Temporal Scenario Modelling and Recognition based on Possibilistic Logic

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Abstract

We propose in this paper a new approach for the modelling and recognition of temporal scenarii. A scenario is represented by three different structures. The first one models the logical dependency between the elements of the scenario, using possibilistic logic, while the second one is the minimal temporal graph representing all temporal constraints between the events. The third structure explains the way the matching between observations and scenarii has to be done. The consistency between the three structures is ensured.

Keywords: temporal reasoning, knowledge representation, possibilistic reasoning

1 Introduction

Situation assessment appears to be a key issue in many fields of application involving complex information processing coming from several sources —the so-called *data fusion problem*—, since it is the crucial step on which all subsequent decisions will rely upon. When the situation is dynamically evolving with time, and if this temporal dimension appears to be a main component in the assessment and subsequent decisions, we are faced with the problem of having a suitable representation of time. Such cases are more the rule than the exception in the real world, let us cite the behaviour of football teams and sheep herds, anti-aircraft defence systems amd many other surveillance systems.

The aim of the paper is to bring a new approach in modelling and recognition of such dynamical situations, where we assume that we have at our disposal typical examples of evolution of situations, or *behaviours*, which can be stored in a database.

These more or less complex behaviours, which we call *scenarios*, are made of sequences of events or elementary actions which follow on from each other. For example, a scenario could be the behaviour of a sheep herd chased by a wolf, an attack by a fighter, a fire hazard in an underground station, etc. In the sequel, we will use the term *activity* to denote an action or an elementary event which is a component of some scenario. Obviously, the duration of each activity, as well as the delay between two activities, are of importance for the recognition.

The recognition of scenarios is mainly based on the matching between observations (measurements and information issued from sensors in a wide sense) and behavioural models. These measurements pertain to the identification of the activity, but also to their dates (beginning, end).

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We do not pretend in this paper to solve the problem in its full generality. Rather, our work was motivated by an underlying application in the anti-aircraft defence area, which has some specific requirements. Our aim was precisely to build an approach able to fulfill them. We give here the main assumptions and requirements stemming from the application field.

incoming information: identification of observed events (activities), with an uncertainty level; dates of beginning and end, or duration (possibly imprecise).

outcoming information: a list of best matching scenarios, with a level of confidence or matching; estimated observation errors and (supposed) missing observations needed to match the scenario in full.

incremental aspect: observations arrive to the system in a random way. For each new piece of information, the system must perform a recognition step and update the current state of knowledge, without having to wait for the whole (or a somewhat large) set of observations.

false alarms and non detections: the system must be able to cope with non detections of activities as well as false alarms. In particular, they must not prevent the recognition of a scenario to be done.

description of scenarios: scenarios being composed with activities, it should be possible to express the fact that some activities are mandatory for the recognition while others are facultative. Also, activities may be related by a logical OR (exclusive or not). Lastly, time modelling should be able to take into account imprecise descriptions, such as "short duration", "about 5 minutes", and so on.

a priori knowledge on scenarios: for example, it should be possible to indicate which scenarios are more frequent or more plausible (in a given context) than others.

real time: the system should be able to perform the (incremental) recognition in real time.

In addition, we make the assumption that only one scenario is going on.

We believe that these requirements are of sufficent general interest to justify the presentation of our approach as a general methodology to tackle this kind of problem. We will situate it among the current approaches of temporal scenario recognition, and limit ourself to a rather conceptual presentation, illustrated with small examples. We do not address in full all issues pertaining to implementation and validation on real scenarios. This will be the subject of future studies.

The paper is organized as follows. Section 2 gives a first intuitive definition of a scenario. Section 3 gives an overview of current approaches, while Section 4 gives a brief overview of possibilistic logic and ATMS. Our approach is detailed in Section 5, and is illustrated on an example (Section 6). Section 7 concludes the paper and discusses several issues not taken into account in our approach and alternative solutions.

2 Definition and example of scenario

We propose the following informal definition of a scenario.

Definition 1 *A* scenario *is the root of a tree, whose nodes are activities or sub-scenarios, such that:*

- *a sub-scenario is a scenario*

- *activities are sub-scenarios which cannot be decomposed further: they are directly observable. As a consequence, they are the leaves of the tree.*
- *an ancestor sub-scenario is composed of all its descendant sub-scenarios*
- *a logical connective links all descendant nodes of an ancestor node*
- *a duration is assigned to each node, and possibly a delay with respect to other nodes. This temporal information may be imprecise.*
- *a plausibility degree or frequency is assigned to the scenario.*

Moreover, we call event *any observation, which is supposed to match with some activity. In other words, "activity" refers to the modelling part, while "event" refers to the recognition part.*

We illustrate this definition by an example.

EXAMPLE 1: Suppose the following description of a scenario (labelled S1) given by an expert.

> At first, activity A is observed, whose duration is about 10', then after a while, activities B and C, which are more or less simultaneous, are observed. Their duration is between 10' and 20'. Activity B is splitted into two sub-activities D and E. In general, both are observed and in this case, it is always D first, followed by E with a delay of about 5', but it is not uncommon to observe only one or the other. In the whole, the scenario lasts between 10' and 30'.

According to our definition, we can draw this scenario under a tree form (figure 1).

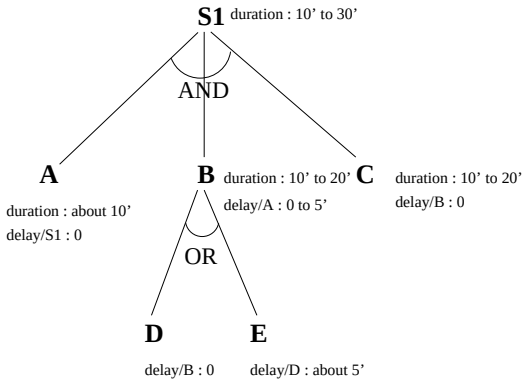

Figure 1: Representation of the scenario of Example 1

We remark that the above tree represents only partially the description given by the expert, concerning activities D and E. We will come back later to this.

3 An overview of current approaches

We try to give a brief overview of main existing approaches for the modelling of temporal scenarios, without pretending to exhaustivity. Our compilation follows in the whole the one made by Eude [17], and incorporates previous research works done in the THALES group [5].

3.1 Modelling temporal information

Our interest here is more on the updating of temporal data than causality and reasoning aspects. Thus, modal logics, reified logics, and temporal possibilistic logic [9] are not considered here. Three types of representation can be distinguished:

symbolic representations: the basic element of the language is a pair [*logical relation* ; *temporal concept*]. We can find in this category the works of Allen [1] and of Mc Dermott [7]. In the work of Allen, the basic primitive is the temporal interval, on which binary relations are defined, such as "before", "after", "covers", "terminates", and so on. By contrast, the basic primitive of Mc Dermott is the instant, and the binary relations are $<, >, =, \neq$. IxTeT (**I**nde**x**ed **T**im**e** **T**able) proposed by Ghallab [20] is a simplification of the logic of Mc Dermott.

numeric representations: thay are based on graphs whose nodes are instants. Links between nodes are disjunctions of intervals of $\mathbb{R}$.

In this category we can find TCSP (Temporal Constraint Satisfaction Problem) and STP (Single Temporal Problem), where temporal relations are respectively disjunctions of closed intervals, and (single) closed intervals. All temporal relations defined by Mc Dermott can be represented by a TCSP, but a STP cannot represent the relation $\neq$, equivalent to ($>$ or $<$).

mixed representations: Kautz [24] has proposed to use two graphs, one of the Allen type where all symbolic relations on intervals can be expressed, and the other of the STP type. The two graphs are of course closely linked, and there are two algorithms able to translate the information of one graph into the other one, with a minimal loss of information.

fuzzy representations: all basic temporal elements (dates, durations, etc.) are represented by fuzzy numbers, i.e. fuzzy sets [37] which are convex and upper semi-continuous (see e.g. a survey in [13]). This enables the modelling of information such as "about 5 minutes". There exist several ways to represent intervals. Steunou [34] and Chen [4] consider that an interval is a pair of fuzzy instants (beginning, end), while Dubois and Prade [14] consider it as a fuzzy set $\mu_{[A,B]}(t)$ obtained by the extension principle, the function being $t = \mathbf{1}_{[a,b]}$. Also, Marin [28] considers it as a triplet of fuzzy numbers (beginning, duration, end).

Godo and Vila [21] propose a Horn clause-like temporal language called FTL based on a general notion of duration or metric temporal distance. The basic predicate is $Fuzzdist(t, t', \pi)$, where t, t' denotes the beginning and end of some events, and π is a fuzzy set representing a fuzzy constraint on the time interval between t and t' (see also [30] for an equivalent presentation based on possibilistic logic with fuzzy constants).

