Anytime Synthetic Projection: Maximizing the Probability of Goal Satisfaction

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Introduction
We are interested in a continuum of plan-guided systems, from those that can operate entirely off-line, where complete plans are produced in advance and later used by independently competent execution systems, to those systems that are embedded in the situations for which their plans are generated. These embedded systems are especially interesting since they must close the loop between plan formation and plan execution in their environment. For an embedded system, simply generating a plan is not enough; such a system must instead incrementally coerce its environment to conform with its goals. The key tasks for an embedded system are resource-bounded incremental plan synthesis and reactive behavior using appropriate plans in a closed-loop fashion.

The work presented in this paper extends existing theory in the areas of temporal projection, anytime algorithms, and plan synthesis for embedded systems. The goals of this paper are to: 1) define the syntax and semantics of behavioral constraints and provide a search heuristic for their satisfaction; 2) define the probability of behavioral constraint satisfaction; 3) describe a synthetic temporal projection algorithm with anytime properties which heuristically maximizes the probability of behavioral constraint satisfaction.

The next section provides relevant background information. The synthetic temporal projection algorithm is then presented by way of a simple example. The paper concludes with a discussion of connections to related research.

Background
Realistic planning and control problems suggest the need for temporally extended goals of maintenance and presentation, in addition to the traditional planning goals of achievement. Our approach employs a language of behavioral constraints which is based on a branching temporal logic (cf Drummond, 1989). As an example, consider the following behavioral constraint, or BC:

\[
\text{(and} \\
\text{(prevent (and (drunk driver) (has-car-keys driver))} \\
\text{7 12)} \\
\text{(achieve (or (at-home me) (have-companion me))} \\
\text{?t1))}
\]

This BC represents a conjunction of two temporally extended goals: the first goal must be false from time 7 through time 12 and the second goal must be true at some arbitrary time in the future. Behavioral constraint semantics are defined in terms of possible behaviors that are synthesized by our temporal projection algorithm. Intuitively, we say that a given projection path \( \omega \) satisfies a behavioral constraint \( \beta \) if and only if all of the formulas in \( \beta \) are true in \( \omega \) over the required time intervals. See appendix A for more details on BC syntax and semantics.

We define a behavioral constraint strategy (or BC strategy) to be a partial order over a set of behavioral constraints. The partial order, denoted by "\(<\)"
indicates both execution and problem solving precedence. Behavioral constraint strategies for a given behavioral constraint are produced using domain- and problem-specific planning expertise. The BC strategy constructed for a given BC indicates a set of subproblems for the projector to satisfy and an order in which to satisfy them. This process is beyond the scope of this paper; please refer to Bresina and Drummond (1990) for more information. The way in which BC strategies are used by the projector is made clear in the next section.

In order to project future possible courses of action our projector needs a causal theory for each domain of application. A causal theory is a set of operators which defines both the actions that the system can take and the exogenous events that can occur in the application environment. The difference between actions and events is simply this: actions can be chosen for execution by the control system under construction (e.g., move in a direction) while the occurrence of events is determined by the system’s environment (e.g., a gust of wind). From the perspective of the projector however, actions and events are similar, and both can be characterized as a situation to situation transition.

The projector explores various possible futures by repeatedly finding enabled operators and applying them to produce new hypothetical situations. The projector creates a directed acyclic graph, where each node denotes a domain situation and each arc is labelled with a domain operator. Projection associates a duration with each operator application and uses this to calculate a time stamp for the resulting situation.

A path in a projection graph denotes a future possible behavior. Projection paths which satisfy a given behavioral constraint are compiled into a set of Situated Control Rules (SCRs) similar to the way that a STRIPS plan is transformed into a triangle table (Fikes et al., 1972). The SCRs indicate the reaction component those actions which will “lead to” the eventual satisfaction of its current behavioral constraint. SCRs are used by the reaction component as a set of local instructions constituting a control program.

See Bresina and Drummond (1990) and Drummond (1989) for more details about our overall architecture. The algorithm described in this paper does not critically depend on the architecture, so many irrelevant details have been suppressed. Our temporal projection algorithm can be used by a variety of systems, in a range of architectures.

