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An Interval-based Temporal Reasoning Scheme

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期間變數에 의거한 시간추출방식

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Abstract

This paper presents a new temporal reasoning scheme based on explicit expression of time intervals. The proposed scheme deals with the general problem of temporal knowledge representation and temporal reasoning and may be used in rule-based systems and qualitative models. Time intervals, not time points, are defined in terms of orders and/or numbers in a quantity space. As a result, the system behavior is represented in the form of partially ordered netwokrs. Such explicit and qualitative description of temporal quantities enables both reduction of ambiguity and parsimonious used of temporal information. Based on the proposed temporal reasoning scheme, a new rule-based qualitative simulation system is being built and evaluated.

1. Introduction

Human knowledge of all dynamic mechanisms and causal systems has depth along the time axis. While most of current reasoning systems and knowledge representation schemes maintain truth tables for sets of facts, the truth of a fact may not be appropriately assessed to be flat T or F in many cases. A fact which is now true may have been false before and the past information may still be indispensable in current reasoning. Any sophisticated world model should have the capability of capturing changes.

Unfortunately, since the early expert systems were not modeled after dynamic causal relationships among facts and events, temporal reasoning

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has remained a side issue until recently in the practical implementation of knowledge-based systems. As the demand grows for intelligent systems to grasp more and more aspects of human knowledge in application domains, temporal reasoning is becoming a weak link.

There has been a wide range of approaches to temporal knowledge representation and temporal reasoning. In this paper, problems in formal temporal reasoning are first discussed and discussion of time handling in qualitative simulation follows. An improvement for both worlds is possible using the concept of quantity space for processing time intervals. Finally, a representation scheme, SEN (State-Event Network) is presented with a supporting quantity space management system.

2. Formal Temporal Reasoning

Allen[2] categorized the approaches to temporal reasoning into four groups. The first is state space approaches, inspired by the classic situation calculus, in which a state is defined to be a description of the world at an instantaneous point in time. Actions are then modeled as functions mapping between states. Naturally, the main problem of this method is that it is too costly to retain a series of states as time passes through many time points.

The second type of approaches is what may be called the data line approaches. In this approaches each fact is indexed by a time point in the form of a calendar date or an integer. As is useful in such applications as temporal databases, this method of representation requires the knowledge of exact time points, which is often unavailable from the human's temporal knowledge. Consequently, these methods possess very limited expressive power and will be excluded in further discussions.

The third temporal reasoning scheme uses before/after chains to represent temporal information. While relative temporal informatioin can directly be handled with this scheme, the search problem to determine temporal relationship between two events may quickly become too large for the practically allowable search time or memory space. The work by Allen[1, 2] is improvement and extension of these methods.

Finally, there are formal models of time including situation calculus and the work by McDermott and his colleagues[10]. Most of those are essenatially point-based theories, and time intervals are derived from the points. On the contrary, as Allen argued properly, humans reason about time more often in terms of intervals rather than time points.

The discussion in this section will be concentrated on Allen's reasoning scheme because it is widely useful for describing dynamic mechanisms. However, the addressed 'scale problem' is common to other approaches which use non-numeric, qualitative time representation.

2-1. The Scale Problem

Allen's formalism of temporal knowledge representation is sufficiently compact and useful for many purposes. He argued that two time intervals must have one of seven possible relationships(i.e., before, during, starts, etc.) or their inverses. But such direct relationships between two intervals are not sufficient to deal with all types of temporal knowledge about intervals. For instance, 'state Y begins after state X ends' forms the relation 'before' in Allen's scheme. There is no way to describe how long after state X ends state Y begins.

Formally, his representation may be said using ordinal scale. It is not full interval scale in that the lengths of two intervals are not always comparable. Instead, the relationships determine only the orders between starting time points and ending time points of intervals. Thus, the lengths of two intervals can be compared only when they start or finish at the same time. Naturally, no operations like addition or subtraction are possible among time intervals. For example, the sentence 'process A and B can serially be finished while process C continues' can not be described.

More expressing power for termporal knowledge representation may be achieved by employing true interval scale for the lengths of time intervals. To do this, the lengths of durations should be coded in a way that their relative magnitudes are qualitatively described. This fits the concept of quantity space which was developed in qualitative simulation research[7, 19]. The quantity space and a temporal reasoning scheme based on it will be discussed later in this paper.

