Observation Filtering: from Qualitative Simulation to Qualitative Observer

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Abstract

Qualitative simulation as one of the main techniques in qualitative reasoning has the great potential to solve engineering problems, only if the difficulty of ambiguity can be overcome. On the other hand in many applications measurements are available and can be used to reduce the ambiguity. We propose in this paper *Qualitative Observer*, which is based on qualitative simulation and applied by *Observation filtering* technique, to provide a framework, in which this kind of information can be utilized to reduce accumulated ambiguity and to avoid spurious solutions.

1. Introduction

If sufficient information about a system is not available, such that no quantitative model can be established to give a real-valued behavioral description about it over time, one has to turn to alternative way of modeling, making use of the available incomplete information to build qualitative models, on which an analysis and reasoning to it can be carried out. Qualitative simulation as one of the main techniques in qualitative reasoning has the great potential to play a very important role to solve engineering problems.

However, due to the ambiguity of qualitative representation and calculus, a great number of the behaviors may be produced and seems to intractable, it often obscures the resulting real behavior of systems. The existing filtering techniques can not handle it in a complete satisfactory way. We believe that a further development will be still necessary before it can be extensively applied in engineering.

The work reported in this paper is one of the efforts to the goal. The *qualitative observer* (QOB) will be proposed, which is composed of qualitative simulation on the basis of conventional filtering techniques as well as our innovation: Observation filtering technique.

The paper is organized as following: next section we will briefly review qualitative simulation techniques; In section 3 observation filtering will be introduced in detail. An example of damped spring in the following section shows the effect of the observation filtering technique. A concept of the application of QOB to Instrument fault detection (IFD) is presented in section 5. Finally we conclude the paper after a discussion.

2. Qualitative Simulation of Continuous Systems

2.1 QDE and Qualitative Behaviors

In building the qualitative model (here we mean qualitative differential equation, QDE) of a system, one requires two sorts of knowledge about it:

• the structural description of a system, which is the specific, case-dependent information.

• the knowledge about the behavior of its individual parts, which is the general, case-independent information abstracted from former experience in different contexts.

Then infer the behavior of the complete system from its structure and the behaviors of its parts. Simulation as one of the main tools determines its behavior from the built QDE and the given initial condition.

The description for the structure and the componental behaviors is the constraint model which consists of qualitative variables (functions of time as well) representing the physical parameters of the system and a set of constraints on how those parameters may be related to each other. At any time t a qualitative variable is described by a pair: qualitative magnitude and its derivative (change direction and rate). Each of them takes value from a finite set of distinctions (qualitative values), called quantity space, which is the quantization of the real-number line and denoted as Q_X. The quantity space may be, for instance, three-valued {+,0,-} (de Kleer &

Brown 1984) or such one consisting of open intervals and real-valued landmarks as in QSIM (Kuipers 1986). The constraints such as in QSIM are composed of a variety of constraint primitives:

- arithmetic: ADD(x,y,z), MULT(x,y,z), MINUS(x,y), which constrain the addition, multiplication and negative relationships among variables, respectively.
- functional: $M^+(x,y)$, $M^-(x,y)$, which represent strictly monotonically increasing and monotonically decreasing functions, respectively.
- derivative: DERIV(x,y), which denotes y to be the derivative (with respect to time) of x.

By introducing fuzzy set in representation of quantity space, one may directly extend the functional constraints to nonmonotonical functions in form of fuzzy relations (Shen & Leitch 1993).

A qualitative state is a tuple of qualitative values. For an n-variable system, the qualitative state is an n-tuple, denoted as $s=(q_1, q_2, ..., q_n) \in \boldsymbol{Q}_{X1} \times \boldsymbol{Q}_{X2} \times ... \times \boldsymbol{Q}_{Xn}$. A qualitative behavior is a sequence of states (state chain),