The Projection Algorithm

This section presents our anytime synthetic projection algorithm. We start with a description of the algorithm in operation and then present ways to control the search that is inherent in this approach.

The project algorithm accepts a behavioral constraint and domain causal theory; it attempts to maximize the probability that the reaction component will satisfy the behavioral constraint. Our algorithm is based on the heuristic search paradigm which makes it hard to guarantee that the actual maximum probability will be found. Instead, as is typically done with heuristic search algorithms, we claim only that our algorithm attempts to maximize the probability of goal satisfaction, which we refer to as heuristic maximization.

To simplify the presentation we characterize the projector’s causal theory as a single function called transition. The function transition(s) maps a situation description s to a set of triples <s1, p1, o1> such that p(s1 | s, o1) = p1, where the conditional probability expression has the following interpretation. If o1 denotes an action, then p1 is the probability that s1 will be the resulting situation if o1 is executed in situation s. If o1 denotes an event, then p1 is the probability that s1 will be the resulting situation if o1 occurs in situation s. For a given s, we assume that the possible transitions are mutually exclusive. Notice that this definition of transition(s) makes the Markov assumption by ignoring the particular sequence of operators used to produce s. It is difficult to achieve a complete specification of all possible situation transitions in a realistic domain, and the automatic incremental improvement of the transition function specification is part of our future research agenda.

See figure 1 for an abstract projection graph example. The behavioral constraint strategy β1 < β2 has been selected as an appropriate way to satisfy β. This BC strategy indicates that a path which satisfies β1 composed with a path which satisfies β2 will constitute a path which satisfies β.

Project first calls traverse to find a single path that satisfies β1 < β2 from its “current” situation, s1. Traverse uses the function transition to create situations reachable under the application of a single operator from s1. Not all possible transitions are considered: a filter is used to select a subset of the most probable transitions, and only these are used to produce new successors to s1. In our example only s2 survives the probability filter. The number of survivors under this winnowing operation is determined by a filter-width parameter, corresponding to the filter selection function in Ow and Morton’s (1986) filtered beam search.

A heuristic value is calculated for each successor situation based on the situation’s probability and an estimate of the remaining work required to satisfy β1 from that situation. (This estimation function is explained in more detail below.) Another winnowing process is used to select a subset of these situations that have the highest heuristic value. For our example, this set contains only s2. In general, however, this set will contain a subset of all possible frontier search nodes in the developing projection graph. The number of elements in this set is limited by a beam-width parameter, corresponding to Ow and Morton’s (1986) beam selection function. This set of frontier nodes is passed on to a
projection paths. The algorithm finds high-probability lower bound is satisfy/3. Each probability component is defined below. This number gives us a lower bound which this algorithm's anytime operation. The con-

Figure 1: A Simple Projection Graph Example

recursive call of traverse.
Traverse continues to extend projection paths by selecting possible transitions until it finds a path which satisfies \( \beta_1 \). In the figure, the first satisfactory path discovered is \( s_1 o_1 s_2 o_2 s_3 o_3 s_4 \). Situated Control Rules are now compiled for each situation in this path. The reaction component will thus be given a set of rules of the form: If \( i \) AND \( \beta_1 \) THEN \( a_i \) for \( i = 1, 2, 3 \). At this point, traverse focuses its search for a solution path to \( \beta_2 \) in the subspace anchored at \( s_4 \). This is accomplished by collapsing the set of frontier nodes to the singleton set \( \{s_4\} \). Such a collapse has the effect of requiring any solution path for \( \beta_2 \) to start in the situation terminating the satisfactory path for \( \beta_1 \). Winnowing the set of possibilities in this way helps to control the projector's search by reducing the number of alternative situations in the expanding search frontier.

We call this strategy cut-and-commit, and it is one aspect of the algorithm's anytime operation. The conditions under which this approach is advisable are discussed below.