3.2 Temporal reasoning

Approaches based on CSP (Constraint Satisfaction Problem) are by far the most widely used (see e.g. [32]). They are based on numerical representations of the TCSP or STP type, i.e. each problem is represented by a graph which nodes are instants and arcs are temporal constraints (intervals or disjunction of intervals). It is however possible to consider symbolic constraints. In the sequel, we restrict to the case of STP with numerical constraints. We develop a little more this in what follows, since we will rely on this approach in our method.

A constraint between nodes i and j is denoted $C(i, j) = [a, b]$, which means that the time interval between i and j is a number belonging to the interval $[a, b]$. Elementary operations on constraints are:

- the *inverse* of $C(i,j) = [a,b]$ is defined as the constraint $C(j,i) = [-b,-a]$.
- the *intersection* of two constraints on an arc is defined by $[a,b] \cap [c,d] = [\max(a,c), \min(b,d)]$.
- the *composition* of $C(i,j) = [a,b]$ and $C(j,k) = [c,d]$ is defined by $[a,b] \circ [c,d] = [a+c, b+d]$. It is the basic operation for constraint propagation.

We introduce now some definitions and classical results on consistency. We define at first the *unary constraint* $C(i)$ of node i, as the constraint which limits the possible values of the variable attached to node i.

consistency and inconsistency of a graph: a graph is *inconsistent* if no instanciation of the variables satisfies the constraints. Otherwise, the graph is *globally consistent.*

2-consistency: a graph is 2-consistent if for any instanciation of a node i satisfying $C(i)$, for any node j, there exists an instanciation of j satisfying $C(j)$ and the binary constraint $C(i,j)$. This is also called *arc-consistency.*

k-consistency: a graph is *k-consistent* if any locally consistent instanciation of $k-1$ variables can be extended to a locally consistent instanciation of k variables. *Strong k-consistency* is m-consistency for any $m \leq k$. For a graph with n nodes, n-consistency implies global consistency.

path-consistency: let i,j a pair of nodes for which there exists an instantiation satisfying $C(i,j)$, $C(i)$, and $C(j)$. The graph is *path-consistent* if for any path between i and j, the instanciation can be extended so that all unary and binary constraints on the path are satisfied.

The graph is *complete* if there is an arc between all pair of nodes. A theorem due to Montanari [29] says that for complete graphs, path-consistency is equivalent to 3-consistency.

Two graphs are *equivalent* if they have the same nodes and the same set of solutions. This equivalence relation proves the existence in each equivalence class of a minimal element in the sense of inclusion: it is the *minimal graph*, which contains the most possible restrictive constraints. The following results are noticeable:

- every partial solution of the minimal graph can be extended to a global solution (strong n-consistency)
- if the minimal graph has no empty constraint, then it is globally consistent.

Davis has shown that in the case of numerical STP, 3-consistency filtering leads to a minimal graph. 3-consistency filtering transforms a graph into an equivalent one which is 3-consistent. Algorithms PC1 (Montanari) and its improved version PC2 (Mackworth) implement 3-consistency filtering. For TCSP, it is necessary to decompose into a disjunction of STP's to get a minimal graph by PC1 or PC2.

Concerning the handling of fuzzy temporal constraints, flexible CSP have already been largely studied, e.g. by Fargier, Verfaillie *et al.* [3, 31]. It is possible to adapt to fuzzy constraints concepts of consistency and minimal graph, as well as algorithms for minimal graphs, by replacing standard operations by their fuzzy counterparts (see also [35]). A result similar to the theorem of Montanari can be obtained, which says that, for a graph of non disjunctive flexible constraints, 3-consistency ensures minimality. In FTL, Godo and Vila [21] perform fuzzy constraint propagation through some specific inference rules, some of them corresponding to the above mentionned elementary

operations. A particular rule of interest is the one translating an imprecise predicate *FuzzDist* with certainty degree α to another more imprecise but certain predicate.

Lastly, we just mention other approaches for temporal reasoning. These are distance graphs [6], which is more or less a translation of temporal graphs in terms of distance, IxTeT [20, 8], also based on CSP techniques, and inequalities systems [5].

3.3 Scenario recognition

We suppose to have at our disposal a collection of scenarios, which is an exhaustive representation of the set of situations we wish to recognize. As mentioned in Section 1, we restrict to incremental techniques of recognition, i.e. the scenario has to be identified before it terminates.

Each observation is compared to the elements constituting a scenario.The matching is successfull if the observation is of the same type as the type of the element, and if the observation satisfies all constraints induced by the other elements of the scenario. In what follows, we distinguish between approaches based on logical inference and on temporal aspects.

recognition by logical inference: in the approach of Kautz [24], a structural recognition is performed at first, which consists in doing logical forward inferences on a rule base describing the scenarios. Then, a temporal recognition is done, based on CSP techniques.

There exist other approaches in this category, based on abductive recognition (MATIS [16], SCAN [27]).

recognition based on temporal information: Fontaine [19] proposes to build a graph $G(S)$ for each scenario S, and a graph $\Gamma(\Sigma)$ of the set Σ of observations. The two graphs are then compared, after having been made complete and minimal.

In IxTeT [20], the recognition is based on constraint propagation in a temporal graph.

mixed approach: In FTL proposed by Godo and Vila [21], temporal and atemporal variables are treated in a common language, whose general inference rule is similar to the possibilistic inference of possibilistic logic.

3.4 Synthesis and conclusion

In many cases, the structural and temporal aspects are distinguished (Kautz). The structure of the scenario is often expressed under a logical form, while the temporal aspect is expressed by a graph of instants. The best way to process temporal graphs seems to compute the minimal graph, with adequate algorithms, since this has some theoretical basis. If the graph has no constraint in a disjunctive form (STP), the PC1 algorithm (and its more sophisticated variants) is sufficient.

Temporal recognition is done either by comparison of the graph of observations with the graph of scenarios (Fontaine), or by propagating constraints as soon as new observations are coming (IxTeT).

In many cases, the recognition system merely tells if a scenario is possible or not on the basis of the observations, and do not provide compatibility or matching degree (Fontaine). However, it seems to be desirable to assign such degrees to plausible scenarios, both on a structural and temporal point of view. This would permit to rank the different scenarios selected by the system. In structural recognition, we may wish to take into account the number of identified activities, as well as their relative importance. The more a scenario matches with observations, the higher the confidence degree. On the other hand, all activities have not the same importance to characterize

a scenario, one may even imagine optional activities, whose non observation should not inhibit the recognition of the scenario. Also, due to the presence of imprecise, fuzzy information (dates), it is desirable to be able to define a compatibility degree between an observation modelized by a fuzzy number and an activity of the graph.

To take into account these different needs, Eude [17] proposes to compute a global degree of compatibility between a scenario and observations. The compatibility of the scenario is computed by the aggregation of compatibility degrees at the level of components of the scenario, using a suitable aggregation operator.

The processing of fuzzy information on dates, durations, etc. is not allowed in the above mentionned methods, however, they can be extended in order to take them into account. Eude [17] has developed a method for the processing of fuzzy (or flexible) constraints (FCSP) for scenario recognition, based on previous works on this subject (see e.g. Fargier [18]). Also, the FTL language of Godo and Vila [21] offers an alternative approach for scenario recognition with fuzzy temporal information.

The above analysis, together with the requirements expressed in Section 1, has lead to the approach detailed in Section 5. Here, the idea of Kautz to separate the structural and temporal parts is kept. The temporal aspect is handled classically by CSP techniques. The structural aspect is coded using possibilistic logic (see Section 4), which has the advantage to allow a representation of uncertainty in the modelling of a scenario and observations. Lastly, in order to obtain a matching degree between observations and scenarios which has some expressivity, a third structure is introduced.

4 Basic concepts in possibilistic logic

We give in this section a brief overview of possibilistic logic, restricting to concepts necessary to our study. For a detailed presentation, see e.g. [2, 10, 15].

Let Ω be the set of interpretations. A possibility distribution π on Ω is a function which expresses to which degree each interpretation ω is possible (plausible). $\pi(\omega) = 0$ means that w is impossible, i.e. ω can never occur, while $\pi(\omega) = 1$ means that ω is completely possible, i.e. nothing prevents ω to occur.