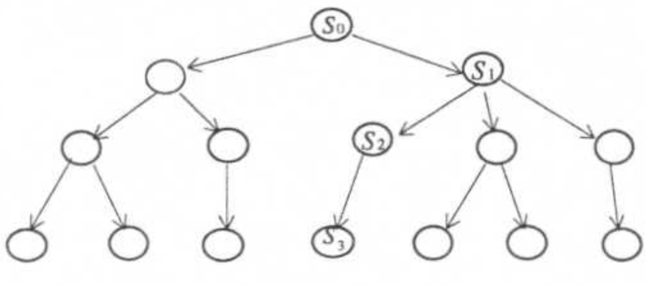

Fig. 1. Treeform state transition diagram

$b=(s_0, s_1, ..., s_k, s_{k+1}, ...)$, where s_{k+1} is the successor state of s_k. The behavioral description can be a graph consisting of the possible future states of the system. Due to the inherent ambiguity of qualitative representation and calculus, the simulated possible behavior (so called envisionment) is in general not unique, but any path through the graph starting at the initial state, as shown in fig. 1.

2.2 Filtering Techniques

The qualitative simulation proceeds by determining all possible transitions in qualitative value permitted to each parameter, then different so called *filtering techniques* are applied to check the consistency between each of the large combinations of qualitative transitions and the known information about the systems, excluding the inconsistent (impossible) ones. Complete state descriptions are then generated from the filtered tuples and these new states are made children states of current state. If more than one qualitative change is possible, the current state has

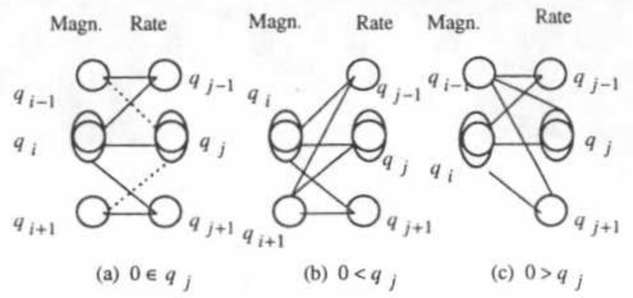

Fig. 2 Possible transitions

multiple successors, and the simulation produces a branching tree of states.

The possible transitions of each parameter can be independently determined by using continuity of the variable and its derivative. Suppose the magnitude and the rate of change of a variable x be q_i and q_j, where both q_i and q_j are the qualitative values in a quantity space $\boldsymbol{Q}_X$. q_{i+1} and q_{i-1} are the adjacent qualitative values of q_i, similar relationship between q_{j+1}, q_{j-1} and q_j. All of them belong to $\boldsymbol{Q}_X$, and q_k is smaller than q_l, iff $k<l$. We have the possible transitions as illustrated in fig. 2. The pairs that are produced by connecting an M-node and a R-node with a line, are possible transitions. Double circles represent the values in the current state. Note that the case (a) contains the situation where qualitative value *zero* could be an interval including real number *0*. This corresponds our experience: as soon as the behavioral difference of a variable in a system enters and stays in a small zone near zero, we say that the variable has reached its steady state; otherwise a real steady state will never be reached for most continuous systems. The imaginary line connection tells the extra possibilities in that case.

In terms of the information supplied, there are several sorts of filtering techniques:

- *Constraint filtering*. It makes use of the explicit relations among variables in a model. With the help of Waltz algorithm, the space of possible successor state (a subspace of the cross-product of the parameter values) is efficiently pruned: Kuipers 1986 and Weld & de Kleer 1990.
- *Temporal filtering* from Shen & Leitch 1993 and Weld 1990, which applies the temporal information the qualitative values imply. For more see section 2.3.
- *Global filtering* uses the pre-knowledge about the system, not necessarily including in QDE. For example, one can check and compare the states with the historical ones, excluding the possible repeat or constant states (Kuipers 1986); or implement non-intersection filtering by Struss 1988 and Lee & Kuipers 1988, which is limited to a second order system and may become very complicated for

a higher order system; or energy constraint filtering (Fouche & Kuipers 1992), etc.

- *Observation filtering*: with extra information the system itself provides. It will be explained in next section.

A rational architecture of their arrangement may be shown

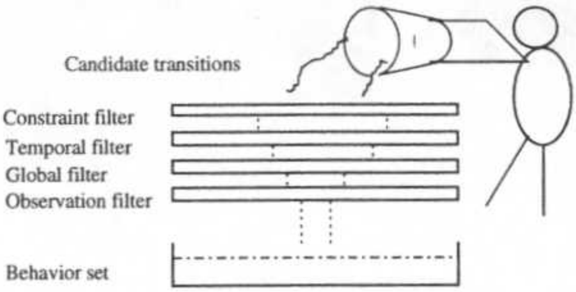

Fig.3 Filtering techniques

as in fig. 3. The finer is a filter, the more specific information it needs and the lower it should be laid.