3. Time Handling in Qualitative Models

The concept of qualitative time plays a central role in modeling of dynamic worlds, an area known as qualitative modeling research. Qualitative modeling has been one of the newer research areas in artificial intelligence since the mid-1970's. Unlike conventional (i.e., numeric) computer simulation, a qualitative model uses qualitative descriptions of essential information in the system to represent the current system state and to calculate future states. The important advantages claimed by this approach are its resemblance to human reasoning about mechanisms, the parsimonious use of information, the capability of explanation, and robustness. These characteristics make qualitative models potentially useful in training[8] and aiding [12] of operation, monitoring, and fault diagnosis.

The basic techniques of qualitative simulation proposed by De Kleer and Brown[4], Kuipers[9], and Forbus[7] are among the most well known. They have more fundamental characteristics in common than differences[3]. One of the commonalities is that time is represented as a sequence of time segments. That is, any time point at which an event occurs should be determined on the time axis and hence in relationship to the time points of all other events before and after it. Only the order of events is significant in the reasoning while the lengths of intervals are irrelevant. Although such handling of time has been regarded quite natural for qualitative simulation, the idea of completely ordered sequence of time points imposes great limitations on the qualitative reasoning about complex dynamic systems.

In order to support such dynamic modeling, the temporal reasoning scheme is required to be both efficient and expressive. Generality is also vital since the systems to be modeled are diverse in time scope and the characteristics of underlying dynamics.

3-1. The Problem of Temporal Ambiguity

A problem with the single-line time axis is that insignificant ambiguities increases the complexity of reasoning. Whenever the order of two events is not readily determinable, there arises a 'burst' into two or more possible paths of future events. Such ambiguity may or may not be significant in predicting the meaningful future state of a system. In many cases, a subsequent 'merge', a same system state reached through either paths, may relieve the situatiion. In human reasoning, many occasions of the burst/merge would not be attended to in detail.

For example, suppose the current system state contains states A and B and is denoted by {A B}. State A leads to a sequence of states A → C → D and state B leads to another sequence B → E. Then the future system state would transit through either {A E} or {C B} as shown in Fig. 1. However, if the combination of A, E or C, B does not affect the two paths of system behavior, the final resultant state will unambiguously be {D E}. Whether C occurs before E does not need to be determined unless {A E} or {C B} itself carries some significance. This example indicates that the reasoning scheme.should allow parallel paths of situation development without trying to generate all the completely ordered sequences.

In contrast with the above example, humans would use partial ordering of events when needed for unambiguous reasoning as diagrammed in Fig. 2. It is reasonable to believe that if such partial ordering of events is facilitated a qualitative model following more closely the human mental models may be built.

The second problem is that the completely ordered event sequence is implied by the assumption that the orders of events can be derived from the system dynamics. Explicit description of the lengths of time intervals is not employed. As a result, system behavior involving combination and intervention among states may not be inferred in a straightforward way. It is when the combination or intervention affects a next state that an ambiguous order of events hampers the model's predictive power most seriousley.