Traverse continues its search to satisfy \( \beta \) by finding a projection path which satisfies \( \beta_2 \) from \( s_4 \). In our figure, the eventual satisfactory path for \( \beta_2 \) is \( s_4 o_4 s_6 o_6 s_9 o_9 \). This path is passed to the SCR compiler producing another set of SCR's for the satisfaction of \( \beta_2 \). The probability for the path \( s_1 \) through \( s_4 \) can be calculated from \( p(s_{i+1}|s_i,a_i) \), \( i = 1, \ldots, 6 \) (as defined below). This number gives us a lower bound on the probability that the reaction component will satisfy \( \beta \). Assuming that there is still time before the reaction component must take action, we can increase this probability by finding additional paths which also satisfy \( \beta \). Each additional path will serve to increase the lower bound on the reaction component's probability of satisfying \( \beta \).

Robustify is our algorithm for finding additional projection paths. The algorithm finds high-probability deviations from the single existing solution path and calls traverse to find alternative paths which recover from each deviation. A deviation is a transition in a situation which produces a new situation from which there does not yet exist a satisfactory path. For example, when robustify is applied to the path \( s_1 o_1 s_2 o_2 s_3 o_3 s_4 \), it finds that the transition to \( s_5 \) via \( o_3 \) has a high probability of occurring in \( s_2 \). Traverse is used to recover from this deviation by synthesizing an alternate path, \( s_1 o_1 s_2 o_2 s_3 o_3 s_4 \), which also satisfies \( \beta_1 \). Similarly, robustify finds that the transition from \( s_5 \) to \( s_9 \) via \( o_9 \) has high probability and calls traverse to synthesize the path \( s_4 o_4 s_6 o_6 s_9 o_9 o_9 o_9 \). Each additional path serves to increase the probability that \( \beta \) will be satisfied by increasing the probability that each of its component constraints, \( \beta_1 \) and \( \beta_2 \), will be satisfied.

Situated Control Rules are compiled for each new subpath synthesized by traverse; in our example, new SCR's are created for \( s_2, s_8, s_9, s_5 \), and \( s_10 \). This incremental deviate-and-recover strategy is another aspect of the algorithm's anytime operation. As each new path is found, SCR's are given to the reaction component to help it deal with ever more of the possible domain situations in which it might find itself.

Controlling the Search

Situation probability and estimated remaining work were used in traverse to define a heuristic evaluation function. The heuristic value for a situation \( s \), with respect to a BC \( \beta \), is computed as: \( h(s, \beta) = K_1 p(s) + K_2 r(t(s, \beta)) \), where \( p(s) \) is the probability of situation \( s \) and \( r(t(s, \beta)) \) is the estimated remaining work required to satisfy \( \beta \) from \( s \). The user-provided weights, \( K_1 \) and \( K_2 \), determine the relative importance of low-cost and high-probability in the computation of \( h \) and, hence, affect the type of solutions synthesized by traverse. These parameters must be tuned as required for each domain of application. This section gives def-
initations for estimated remaining work and path probability, and more clearly explains the role of behavioral constraint strategies in controlling search.

Estimated remaining work

For planners concerned only with conjunctive goals of achievement, a heuristic based on situation difference gives reasonable results (Nilsson, 1980); to handle behavioral constraints we have generalized the notion of situation difference to that of remaining work per time.

Our heuristic uses two global parameters, \( KW \) (keep work) and \( CW \) (change work), which relate predicate truth value to work. The parameter \( KW \) denotes the minimum work per unit time to keep the truth value of a predicate constant. The parameter \( CW \) denotes the minimum number of work units required to change the truth value of a predicate. We assume that facts change instantaneously and \( CW \) estimates the minimum work required to change the truth value of a randomly selected predicate. A user must set these parameters as required for each application domain.

We define the remaining work per time \( rw(s, \beta) \) to be \( rw(s, \beta) = rt(s, \beta) \), where \( rw(s, \beta) \) is the remaining work necessary to satisfy \( \beta \) from \( s \) and \( rt(s, \beta) \) is the remaining time in which to do the work. The remaining time can be easily estimated from \( \beta \) and \( s \). Let \( s \) be a situation, and let \( \tau_n \) be the time stamp of \( s \). The numerator of our equation, \( rw(s, \beta) \), can then be defined as shown in table 1.

