

Being Committed to Qualitative Simulation

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ABSTRACT

We present a simple but potentially extremely powerful technique for associating degrees of commitment to the possible behaviours produced by qualitative simulation algorithms. The 'distance' between the predicted successor states and those determined from local propagation through the constraints is used to determine the most likely state and hence prioritise the behaviours. The method forms a basis for a technique for performing progressive reasoning to cope with real-time constraints. In this manner, the most likely solution is generated first and the subsequent behaviours are only generated if higher priority behaviours fail. Ultimately all possible behaviours are generated, as in current algorithms, and the soundness of qualitative predictions is guaranteed. The approach is applicable to any non-constructive simulation algorithm (e.g. QSIM and its derivatives).

1. Introduction

The major goal of qualitative simulation research is to develop techniques for generating a description of the behaviour from a structural model that captures only those distinctions that are necessary for the purpose for which the qualitative model has been constructed. Such distinctions determine the necessary *precision* of the description of a system's behaviour. Models that generate behaviours (solutions) with less precision than that of a given reference model have been called *abstraction models* [9, 17]. In which case, qualitative models are abstractions of real-valued models and form a major contribution that AI is currently making to the modelling of physical systems. However, other properties of behaviours can also be defined. In particular, the accuracy of the behaviour, with respect to a reference behaviour, can also be altered by generating *approximate* models. Such models can be obtained by either intentionally reducing the number of variables contained in the model or by replacing known functional relationships with simpler approximate ones. Whilst this approach has been extensively developed within conventional dynamic (numerical) system theory it has not yet been significantly explored within qualitative reasoning techniques. A third 'dimension' upon which behaviours can be classified concerns the degree of *commitment* associated with a given state, behaviour or, indeed, (constraint-based) model. This degree of commitment is important in the representation of complex and/or ill-defined systems [11] as it allows inherent uncertainty to be represented explicitly. It is fundamentally different from modifying the precision through

abstraction. In abstraction complete certainty is still assumed albeit in a lower resolution quantity space. Whereas, in commitment uncertainties in real-world modelling are explicitly represented. In spite of uncertainty being a major attribute of Artificial Intelligence approaches to knowledge representation, it has yet to be fully explored within approaches for Qualitative Reasoning. Up to date, only a few proposals [3, 4, 12, 13] have been made incorporating uncertainty within Qualitative Reasoning.

Those properties of models pointed above are, in fact, independent and can be used to generate a space of potential models reflecting the variation of the associated properties of the description of the behaviour. In our view the reason that the QR community almost entirely focuses on abstraction operations [19], is in the proper preoccupation with maintaining the formal properties of the simulation algorithm. However, we argue, in this paper, that by incorporating uncertainty we can associate degrees of commitment to behaviours which offer very significant advantages for practical applications. Loosely speaking, we can use commitment to prioritise behaviours, thereby making qualitative simulation more effective and practical approaches e.g. time-constrained simulation or model-based diagnosis [5, 10, 14] much more feasible.

In present approaches to qualitative simulation, except for FuSim [13], the worst case solution is always assumed. That is, all *theoretically* possible successor states of a present state are maintained and, in fact, propagated with equal status. This, of course, leads to the generation of spurious behaviours that discredits qualitative simulation in the eyes of application engineers, in that, such multiple behaviour predictions are at variance with the uniqueness of the behaviour of the physical world. However, attaching an uncertainty measurement to those potential successor states, and hence a commitment to an associated behaviour, allows prioritised generation of behaviours or an efficient mechanism for their use within applications e.g. diagnosis. This allows a progressive approach to reasoning that first generates or utilises the 'most likely' behaviour and only progresses to other less committed behaviours if the behaviours considered fail to meet the purpose of the application system. Thus, ultimately, the soundness of the algorithm is still retained, however, a significant improvement in efficiency is possible by exploring the higher priority behaviours first.

In this paper, we present a basically simple technique for assigning commitment to states and hence priorities to behaviours. The approach is not restricted to techniques that utilise uncertainty in the definition of the quantity space such as FuSim, but can easily be incorporated within any non-constructive 'crisp' simulation algorithm (zero uncertainty) e.g. QSIM [7], HR-QSIM [18], etc. The following sections give formal definitions of our approach to assigning commitment to states and to describing methods for propagating priority measures for a particular behaviour. We then outline the potential uses of the technique which appear to us to be very significant indeed. Finally, we conclude and suggest some of the many possible extensions to the method.