For every formula φ, we define their *possibility* and *necessity* degree by:

$$\Pi(\varphi) = \sup_{\omega|\omega\models\varphi} \pi(\omega) \quad (1)$$

$$\mathrm{N}(\varphi) = 1 - \Pi(\neg\varphi) = \inf_{\omega|\omega\models\neg\varphi} (1 - \pi(\omega)). \quad (2)$$

We have the following properties:

(i) $\Pi(\bot) = 0, \quad \mathrm{N}(\top) = 1.$

(ii) $\forall\varphi,\psi,\ \Pi(\varphi \vee \psi) = \max(\Pi(\varphi), \Pi(\psi)).$

(iii) $\forall\varphi,\psi,\ \mathrm{N}(\varphi \wedge \psi) = \min(\mathrm{N}(\varphi), \mathrm{N}(\psi)).$

$\mathrm{N}(\varphi) = 1$ means that φ is certainly true, while $1 > \mathrm{N}(\varphi) > 0$ means that φ is somewhat certain and $\neg\varphi$ not certain at all. $\mathrm{N}(\varphi) = \mathrm{N}(\neg\varphi) = 0$ corresponds to total ignorance. $0 < \Pi(\varphi) < 1$ means that φ is not certain at all and $\neg\varphi$ is somewhat certain, and $\Pi(\varphi) = 0$ means that φ is certainly false.

We define the notion of *necessity valued formula* or *N-formula* by a pair $(\varphi \quad \alpha)$, with $\alpha \in [0,1]$ representing the degree of certainty of formula φ. More precisely, $(\varphi \quad \alpha)$ means that $\mathrm{N}(\varphi) \geq \alpha$.

We write $\pi \models (\varphi \quad \alpha)$ if and only if $N(\varphi) \geq \alpha$, where N is the necessity induced by π. If $\mathcal{F} = \{(\varphi_1 \quad \alpha_1), \ldots, (\varphi_n \quad \alpha_n)\}$ then $\mathcal{F} \models (\varphi \quad \alpha)$ if and only if $\forall \pi, \pi \models \mathcal{F}$ implies $\pi \models (\varphi \quad \alpha)$. The following deduction theorem can be shown:

$$\mathcal{F} \cup \{(\varphi \quad 1)\} \models (\psi \quad \alpha) \text{ if and only if}$$
$$\mathcal{F} \models (\varphi \rightarrow \psi \quad \alpha).$$

The consistency degree of $\mathcal{F}$ is defined by $\mathrm{Coh}(\mathcal{F}) = \sup_{\pi \models \mathcal{F}} \sup_{\omega \in \Omega} \pi(\omega)$. It expresses to which degree it exists an interpretation which satisfies $\mathcal{F}$. The inconsistency degree is then $\mathrm{Incoh}(\mathcal{F}) = 1 - \mathrm{Coh}(\mathcal{F})$.

The most widely used resolution principle is the following:

$$\frac{\mathrm{N}(p \vee q) \geq \alpha \qquad \mathrm{N}(\neg p \vee r) \geq \beta}{\mathrm{N}(q \vee r) \geq \min(\alpha, \beta).}$$

It is consistent and complete for refutation.

Possibilistic logic has served as a basis for extending the concept of ATMS (Assumption Truth Maintenance System) of De Kleer, hence the name *possibilistic* ATMS, or Π-ATMS [2].

Generally speaking, a Π-ATMS is able to answer the following questions:

(i) Under what configuration of assumptions is a fact d certain to a given degree?

(ii) What is the inconsistency degree of a given configuration of assumptions?

(iii) In a given configuration of assumptions, to which degree each observed fact is certain?

Usually propositional variables are split into *hypotheses* and *non-hypotheses*. The hypotheses are all variables which can be input of the system (observations in our case). Non-hypotheses are all other variables. Like clauses, hypotheses and non-hypotheses are (necessity-) valued.

In what follows, $\mathcal{F} = \{(\varphi_1 \quad \alpha_1), \ldots, (\varphi_n \quad \alpha_n)\}$ is a set of Horn N-clauses. A *fact* is a particular clause, generally formed with non-hypotheses.

Let $\mathcal{E}$ be a set of valued hypotheses. We say that:

(i) $[\mathcal{E} \quad \alpha]$ is an *environment* of a fact d if $\mathcal{E} \cup \mathcal{F} \models (d \quad \alpha)$, where the hypotheses of $\mathcal{E}$ are considered as certain.

(ii) $[\mathcal{E} \quad \alpha]$ is a *α-environment* of d if $[\mathcal{E} \quad \alpha]$ is an environment of d and if for all $\alpha' > \alpha$, $[\mathcal{E} \quad \alpha']$ is not an environment of d (α is maximal).

Let d be a fact. The *label* of d is the unique set of environments of d

$$L(d) = \{[\mathcal{E}_i \quad \alpha_i], i \in I\},$$

where all hypotheses in the $\mathcal{E}_i$'s are certain, and which satisfy the 4 following properties:

consistency: $\forall [\mathcal{E}_i \quad \alpha_i] \in L(d)$, $\mathrm{Incoh}(\mathcal{E}_i \cup \mathcal{F}) < \alpha_i$.

relevance: $L(d)$ contains only environments of d.

completeness: all minimal α-environments of d are present in $L(d)$.

minimality: $L(d)$ does not contain two environments $[\mathcal{E}_1 \quad \alpha_1]$ and $[\mathcal{E}_2 \quad \alpha_2]$ such that $\mathcal{E}_1 \subset \mathcal{E}_2$ and $\alpha_1 \geq \alpha_2$.

The notions of context, interpretation and candidate have also been translated in the possibilistic framework. Efficient algorithms for computing labels have been proposed and implemented [2].

5 A new approach to scenario modelling

As it has been said at the end of Section 3.4, we introduce three distinct structures, each having its role in the recognition.

the decomposition tree of the scenario in observable activities or sub-scenarios. This tree represents the structure of the scenario, on a logical point of view. Temporal information, as well as information about the relative importance of activities in the recognition of the scenario do not appear here.

the temporal graph describing the time sequence of the different activities. Nodes of the graph are instants, while arcs bear constraints of delay between instants.

the aggregation tree of activities and sub-scenarios describes in a precise way how the components of the scenario intervene for its identification (importance of activities, conjunction or disjunctions between components, compensatory effects, etc.). It is structurally identical to the decomposition tree, and is a refinement of the decomposition tree (this will be detailed in Section 5.4).

In what follows, we will detail individually each structure, then we will explain the link between them, and finally give the recognition algorithm. We will not consider fuzzy temporal constraints (see however Section 7).

5.1 Structural aspect

The decomposition tree is constituted by a root, which is the scenario itself, nodes, which are sub-scenarios, leaves, which are observable activities, and logical connectives between links, which are limited to AND, OR (for XOR, see Section 7). In the case of Example 1, the corresponding decomposition tree is given in Fig. 2. This structure is now expressed with Horn N-clauses, which will be used in a Π-ATMS (see Section 4) for the recognition phase, in the following way:

- propositional variables correspond to the nodes of the tree, including the leaves and the root.
- hypotheses correspond to leaves, while all other nodes are non-hypotheses.
- each scenario or sub-scenario S is translated into a Horn N-clause of the following form:

$$(\neg A_1 \vee \neg A_2 \vee \cdots \vee \neg A_q \vee \neg S_1 \vee \neg S_2 \vee \cdots \vee \neg S_r \vee S \quad \alpha)$$

  where $A_1, \ldots, A_q$ are activities, $S_1, \ldots, S_r$ sub-scenarios of S, α a certainty degree attached to the clause, and all A_i, S_i are linked by a AND in the decomposition tree. In case of OR, we split into $q + r$ clauses.

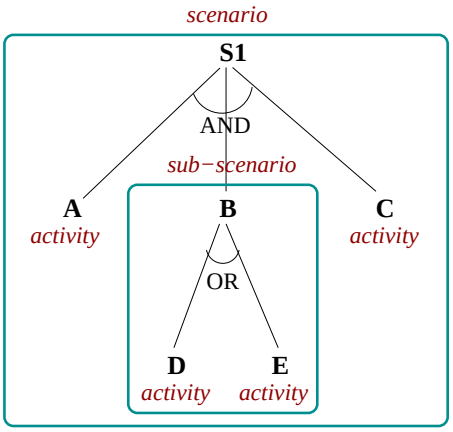

Figure 2: Decomposition tree of scenario of Ex. 1

- clauses expressing the (a priori, i.e. when no observation is available) credibility of each scenario, of the form $(S \quad \alpha)$.

In the case of Fig. 2, we obtain (certainty degrees are arbitrary here):

$$\begin{aligned} (\neg A \vee \neg B \vee \neg C \vee S_1 \quad & 1) \\ (\neg D \vee B \quad & 0.8) \\ (\neg E \vee B \quad & 0.9) \\ (S_1 \quad & 0.2) \end{aligned}$$

We detail now the recognition phase. We suppose to observe events, translated into clauses by $(A \quad \alpha)$, where A is the activity corresponding to the observed event, identified with a certainty degree α. For each new clause φ, the following steps are performed:

1. φ is added to the knowledge base $\mathcal{F}$. All tautologies and clauses subsumed by φ are removed from $\mathcal{F} \cup \{\varphi\}$, the resolution principle is applied, and again subsumed clauses are removed.