In the above example, if {A E} produces state

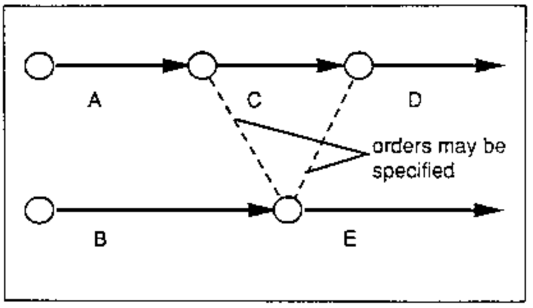

Fig. 2. Partial Ordering of Events

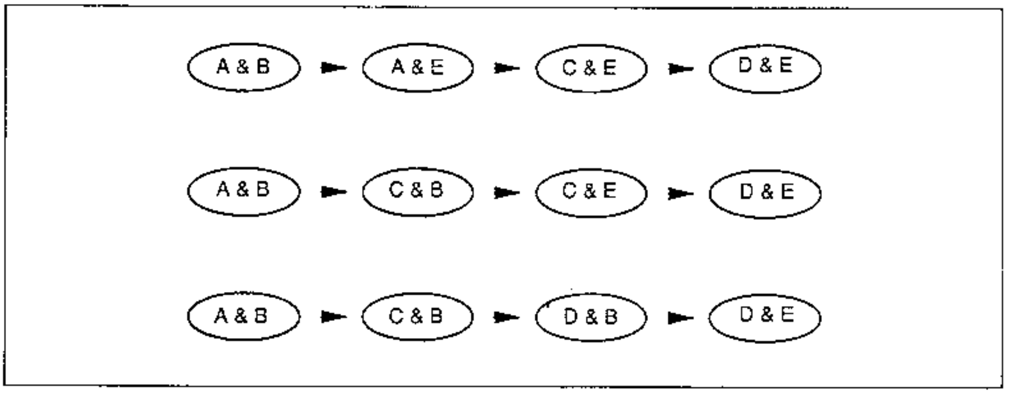

Fig. 1. Possible Paths of the System State

F which in turn is mandatory for the development of C $\rightarrow$ D, then whether B $\rightarrow$ E arises before A $\rightarrow$ C becomes critical for the success of the operation. A way of describing the relative lengths of the transition time for those rules is called for. When this temporal information is lacking, no compensation is possible no matter how smart the reasoning system is.

4. Handling Temporal Causalities

4-1. Time Intervals in the Quantity Space

The quantity space is a partial ordering on physical variable values. The partial ordering occurs because not all comparisons are relevant to understanding the physical system qualitatively. For example, consider a valve between two containers, A and B. When the valve is opened, the resulting behavior is determined by the pressures in two containers. The pressure at other unconnected points in the system does not affect the above result. The partial ordering may form a network of variables and constants with the links of ordinal relationships.

When the time intervals that are related to process and states are defined in the quantity space, the system behavior also takes the form of a network due to the resultant partial ordering among the states. This allows the knowledge engineer to input only the necessary specifications on the lengths of time intervals. When temporal ambiguity arises, more information about the involved time intervals may be sought and input to resolve it.

4-2. State-Event Network(SEN)

The proposed new temporal reasoning scheme is centered around a concept named State-Event Network(SEN). The syntax for knowledge description is similar to the rules in expert systems. The difference is in that a rule in SEN may contain a time interval variable and some intervening states besides the cause and conclusion. Moreover, a consequential state may be specified with a duration denoted by an interval variable. SEN handles those time intervals as ordinary quantities in the quantity space allowing them to have partial orders with each other.

The 'temporal rules' are dynamic while the rules in conventional rule-based systems are static. When a conventional rule-based system finds two rules to fire, it selects one either randomly or according to the preappointed priority. When SEN faces several rules to fire, it calculates the time points of the consequences and, if comparison is possible, executes the earliest one. Thus, the order of consequences is dynamically scheduled based on the accumulated time intervals along the event paths, not based on the fixed priority assigned to each rule. In cases it is not possible to determine the order, SEN assumes that the ambiguity is insignificant and proceeds in parallel starting with all the matched rules. A SEN simulation model can be built interactively to reduce ambiguity by trial and error. Once built, the model can be tested against ambiguity, which may be resolved in many cases by adding more temporal knowledge to the model.

The example in the previous section can be diagrammed as shown in Fig. 3. The nodes denote events and the horizontal arrows denote states. The vertical lines represent temporal relations that affect or cause other states. Although such a diagram cannot translate all system descriptions that

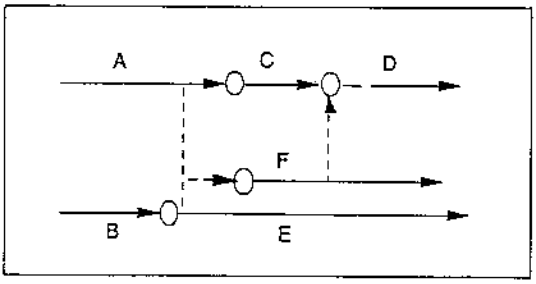

Fig. 3. A Simple SEN Diagram

the SEN is capable of handling, the figure provides insight on how the partial ordering of events operates.