2. Priorities of Qualitative Behaviours

A behaviour of a system variable within qualitative simulation is described by a sequence of temporally ordered qualitative states of that variable no matter whether the behaviour is a complete or a partial one. Thus, the determination of the priority associated with a behaviour will then be dependent upon the commitment associated with all the states that the behaviour consists of. In this section the state priority and the algorithm for computing state priorities are therefore discussed first. Based on this, techniques for computing the priorities of qualitative behaviours are then presented.

2.1. State Priority

Over the last few years a family of qualitative simulation algorithms [1, 13, 18] have been developed from the seminal work of Kuipers [7]. This proposed a highly innovative non-constructive approach to the propagation of system states. In this method, the system model, usually a set of (qualitative) constraints, is used within a non-constructive 'generate-and-test' procedure that first determines all possible successor states based on assuming continuity of system variables and then removes those states that are inconsistent with the system model and other known system properties. This has the very great advantage that the quantity space remains finite but suffers from the inevitable problem that, due to the inherent ambiguity of the underlying qualitative calculi [15], not all physically impossible behaviours are removed. This results in a set of behaviours that contain the qualitatively correct behaviour but also other spurious behaviours that do not reflect any real situations. Spurious behaviours often tend to obscure the 'real' behaviour hence making qualitative simulation less attractive to application engineers, though much progress has been made in developing so-called global filters [6, 8, 16] that can reduce the number of such behaviours.

To formalise the presentation, without losing generality, it is assumed that a finite set of possible states for each variable survive all possible filterings and that this set is denoted by $S = \{s_1, s_2, \dots, s_n\}$. Apparently, even in the worst case where no possible next states produced by the use of continuity are filtered, the cardinality of this set, n , is a small number. For instance, in QSIM, HR-QSIM, and FuSim n cannot be larger than 3, 4, and 6 respectively. Within this set, each element s_i , $i = 1, 2, \dots, n$, represents a pair of qualitative magnitude and qualitative rate-of-change and can be denoted by (A_i, B_i) . With the exception of FuSim, all other qualitative simulation algorithms treat the successor states that remain after constraint filtering as equally likely and, hence, propagate each state with equal priority. If any possible successor state intersects with the constraints it is retained; no information about the degree of matching is utilised or indeed generated. However, intuitively, those states that maximally intersect with the constraints can be considered as more likely and therefore can be given a higher degree of commitment and hence priority in further processing. We propose that the commitment of a particular state within such a set of possible states can be determined by a metric function that can faithfully represent certain preference criteria. Notationally, for each possible new state s_i the priority is represented by $\rho(s_i)$, where $\rho(s_i) = j$, $j \leq n$, indicates that s_i is the j th preferable state, namely the i th state is of the j th priority.

For convenience, in the following discussion, those possible states of a system variable generated by following the possible state transition tables and/or rules (based on continuity) [7, 13, 18] are called predicted states of the variable and those obtained by performing local propagation of the predicted states of other system variables throughout a set of constraints or the system model are termed propagated states. The basic criterion used herein is to assign the highest priority to a predicted state that maximises the possibility degree to which the state is considered to be the actual one. A predicted state of a particular variable is said to be the most possible actual state of the variable if it results in the shortest distance between all the predicted states of the variable and their corresponding propagated states. This can be better understood by considering the following simple example based on the 4-tuple parametric representation $[a, b, \alpha, \beta]$ of the fuzzy number used in FuSim. However, we emphasise that the development is not restricted to fuzzy quantity space but is applicable to any 'crisp'

interval based non-constructive algorithm.

Suppose that a system has three system variables $\{a, b, c\}$ related by the addition constraint $c = a + b$ and that these variables take values from a fuzzy quantity space. Consider that, based on continuity, two possible successor states are *predicted* as follows:

$$\begin{aligned} & \{([10, 12, 0.1, 0.1], [4, 5, 0.1, 0.1]), \\ & \quad ([3, 4, 0.2, 0.2], [6, 7, 0.2, 0.2]), \\ & ([13.5, 16.5, 0.3, 0.3], [10, 12, 0.3, 0.3])\}, \\ & \{([10, 12, 0.1, 0.1], [4, 5, 0.1, 0.1]), \\ & \quad ([3, 4, 0.2, 0.2], [6, 7, 0.2, 0.2]), \\ & ([4, 13, 0.3, 0.3], [10, 12, 0.3, 0.3])\}, \end{aligned}$$