2. Compute labels of all scenarios. The label of a scenario contains all minimal environments (i.e. in our case, a list of observable activities), which will enable the recognition of the scenario with a given degree of certainty.

Let us apply this procedure to our example, supposing we have observed D, E, A modelized by $(D \quad 0.7)$, $(E \quad 0.6)$, $(A \quad 1)$. The new base is now:

$$\begin{aligned}(\neg B \vee \neg C \vee S_1 \quad & 1)\\ (A \quad & 1)\\ (\neg E \vee B \quad & 0.9)\\ (\neg D \vee B \quad & 0.8)\\ (\neg C \vee S_1 \quad & 0.7)\\ (D \quad & 0.7)\\ (B \quad & 0.7)\\ (E \quad & 0.6)\\ (S_1 \quad & 0.2)\end{aligned}$$

The label of S_1 is then:

$$\{\{B, C\}_1, \{C\}_{0.7}, \{\}_{0.2}\}$$

This result says that, if we observe (with certainty) B and C, we can identify S_1 with full certainty; if we observe only C, then S_1 will be inferred with a certainty 0.7. Lastly, in the absence of further observation, S_1 will be inferred with a certainty degree 0.2, which corresponds to the a priori knowledge.

5.2 Temporal aspect

We use here a graph of temporal constraints, treated by a minimalization algorithm (PC1 or others). The temporal graph is constituted by:

- nodes representing instants (beginning and end) of the scenario, all sub-scenarios and activities.
- arcs with delay constraints existing between two nodes, as they are specified by the expert in the description of the scenario.

To obtain this graph, it is necessary to build at first a Gantt chart, where the begininng and end instants of all activities, sub-scenarios and the scenario itself, with the following conventions:

- vertical lines indicates simultaneity.
- δ_A indicates the duration of activity (or (sub)-scenario) A.
- the symbol $\Delta_{\langle A,B\rangle}$ indicates a delay between the beginning of A (denoted $\langle A$), and the end of B (denoted $B\rangle$), and similarly for delays between $A\rangle, \langle B$, etc.

Figure 3 shows the Gantt chart corresponding to Example 1. Question marks indicate that the concerned information is not available. A problem however exists since the description of the scenario does not indicate which activity terminates the scenario (B or C?), and similarly for sub-scenario B (D or E?). To solve this problem, we can either fix arbitrarily these limits (this is done in Fig. 3, considering that B terminates S_1 and E terminates B), or consider as many scenarios as there exist different possibilities for fixing the limits, or write as a constraint the fact

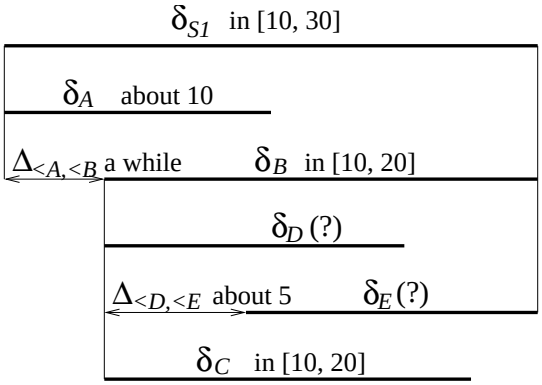

Figure 3: Gantt chart of scenario of Example 1

that an ancestor sub-scenario A begins with the beginning of its first descendant sub-scenario, and terminates with the end of the last descendant sub-scenario, specifically:

$$t_{\langle A} = \min_{B \text{ descendant of } A} t_{\langle B}$$
$$t_{A\rangle} = \max_{B \text{ descendant of } A} t_{B\rangle}$$

However, such constraints cannot be expressed in our temporal graph as defined above. We need for this more evolved language for constraints, such as CLAIRE/Eclair [26].

Supposing that E terminates B and B terminates S_1, the graph obtained is given in figure 4. We have assigned arbitrarily the interval $[10, 20]$ for δ_E and δ_D.

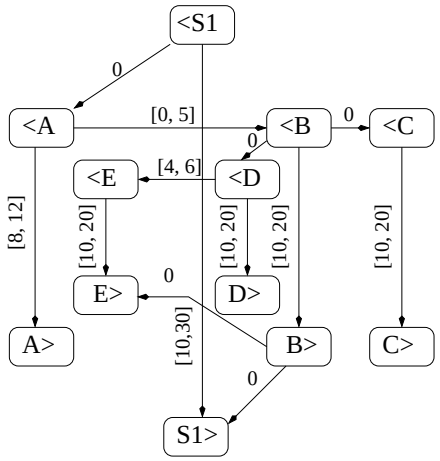

Figure 4: Temporal graph of scenario of Example 1

Once the graph is defined, we must make it complete by linking all nodes together. For these new arcs, we choose very loose constraints. Then we make the graph minimal. Figure 5 shows the result, where for the sake of readability, we have put only those arcs already present in the original graph. Bold figures indicates constraints which have been updated. Since no constraint is empty, the graph has a solution.

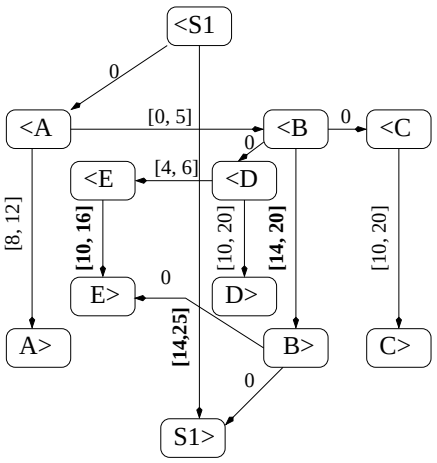

Figure 5: Minimal temporal graph of the scenario of Example 1

We detail now the recognition part. We suppose to observe one or several events, corresponding to activities $A_1, A_2, \ldots$, on which we have temporal information, either of duration, or delay with respect to other activities, or dates. Let $\mathcal{C}$ be the list of constraints obtained from these informations. For each constraint $C(i,j)$ in $\mathcal{C}$, we perform:

$$C^*(i,j) \leftarrow C^*(i,j) \cap C(i,j)$$

where $C^*(i,j)$ is the corresponding constraint of the minimal graph. Calling G' the modified graph, we compute the corresponding minimal graph. If the graph has an empty constraint, then the observations cannot belong to the considered scenario. The procedure is repeated whenever there are new coming observations.

Let us illustrate this procedure with our Example 1. We suppose that events are observed, corresponding to activities A and D (E is no more observed), with the following temporal informations:

- duration of A : between 10' and 14' ;
- duration of D : between 18' and 20' ;
- delay between the beginning of A and the end of D : between 15' and 20'.

After modification and minimalization of the graph, we obtain the graph of Figure 6. Since no constraint is empty, observation matches the scenario for the temporal aspect.

5.3 Matching

The last step consists in computing a degree of matching between observations and a given scenario. The aggregation tree expresses in a precise way the importance of the recognition of each node in the whole process of recognition, as well as the type of logical connective (in a broad sense) which links the descendant nodes of a node. This connective can be of conjunctive type, disjunctive type, of compensatory type (see hereafter), or any combination of them, including unary connectives as the negation.

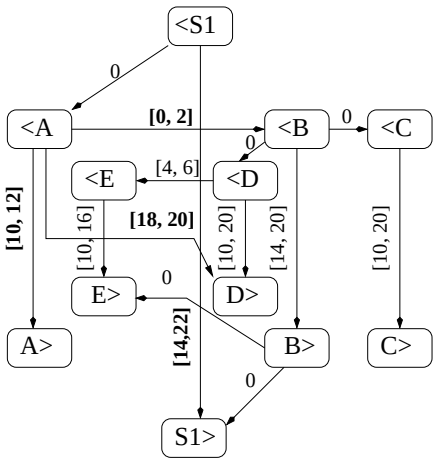

Figure 6: Minimal temporal graph after minimalization

The aggregation tree has the same structure than the decomposition tree. The choice of the connectives, and importance weights if the connectives are weighted, can be done by considering the behaviour of the connectives and the description of the expert.