5. The Quantity Network

A quantity space management system, named Quantity Network(QN) was developed to support qualitative reasoning on quantities. The quantity system should be independent of the dynamics or simulation models in the same manner as the arithmetic system is. This is especially important for dealing with both physical and temporal quantities without discrimination. To be independent, the quantity system should for itself preserve historically derivable information for each quantity. When working with QN, the inference engine need not be concerned with propagating and keeping trace of facts as long as the facts are about quantities. The network representation of QN and defining working memory for each quantity help the efficiency of its independent housekeeping of the quantity world.

QN is a multi-order implementation of the quantity space. In QN, the value of a quantity is defined as a 'frame' containing a set of ordinal relationships the quantity has with other quantities and numbers. All the user system should do is store a qualitative value in the network, change it whenever required, and use it for comparison with other values. QN will automatically update all the values it keeps and add more ordinal relationships whenever doing so is necessary for preserving all historically derivable relationships.

Frame of quantities form a network as shown in Fig. 4a. The partial ordering priciple and use of real numbers are obvious. The vertical placement of quantities are meaningful only when the quantities are connected to each other.

QN has a 'sticky' memory. For example, when the quantity A in Fig. 4a moves up so that the order between A and D or E as well as the order between B and E would be lost. But, in addition to retaining the old links $A>C$ and $C=B$, QN manages to add the links $C<D$, $C<E$, and $C<120$ so that no justifiable informatiion is lost(Fig. 4b).

QN incorporates the use of Working Memory (WM) to preserve the results of efforts performed to investigate ordinal relationships through the network. Every quantity has a working memory frame that contains the information to guide search in the network. Thus, once an area has been searched for some inquiry, the next search in that area will be much faster than the first time.

Finally, QN can handle as many differential orders as the computing environment allows. Derivative values in an order are propagated to higher orders as time advances.

QN does not care if a quantity is a physical variable or a time element. In this property, QN plays a similar role to the real number system used in quantitative models.

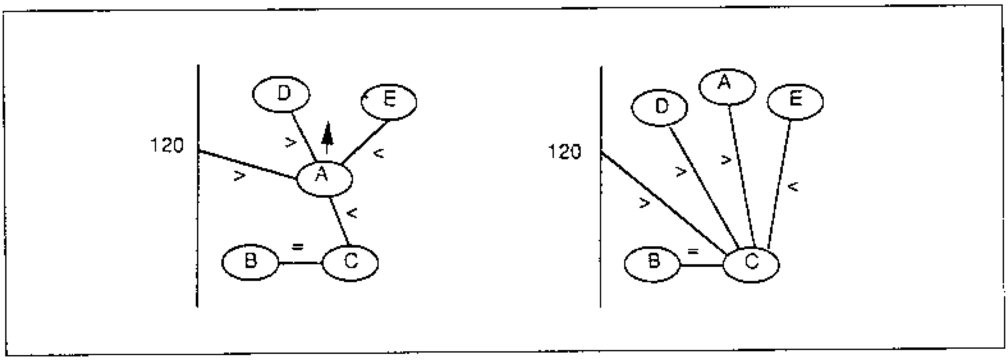

Fig. 4a. Quantity Network

Fig. 4b. After A Moved Up

6. Discussion

The temporal reasoning scheme proposed in this paper may more closely simulate the human experts' reasoning about system behavior in many domains. The most notable feature of the reasoning scheme is the expression of time intervals in a quantity space, which states their relative lengths compared to each other.

The differences between SEN/QN and other qualitative models can be explained by their different objectives. Since the purpose of this system is to emulate human reasoning, which may not be the main cause of other qualitative models, the system is more of an extension of rule-based reasoning systems. A premise is that rule-based reasoning is closer to the human reasoning about mechanisms than is direct qualitative translation of the laws of physics. When a model can more conveniently represent the human expertise about a mechanism, it would be more practical to use this model for human-computer cooperation in decision making and problem solving in large scale systems.

The methodology used in this system may well be generalized for developing expert systems that have better temporal reasoning capability. Temporal knowledge management for a database can also be benefited by assigning time variables to the facts it contains. The time variables are defined in a SEN network which is dynamically recalculated and reaaranged according to the dynamic rules.

The system was written in Allegro CommonLisp on a Macintosh II computer and is currently being refined. Its verification is also in progress through experimental modeling of a variety of mechanisms.

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