where, for instance, $([3, 4, 0.2, 0.2], [6, 7, 0.2, 0.2])$ denotes a fuzzy qualitative state of the variable b with $[3, 4, 0.2, 0.2]$ and $[6, 7, 0.2, 0.2]$ representing the qualitative magnitude and the qualitative rate-of-change of b at this state, respectively. Evaluating the constraint a *propagated* state for the variable c , $([13, 16, 0.3, 0.3], [10, 12, 0.3, 0.3])$, can be obtained since

$$\begin{aligned} [13, 16, 0.3, 0.3] &= [10, 12, 0.1, 0.1] + [3, 4, 0.2, 0.2], \\ [10, 12, 0.3, 0.3] &= [4, 5, 0.1, 0.1] + [6, 7, 0.2, 0.2]. \end{aligned}$$

Clearly, both predicted states will survive the constraint filtering as shown in figure 1 (where two dotted fuzzy numbers denote the predicted qualitative magnitude values of the variable c and the highlighted one expresses the propagated qualitative magnitude) and also reflected by the following:

$$[13.5, 16.5, 0.3, 0.3] \cap [13, 16, 0.3, 0.3] \neq \Phi,$$

and

$$[4, 13, 0.3, 0.3] \cap [13, 16, 0.3, 0.3] \neq \Phi;$$

with both predicted rates of change being equal to the propagated one.

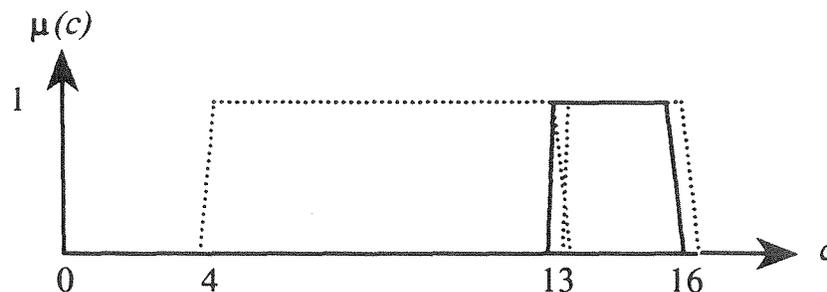


Figure 1. *Intersections between Predicted and Propagated Values*

Although maintaining both $([13.5, 16.5, 0.3, 0.3], [10, 12, 0.3, 0.3])$ and $([4, 13, 0.3, 0.3], [10, 12, 0.3, 0.3])$ as the possible states of c guarantees the soundness of the algorithm, only one of the two states actually reflects the correct qualitative abstraction of the real behaviour. From this example, it seems intuitive that the predicted state $([13.5, 16.5, 0.3, 0.3], [10, 12, 0.3, 0.3])$ of the variable c is much closer to the propagated state and hence more likely to corresponds to the real state than $([4, 13, 0.3, 0.3], [10, 12, 0.3, 0.3])$. If this distance information is not evaluated

and recorded it is lost and cannot subsequently be used to compare the possible behaviours. In this example, the predicted and propagated values of the rates of change of the variables match. This simplifies the above discussion but is not a necessary condition and will be removed in later developments.

2.2. Distance Metric

In order to determine the state priority, an explicit distance metric that is able to measure the difference between two qualitative values and further between two qualitative states is required. Of course, the concrete representational form of such a metric is dependent upon the detailed representation of the physical quantities or the quantity space adopted by a particular qualitative simulator. However, the following three basic properties of a 'metric' $D(.,.)$ must be held, where s_1 and s_2 are used to describe the predicted qualitative states and \hat{s}_1 and \hat{s}_2 represent their corresponding propagated qualitative states of a single variable:

- 1) If s_1 equals \hat{s}_1 , $D(s_1, \hat{s}_1) = 0$.
- 2) If s_1 does not equal \hat{s}_1 , $D(s_1, \hat{s}_1) > 0$.
- 3) In any case, $D(s_1, \hat{s}_1) = D(\hat{s}_1, s_1)$, and $D(s_1, s_2) \leq D(s_1, \hat{s}_1) + D(s_2, \hat{s}_2)$.

