Temporal Constraints Approximation from Data about Medical Procedures

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Abstract

Proposing a treatment to patients is one of the physicians' most common tasks. There are different elements that influence the decision of a physician to propose an appropriate treatment. Formal intervention plans (FIPs) are formal structures representing health care procedures to assist patients suffering from particular ailments or diseases. The introduction of temporal constraints in FIPs is a difficult task that physicians are not used to. This difficulty can be overcome with mechanisms to generate temporal constraints directly from the existing data on patient treatments. We have chosen the SDA formalism to represent FIPs. Here, our objective is to approximate time constraints from patient state transition sequences and as a generalization of the times assigned to each transition (or patient evolution). This approximation is used to construct the time dimension of FIPs.*

1. Introduction

Medical treatments can be described as sequences of medical actions as observe signs and symptoms, or order interventions, prescriptions, tests, etc., that a physician performs on a particular patient. There are different elements that may influence the physician to decide on an appropriate treatment: being aware of similar clinical cases, knowing about the advances in the treatment of a particular disease, using information computer systems, etc.

In order to keep track of all the advances on a particular disease, *Clinical Practice Guidelines (CPGs)* are published to gather all this knowledge as statements that assist physicians to make appropriate healthcare decisions. They use to cover health maintenance, prevention, diagnosis, treatment, patient self-care and education. CPGs are a set of plans for the management of patients who have a particular disease [5].

CPGs contain the health care knowledge that Formal Intervention Plans (FIPs) [2] use to represent health care procedures to assist patients suffering from one or several ailments or diseases. There are different languages to represent FIPs in a formal way: PROforma [6], Asbru [1], EON [7], SDA* [2], etc. Some of them are very complete from a medical point of view and therefore difficult to manage by untrained physicians (e.g. Asbru or EON), some are oriented to the description of health care activities as processes (e.g. Asbru) rather than as an explicit representation of the treatment as an explicit procedure, and some others are limited in the representation of time (e.g. PROforma). Among them, SDA* is the formalism for FIPs representation that better meets all the requirements of simplicity and time representation that our work requires. SDA* stands for state-decision-action notation and it represents FIPs as SDA* diagrams, each diagram containing nodes of the sorts state, decision or action. See an example in Figure 1. *Action nodes* describe as squares medical orders concerning medication and clinical procedures that are recommended to perform, maintain or avoid. *Decision nodes*