The function \( \text{min-true}(\psi, s) \) gives the minimum number of predicates in the formula \( \psi \) that are true in situation \( s \). Similarly, \( \text{min-false}(\psi, s) \) gives the minimum number of false predicates. These terms, together with \( CW \) and \( KW \), produce an optimistic estimate of the amount of remaining work.

For example, consider the evaluation of \( rw(s, (\text{maintain } \psi, \tau, \tau)) \). The formula \( \psi \) must be maintained from time point \( \tau_n \) through time point \( \tau_n \), from situation \( s \) with time stamp \( \tau_n \). The appropriate definition in table 1 has two terms: the first term describes the work required to keep the minimum number of true predicates in \( \psi \) true from \( \tau_n \) through \( \tau_n \); the second term deals with the work required to change the minimum number of false predicates in \( \psi \) to be true, and the work required to keep these predicates true from \( \tau_n \) through \( \tau_n \). The classical situation difference heuristic is a degenerate form of these measures, where work is measured in the number of predicates that must be made true and where there is no cost for keeping predicates true over time.

Goal Satisfaction Probability

Our description of traverse depended on the ability to combine individual transition probabilities into aggregate projection path probabilities; this section explains how this is accomplished.

Let \( G = (S, T) \) be a projection graph, where \( S \) is a set of possible situations and \( T \) is a set of situation-to-situation transitions; let \( s \in S \) be a particular situation, and let \( w = s_1 o_1 s_2 o_2 \ldots o_{n-1} s_n \) be a path in \( G \). The path probability of \( w \) is defined to be the product of the transition probabilities in \( w \): \( p(w) = \prod_{i=1}^{n} p(o_{i} \mid s_{i-1}, s_{i}) \).

For a situation \( s \), the situation probability is defined as the sum of the path probabilities of all paths from the unique starting situation of \( G \), \( ss \), to \( s \): \( p(s) = \sum p(w) \) summed over \( \{w : w = s_1 o_1 \ldots o_{n-1} s_n \text{ is a path in } G, s_1 = ss, \text{ and } s_n = s\} \).

Finally, we can define the probability that a behavioral constraint, \( \beta \), is satisfied by a projection graph, \( G \), as the sum of the probabilities of all paths in \( G \) anchored at the unique starting situation \( ss \) which satisfy \( \beta \): \( p(\beta \mid G) = \sum p(w) \) summed over \( \{w : w = s_1 o_1 \ldots o_{n-1} s_n \text{ is a path in } G, s_1 = ss, \text{ and } w \text{ satisfies } \beta\} \).

The probability that the reaction component will satisfy a BC \( \beta \) under the guidance of the SCRs compiled from a projection graph \( G \) is bounded below by \( p(\beta \mid G) \). The probability \( p(\beta \mid G) \) is a lower bound because the reaction component might have access to other SCRs relevant to \( \beta \) which cover situations that are not in \( G \).

Behavioral Constraint Strategies

As mentioned above, a behavioral constraint strategy is a partial order over a set of behavioral constraints. A given BC strategy controls search by giving the projector a set of behavioral constraints to satisfy and an order in which to satisfy them. A BC strategy is satisfied when each of its component constraints is satisfied in an order consistent with the given partial order.

To make this idea more precise, let \( (\Gamma, <) \) be a BC strategy, where \( \Gamma \) contains \( n \) behavioral constraints; let \( \Theta \) be the set of all total orders over \( \Gamma \) compatible with