Besides classical connectives from binary logic, the theory of fuzzy sets offers a large range of (weighted or not) connectives, which permits to combine in a very flexible way degrees of matching defined e.g. on $[0, 1]$ (see e.g. [11, 23]). We do not detail here this topic, but we just mention the main families, focusing on ordered weighted averages (OWA), which are of particular interest here.

minimum and maximum They correspond to the classical AND and OR respectively. More generally, triangular norms and co-norms [33] (t-norms and t-conorms for short) are associative connectives which generalize conjunction and disjunction (see the monograph [25] for details). The greatest t-norm is minimum, and the smallest t-conorm is maximum.

mean operators They are comprised between minimum and maximum, and express some compensatory effect between matching degree, i.e. a low (high) matching degree can be compensated by a high (low) one, which is never the case with triangular norms and conorms. Common examples are the (weighted) arithmetic mean, the geometric mean, etc. However, it should be noted that mean operators have no clear logical interpretation, so that their use should be avoided in this context.

weighted mimimum and maximum [12] They extend the minimum and maximum in the following sense. Let $w_1, \ldots, w_n$ be a set of weights in $[0, 1]$ such that $\max_i w_i = 1$. The weighted minimum and maximum are defined by:

$$\begin{aligned} \mathrm{wmin}_{w_1,\ldots,w_n}(a_1, \ldots, a_n) &= \min_{j=1}^{n}(\max((1 - w_j), a_j)) \\ \mathrm{wmax}_{w_1,\ldots,w_n}(a_1, \ldots, a_n) &= \max_{j=1}^{n}(\min(w_j, a_j)) \end{aligned}$$

The meaning of the weighted minimum is the following in our context: a node is recognized (high degree of matching) if all its important descendant nodes are recognized.

ordered weighted average (OWA) [36] Let $w_1, \ldots, w_n$ be a set of weights in $[0,1]$ such that $\sum_i w_i = 1$. The OWA connective is defined as:

$$\mathrm{OWA}_{w_1,\ldots,w_n}(a_1, \ldots, a_n) = \sum_{i=1}^{n} w_i a_{\sigma(i)}$$

where σ is a permutation of indices such that $a_{\sigma(1)} \leq \cdots \leq a_{\sigma(n)}$. These connectives include minimum and maximum as particular cases, and have the meaning of a fuzzy quantifier, i.e. in our context a node is recognized if *most of* (or *a few, about half*, etc.) its descendant nodes are recognized.

Coming back to our example described in Section 2, it is clear that S_1 is formed by the conjunction of A, B, C without weight, hence the minimum is used. For B, we deduce from the description that:

- if D and E are observed, then the recognition of B is completely satisfied. This is translated by $\mathcal{H}(1,1) = 1$, if 1 indicates the maximal matching degree.
- if only one of the two is observed, we recognize also B, but to a less extent. We may suggest for example $\mathcal{H}(0,1) = \mathcal{H}(1,0) = 0.7$.

In this case, the OWA connective is suitable, with weights $w_1 = 0.3$, $w_2 = 0.7$, as it can be easily checked. Finally, our aggregation tree is given on Figure 7.

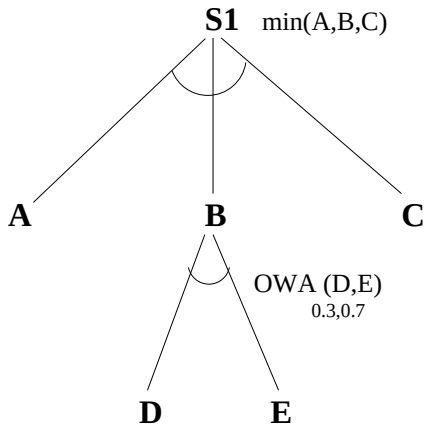

Figure 7: Aggregation tree of scenario of Example 1

We describe now the matching procedure. Let S be a scenario involving activities $A_1, \ldots, A_n$, and $\mathcal{A} \subset \{A_1, \ldots, A_n\}$ be the subset of observed activities.

Step 1: Compute the matching degree between the observation A' and an activity A of S, denoted $\mathrm{comp}(A', A)$, for every $A \in \mathcal{A}$. This degree takes into account attributes of A, but it may consider also temporal information (see Eude [17]).

Step 2: For each non empty environment $\mathcal{E}$ of the label of S, not containing sub-scenarios, compute the matching degree of $\mathcal{E}$ as follows:

1. For any activity $A \in \mathcal{E}$, assign a matching degree of 1 (it may subsume the degree computed in Step 1, when A is observed).
2. Apply recursively the following formulas to each sub-scenario S_i according to the aggregation tree:
   - if S_i is a conjunction of p descendant nodes $A_{i_1}, \ldots, A_{i_p}$ expressed by a clause of certainty degree α_i, then
   $$\text{comp}(S_i) = \min(\mathcal{H}_i(\text{comp}(A_{i_1}), \ldots, \text{comp}(A_{i_p})), \alpha_i)$$
   - if S_i is a disjunction of p descendant nodes $A_{i_1}, \ldots, A_{i_p}$ expressed by p clauses of certainty degree α_{i_j}, $j = 1, \ldots, p$, then
   $$\text{comp}(S_i) = \mathcal{H}_i(\min(\text{comp}(A_{i_1}), \alpha_{i_1}), \ldots, \min(\text{comp}(A_{i_p}), \alpha_{i_p}))$$

   where $\mathcal{H}_i$ is the connective of sub-scenario S_i.

The above procedure ensures that the decomposition tree is consistent with the aggregation tree, so that te maching degree of S is a refinement of the certainty level of S, see Section 5.4 for precise definitions and proofs.

Let us comment briefly about Step 2. Environments of the label of S give the certainty degree of S if all activities and sub-scenarios in $\mathcal{E}$ *were observed with certainty.* Hence, environments containing sub-scenarios are discarded since sub-scenarios are not observable, and matching degrees of all $A \in \mathcal{E}$ are set to 1. Now, the precise usage of the matching degrees of all environments depends on the application and what is aimed at. Environment $\mathcal{E}_0 := \{A_1, \ldots, A_n\} \backslash \mathcal{A}$ is of particular interest since it contains exactly all unobserved activities. If the aim is to decide at some instant which scenario is the most plausible on the basis of all observed activities, we suggest to choose the one with highest matching degree for $\mathcal{E}_0$. If one is interested in making other assumptions (e.g. what if observed activity A were observed with full certainty ?, etc.), one may look at other environments.

Continuing our example, let us take the label of S_1 computed in Section 5.1, with the above chosen connectives. The only non empty environment which does not contain sub-scenarios is $\{C\}_{0.7}$ (which is $\mathcal{E}_0$). We obtain:

$$\begin{aligned}\text{comp}(S_1) &= \min(\min(1, \text{OWA}_{0.3,0.7}(\min(0.7, 0.8), \min(0.6, 0.9)), 1), 1) \\ &= 0.67.\end{aligned}$$

Observe that the result is slightly inferior to 0.7, since an OWA is more conjunctive than OR.

5.4 General algorithm

We describe in this section the whole process of recognition. We suppose that the scenarios are all modelized by the three structures described above. The problem to solve is the cohabitation of these three structures so that they can assume their role without conflict. We carefully examine this point in the sequel.

Temporal graph/Decomposition tree Let Σ be the knowledge base of the Π-ATMS. The problem is that Σ contains the description of all scenarios and all observations. Clearly, if the temporal recognition module says that S_i is not possible, the clauses relative to S_i in Σ should be inhibited.

We propose the following solution. Let S_1, S_2 be two scenarios, whose activities and sub-scenarios are denoted $A, B, C, \ldots$, some of them being possibly in common. We introduce a propositional variable for all nodes of each scenario. Even if some nodes are in common, they will be labeled as different variables $A_1, B_1, \ldots, A_2, B_2, \ldots$. If the scenario S_1 is not compatible with the temporal graph, we will put in the knowledge base only observations for S_2, i.e. $A_2, B_2, \ldots$.

Temporal graph/Aggregation tree The problem which may occur is the following: let A be a sub-scenario composed with activities B and C linked by an OR. Let us suppose that B and C are observed, that B satisfies the temporal constraints, but not C. This will cause the rejection of the scenario. However, since A can be only recognized by B, it would be better to say: *"sub-scenario A is recognized, and observation C seems to belong to another scenario which is going on"*.

In our case, we suppose that only one scenario is going on, hence this situation cannot occur. However, if one would like to avoid this situation, it suffices to decompose each scenario including OR connectives in several scenarios without OR.

Decomposition tree/Aggregation tree The compatibility between these two structures implies that the connective of classical binary logic in the decomposition tree is an approximation (preferably a restriction to $\{0, 1\}$) of the corresponding one in the aggregation tree. We suggest:

- triangular norms, weighted minimum correspond to AND, while triangular co-norms and weighted maximum correspond to OR.
- OWA may correspond to either OR or AND, depending on the weights. Yager has proposed a degree of orness [23] attached to any OWA connective. If it is above 0.5, we may consider that the closest connective is OR. The question is less easy for other mean connectives, which have no clear logical interpretation, and each case should be considered individually. It seems however reasonable to approximate a weighted sum by an OR, since a low matching degree for one item does not necessarily implies a low global degree.