Apparently, this is an analogue of the axioms of a classical metric. Various distance metrics can be defined for this purpose and each reflects a different emphasis of both the simulator used and the criteria for priority determination. For instance, we utilise a distance metric already proposed by the authors to realise the approximation principle within the FuSim algorithm. In fact, this metric is general enough to be used for 'crisp' algorithms, however, other metric functions may also be developed and utilised in such cases. Within FuSim a distance function $d(.,.)$, used to find the difference between any two fuzzy qualitative values A and \hat{A} , is given as the following:

$$d(A, \hat{A}) = [(Power(A) - Power(\hat{A}))^2 + (Centre(A) - Centre(\hat{A}))^2]^{\frac{1}{2}},$$

where , for 4-tuple parametric fuzzy numbers,

$$Power([a, b, \alpha, \beta]) = \frac{1}{2}[2(b - a) + \alpha + \beta],$$

$$Centre([a, b, \alpha, \beta]) = \frac{1}{2}[a + b].$$

For simplicity, the common coefficient, 1/2, on the right hand side of the above two expressions can be omitted when substituting these expressions into the distance expression [13].

It is important to notice that this distance function produces a distance measure between two qualitative values. However, each qualitative state within a qualitative simulation algorithm is denoted by a pair of two qualitative values, one representing the qualitative magnitude and the other describing the qualitative rate-of-change. For two qualitative states (A, B) and (\hat{A}, \hat{B}) , distance between the values of their qualitative magnitudes $d(A, \hat{A})$ and that between their rates of change $d(B, \hat{B})$ are usually different. To ensure a correct commitment to the possible states, the following synthesised distance $D(.,.)$, based on the function $d(.,.)$ is used to measure the difference between two states (A, B) and (\hat{A}, \hat{B}) :

$$D((A, B), (\hat{A}, \hat{B})) = \max \{d(A, \hat{A}), d(B, \hat{B})\}.$$

It is straightforward to prove that $D(.,.)$ satisfies the three basic properties of a distance metric given previously.

Using such a distance function, the distances between the predicted states,

$$s_{c1} = ([13.5, 16.5, 0.3, 0.3], [10, 12, 0.3, 0.3])$$

and

$$s_{c2} = ([4, 13, 0.3, 0.3], [10, 12, 0.3, 0.3]),$$

and the propagated state,

$$\hat{s}_{c1} = \hat{s}_{c2} = ([13, 16, 0.3, 0.3], [10, 12, 0.3, 0.3]),$$

of the variable c in the example given in the preceding sub-section can be computed such that:

$$\begin{aligned} D(s_{c1}, \hat{s}_{c1}) &= 1, \\ D(s_{c2}, \hat{s}_{c2}) &= 288. \end{aligned}$$

Based on this, it is considered that s_{c1} is much more likely to include the actual 'real' state and, therefore, a higher commitment can be assigned to it.

It is important to emphasise that the above-shown distance metric is also suitable for determining distances between (crisp) interval-valued qualitative states. This is due to the fact that if the parameters α and β within the 4-tuple representation of a fuzzy qualitative value (i.e., a fuzzy number) $[a, b, \alpha, \beta]$ are both assigned to be 0 this fuzzy number degenerates to an ordinary real interval.

2.3. Computational Method for State Priority

Having defined a distance metric $D(.,.)$, the priority of a state can then be assigned. A general computational method for this purpose will be presented later in this sub-section. To better understand the technique for determining state priority, let us investigate a simplest case first. Suppose that only one constraint, $z = x + y$, within a system model involves the variable z and that, after local filtering, the following N three-tuples of qualitative states remain as the possible new state combinations of the variables x, y, z :

$$\{(A_{xi}, B_{xi}), (A_{yi}, B_{yi}), (A_{zi}, B_{zi})\}, \quad i = 1, 2, \dots, N.$$

From this, a set of propagated states $(\hat{A}_{zi}, \hat{B}_{zi})$ for the variable z can be obtained, resulting from summing the respective predicted possible qualitative magnitudes and rates of change of the variables x and y , namely,

$$\begin{aligned} \hat{A}_{zi} &= A_{xi} + A_{yi}, \\ \hat{B}_{zi} &= B_{xi} + B_{yi}. \end{aligned}$$

Using the given distance metric, for each $i, i = 1, 2, \dots, N$, the distance between (A_{zi}, B_{zi}) and $(\hat{A}_{zi}, \hat{B}_{zi})$ can be calculated.