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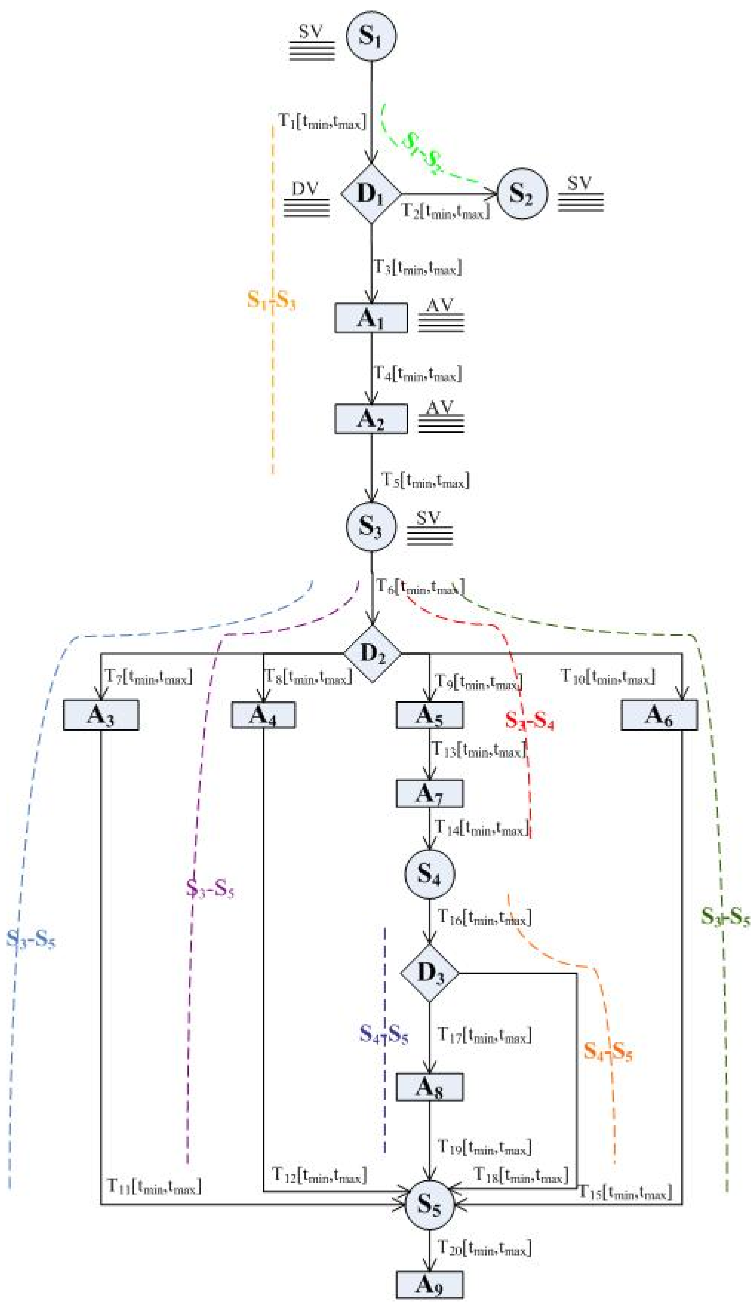
represent with rhombuses points of branching that allow alternative clinical treatments considering weather a patient fulfils a condition or not. *State nodes* indicate patient health descriptions as circles [5]. In a SDA* diagram, action orders, decision conditions and state descriptions are represented with terms. Besides a set of terms and the corresponding values, states, decisions and actions may contain a time constraint for each term.

SDA* representation of FIPs can be provided by medical institutions as guidelines for making appropriate health care decisions considering patient treatment (*explicit* FIPs), or as a representation of the treatments delivered to a group of patients and stored as a set of data in the hospital databases (*implicit* FIPs) [3]. Very often, FIPs are *timeless*, which means that there is not an explicit time labelling of terms because either physicians have difficulties



S_1: Symptoms, physical findings of Atrial Fibrillation, Atrial Flutter or incidental ECG finding

S_2: Out of guideline

S_3: Patient stabilized

S_4: Recurrent Atrial Fibrillation controlled

S_5: Atrial Fibrillation or Atrial Flutter controlled

D_1: ECG confirms Atrial Fibrillation and/or Atrial Flutter?

D_2: First detected episode of Atrial Fibrillation, duration known < 48 hours or
first detected episode of Atrial Fibrillation, duration known ≥ 48 hours or unknown duration or
recurrent Atrial Fibrillation or
recurrent Atrial Flutter?

D_3: Symptoms adequately controlled?

A_1: Hemodynamic stabilization and acute rate control

A_2: Assessment of potentially reversible causes, comorbidities, risk factors for thromboembolism and bleeding, special situations

A_3: Observation, DC or Antiarrythmics cardioversion

A_4: Anticoagulation and cardioversion, or chronic rate control and chronic anticoagulation

A_5: Chronic rate control

A_6: Electrophysiology consult

A_7: Assessment for chronic anticoagulation – risk of thromboembolism and bleeding

A_8: Intermittent cardioversion, antiarrythmics or electrophysiology consult

A_9: Patient education

Figure 1: Formal Intervention Plan for Atrial Fibrillation

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defining general time constraints for some diseases or there is none mechanism which would help us to explicitly obtain temporal constraints for FIPs. Fortunately, data saved in hospital databases are primarily time dependent and therefore they can be used to obtain time constraints for FIPs.

So, our proposal is to approximate time constraints considering patients' data of a particular disease for timeless FIPs represented as SDA* diagrams. Patients' data should be in the form of sequences of *state transitions* with indications on the elapsed time between consecutive states in the evolution of the patients. Here, time constraints will be represented as *time intervals* for the connectors between the states, the decisions, and the actions of the SDA* diagram. These constraints may be accepted by physicians or be the starting point for them to refine the time dimension of FIPs.