These general facts being established, we study in detail how to ensure the consistency between the structures. We propose the following definition of consistency.

Definition 2 *The computation of the matching degree is consistent with the machinery of the* Π*-ATMS if for all scenario S, for all set $\mathcal{A}$ of observed activities, the matching degree of S is equal to its certainty level, for any environment belonging to the label of S, whenever the connectives of the aggregation tree coincide with the logical connectives of the decomposition tree (i.e. AND is minimum, and OR is maximum).*

If the computation is consistent, then we can speak of *refinement*, since the (fuzzy) connective is supposed to model more accurately the description of the scenario given by the expert. A consistent computation has the following consequences, which gives some insight for the choice of connectives. Let us consider a sub-scenario S, whose certainty level computed by the Π-ATMS is α. In the case of conjunctions, and if $\mathcal{H}$ is a t-norm, we obtain $\text{comp}(S) \leq \alpha$, since all t-norms are smaller than the minimum. Hence, one should use a t-norm instead of minimum only if one wishes to penalize non-compatibility. If one wishes to put weights, the weighted minimum can be used. In this case, $\text{comp}(S) \geq \alpha$. It means that a weak matching for non important nodes does not penalize the global matching degree, a desirable property. The case of disjunction works dually.

We proceed in two steps. First we consider a complete set of observations (i.e. all activities of the scenario have been observed).

Proposition 1 *Let S be a scenario involving activities $A_1, \ldots, A_n$ such that the decomposition tree and aggregation tree have the same logical connectives, i.e. AND correspond to "min" and OR corresponds to "max". Suppose all activities have been observed, with certainty degrees $\alpha_1, \ldots, \alpha_n$. Then the global matching degree is equal to the certainty level for any $\alpha_1, \ldots, \alpha_n \in [0,1]$ iff all clauses describing the scenario are certain.*

Proof: Recall that the two trees have the same structure. Two cases can happen: either a sub-scenario is described with an AND connective, or it is described with an OR.

Let us consider the first case, i.e. a sub-scenario S described by the clause:

$$(\neg A_1 \vee \neg A_2 \vee \cdots \vee \neg A_n \vee S \quad \beta).$$

Let us consider a complete set of observations, described by the clauses $(A_i \quad \alpha_i)$, $i = 1, \ldots, n$. Then the resolution principle gives the following clause:

$$(S \quad \min(\beta, \alpha_1, \ldots, \alpha_n)) \tag{3}$$

On the other hand, the matching degree of S is $\min(\alpha_1, \ldots, \alpha_n)$.

Consider now the second case, i.e. a sub-scenario described by the set of clauses:

$$\begin{array}{rr} (\neg A_1 \vee S & \beta_1) \\ \vdots & \vdots \\ (\neg A_n \vee S & \beta_n) \end{array}$$

and consider observations like above. Then the resolution principle leads to

$$(S \quad \max(\min(\beta_1, \alpha_1), \ldots, \min(\beta_n, \alpha_n)) \tag{4}$$

Now, the matching degree of S_i is $\max(\alpha_1, \ldots, \alpha_n)$.

Clearly, in both cases, the matching degree is equal to the certainty level for any $\alpha_1, \ldots, \alpha_n \in [0,1]$ iff $\beta = 1$ and $\beta_i = 1$, $i = 1, \ldots, n$. The fact that any scenario is an arbitrary combination of the two above cases completes the proof. ■

When the clauses are not fully certain, the proof of Prop. 1 tells us that we have to replace the usual matching degrees by formulas (3) and (4) for the cases of sub-scenarios formed with AND and OR respectively, so that we have the following result.

Corollary 1 *Under assumptions of Prop. 1, the following computation is consistent with the* Π*-ATMS. For any sub-scenario S_i associated to a connective $\mathcal{H}_i$,*

- *if S_i is a conjunction of p descendants nodes A_{i_j}, $j = 1, \ldots, p$, expressed by a clause of certainty degree α_i, take*

$$\mathrm{comp}(S_i) = \min(\mathcal{H}_i(\mathrm{comp}(A_{i_1}), \ldots, \mathrm{comp}(A_{i_p})), \alpha_i) \tag{5}$$

- *if S_i is a disjunction of p descendants nodes A_{i_j}, $j = 1, \ldots, p$, expressed by p clauses of certainty degree α_{i_j}, $j = 1, \ldots, p$, take*

$$\mathrm{comp}(S_i) = \mathcal{H}_i(\min(\mathrm{comp}(A_{i_1}), \alpha_{i_1}), \ldots, \min(\mathrm{comp}(A_{i_p}), \alpha_{i_p})) \tag{6}$$

The second step is to deal with the case where all activities have not (yet) been observed.

Proposition 2 *Let us consider scenario S described by certain clauses involving activities $A_1, \ldots, A_n$, and an incomplete set of observations (i.e. some activities, say $A_{i_1}, \ldots, A_{i_q}$, are not yet observed). We suppose in addition that the connectives of the aggregation tree coincide with the logical connectives of the decomposition tree. Then the global matching degree of S is equal to the certainty level α of any non empty environment $\mathcal{E} \subset \{A_1, \ldots, A_n\}$ in the label of S iff* $\mathrm{comp}(A_i) = 1$, *for all $A_i \in \mathcal{E}$. In particular, $\mathcal{E}_0 = \{A_{i_1}, \ldots, A_{i_q}\}$ is the smallest one of such environments.*

Proof: Since $\mathcal{E} \cup \mathcal{F} \models (S \quad \alpha)$, and all variables in $\mathcal{E}$ are certain, the matching degree is equal to α iff $\mathrm{comp}(A_i) = 1$, $\forall A_i \in \mathcal{E}$ (proceed as in the proof of Prop. 1). Now, by construction of S, $\mathcal{E}_0$ is in the label of S, and the only environment belonging to the label properly included in $\mathcal{E}_0$ is the empty one. Indeed, any environment $\mathcal{E} \subsetneq \mathcal{E}^0$ has a certainty level equal to the one of the empty environment, since at least one activity is not recognized. But then it does not belong to the label due to the minimality requirement (see Section 4). ■

General algorithms We give below the algorithms of modelling and recognition of scenarios, based on the three structures (algorithms A.1 and A.2). Scenarios are denoted by $S_1, S_2, \ldots$, while observable activities and sub-scenarios are denoted $A, B, C, \ldots$.

for all scenarii S_i, $i = 1, \ldots, n$, **do**
  build the knowledge base Σ_i :
    $\Sigma_i = \emptyset$;
    tagg the propositional variables involved in S_i with i: $A_i, B_i, \ldots$;
    choose logical connectives from the description of the
    scenario for building the decomposition tree;
    decompose the scenario into clauses; put in Σ_i;
    add a priori knowledge ($S_i \quad \alpha_i$) if any in Σ_i;
  build temporal graph G_i :
    create nodes $\langle A_i$ and $A_i \rangle$ for every $A_i \in S_i$;
    build temporal diagram;
    translate into temporal constraints;
    complete the graph;
    compute the minimal graph G_i;
  build aggregation tree in accordance with the
  decomposition tree;
od
$\Sigma = \cup_{i=1}^{n} \Sigma_i$;

Algorithm A.1. Construction of the model

5.5 Comments

The method presented above fulfills the requirements given in Section 1. More specifically,

incoming information: they are used.

outcoming information: the aggregation tree gives the global matching degree for any scenario selected by the Π-ATMS. Moreover, the Π-ATMS gives all non-detections (labels). One can find out false alarms (observations which are not associated to scenarios), and false identifications.

$\mathcal{S} = \{S_1, \ldots, S_n\}$;
for every set of observations $\{(O_1 \quad \beta_1), \ldots, (O_m \quad \beta_m)\}$ **do**
; β_j is the certainty degree for observation O_j to be some activity A.
; observations matching with several activities are duplicated,
; with suitable certainty degree
for every $S_i \in \mathcal{S}$ **do**
intersect temporal information with corresponding constraints in G_i;
compute the minimal graph G_i';
if there exists an empty constraint in G_i'
then
$\mathcal{S} \leftarrow \mathcal{S} \setminus S_i$; removal of S_i
else
put in Σ all clauses $(A_i \quad \beta_i)$, $A_i \in S_i$, pertaining to
observations $(O_j \quad \beta_j)$;
fi
od
for all $S_i \in \mathcal{S}$ **do**
compute $L(S_i)$ the label of S_i;
; $L(S_i) = \{\mathcal{E}^1_{i,\alpha_1}, \ldots, \mathcal{E}^p_{i,\alpha_p}\}$, where $\mathcal{E}^j_{i,\alpha_j}$ is an
; environment of S_i, with certainty α_i
for all non empty $\mathcal{E}^j_{i,\alpha_j}$ containing no sub-scenario, such that $\alpha_j >$threshold **do**
compute matching degree for S_i, taking β_j for nodes
corresponding to observation O_j, and 1 for nodes
in $\mathcal{E}^j_{i,\alpha_j}$, the latter being prioritary;
od
od
od

Algorithm A.2. Recognition of scenarios

incremental aspect: the system is clearly incremental.

false alarms and non detections: see above (outcoming info)

description of scenarios: it is possible to take into account any connective for the matching part, not for the reasoning part. On the other hand, if one use flexible CSP [17, 18], it is possible to take into account fuzzy descriptions of scenarios.

a priori knowledge on scenarios: clauses $(S \quad \alpha)$ indicate a priori knowledge.

real time: the system seems to be able to cope with real time, although no real experiment has been done for the moment. Indeed, for a Π-ATMS including only Horn clauses, complexity is a linear function of the size of the knowledge base. Concerning CSP, the complexity of PC1 is $O(n^3)$, n being the number of nodes in the graph, but there exist much more efficient algorithms. On the other hand, the use of fuzzy constraints multiplies the complexity by a factor $\log p$, where p is the number of α-cuts used for describing the fuzzy sets [17].