With respect to a particular quantity space, both states (A_{zi}, B_{zi}) and $(\hat{A}_{zi}, \hat{B}_{zi})$ should ideally be identical to each other, or, equivalently, $D((A_{zi}, B_{zi}), (\hat{A}_{zi}, \hat{B}_{zi}))$

should be equal to 0 (if they both are supposed to reflect the underlying unique 'real' state of the variable z). However, due to the nature of (fuzzy) interval algebra or theoretically unavoidable qualitative ambiguity, this cannot be always satisfied. This leads to a difference between the two and the difference is directly represented by the measured distance $D((A_{zi}, B_{zi}), (\hat{A}_{zi}, \hat{B}_{zi}))$. Intuitively, the larger this distance is the less likely the state (A_{zi}, B_{zi}) will be the actual one and, hence, the lower the degree of the commitment that should be assigned to this state. From this point of view, any monotonically decreasing function of the distance metric can be used to measure the degree of commitment that a particular state is associated with provided that the monotonical function employed maps 0 to *full* commitment. Notice that, however, generating degrees of commitment to different possible qualitative states is aimed at prioritising such states in order to perform progressive simulation from the most likely state. Thus, information embedded in the distance metric function itself is sufficient for the purpose of determining state priorities. We shall, therefore, omit the discussion about the concrete forms of the monotonical decreasing functions (which may be instantiated in an infinite number of ways) but exploit the distance metric to meet the same end.

Different tuples of predicted states associated with the variables x , y , and z usually result in different distances between the predicted states of z and their corresponding propagated ones. This forms the very basis to prioritise the predicted possible states. In fact, when distances between $s_i = (A_{zi}, B_{zi})$ and $\hat{s}_i = (\hat{A}_{zi}, \hat{B}_{zi})$, $i = 1, 2, \dots, N$, are obtained, the state priorities can then be determined such that $\rho(s_i) = \rho((A_{zi}, B_{zi})) = j$ if

$$D(s_i, \hat{s}_i) = \min\{\{D(s_k, \hat{s}_k) \mid k = 1, 2, \dots, N\} - \{D(s_l, \hat{s}_l) \mid l < j\}\}.$$

Following this rule, for example, the state with the highest priority ($\rho((A_z, B_z)) = 1$) will be the one that satisfies:

$$D((A_z, B_z), (\hat{A}_z, \hat{B}_z)) = \min\{D((A_{zk}, B_{zk}), (\hat{A}_{zk}, \hat{B}_{zk})) \mid k = 1, 2, \dots, N\}.$$

The above discussion is based on the simplified case where only one constraint within the system model involves the variable z . When there are several constraints sharing this variable the corresponding computational method will, of course, become more complex. To extend this to a general situation, it requires a clarification of two basic notions, constrained variables and constraining variables, regarding the position at which a particular variable appears in a given constraint. Informally speaking, a single variable on one side of the given constraint is termed the constrained variable while those appearing on the other side are called constraining variables. With respect to such a distinction amongst system variables, it should be emphasised that causal implications are not used in the generation of the behaviours but rather the notions of constrained and constraining variables are only used in the calculation of the distance metric and hence for the associated priority. As discussed in [13, 15], if the values of the constraining variables are known, the value which the constrained variable should take can be obtained by performing the operation on the values of the constraining variables. However, in general, an unknown value of a constraining variable cannot be found by solving the equation as it can be done in solving numerical equations (e.g., via transposition) due to the lack of inverse operations. Fortunately, this problem is avoided within a qualitative simulation process since, there, each variable has a set of known values (generated by continuity) and constraints are used to check for the

consistency amongst values taken by different variables instead of propagating them to find unknowns. However, difficulty arises when trying to obtain the locally propagated state of a constraining variable for determining the distance measure to assign state commitment. It is necessary, therefore, to separate these constraints into two groups, one consisting of those with the shared variable being constrained and the other containing the constraints within which the shared variable acts as a constraining variable. For each constraint of the first group, a set of distances can be obtained in the same way as explained above for the special case. For any constraint belonging to the second group, the following approximate method is utilised. For a tuple of predicted states associated with the corresponding constraint, find the distance between the predicted state and the propagated state of the constrained variable within this constraint and, then, treat such a distance measure as that of each of the constraining variable.

