Temporal Matching:
Recognizing Dynamic Situations from Discrete Measurements

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Abstract

The converse problem of measurement interpretation is event recognition. In situations which are characterized by a specific order of events, a single snapshot is not sufficient to recognize an event. Instead one has to plan a measurement sequence that consists of observations at more than one time point. In this paper we present an algorithm for planning such an observation sequence based on the specification of the event and discuss the problem of giving a meaningful definition of a 'successful match of a measurement sequence against a situation description'.

1 Introduction

Conventionally, in Qualitative Reasoning the term *measurement interpretation* stands for the task of explaining a given set of measurements by reconstructing a section of the system's envisionment that accounts for all of the measurements (for examples, see [Forbus83], [Forbus86], ISimmons82]). In a diagnostic setting measurement interpretation is useful when observations have already been made (e.g. by automatic sampling of quantities) but a hypothesis has not yet been formed.

Frequently, though, we are faced with the opposite situation: given a hypothesis we must determine a set of observations that will support it. Things become complicated when the hypothetical behavior is characterized by a specific sequence of events. We have found examples for this case while constructing MOLTKE, an expert system for the diagnosis of CNC-machining centers [ANRR88]. A medical domain in which temporally distributed symptoms play a role is described in [Tsotsos85]. Verifying that such a behavior is occurring is the aim of *temporal event recognition;* it necessarily requires planning a measurement sequence that consists of observations at more than one time point. In this paper we discuss the problem of giving a meaningful definition of a 'successful match of a measurement sequence against a situation description' and present an algorithm for planning and matching an observation sequence.

2 An example

Consider the following example from MOLTKE's domain: One possible cause for an undefined position of the tool magazine is a faulty limit switch. This cause can be ruled out if the status registers IN20 and IN30 of the CNC control system show the following behavior: at the beginning both registers contain the value 1. Then IN20 drops to 0, followed by IN30. Finally, both return to their original values in the reverse order.

The situation is illustrated in the following figure:

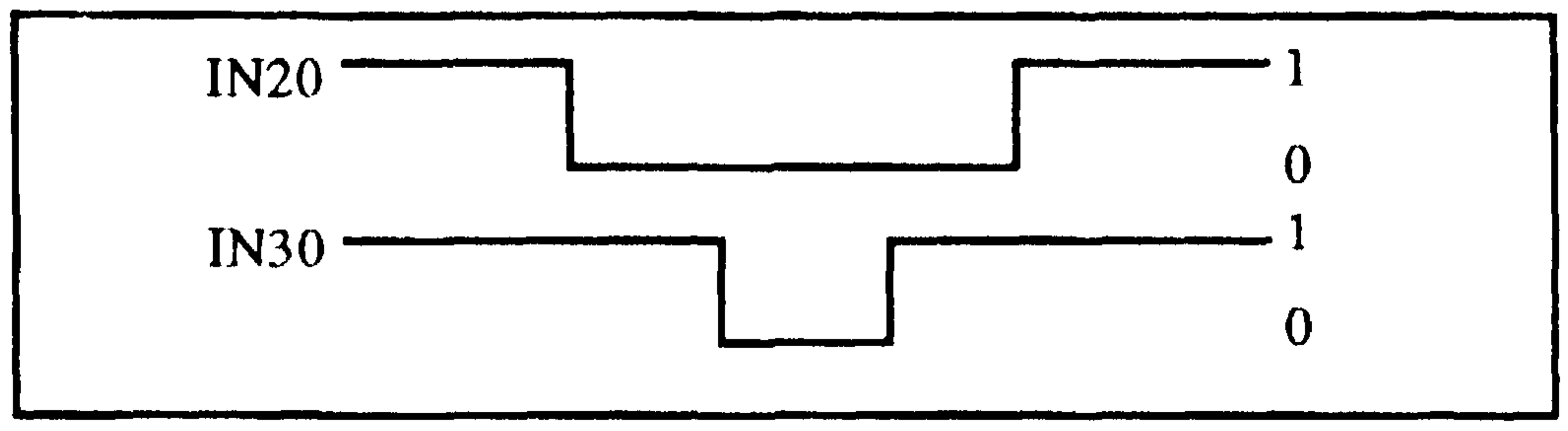

Fig. 1 - An example for a dynamic situation

If we want to recognize an occurrence of this situation we have to solve two problems:

- We have to plan an observation sequence for IN20 and IN30 that can be observed only in this particular situation.

- If at any point partway through the plan we are confronted with an unexpected measurement we have to be able to decide whether this piece of information is compatible with the situation or not.

The solution to the first problem depends on the assumptions we make about measurements. When we speak of a measurement we mean an observation of the amount of a specific quantity at a specific time point, made cither by a human observer or by a sensor. For our purposes measurements are characterized by the following properties:

(MI) No two measurements can take place at exactly the same time.

(M2) All measurements are discrete, i.e. the amount of a quantity is measured at a time point rather than over an interval.

Axiom (M2) immediately poses the problem that the period over which a situation occurs cannot be covered with measurements. Consequently, we have to define a weaker criterion: we would like to be able to derive from the situation a specific measurement sequence such that if this sequence has been observed and all possible additional measurements fit in we are sure that no other situation can have occurred modulo the resolution of our measurement techniques. In our example, we would insist on observing IN30 = I again after IN20 = 0 has been measured to make sure that IN30 does not drop to 0 before IN20 does. If on the other hand our initial measurement for IN30 had been IN30 = 0, we would have rejected an occurrence of the

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situation because there is no way of fitting in this observation at the beginning of the situation.