2.3 Temporal Duration of Qualitative States

Making use of the available temporal information to eliminate some inconsistent combinations from candidate transitions has been studied by Weld 1990 and Shen & Leitch 1993. While in Weld's HR-QSIM, the time lengths could be *0, negl, fin,* and *inf,* four qualitative values; on the other hand, in FuSim by incorporating some quantitative information into qualitative models, Shen and Leitch were able to calculate the temporal durations in the form of intervals.

The *persistence time* is defined as a duration a qualitative state lasts. In the case that only crisp intervals (including single real numbers) are taken as qualitative values in a quantity space, the *arrival time* vanishes. The temporal filtering is implemented by checking if there is a common temporal interval, during which all variables take their respective values determined by the successor state.

In order to estimate when the *n*th state in a behavioral path appears for interpretation of the behavior, we define the temporal duration within which the behavior passes through a state as *passing time*.

Suppose $t_1^{(i)}$ and $t_2^{(i)}$ are the possible minimum and maximum durations respectively for the *i*th qualitative state, before transiting to next one, then *passing time* and *persistence time* for the *i*th state are:

$$t^{(i)}_{passing} = [t_1^{(i)}, t_2^{(i)}] \qquad (1)$$

$$t^{(i)}_{persis.} = [0, t_2^{(i)}] \qquad (2)$$

Let $[T_1^{(n)}, T_2^{(n)}]$ (n≥1) be the temporal interval associated with the *n*th qualitative state $S^{(n)}$, which is in a behavioral branch (state chain), i.e. it is predicted that this state occurs only during the time between $T_1^{(n)}$ and $T_2^{(n)}$. In qualitative simulation they are calculated as following:

$$[T_1^{(n)}, T_2^{(n)}] = \sum_{i=0}^{n-1} t^{(i)}_{passing} + t^{(n)}_{persis.}$$
$$= [\sum_{i=0}^{n-1} t_1^{(i)}, \sum_{i=0}^{n} t_2^{(i)}] \qquad (3)$$

3. Observation Filtering

3.1 Basic Idea and Assumptions

In spite of the existing techniques that are exerted in simulation procedure on possible qualitative state successors in order to reduce the ambiguity, it remains too many combinations of possible behavioral paths in a complex system with many variables, which hinders these methods from being effectively used in most applications and results in following contradictories:

- The limitation of memory space vs. the increasing states to be stored.
- Rough temporal information against the need to track the behaviors synchronously, such as fault diagnosis.

The main restriction of the existing methods in modeling is that one has to concern how the whole family of systems sharing common structure will behave, thus the specific information about the system under consideration can not be utilized.

However in many cases such as control and fault detection (not in design) only the behavior of the specific system would be taken into consideration. Giving up the "Soundness" makes it possible to develop the so called *observation filtering* technique with the help of measurements to reduce accumulated ambiguity and to avoid the spurious solutions.

Three assumptions are made by our current method:

- The qualitative model reflects the process in that it abstracts the parameters in real world rather than approximates them like an analytical model and the simulation procedure guarantees that the simulated behavior covers the real one. Thus the observation filtering procedure is in fact a process of selection, which is made after the candidates are generated by simulation.
- Initial qualitative state is known.
- Measurement is free form noise; in other words its effect can be either neglected or included in the qualitative model.

The principle of *observation filtering* is that the simulated qualitative behavior of a variable must cover its counterpart of measurement obtained from current system, otherwise the simulated behavioral path is inconsistent and can be eliminated.

3.2 Qualitative Observer

In addition to *constraint, temporal* and *global filtering* we check the consistency of possible successor states with the observations which are taken within the temporal intervals labeled on those successor states, so *observation filtering*, is exerted on the remaining possible successors. Besides the introduction of measurements can greatly reduce the length of predicted temporal intervals, which, accumulating the error of estimations, become larger and larger in FuSim (also see (3)).