Once the distance measures, of a variable, associated with each constraint have been determined the overall priority of a particular state of the variable can then be easily adjudged by ordering all the distance measures from the smallest to the largest and assigning the state attached with the smallest distance to the highest priority while that with the largest distance to the lowest priority. Summarising the discussion presented above results in a basic algorithm for computing the state priorities of system variables. In principle, for computational efficiency, the determination of state priority can be carried out while performing the constraint filtering through the use of the Waltz filter [7, 13, 18]. However, for the sake of clearer presentation, the algorithm outlined below is to be executed after accomplishing local filtering.

- Step 1) For each variable x find all constraints relating to it.
- Step 2) When x is the constrained variable within a constraint, find the N propagated qualitative states of the x $\{(\hat{A}_i, \hat{B}_i) \mid i = 1, 2, \dots, N\}$ by operating on the values of constraining variables; where N is the number of the tuples of the predicted possible states associated with this constraint; find the distances between (A_i, B_i) and (\hat{A}_i, \hat{B}_i) respectively:

$$\{D((A_i, B_i), (\hat{A}_i, \hat{B}_i)) \mid i = 1, 2, \dots, N\},$$

or

$$\{\max\{d(A_i, \hat{A}_i), d(B_i, \hat{B}_i)\} \mid i = 1, 2, \dots, N\};$$

then, attach each resulting distance measure to its corresponding predicted possible state of x and go to Step 4.

- Step 3) When x is a constraining variable, for each of its possible states within the set of predicted state combinations (i.e., the tuples of possible states associated with the constraint) find the propagated state of the constrained variable (not the x) within the constraint and then the distance between this propagated state and its respective predicted state; attach so resulting distance to the possible state of the constraining variable x .
- Step 4) Redo Step 2 or Step 3 until all the predicted states associated with all the constraints that are related to x have been attached with distance measures.
- Step 5) Prioritise the states of x such that $\rho((A_i, B_i)) = j, i = 1, 2, \dots, M$, if

$$D_i = \min\{\{D_k \mid k = 1, 2, \dots, M\} - \{D_k \mid k < j\}\},$$

where D_i , $i = 1, 2, \dots, M$, is the distance label attached with state (A_i, B_i) and M is the total number of possible states of the variable x associated with all the constraints.

It is worth emphasising that, within traditional qualitative simulation algorithms, in order to guarantee the generation of the correct behaviour all the states of a variable remaining after filtering (A, B) , $i = 1, 2, \dots, N$, are treated equally likely so long as the intersections between (A, B) and their respective (\hat{A}, \hat{B}) are not empty (strictly speaking, the intersections here should be those between A and \hat{A} and those between B and \hat{B}). Further, as pointed out earlier, the method for determining state priority is not restricted to simulation algorithms that can explicitly represent uncertainty within qualitative states. Instead, it can be readily extended or modified to increase the simulation effectiveness in crisp interval based techniques. Take QSIM as an example, the above algorithm can be utilised within its simulation mechanism provided that the distance metric between two qualitative states, $D(\dots)$, employed in the previous analysis is substituted with the distance metric between two qualitative magnitude values i.e. $d(\dots)$. This is due to the fact that the rates of change of a system variable only takes three sign values and, therefore, there does not exist a measurable difference between the predicted rate-of-change and the respective propagated rate-of-change after accomplishing local filterings. As a positive result of this, the calculations required for determining distances can be considerably reduced. Nevertheless, it should be noticed that this is possible only in the case when the landmarks are represented by known real numbers, or as in more recent reasoners like Q3 [1], when semi-quantitative information is utilised.

2.4. Behavioural Priority

It is natural, with each possible new state having been prioritised, to generate a system's behaviour from the state assigned with the highest priority. A useful strategy to perform effective qualitative simulation can then be described as follows. Start with a given initial state and predict the next possible states. Then, find the highest prioritised state and perform further simulation from this state. Repeat this at each simulation stage (of prediction and local filtering) unless at some stage the highest prioritised state has an attached distance label less than that attached with the second highest prioritised state at the previous simulation stages. In which case, the simulation will carry on from the predicted state labeled with the second shortest distance measure within one of the behavioural branches that were temporarily terminated earlier.