The rest of the paper is divided into four main sections. In section 2 a brief introduction to SDA* notation of FIPs and the sort of time constraints this representation admits are provided. Section 3 describes the data and the statistical models that sustain the process of generating time constraints in the FIP. Section 4 contains the conclusions of the work and some future extensions. Section 5 is for acknowledgements and section 6 for the references.

2. Time constraints in medical treatments

SDA* is a formalism to represent FIPs [2]. In the SDA* model, states represent each relevant condition in which a patient can be found. Each *state node* contains the set of terms which represent the signs and the symptoms of a particular patient at the moment of making an observation; *decision nodes* provide decision criteria to derive the treatment in one or other direction considering the patient's current signs and symptoms, and *action nodes* represent the activities which should be taken as a result of an earlier made decision.

For each disease D, $T_D = \{t_1, t_2, \ldots, t_n\}$ represents a set of terms related to D. These terms can be state, decision or action terms depending on whether they are able to be involved in the description of a SDA* state, decision or action, respectively. $SV \subset T_D$ is the set of *state terms* that are used to determine the condition of a patient considering some disease. $DV \subset T_D$ is the set of *decision terms* that can be used to derive the treatment to some or some other medical actions. $AV \subset T_D$ is the set of *action terms* representing the individual medical actions a physician may prescribe in the treatment of the disease the SDA* diagram represents. See for example, *atrial fibrillation* treatment [4] in Figure 1.

FIPs as SDA* diagrams determine two sorts of temporality: micro-temporality and macro-temporality. *Micro-temporality* is assigned to the terms in T_D and it affects states, actions and decisions. It is represented as a triplet $[s_t, e_t, f_t]$ on the term $t \in T_D$; where s_t stands for the start time of t, e_t for the ending time, and f_t for the frequency. For example, if we are observing the term *persistent-headache* (*PH*) with temporal values [*1M, 2d, 12h*] in a SDA* state or condition it would mean that *PH* was part of the patient condition since one month (*1M*) ago and till two days (*2d*) ago, and that *PH* was observed every twelve hours (*12h*). Micro-temporality in action terms would mean that the action must start after s_t time till e_t units of time have passed, and that the application of the action the term represents has a frequency f_t (e.g. take *antimigrainous-agent* for two weeks every eight hours would have a macro-temporality [-, *2w*, *8h*]).

The other type of temporality that we have identified is *macro-temporality*. This time constraint is related to the connectors between nodes in the SDA* diagrams (see T_1, T_2, etc. in Figure 1). For each connector C_{ij} of the SDA* diagram we define macro-temporality as an interval $[t_{min}, t_{max}]$, where t_{min} stands for the minimum time that has to pass before the treatment evolves from the i-th node to the j-th node of the SDA* diagram, and t_{max} stands for maximum time possible before that evolution happens. Notice that [t_{min}, t_{max}] intervals denote time constraints which have to be fulfilled before the treatment of the patient proceeds with the next node of the SDA* diagram.

3. Approximation of time constraints for FIPs

Despite the relevance of micro-temporality, this paper is exclusively concerned with SDA* time constraints in the form of macro-temporality. Our primary goals are to generate macro-temporalities from a provided set of temporal data and to introduce them in a FIP. Input data will follow a particular *data model* to represent sequences of state transitions of the patients under study, and FIPs will be timeless structures representing health care treatments as SDA* diagrams in which different connectors exist: connectors whose starting node is a state (C_{SS}, C_{SD}, C_{SA}), a decision (C_{DS}, C_{DD}, C_{DA}) or an action (C_{AS}, C_{AD}, C_{AA}).

3.1. The data model

Health care is based on the concept of encounter. In this context, an *encounter* is defined as a meeting between a health care professional and a patient in order to *assess the patient's condition and to determine the best medical course of action*. For each encounter, a common practice is to take down the current patient condition (i.e. signs and symptoms) together with the actions derived from the visit (e.g. prescriptions and other medical orders).