Luenberger Observer (Luenberger 1971) works with the same inputs provided to a real system and the outputs measured from it to tell the behavior of the inner state variables (unmeasurable) over time. Under the *observation filtering* the concept of *Observer* in system theory and control engineering can be introduced. Because of the applied inputs and outputs of a system it is not a simulation any more, but a typical *state observer*, as shown in fig. 4. Since the model used to build the observer is qualitative, the predicted behaviors of the state variables output from this kind of observer are qualitative as well and not unique as acquired from qualitative simulation.

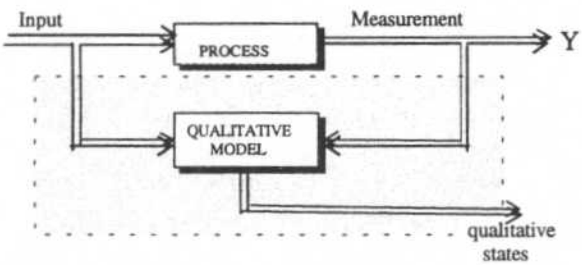

Fig. 4. Qualitative State Observer

The main difference between typical *Luenberger Observer* and our current *Qualitative Observer* is the need of knowing initial state for the latter. Being untrivial, *Luenberger Observer* feeds the differences between real measured values and the corresponding predicted ones back to the input terminal and produces a convergent behavior at the steady state, with respect to the initial difference. This may be achieved by a future *Qualitative Observer.*

3.3 Algorithm Description of Observation Filtering

Let $v(\cdot)$ and $V(\cdot)$ represent the measurement and the corresponding qualitative value simulated, respectively. With the measured values at t_m' and t_m ($t_m' < t_m$), the known qualitative state $\mathbf{S}^{(n-1)}$ and candidate transition state $\mathbf{S}^{(n)}$, the observation filtering can be implemented by following procedures:

1. If $t_m' \in [T_1^{(n-1)}, T_2^{(n-1)}]$, $v(t_m')$ and $V([T_1^{(n-1)}, T_2^{(n-1)}])$ are compared and consistent, then

$$T_1^{(n)\prime} = t_m' \qquad (4)$$

$$T_2^{(n)\prime} = t_m' + t_2^{(n-1)} + t_2^{(n)} \qquad (5)$$

2. According to the relationship among the next sampling time t_m, the temporal intervals $[T_1^{(n-1)}, T_2^{(n-1)}]$ and $[T_1^{(n)}, T_2^{(n)}]$ labeled on $\mathbf{S}^{(n-1)}$ and $\mathbf{S}^{(n)}$, respectively, there exist following four possibilities:

(A) If $t_m \in [T_1^{(n-1)}, T_1^{(n)})$, compare measurement $v(t_m)$ with $V([T_1^{(n-1)}, T_2^{(n-1)}])$:

a) if they are consistent, we modify the time interval $[T_1^{(n)}, T_2^{(n)}]$ for the *n*th state $S^{(n)}$:

$$T_1^{(n)} = t_m \qquad (6)$$

$$T_2^{(n)} = T_2^{(n)\prime} \qquad (7)$$

Because $T_2^{(n)} - T_1^{(n)} = t_2^{(n-1)} + t_2^{(n)} + t_m' - t_m$ and $T_2^{(n)\prime} - T_1^{(n)\prime} = t_2^{(n-1)} + t_2^{(n)}$, obviously

$$T_2^{(n)} - T_1^{(n)} < T_2^{(n)\prime} - T_1^{(n)\prime} \qquad (8)$$

b) if they are inconsistent, then remove $\mathbf{S}^{(n)}$ from next candidate transition states. The evolution from this state needs not be taken into account. This branch is pruned.

(B) If $t_m \in [T_1^{(n)}, T_2^{(n)}] \cap [T_1^{(n-1)}, T_2^{(n-1)}]$, compare measurement $v(t_m)$ with both $V([T_1^{(n)}, T_2^{(n)}]$ and $V([T_1^{(n-1)}, T_2^{(n-1)}])$:

a) if $v(t_m)$ and $V([T_1^{(n)}, T_2^{(n)}]$ are consistent, we have the time interval $[T_1^{(n+1)}, T_2^{(n+1)}]$ for the *n+1*th state $\mathbf{S}^{(n+1)}$:

$$T_1^{(n+1)} = t_m \qquad (9)$$

$$T_2^{(n+1)} = t_m + t_2^{(n)} + t_2^{(n+1)} \qquad (10)$$

b) if $v(t_m)$ and $V([T_1^{(n-1)}, T_2^{(n-1)}]$ are consistent, the time interval $[T_1^{(n)}, T_2^{(n)}]$ for the *n*th state $\mathbf{S}^{(n)}$ is recalculated by (6) and (7).

c) if neither of them are consistent, then $v(t_m)$ is suspended for this branch and go to the third step.

