. 33–42). Edinburg.

Badaloni, S., & Falda, M. (2006a). About tractability of fuzzy temporal qualitative algebra QA^{fuz}. *Proceedings of IPMU 2006* (pp. 45–48). Paris.

Badaloni, S., & Falda, M. (2006b). Temporal characterization of ill-known diseases. *Proceedings of the International Workshop on Intelligent Data Analysis in Biomedicine and Pharmacology* (pp. 17–22). Verona.

Badaloni, S., & Giacomin, M. (2006). The algebra IA^{fuz}: a framework for qualitative fuzzy temporal reasoning. *Artificial Intelligence, 170*(10), 872–908.

Badaloni, S., Falda, M., & Giacomin, M. (2004). Integrating quantitative and qualitative constraints in fuzzy temporal networks. *AI Communications,17*(4),183–272.

Badaloni, S., Falda, M., & Giacomin, M. (2007a). Fuzzy extensions of qualitative algebra tractable fragments. *Proceedings of the Workshop on Spatial and Temporal Reasoning* (pp. 11–15). Hyderabad.

Badaloni, S., Falda, M., & Giacomin, M. (2007b). Solving temporal over-constrained problems using fuzzy techniques. *Journal of Intelligent and Fuzzy Systems, 18*(3), 255–265.

Barro, S., Marín, R., Mira, J., & Paton, A. (1994). A model and a language for the fuzzy representation and handling of time. *Fuzzy Sets and Systems, 175*, 61–153.

Dechter, R. (2003). *Constraint processing*. San Mateo, CA: Morgan Kaufmann.

Dechter, R., Meiri, I., & Pearl, J. (1991). Temporal constraint networks. *Artificial Intelligence, 49*, 61–95.

DiCesare, F., Sahnoun, Z., & Bonissone, P. P. (1990). Linguistic summarization of fuzzy data. *Information Sciences, 52*, 141–152.

Dubois, D., Fargier, H., & Prade, H. (1996). Possibility theory in constraint satisfaction problems: Handling priority, preference and uncertainty. *Applied Intelligence, 6*, 287–309.

Engelberg, S. (1999). "Punctuality" and verb semantics. *23rd Annual Penn Linguistics Colloquium* (pp. 127–140).

Falda, M. (2007). Disjunctive temporal problem with classes. *Proceedings of FUZZ-IEEE'07* (pp. 1812–1817). London.

Godo, L., & Vila, L. (2005). Possibilistic temporal reasoning based on fuzzy temporal constraints. *Proceedings of IJCAI95* (pp. 1916–1922). Montreal.

Keravnou, E. T. (2002). Temporal constraints in clinical diagnosis. *Journal of Intelligent and Fuzzy Systems, 12*(1), 49–67.

Meiri, I. (1996). Combining qualitative and quantitative constraints in temporal reasoning. *Artificial Intelligence, 87*, 343–385.

Poutanen, S.M., Low, D. E., Henry, B., Finkelstein, S., Rose, D., Green, K., et al. (2003). Identification of severe acute respiratory syndrome in Canada. *The New England Journal of Medicine, 348*(20), 1995–2005.

Pujari, A. K., Kumari, G. V., & Sattar, A. (1999). INDU: An interval and duration network. *Australian Joint Conference on Artificial Intelligence* (pp. 291–303). Sydney.

Schwalb, E., & Vila, L. (1998). Temporal constraints: A survey. *Constraints: an International Journal, 2*, 129–149.

Steimann, F. (2001). On the use and usefulness of fuzzy sets in medical AI. *Artificial Intelligence in Medicine, 21*, 131–137.

Vilain, M., Kautz, H., & van Beek, P. (1989). Constraint propagation algorithms for temporal reasoning: A revised report. D. S. Weld, J. de Kleer (Eds.), *Readings in qualitative reasoning about physical systems*. San Mateo, CA: Morgan Kaufmann (pp. 373–381).

Wainer, J., & Sandri, S. (1999). Fuzzy temporal/categorical information in diagnosis. *Journal of Intelligent Information Systems, 11*, 9–26.