Such a strategy can be graphically illustrated in figure 2 through a simple example. Without losing generality, suppose that the given initial state is represented by s_{01} with $\rho(s_{01}) = 1$ and that three immediate successor states are produced: s_{11} , s_{12} , and s_{13} that survive constraint filtering. If the distance measures associated with these three states are 0.6, 0.8, and 0.9 respectively, their corresponding state priorities can then be determined such that $\rho(s_{11}) = 1$, $\rho(s_{12}) = 2$, and $\rho(s_{13}) = 3$. From this, the next possible states are first generated from state s_{11} and, as shown in the figure, we have $\rho(s_{21}) = 2$, $\rho(s_{22}) = 1$, and $\rho(s_{23}) = 3$. From state s_{22} , currently the highest prioritised one, two future states, s'_{31} and s'_{32} are obtained. However, the distances (0.8 and 1.0) labeled with these two new states are both larger than that (0.7) attached to the second highest prioritised state s_{21} and, thus, further prediction from s_{22} is halted, although states s'_{31} and s'_{32} can still be prioritised between themselves. The

simulation process will then carry on from state s_{21} that was temporarily stopped as the figure shows, producing the next highest prioritised state s_{32} .

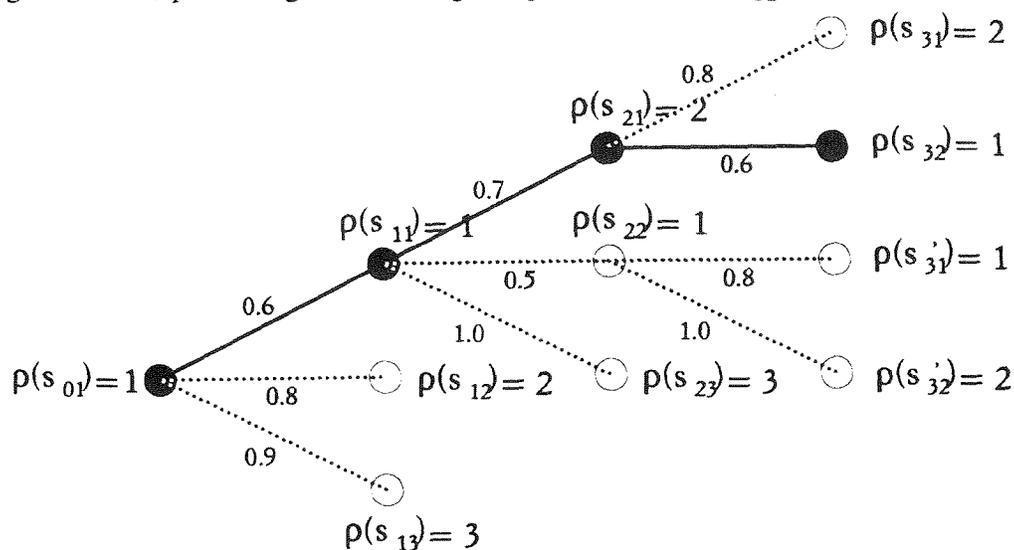


Figure 2. Progressive Simulation Strategy

Once the state priorities are determined the priority assigned to a particular behavioural branch (such as the partial behaviour consisting of states s_{01} , s_{11} , and s_{21} in the above example) can easily be adjudged. In fact, with respect to the above given simulation strategy, at each simulation stage the ordering in which the partial behaviour from the initial state to one of the present states is generated reflects the priority of this partial behaviour. In terms of using the distance metric we can determine the behavioural priorities by the following method:

Method for computing behavioural priorities: For the partial behavioural branches generated so far, B_i ($i = 1, 2, \dots, n$), each of which consists of a sequence of (predicted) states $\{s_{i0}, s_{i1}, \dots, s_{iN}\}$ and is consequently labeled with a sequence of distance measures $\{D_{i1}, D_{i2}, \dots, D_{iN}\}$, the behaviour B_i is said to have the j th priority if

$$c(B_i) = \min\{c(B_k) \mid k = 1, 2, \dots, N\} - \{c(B_k) \mid k < j\},$$

$$\text{where } c(B_i) = \min_{k=1}^N \{D_{ik}\}.$$

This method effectively constitutes a technique for realising progressive reasoning within qualitative simulation. The simulation system will explore the behaviour with the current highest priority thereby maximising the chance of producing a solution within the minimum computation and hence time. If unsuccessful the next highest priority behaviour will be explored and so on until, in the limit, all possible behaviours are generated, ensuring the eventual soundness of the qualitative simulation algorithm used.