(C) If $t_m \in [T_1^{(n)}, T_2^{(n)}]$, but $t_m \notin [T_1^{(n-1)}, T_2^{(n-1)}]$, then compare measurement $v(t_m)$ with $V([T_1^{(n)}, T_2^{(n)}])$:

a) if they are consistent, we have the time interval $[T_1^{(n+1)}, T_2^{(n+1)}]$ for the *n+1*th state $\mathbf{S}^{(n+1)}$ as calculated by (9) and (10).

b) if they are inconsistent, then $v(t_m)$ is suspended for this branch and go to the third step.

(D) If $t_m > T_2^{(n)}$, the measurements are taken after the right end of the temporal interval of the candidate transition state, then $v(t_m)$ is suspended for this branch and go to the third step.

3. If $v(t_m)$ is suspended, from $V([T_1^{(n)}, T_2^{(n)}])$ as the start point continue to evolve for next state transition. The time interval $[T_1^{(n+1)}, T_2^{(n+1)}]$ is calculated with the formulas similar to (3),

$$T_1^{(n+1)} = T_1^{(n)} + t_1^{(n)} \quad (11)$$

$$T_2^{(n+1)} = T_2^{(n)} + t_2^{(n+1)} \quad (12)$$

then compare measurement $v(t_m)$ with $V([T_1^{(n+1)}, T_2^{(n+1)}])$:

(A) If they are inconsistent, $v(t_m)$ continues to be suspended,

a) if $t_m \geq T_1^{(i+1)}$ ($i=n+1,...$) go back to third step and repeat.

b) if for all i (i=n-1, n, ... K), $v(t_m)$ and $V([T_1^{(i)}, T_2^{(i)}])$ are inconsistent and hence $v(t_m)$ has been suspended, $t_m < T_1^{(K+1)}$, then remove the suspended candidate behavior; if all of the behaviors following $S^{(n)}$ are removed then abandon $S^{(n)}$.

(B) If $v(t_m)$ and $V([T_1^{(i)}, T_2^{(i)}])$ are consistent for some i ($i \geq n+1$) then the suspension of $v(t_m)$ is eliminated for this branch. The time interval $[T_1^{(i+1)}, T_2^{(i+1)}]$ is calculated with the same formulas as (9) and (10).

Notes:

1. The rule of a) in case (B) and a) of (C) in the second step confirms the covering of $v(t_m)$ by $V([T_1^{(n)}, T_2^{(n)}])$ and predicts the temporal interval with reduced length compared to simulation, while the rule b) in the case (A) of third step removes the inconsistent possible states and observation filtering is implemented.

2. With rich measurement information, corresponding to the cases addressed by rule a) of (A) and b) of (B) in the second step: the new measured value $v(t_m)$ reconfirms the consistency with predicted successors and hence further shrinks the length of temporal intervals labeled (see (8)); or in the case b) of (A) in the second step: the candidate is excluded for its inconsistency by the recheck.

3. With sparse measurements, corresponding to the cases addressed by rule of (D) in the second step, it degenerates in this step to a simulation.

4. An Example: Damped Spring

Here we adopt a spring-block system that has been used extensively in qualitative reasoning literature, as an example to compare simulation under conventional filtering techniques (constraint and temporal filtering) with observer, which applies additional observation filtering.