The health evolution of a patient can be seen as the sequence of state transitions of the patient through different encounters. So in the *i*-th encounter, a patient P_k is in state S_i^k (described by the observed state terms) and, optionally, receives a *state-caused* treatment A_i (described by the action terms the physician orders). The time between this encounter and the next one is $t_{i\,i+1}$. Very often, among all the possible states a patient can be, only some of them have a meaningful health sense and, hence, some of the patient states in the sequence may be removed (we call them *implicit* states) causing the sequence to have several consecutive state-caused treatments with none intermediate states (see implicit states in Figure 2).

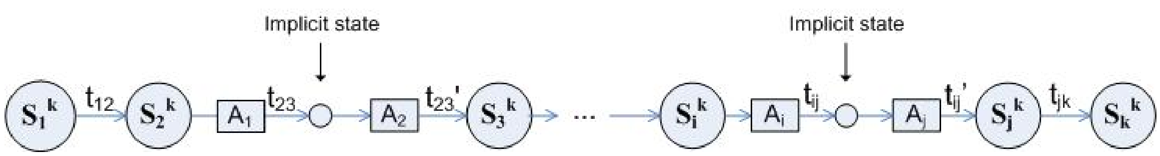

Figure 2: Sequence of state transitions for patient k

The sequences of state transitions of all the patients affected by (and treated of) a particular disease define a data model that describes the input data.

For a particular disease, if the *explicit* states in the data model is the same that the states in the FIP describing the treatment of that disease, then each state-to-state transition of a sequence represents an instance of the sort of patient evolving between two consecutive states in the SDA* diagram. For example, a specific patient with *atrial fibrillation* who evolves from state S_1 (i.e. analysis of the patient symptoms) to S_3 (i.e. stabilized patient) in consecutive visits is a case in Figure 1 that evolves along the dotted line labelled S_1-S_3.

3.2. The meaning of SDA* connectors

In a SDA*diagram the meaning of node connectors can vary according to the sort of nodes the connectors have as starting and ending elements. So, C_{SS}, C_{SD}, and C_{SA} are the names given to connectors going from a state node to a state node, to a decision node or to an action node, respectively; C_{DS}, C_{DD}, and C_{DA} are the names of the nodes going from decision nodes to other nodes, and C_{AS}, C_{AD}, C_{AA} the names of the connectors that start at an action node.

When an SDA* diagram is used to represent a generalization of the sequences of state transitions of several patients, the above connectors have the meanings in Table 1.

Table 1: Meaning of SDA* connectors.

C_{SS}	The physician is not providing a state-caused treatment in a visit (e.g. waiting is the best option).
C_{SD}	Alternative treatments have been observed for patients in a state and a distinction between them is needed (e.g. there is a differential treatment for young and elder patients in the same state).
C_{SA}	All the patients in a state have received the same state-caused treatment.
C_{DS}	Some patients in a state (but not all of them) have received none state-caused treatment (e.g. the application of therapy to a particular type of patient is riskier than waiting or doing nothing).
C_{DD}	The application of a state-caused treatment requires several prior verifications (e.g. alternative treatments depending on several conditions of the patient).
C_{DA}	Some patients in a state (but not all of them) have received a given state-caused treatment.
C_{AS}	Some patients that have received a state-caused treatment evolve to a next state.
C_{AD}	A state-caused treatment makes the patients evolve to an implicit state that in the next encounter some of them deserve another state-caused treatment (e.g. after some actions on a patient several alternative treatments are possible depending on some new information or on some changes in the evolution).
C_{AA}	A state-caused treatment makes the patients evolve to an implicit state that in the next encounter all of them deserve another state-caused treatment (e.g. all the patients that during a visit are prescribed a treatment that make them all, in the next visit, both evolve to non-interesting states and deserve the same common treatment).