All of these intuitive notions will be defined more formally in the next section.

3 Situations, measurements, and matching

3.1 Situations

While figure 1 is a perfectly natural representation of the situation for a human reader, we adopt a representation that is better suited to algorithmic manipulation.

The basic vocabulary for the description of situations comprises quantities, intervals, episodes and value histories. As each of these terms have been used in the literature with varying meanings, we briefly summarize their intended interpretations within this paper.

Intervals are defined as in [Alien/Hayes85]. For the purpose of mapping an interval I onto a global time line we assume the existence of a left (right) endpoint of I which is denoted by L(I) (R(I)).

We assume that quantities q take on qualitative values[1] from some set Dom(q) and change their value only a finite number of times during any situation. A pair <I,v>, where I is an interval of maximal extent during which the (qualitative) value of q is constantly equal to v, is called an episode. The values that a quantity q takes on over a period of time are represented as a value history which is a set of episodes in which the episode intervals form a linear chain related by the interval relation "meets".

DEFINITION: A situation is a triple <Q, H, C> where
- Q is a finite set of quantities;
- $H = \{H_q \mid q \in Q\}$ is a set of value histories and
- $C = \{C_{E,E'} \mid E, E'$ episodes of histories in H$\}$ is a set of constraints specifying the relative positions of the histories w.r.t. each other. Each $C_{E,E'}$ is a disjunction of Allen interval relations ([Allen83])[2] one of which is required to hold from the interval of E to the interval of E*.

In our example, IN20's value history is (E_1=<I_1,1>, E_2=<I_2,0>, E_3=<I_3,1>), IN30's value history is (E_4=<I_4,1>, E_5=<I_5,0>, E_6=<I_6,1>). C contains $C_{E,E'}$ = {m} for each pair E, E' of consecutive episodes in the same history. The relative positions of the epsiodes in the two histories are specified by constraints such as $C_{E4,E2}$ = $C_{E2,E6}$={o}-

Actually the constraints in C are further restricted to convex relations, a subalgebra of Allen's full relation algebra, which are defined in [Nokel89].

The similarity between situations and the format of the envisionments generated by a number of qualitative simulation programs (e.g. HIQUAL [Vo687] or programs based on the episode propagators in [Williams86] and [Decker87]) is not accidental. One goal in a later stage of the project is to use one of these programs to generate the situation descriptions and use them later as complex symptoms in a rule-based diagnostic system. In this system the matching algorithm described in section 4 will be invoked by the rule interpreter whenever a situation is encountered in the condition part of a rule.

We need some more terminology to formalize the relation between situations as patterns and actual occurrences of situations:

DEFINITION: For every set of value histories H let
$P(H) := \{ L(I) \mid H_q \in H, <I,v> \in H_q \} \cup \{ R(I) \mid H_q \in H, <I,v> \in H_q \}$ denote the set of (left and right) endpoints of all episode intervals in all histories of H.

DEFINITION: An instance of a situation S = <Q,H,C> is a mapping D: $P(H) \rightarrow T$ (T dense, totally ordered, without least or greatest element, e.g. $T = \mathbb{R}$), which respects the relations in C.

DEFINITION: An instance D of a situation S = <Q, H, C> occurs in an interval $O \subseteq T$ iff D maps into O and

$$\forall t \in O, q \in Q: (M\ q\ t) = v \Rightarrow \exists <I, v> \in H_q: D(L(I)) \leq t \leq D(R(I)).^3$$

We say that a situation S has occurred when we are not interested in the properties of the particular instance.

3.2 Measurements

DEFINITION: A measurement is a triple <q, t, v>,where q is a quantity, $t \in T$ and $v \in$ Dom(q).

DEFINITION: A measurement sequence M is a finite set of measurements $\{<q_i, t_i, v_i>\}_{i=1,\dots,n}$ where $t_1 < t_2 < \dots < t_n$. Let Int(M) := $[t_1 ; t_n] \subseteq T$.

DEFINITION: A measurement sequence
$M = \{<q_i,t_i,v_i>\}_{i=1,\dots,n}$ is compatible with a situation S if there is an instance D of S that maps into Int(M) and
$\forall i: \exists <I, v> \in H_{q_i}: D(L(I)) \leq t_i \leq D(R(I)) \wedge v = v_i$.

3.3 Matching

The problem of recognizing an occurrence of a situation can be split into two tasks:

(a) planning a desired sequence of observations
(b) matching the actual observations against the situation.

We will discuss (b) first and return to (a) in section 4. Ideally, we would like to define a relation 'matches' between measurement sequences M and situations S in such a way that the following two properties hold:

Completeness: $\forall S\ \forall M$: M determines S => matches (M, S)

[1] Stated in another way, all continuously changing quantities have been replaced by discrete ones by imposing an order-preserving equivalence relation on their values.

[2] We abbreviate interval relations as usual, e.g. m for "meets", o for "overlaps" and so on.

[3] (M q t) is borrowed from QPT notation and means "the (magnitude of the) amount of q at timepoint t". M is a total function.