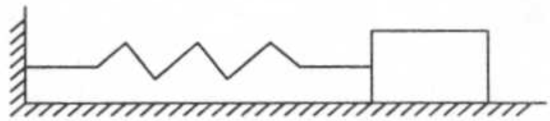

Fig. 5 A spring-block

As shown in fig.5, the system consists of a block connected to a spring laying on a horizontal table. The displacement of the block from its rest position is described by a variable *x*. There is friction between the block and the table. Suppose *v* represents its velocity. Each of these variables has a normalized numerical range [-1, 1]. Their qualitative counterparts take value from the quantity space illustrated in fig.6, with each qualitative value corresponding to the perceived meaning:

Q = {n_big, n_medium, n_small, near_zero, p_small, p_medium, p_big}

According to the scheme of simulation, each qualitative variable is described by a pair, i.e. its magnitude and rate of change (derivative). The physical system can be modeled by following QDE:

$$deriv\ x = v \quad (13)$$

$$deriv\ v = -x - p\_medium * v \quad (14)$$

where the friction coefficient is assumed to be p_medium.

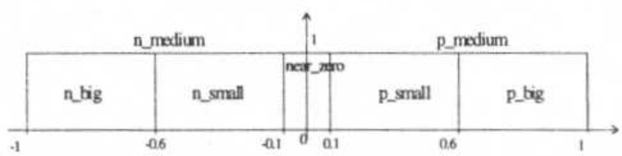

Fig. 6. Quantity space in example

Suppose that at beginning the block is moved away from the equilibrium point to x=0.6 and then let go, the initial states of the variables x and v are <*p_medium, near_zero*> and <*near_zero,n_medium*>, respectively.

With the qualitative model and initial states we can go ahead to carry on simulation. Given a simulation step, the result is a state transition tree (see fig.1), with each branch corresponding to a possible behavior. The total numbers of behaviors with respect to different simulation steps are shown in the left column of table 1.

Next the observation filtering is exerted on the simulated behaviors, with measurement of *x*, *v* and both of *x* and *v*, respectively. The sampling periods are 0.1

seconds. The corresponding results are in the right three columns of table 1.

Table 1

simulation steps	Simulation	Observer		
		Meas. of x	Meas. of v	Meas. of x & v
2	8	8	8	8
3	38	25	33	24
4	193	93	102	80
5	941	379	336	272
6	4616	1681	1326	1009
7	22801	7068	5231	3685
8	112572	26606	19086	12823
9	545335	87397	63602	41776

This comparison shows that the observation filtering play a significant role in reduction of possible behavioral chains of states. With more simulation steps the rate of reduction arises. Its another advantage is the shrink of the predicted time intervals associated with states. Especially if an interval is unlimited long (when for instance the rate of change of the variables of a state equals to zero or across zero), then the intervals of the successors are all unlimited in simulation (see formula (3)), while those of Qualitative Observer do not inherit the unlimitedness (see formula (4) (5) and (9) (10)).

5. Application of QOB to FDI Systems

Analogous to the employment of analytical observers in fault detection and isolation (FDI), discussed in Automatic Control community, QOB is able to serve as a substitute in the case where no complete information or acceptably precise quantitative model is available. The principle of fault detection is to track the dynamical behaviors of the system with the aid of their estimations, which can be got by simulation or observation. In this part we will apply QOB, as an extension of qualitative simulation, to instrument fault detection and isolation (IFD) systems.

Following *dedicated observer scheme* (DOS) proposed by Clark 1978 and *generalized observer scheme* (GOS) by Frank 1987, different outputs can be supplied to distinct observers in a bank, then estimate the states and then the outputs. By comparing the estimated outputs with measured ones, a decision logic is applied to prognosticate if there are faults in the sensors and which one is faulty. Next we extend these schemes to qualitative versions, namely QDOS and QGOS.

5.1 Qualitative Dedicated Observer Scheme

As shown in fig. 7, each observer in DOS is driven by a different single sensor output, and the states are estimated, then check the state variables from different observers, whether there is a common intersection set for each of them.. There is no need for a threshold logic as used in original scheme any more. This threshold, due to the inaccuracy of models, has been set nonzero and decided often by trial and error method.