Lastly, it is possible to provide mathematical justifications of our choices in this approach:

- possibilistic logic is complete and consistent: every deduced formula is semantically true, and every semantically true formula can be deduced.

- Π-ATMS allows to manage assumptions and to rank them by certainty degrees.
- the CSP framework for the processing of temporal constraints guarantees that the graph contains all solutions of the problem, and only solutions (minimal graph).
- the use of large families of connectives issued from fuzzy set theory allows a precise modelling of the expertise.
- consistency between certainty level inferred by the Π-ATMS and matching degree is ensured.

6 Example

We illustrate the whole procedure on a simple example. We consider two scenarios with the following description.

> SCENARIO S_1: activity A is observed first, whose duration is between 10' and 20'. Activity A is in fact composed of 2 sub-activities C and D; C begins first. with a duration between 5' and 10', then when C is finished, after a delay of 5' to 10', D starts, with a duration of 5' to 10'. 10' to 20' after the beginning of A, another activity B begins and lasts 10' to 20'. It is essential to observe B in order to identify S_1. On the whole, the scenario lasts between 20' and 30'.
>
> SCENARIO S_2: activity A' starts first, with a duration of 10' to 15'. Activity A' is composed of sub-activities C and D, with C beginning and lasting 5' to 10', then when C is finished, after a delay of at most 5', D begins and lasts 5' to 10'. When A' is finished, another activity E begins after a delay of at most 10', and lasts in general from 10' to 20'. It is essential to observe A' for the identification of the scenario. On the whole, the scenario lasts between 30' and 40'.
>
> S_2 is less frequent than S_1.

From the description, we can build the decomposition trees and aggregation trees of the two scenarios (Fig. 8 and 10), as well as the temporal diagram (Fig. 9 and 11). Note that a weighted minimum has been used for S_1 and S_2. The knowledge base is given below:

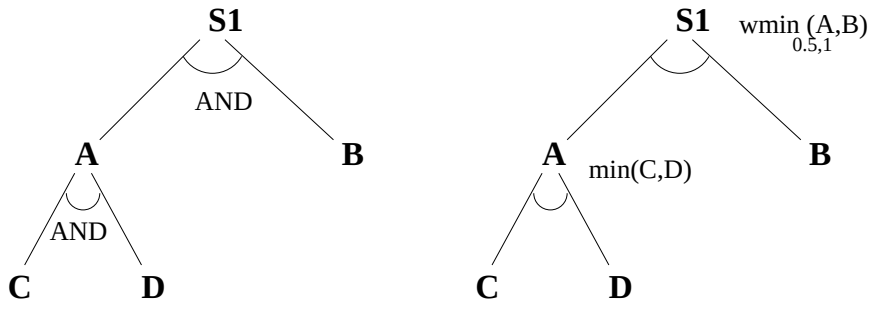

Figure 8: Decomposition tree (left) and aggregation tree (right) of scenario S_1

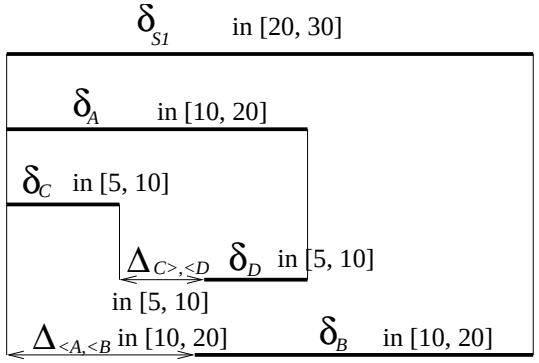

Figure 9: Temporal diagram of scenario S_1

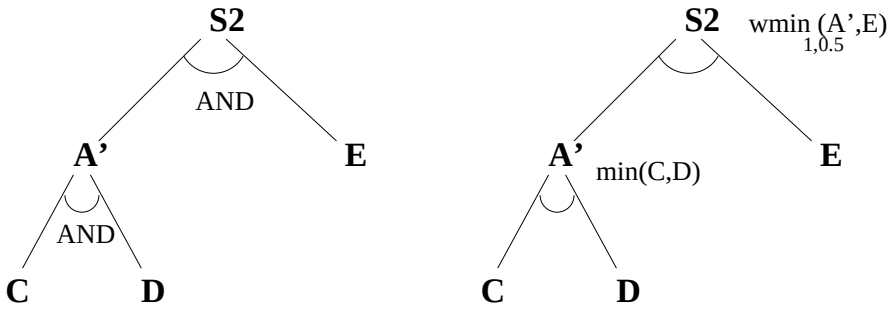

Figure 10: Decomposition tree (left) and aggregation tree (right) of scenario S_2

$$
\begin{aligned}
(\neg A_1 \vee \neg B_1 \vee S_1 \quad & 1) \\
(\neg C_1 \vee \neg D_1 \vee A_1 \quad & 0.8) \\
(\neg A_2 \vee \neg E_2 \vee S_2 \quad & 1) \\
(\neg C_2 \vee \neg D_2 \vee A_2 \quad & 0.8) \\
(S_1 \quad & 0.2) \\
(S_2 \quad & 0.1)
\end{aligned}
$$

The minimal complete graphs of the two scenarios are given under a matrix form in Tab. 6. We suppose to observe C and D with a certainty level of 0.7 and 0.8 respectively, with the following temporal information:

- duration of C is between 8' and 12'
- duration of D is between 5' and 8'
- delay between $C\rangle$ and $\langle D$ is between 4' and 6'.

Updating the graphs and after minimalization, we find that the graph of S_2 has an empty constraint, thus S_2 is impossible. The empty constraint is the one which links $\langle C$ to $D\rangle$. Indeed, this constraint is [10,15] in the minimal graph, but the data on C and D leads to [17,25].

Let us modify the temporal data so as to keep the two scenarios. This can be achieved with:

- duration of C is between 5' and 8'

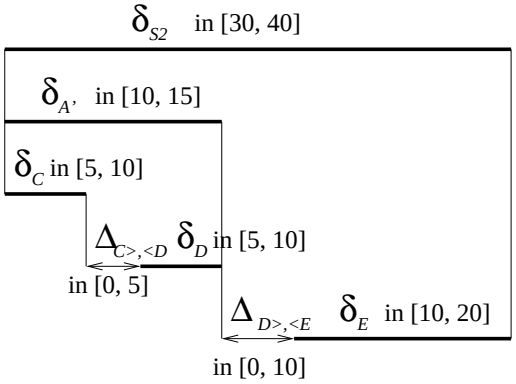

Figure 11: Temporal diagram of scenario S_2

- duration of D is between 5' and 8'
- delay between $C\rangle$ and $\langle D$ is between 4' and 6'.