Macro-temporality constraints in the form of $[t_{min}, t_{max}]$ intervals affect to some of the above sort of connectors: C_{SS}, C_{AS}, C_{AD}, and C_{AA}; but not to the rest, for which they are defined as the constant [0, 0] (i.e. lack of delay or instantaneous transition).

In C_{SS} connectors, macro-temporality is obtained from the times between consecutive encounters in which the patient has not received any treatment as a consequence of the first encounter (see, for example, times t_{12} and t_{jk} of transitions $S_1^k \rightarrow S_2^k$ and $S_j^k \rightarrow S_k^k$ in Figure 2). In C_{AS} connectors, macro-temporality is calculated from the times between consecutive encounters in which, during the first encounter the physician ordered the actions A, and in the second encounter the patient had evolved to state S (see, for example, times t_{23}' and t_{ij}' in the edges $A_2 \rightarrow S_3^k$ and $A_j \rightarrow S_j^k$ in Figure 2). Finally in C_{AD} and C_{AA} connectors, macro-temporality is a combination of the times between consecutive encounters in which a treatment was proposed during the first visit and the state of the patient in the second visit is implicit, i.e. lacking of medical interest; (see, for example, times t_{23} and t_{ij} in the edges departing form A_1 and A_i in Figure 2).

The difference in the macro-temporalities of C_{AD} and C_{AA} connectors is in the fact that the first one is applied when *not* all the patients in encounters with the same implicit state receive the same state-caused treatment (i.e. in Figure 2, A_2 is the same for all the patients if they arrive in the first implicit state in some encounter and A_j is identical for all the patients arriving in the second implicit state). On the contrary, if all the patients that show sequences of state transitions in which the same implicit state (i.e. the state description of the patient during the encounter) is always followed by the same state-caused treatments, then a decision node will not be needed in the SDA* diagram that will connect two consecutive action nodes.

3.4. The statistical model

Considering the data model described in section 3.1, for each pair of consecutive (*explicit* and/or *implicit*) states S_i, S_j and time between them t_{ij}, the sample of t_{ij} times of all the

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transitions from S_i to S_j taken from all the patient sequences available is considered to approach a normal distribution for which $\bar{t}_{ij}$ represents the mean of all t_{ij} values, and $S_{t_{ij}}$ the standard deviation of that same sample. Then, equation 1 is used to calculate the macro-temporality that describes the time constraint that affects the patients evolving from S_i to S_j in the SDA* diagram. In the equation, t_n is the z-value of a t-student distribution.

$$t = \bar{t}_{ij} \pm t_n \cdot S_{t_{ij}} \quad (1)$$

As shown in Figure 1 the calculated macro-temporalities between consecutive states S_i, and S_j are assigned to the connectors ending in S_j. If S_j is an *explicit* state the connector will be of the sort C_{SS} or C_{AS} (e.g. T_5, T_{11}, T_{12}, T_{14}, T_{15}, and T_{19} in Figure 1) but if it is an *implicit* state the connector will be C_{AD} or C_{AA} (e.g. T_4 and T_{13}).

4. Conclusions and Future Work

We have introduced an approach for time constraint approximation from data on medical procedures. FIPs use clinical guidelines to assist physicians in making appropriate medical decisions. We use the SDA* formalism for FIP representation. There is none explicit time constraint representation and there is none mechanism to help us to obtain them explicitly. We have decided to introduce time constraints from existing patients' temporal data. A t-student statistical method is used to approximate the time intervals of the SDA* connectors. Our approach can help physicians to obtain and represent temporal knowledge in the FIPs. With these time constraints, physicians can be supported in making time decisions.

Our next objective is to obtain real data from different hospitals and generate macro-temporalities with the proposed approach. We are interested in seeing how much the results will differ between hospitals. For the same SDA* there will be different time intervals which will be used to find the optimum. This will be useful for physicians to see how far to the optimum their treatment times are. We are also interested in comparing different FIPs of the same disease with the macro-temporalities generated from the same data. The objective would be to calculate dispersion of time intervals. This would help us to compare and decide which FIP is more appropriate for a particular patient from a time point of view.

5. Acknowledgements

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