It is interesting to notice that, within the Fuzzy Qualitative Simulation developed by the authors, the behaviours generated have been implicitly assigned with certain degrees of commitment using the distance metric shown earlier and further prioritised through the use of the *approximate principle* [13]. Originally, this principle is utilised to ensure the closure of the quantity space such that the resulting values from operations amongst qualitative values remain within the space. The application of the

approximate principle, of course, results in a reduction in the behaviours. However, the 'real' behaviour may be missed, thereby losing the soundness property of qualitative simulation. The technique for progressive reasoning based on explicit priorities effectively extend our approach so that the most likely behaviour, as determined by the approximate principle, is explored first.

3. Potential Application of Prioritised Behaviours

We have presented a basically simple but yet potentially very useful technique for making qualitative simulation more efficient and hence more attractive for practical applications. The potential uses include any application tasks for which efficiency is important such as real-time model-based diagnosis of dynamic systems [5, 10, 14] and real-time critical-event simulation [2]. We have not yet applied the proposed technique to any of our current applications but intend to do so in the very near future. At this stage, therefore, we can only outline the potential for our technique.

For real-time critical event simulation we envisage using the technique within FuSim to predict whether a particular critical event (state) will follow from the present state of the system. Advanced warning of such a state can be very important to operation staff, allowing shut-down or corrective action to be initiated. Obviously, the procedures are usually time-critical. In such situations, exploring the most likely behaviour first result in a possible reduction in computation time and hence maximising advanced warning, whilst still avoiding false negative predictions.

Within real-time model-based diagnosis of dynamic systems, the use of prioritised behaviours offers several distinct advantages. In such applications qualitative simulation is used to produce predictions of the evolution of a physical plant that are synchronously compared to the evolution of the observations from the real plant to detect discrepancies [10, 14]. If no discrepancy exists then the (normal) model currently being simulated reflects the real operation condition of the plant and the plant is assumed to be working normally. However, even in this case, the computation time of the qualitative simulation is required to be fast enough so that the generation of the next simulated system state occurs faster than the evolution of the real process. For processes with relatively fast dynamics, say less than 1 second transient response, this presents a problem even for current affordable computers. Prioritising the behaviour generation allows progressive reasoning and thereby easing the time-criticality of the simulation.

When fault conditions are present, i.e. the predicted behaviour does not match the observed state, the plant model is modified until a new predicted state is generated that does match the observed state and, hence, the possible fault associated with the modified model (constraint) is identified. The key is, of course, to find a suitable method for making model adjustments. The authors have proposed a method which they call *iterative search* [10] that provides a systematic way of exploring model adjustment that might result in a reduction of discrepancy between the observed and predicted behaviours. An important advantage of this is that, in principle, it does not require explicit fault models, although they may be used if available. However, this potentially results in exploring a number of models, at different stages of prediction, an attempt to get the best match (that minimises discrepancy metric). The use of prioritised behaviours offers the prospect of a significant reduction of the computation required to realise this method. Whenever a predicted behaviour is explored that obtains a matching between predicted and observed behaviours less than a prescribed

threshold of the discrepancy metric the search procedure could be halted, and the associated fault reported as a possible cause. Further, the degree of commitment implied by the priority can be combined with the value of the resultant discrepancy metric to produce an 'integrated' measure reflecting both the likelihood of that behaviour being the correct one (of the assumed underlying fault happening in the physical plant) and the degree of correspondence between observed and predicted values. Such possibilities seem to us to be a very exciting prospect for real-time applications of qualitative simulation.

4. Conclusion

We have proposed a simple but potentially very powerful technique for prioritising the behaviours generated by qualitative simulation algorithms. Although the presentation and associated examples utilise the fuzzy quantity space employed in FuSim [13], this is not essential and, in fact, as discussed in the paper, the technique is equally applicable to other non-constructive simulation algorithms [1, 7, 18]. The method forms a basis for a technique for performing progressive reasoning to cope with real-time constraints. In this manner, the most likely solution is generated first and the subsequent behaviours are only generated if higher priority behaviours fail. Ultimately all possible behaviours are generated, as in current algorithms, and the soundness of qualitative predictions is guaranteed. The technique has relevance to any application where computational resources are important.

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