Adding the clauses $(C_1 \quad 0.7), (D_1 \quad 0.8), (C_2 \quad 0.7), (D_2 \quad 0.8)$ to the knowledge base and performing the inference, we find:

$$\begin{aligned}
(\neg A_1 \vee \neg B_1 \vee S_1 \quad & 1) \\
(\neg A_2 \vee \neg E_2 \vee S_2 \quad & 1) \\
(\neg C_1 \vee \neg D_1 \vee A_1 \quad & 0.8) \\
(\neg C_1 \vee \neg B_1 \vee S_1 \quad & 0.8) \\
(\neg C_2 \vee \neg D_2 \vee A_2 \quad & 0.8) \\
(\neg C_2 \vee \neg E_2 \vee S_2 \quad & 0.8) \\
(D_1 \quad & 0.8) \\
(D_2 \quad & 0.8) \\
(\neg C_1 \vee A_1 \quad & 0.8) \\
(\neg C_2 \vee A_2 \quad & 0.8) \\
(C_1 \quad & 0.7) \\
(C_2 \quad & 0.7) \\
(A_1 \quad & 0.7) \\
(A_2 \quad & 0.7) \\
(\neg B_1 \vee S_1 \quad & 0.7) \\
(\neg E_2 \vee S_2 \quad & 0.7) \\
(S_1 \quad & 0.2) \\
(S_2 \quad & 0.1)
\end{aligned}$$

The labels of S_1 and S_2 are:

$$\begin{aligned}
L(S_1) =& \{\{A_1, B_1\}_1, \{C_1, B_1\}_{0.8}, \{B_1\}_{0.7}, \{\}_{0.2}\} \\
L(S_2) =& \{\{A_2, E_2\}_1, \{C_2, E_2\}_{0.8}, \{E_2\}_{0.7}, \{\}_{0.1}\}
\end{aligned}$$

scenario S1

<S1	S1>	<A	A>	<B	B>	<C	C>	<D	D>	
[0, 0]	[20, 30]	[0, 0]	[15, 20]	[10, 20]	[20, 30]	[0, 0]	[5, 10]	[10, 15]	[15, 20]	<S1
	[0, 0]	[-30, -20]	[-15, 0]	[-20, -10]	[0, 0]	[-30, -20]	[-25, -10]	[-20, -5]	[-15, 0]	S1>
		[0, 0]	[15, 20]	[10, 20]	[20, 30]	[0, 0]	[5, 10]	[10, 15]	[15, 20]	<A
			[0, 0]	[-10, 5]	[0, 15]	[-20, -15]	[-15, -10]	[-10, -5]	[0, 0]	A>
				[0, 0]	[10, 20]	[-20, -10]	[-15, 0]	[-10, 5]	[-5, 10]	<B
					[0, 0]	[-30, -20]	[-25, -10]	[-20, -5]	[-15, 0]	B>
						[0, 0]	[5, 10]	[10, 15]	[15, 20]	<C
							[0, 0]	[5, 10]	[10, 15]	C>
								[0, 0]	[5, 10]	<D
									[0, 0]	D>

scenario S2

<S1	S1>	<A	A>	<E	E>	<C	C>	<D	D>	
[0, 0]	[30, 40]	[0, 0]	[10, 15]	[10, 25]	[30, 40]	[0, 0]	[5, 10]	[5, 10]	[10, 15]	<S1
	[0, 0]	[-40, -30]	[-30, -15]	[-20, -10]	[-0, 0]	[-40, -30]	[-35, -20]	[-35, -20]	[-30, -15]	S1>
		[0, 0]	[10, 15]	[10, 25]	[30, 40]	[0, 0]	[5, 10]	[5, 10]	[10, 15]	<A
			[0, 0]	[0, 10]	[15, 30]	[-15, -10]	[-10, -5]	[-10, -5]	[0, 0]	A>
				[0, 0]	[10, 20]	[-25, -10]	[-20, -5]	[-20, -5]	[-10, 0]	<E
					[0, 0]	[-40, -30]	[-35, -20]	[-35, -20]	[-30, -15]	E>
						[0, 0]	[5, 10]	[5, 10]	[10, 15]	<C
							[0, 0]	[0, 5]	[5, 10]	C>
								[0, 0]	[5, 10]	<D
									[0, 0]	D>

Table 1: Matrices of minimal complete graphs of S_1 and S_2

Restricting to the examination of minimal environments $\mathcal{E}_0$ (i.e those being the set of all unobserved activities), we can conclude that:

- scenario S_1 will be recognized with certainty 0.7 if we observe B with certainty
- scenario S_2 will be recognized with certainty 0.7 if we observe E with certainty

The computation of the matching degrees gives:

$$\text{comp}(S_1) = \text{wmin}_{0.5,1}(\min(\min(0.7, 0.8), 0.8), 1) = 0.7$$
$$\text{comp}(S_2) = \text{wmin}_{1,0.5}(\min(\min(0.7, 0.8), 0.8), 1) = 0.7$$

This is consistent with the decision of the ATMS.

Now, if C were observed with certainty, the environments $\{C_1, B_1\}_{0.8}$ and $\{C_2, E_2\}_{0.8}$ of $L(S_1)$ and $L(S_2)$ respectively tell us that S_1 and S_2 would be recognized with certainty degree 0.8. As it is easy to check, this can be also retrieved from the computation of matching degrees as above.

Lastly, suppose that we receive an ambiguous observation, similar to B and E, with certainty degrees 0.4 for B and 0.3 for E. Let us suppose that the temporal constraints are satisfied for S_1 and S_2, so that no scenario is eliminated. The global matching degrees are:

$$\text{comp}(S_1) = \text{wmin}_{0.5,1}(\min(\min(0.7, 0.8), 0.8), 0.4) = 0.4$$
$$\text{comp}(S_2) = \text{wmin}_{1,0.5}(\min(\min(0.7, 0.8), 0.8), 0.3) = 0.5$$

Although B is more plausible than E, B is essential for the identification of S_1, while E is much less. Therefore, scenario S_2 is more plausible.

7 Discussion and concluding remarks

In this paper, we have presented the foundations of a new approach to scenario modelling and recognition, based on possibilistic logic, CSP, and aggregation connectives of fuzzy set theory. Although we have shown that our approach satisfies all requirements and is mathematically sound, some aspects could have been defined differently, or may be further extended.

The first point concerns possibilistic logic and time. In our approach, time does not intervene in clauses in our knowledge base. However it would have been possible to include this aspect, by using dynamical certainty degrees. Let us suppose we have to translate the following piece of expertise:

Scenario S is formed with activities A and B (mandatory). Moreover B must be before A.

It is clearly a conjunction, with a precedence constraint. We can translate this in the following way:

$$(\neg A \vee \neg B \vee S \quad \alpha)$$

with α the certainty degree that "B is observed before A is observed". This is clearly a degree which is computed dynamically, as soon as A and B are observed.

The second point concerns the choice between abductive reasoning and deductive reasoning. We have chosen the second solution, although the first one appears as a more natural choice, in the view of the available information. When the expert says:

In scenario S_1, there is always A, B and C together

it does not mean that the observation of A, B, C necessary entails the recognition of S_1. Indeed, it may exists other scenarios where A, B, C appear jointly. In this case, we cannot write:

$$(\neg A \vee \neg B \vee \neg C \vee S_1 \quad 1)$$

and we must put a value for α which takes into account the possible existence of other situations where the observation of A, B, C permits to infer something different. It would be better to choose an *abductive* modelling, more faithful to the spirit of the expertise, which would be:

$$(S_1 \rightarrow A \wedge B \wedge C \quad \alpha)$$

In this case, observations are hypotheses, and scenarios and sub-scenarios are non-hypotheses. We will compute the label of observations, which will be explained by the scenarios and sub-scenarios (or preferably only scenarios).

The third point concerns the logical connective XOR, which was not considered in our development since it raises some difficult issues. The case of XOR leads to clauses which are not Horn N-clauses. This causes computation problems since practical implementations of Π-ATMS do suppose Horn N-clauses, but this does not entail theoretical limitations since the resolution principle can still be applied. More specifically, for a scenario S with certainty α being defined by $A_1, \ldots, A_n$ linked by a XOR, we use the equivalent expression

$$(A_1 \wedge \neg A_2 \wedge \cdots \wedge \neg A_n) \vee (\neg A_1 \wedge A_2 \wedge \neg A_3 \wedge \cdots \wedge \neg A_n) \vee \cdots \vee (\neg A_1 \wedge \cdots \wedge \neg A_{n-1} \wedge A_n) \quad (7)$$

This is translated as follows:

$$\begin{aligned} (\neg A_1 \vee A_2 \vee \cdots \vee A_n \vee S \quad \alpha) \\ (A_1 \vee \neg A_2 \vee A_3 \vee \cdots \vee A_n \vee S \quad \alpha) \\ \vdots \quad \vdots \\ (A_1 \vee \cdots \vee A_{n-1} \vee \neg A_n \vee S \quad \alpha) \end{aligned}$$

A more cumbersome problem is that to infer S in the above situation, we have to observe e.g. A_1 and $\neg A_2, \ldots, \neg A_n$. The actual meaning of observing the "absence of an activity" may raise an interpretation problem, since not observing A_2 is not (always) equivalent to the absence of A_2. Moreover, this will obscure the use of environments which contain yet not observed activities.

A last topic already addressed concerns the presence of fuzzy (flexible) temporal constraints, which would constitute a more faithful modelling of the expertise (see Section 3.2). This will induce a higher computational cost, which however remains reasonable once simple representations of temporal constraints are adopted (e.g. trapezoidal fuzzy constraints).

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