### Table 1: Definition of \( rw(s, \beta) \)

<table>
<thead>
<tr>
<th>Condition</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>( rw(s, (\text{and } \beta_1 \ldots \beta_n)) )</td>
<td>( \sum_{i=1}^{n} rw(s, \beta_i) )</td>
</tr>
<tr>
<td>( rw(s, (or \beta_1 \ldots \beta_n)) )</td>
<td>( \min_{i=1}^{n} rw(s, \beta_i) )</td>
</tr>
<tr>
<td>( rw(s, (\text{maintain } \psi, \tau, \tau)) )</td>
<td>( KW \cdot \text{min-true}(\psi, s) \cdot (\tau - \tau_n) + \text{min-false}(\psi, s) \cdot (\text{cw} + KW \cdot (\tau - \tau_s)) )</td>
</tr>
<tr>
<td>( rw(s, (\text{prevent } \psi, \tau, \tau)) )</td>
<td>( KW \cdot \text{min-true}(\psi, s) \cdot (\tau - \tau_n) + \text{min-false}(\psi, s) \cdot (\text{cw} + KW \cdot (\tau - \tau_s)) )</td>
</tr>
<tr>
<td>( rw(s, (\text{maintain } \phi \varphi)) )</td>
<td>( KW \cdot \text{min-true}(\phi, s) + \text{cw} \cdot \text{min-false}(\psi, s) )</td>
</tr>
<tr>
<td>( rw(s, (\text{prevent } \phi \varphi)) )</td>
<td>( KW \cdot \text{min-true}(\phi, s) + \text{cw} \cdot \text{min-false}(\psi, s) )</td>
</tr>
</tbody>
</table>
The objective for traverse is to synthesize a path \( w = w' \circ w'' \circ \cdots \circ w^n \), such that there exists a total order \( \theta \) where for each \( w_k \), \( w^{k+1} \in w \), there exists \( \beta < \beta' \in \theta \) such that \( w' \) satisfies \( \beta \) and \( w^{k+1} \) satisfies \( \beta' \). Furthermore, each \( \beta \in \Gamma \) must be satisfied by one \( w \) in \( w \). The "\( \circ \)" operator represents path composition defined as follows: \( w \circ w' = s_1 s_2 s_3 \cdots s_i s'_1 s'_2 s'_3 \cdots s'_j \), where \( w = s_1 s_2 s_3 \cdots s_i \) and \( w' = s'_1 s'_2 s'_3 \cdots s'_{j} \). If the union of \( s_i \) and \( s'_i \) is consistent, else \( w \circ w' \) is undefined.

Consider the simple example used above where the BC strategy is \( \beta_1 < \beta_2 \). In the ideal case, for each path \( w^1 \) that satisfies \( \beta_1 \), there exists a path \( w^2 \) that satisfies \( \beta_2 \) such that \( w^1 \circ w^2 \). In this case, our cut-and-commit strategy will never be forced to backtrack over the first solution found for \( \beta_1 \), and the policy of immediate SCR compilation is risk-free. However, it is not always possible to construct such ideal BC strategies. More typically only a subset of the paths which satisfy \( \beta_1 \) can be extended to also satisfy \( \beta_2 \). In this case, the projector might have to backtrack to find another solution to \( \beta_1 \). If such backtracking occurs, then (at least some of) the SCRs that were compiled from a rejected solution to \( \beta_1 \) are not appropriate in the context of \( \beta_1 < \beta_2 \). However, they may be appropriate in the context of another BC strategy and hence could still prove useful.

In this paper, we do not address what the reactor does when more than one SCR is applicable. This issue is part of our current research effort; we are developing a SCR conflict resolution strategy based on the BC strategy context for which an SCR is appropriate in combination with the transition probability and the remaining work estimates associated with an SCR. In our ongoing research on the interaction between the projector and the automatic production of behavioral constraint strategies, one future topic will be techniques for assessing and reducing the risk of backtracking over the inter-behavioral constraint "cut" points.

Discussion

A triangle table (Fikes et al., 1972) is analogous to what you get after running traverse only once, a universal plan (Schoppers, 1987) is analogous to what you get by doing exhaustive search of the space of possible domain situations. A triangle table is like a set of SCRs designed to deal with each situation in a sequence of situations, and a universal plan is like a set of SCRs which has 100% coverage of the space of situations. Ginsberg (1989) has argued against the practicality of universal plans. He has suggested that for "cognitive tasks", a system should be able to enhance its performance by expending additional mental resources. Our projection algorithm does exactly this. Under our approach, additional computation time serves to increase the probability of goal satisfaction.

There are various architectures addressing the real-time embedded control problem. Representative approaches include Brooks' (1985) subsumption architecture, Nilsson's action nets (Nilsson et al., 1990), Maes' (1990) spreading activation approach, and the situated automata of Rosenschein and Kaelbling (Rosenschein, 1989; Rosenschein & Kaelbling 1986; Kaelbling, 1987a,b, 1988). Each of these approaches gives a designer a language and methodology for specifying a control system.

Brooks' (1985) subsumption architecture provides an elegant way of organizing the functional components of an embedded control system. The subsumption architecture "model" of embedded execution is richer than our simple IF-THEN Situated Control Rule view. However, we are able to synthesize SCRs automatically from a given behavioral constraint and causal theory describing a particular application domain. To our knowledge, Brooks has not yet addressed the automatic synthesis of subsumption architecture instances.

Nilsson's action nets (Nilsson et al., 1990) provide another methodology and language for the description of embedded systems. Nilsson's view of closed-loop homeostatic servo mechanisms is appealing, and early results are promising. Our work differs in providing a more expressive language of behavioral constraints and by using information about situation probability to control search.

Maes' (1990) system employs a spreading activation approach for dynamic action selection and can be viewed as a form of on-line action synthesis. The behavior of Maes' algorithm depends on a number of global parameters which are set by the user based on (among other factors) characteristics of the environment and the specific goal to be achieved. Hence, if the nature of the environment changes or if the desired goal changes, the user will need to re-tune the parameters. Our work differs by explicitly searching through the space of possible futures. A behavioral constraint is one of the algorithm's inputs; hence, changes in the system's goals are taken into account automatically. Changes in the nature of the environment would be reflected in the transition probabilities; hence, updated probabilities would appropriately influence the projection search.*

The most closely related work is that of Rosenschein and Kaelbling (Rosenschein, 1989; Rosenschein & Kaelbling 1986; Kaelbling, 1987a,b, 1988). Kaelbling's GAPPS system is a compiler which translates goal reduction expressions into directly executable circuits. However, a person writing GAPPS goal reductions must essentially do their own temporal projection; that is, it is the person's responsibility to guarantee that the rules, once sequenced, will "lead to" goal satisfaction. In contrast, our approach defines a temporal projection mechanism which sorts out the effects...

*We have not yet implemented the automatic update of transition probabilities.
of various action sequences automatically. Of course, we potentially pay a greater computational cost by carrying out this search. Additionally, the GAPPS system, and the REX language on which it is based, have a great deal to say about bounded reaction time in terms of the circuits synthesized from higher-level expressions. We are not currently addressing this issue.

We stress the synthetic nature of our projector to distinguish it from analytic projection (Dean & McDermott, 1987; Hanks, 1990). An analytic projector is used by a planner to validate plans while a synthetic projector combines operator selection and validation in the same algorithm. The analytic/synthetic distinction is largely one of perspective, since it is possible to view a planner–analytic projector pair as a complete system which performs synthetic projection.

Hanks (1990) greatly extended the capabilities of temporal projection systems by adding information regarding probability. Dean and Kanazawa (1988) also use similar information. The techniques of Hanks, Dean and Kanazawa can be used to judge the probability that a given fact will be true at an arbitrary point in the future. We can imagine providing such an inferential facility, but for now, we permit only calculations of individual situation probability. The algorithms of Hanks, Dean and Kanazawa can perform more powerful inferences.

Dean and Boddy (1988) have characterized an anytime algorithm as one which can be asked for an answer at any point, where the algorithm's answers are expected to improve the longer it is allowed to run. Our use of traverse and robustify satisfy this characterization, in the sense that a set of SCRs is available for the reactor at any point in time, and in the sense that the set of SCRs "improves" over time by incrementally increasing goal satisfaction probability. We have identified two ways in which a synthetic temporal projection algorithm can be considered "anytime": first, by using our cut-and-commit search strategy based on behavioral constraint strategies; and second, by recursively employing our deviate-and-recover strategy to manage probable errors.

Our cut-and-commit approach ameliorates the complexity of the projection search. To see this, suppose that the average branching factor in the projection is δ, and suppose that an eventual solution path is of length n. This means that breadth-first search would have to project in the worst case, δn + 1/2 many situations to find a successful path. Suppose that the projector's BC strategy is totally ordered and is of length c. In the worst case, the number of situations that traverse must project is cδn/(c+1)2 − 2c. As c approaches n, the number of situations we must consider falls off dramatically. This assumes, of course, that no backtracking occurs. As c increases, the projection takes on the shape of a series of small trees connected end-to-end, rather than one large tree running from start to finish. The larger c is, the smaller the computation's anytime "grain size" becomes.

We have designed and implemented a simulator for an experimental domain called the Reactive Tile World. The Reactive Tile World exhibits exogenous events and temporally extended goals of maintenance and prevention. We are in the process of empirically validating our projection algorithm on a suite of Reactive Tile World test problems.

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Appendix A: Behavioral Constraint Syntax and Semantics

A behavioral constraint (BC) is an expression constructed according to the following grammar. We use the symbol β to stand for an arbitrary BC and the symbol | to indicate alternatives.

\[
\beta \rightarrow (\text{and } \beta_1 \beta_2 \ldots \beta_n) \mid (\text{or } \beta_1 \beta_2 \ldots \beta_n) \\
\beta \rightarrow (\text{maintain } \psi \tau_1 \tau_2) \mid (\text{prevent } \psi \tau_1 \tau_2) \\
\beta \rightarrow (\text{maintain } \psi \varphi \varphi) \mid (\text{prevent } \psi \varphi \varphi) \\
\psi \rightarrow (\text{and } \psi_1 \psi_2 \ldots \psi_n) \mid (\text{or } \psi_1 \psi_2 \ldots \psi_n) \\
\psi \rightarrow \text{predicate}
\]

We use ψ to denote a formula, τ to denote a time point constant, and φ to denote a time point variable. Time points are natural numbers. A variable is indicated by a question-mark, for instance: ?t. All variables are implicitly existentially quantified. We currently use time point variables only to express those goals of "achievement" or "destruction" which are not required to occur at a predetermined point in time; these goals are given the following syntactic forms: (maintain ψ φ φ) ≡ (achieve ψ φ) and (prevent ψ φ φ) ≡ (destroy ψ φ).

Behavioral constraint semantics are defined in terms of projection graph paths. Let \( w = s_0, s_1, s_2, \ldots, s_n \) be a projection graph path; let \( t_s(e) \) denote the time stamp of situation s; and let \( \beta \) be a behavioral constraint. Then \( w \) satisfies \( \beta \) under the following conditions.
\[ w \models (\text{and } \beta_1 \ldots \beta_n) \]
\[ \text{iff } \forall i \in \{1 \ldots n\}: w \models \beta_i \]
\[ w \models (\text{or } \beta_1 \ldots \beta_n) \]
\[ \text{iff } \exists i \in \{1 \ldots n\}: w \models \beta_i \]
\[ w \models (\text{maintain } \psi \; \tau_1 \; \tau_2) \]
\[ \text{iff } \exists s_i \in w: ts(s_i) \leq \tau_1 \text{ and } s_i \models \psi \text{ and } \forall s_j \in w, j \neq i: s_j \models \psi \text{ or } ts(s_j) > \tau_2 \]
\[ w \models (\text{prevent } \psi \; \tau_1 \; \tau_2) \]
\[ \text{iff } \exists s_i \in w: ts(s_i) \leq \tau_1 \text{ and } s_i \nvdash \psi \text{ and } \forall s_j \in w, j \neq i: s_j \nvdash \psi \text{ or } ts(s_j) > \tau_2 \]
\[ w \models (\text{maintain } \psi \; \varphi \; \varphi) \]
\[ \text{iff } \exists s_i \in w: s_i \models \psi \]
\[ w \models (\text{prevent } \psi \; \varphi \; \varphi) \]
\[ \text{iff } \exists s_i \in w: s_i \nvdash \psi \]
\[ s \models (\text{and } \psi_1 \ldots \psi_n) \]
\[ \text{iff } \forall i \in \{1 \ldots n\}: s \models \psi_i \]
\[ s \models (\text{or } \psi_1 \ldots \psi_n) \]
\[ \text{iff } \exists i \in \{1 \ldots n\}: s \models \psi_i \]
\[ s \models \text{predicate} \]
\[ \text{iff } \text{predicate} \in s \]

References