We assume that a system with three outputs is considered. Let $\hat{X}^0$ denote the set of qualitative behaviors of state variables simulated (without observation filtering). In fig.7 X_{y_i} is the set of behaviors removed from $\hat{X}^0$ after the consistency check by the ith output y_i . $\hat{X}_i^1$ is the resultant of the ith observer and hence the complement of X_{y_i} in $\hat{X}^0$. We have

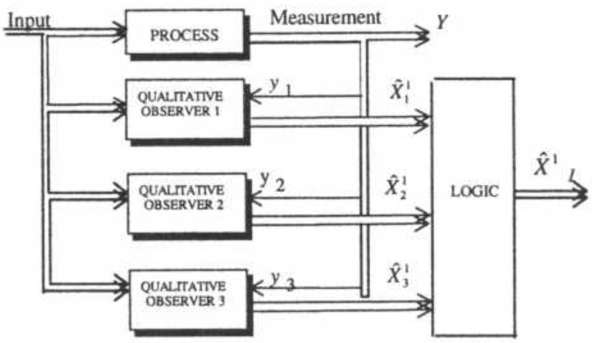

Fig. 7. Dedicated Observer Scheme

$$\hat{X}_i^1 = \hat{X}^0 - X_{y_i} = \hat{X}^0 \cap \overline{X}_{y_i} \qquad (15)$$

for i = 1, 2, 3. We define $\hat{X}^1{}_I$ and $\hat{X}^1{}_U$ are the intersection and union of behavior sets after observation filtering driven by one output, respectively, representing the resultant possible behaviors and the total number of behavioral sequences of states or the paths to be stored.

$$\hat{X}^1{}_I = \hat{X}_1^1 \cap \hat{X}_2^1 \cap \hat{X}_3^1 \qquad (16)$$

$$\hat{X}^1{}_U = \hat{X}_1^1 \cup \hat{X}_2^1 \cup \hat{X}_3^1 \qquad (17)$$

If a fault occurs, for example in the second sensor, it can be detected by $\hat{X}^1{}_I = \varnothing$. Furthermore, if $\hat{X}_1^1 \cap \hat{X}_2^1 = \varnothing$, $\hat{X}_2^1 \cap \hat{X}_3^1 = \varnothing$, and $\hat{X}_1^1 \cap \hat{X}_3^1 \neq \varnothing$, the fault can be located to be in the second measurement.

5.2 Generalized Observer Scheme

As an alternative, in fig. 8 an observer dedicated to a certain sensor is driven by all output except that of the respective sensor. This IFD scheme allows one to detect and isolate only a single fault in any of the sensors, however, in original version with increased robustness with respect to m-2 unknown inputs, where m is the number of outputs.

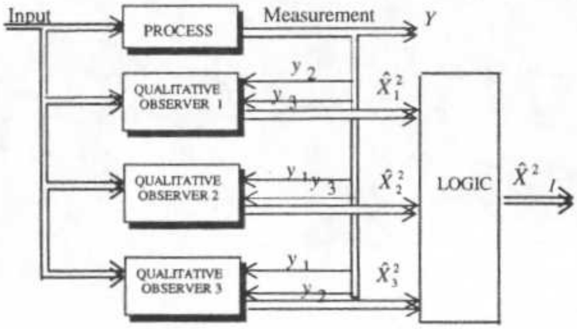

Fig. 8. Generalized Observer Scheme

In fig.8 $X_{y_l y_m}$ is the set of behaviors removed from $\hat{X}^0$ after the consistency check by the lth and mth outputs y_l and y_m. $\hat{X}_i^2$ is the resultant of the ith observer and hence the complement of $X_{y_l y_m}$ in $\hat{X}^0$, where l, m, i $\in \{1,2,3\}$ and are unequal to each other. We have

$$\hat{X}_i^2 = \hat{X}^0 - X_{y_l y_m} = \hat{X}^0 \cap \overline{X}_{y_l y_m} \quad (18)$$

$$X_{y_l y_m} = X_{y_l} \cup X_{y_m} \quad (19)$$

Similar to the case in QDOS, we define $\hat{X}^2{}_I$ and $\hat{X}^2{}_U$ are the intersection and union of behavior sets after observation filtering driven by two outputs, respectively, representing the resultant possible behaviors and the total number of behavioral sequences of states or the paths to be stored.

$$\hat{X}^2{}_I = \hat{X}_1^2 \cap \hat{X}_2^2 \cap \hat{X}_3^2 \quad (20)$$

$$\hat{X}^2{}_U = \hat{X}_1^2 \cup \hat{X}_2^2 \cup \hat{X}_3^2 \quad (21)$$

If $\hat{X}^2{}_I = \varnothing$, a fault is detected. If $\hat{X}_1^2 = \varnothing$, $\hat{X}_2^2 \neq \varnothing$ and $\hat{X}_3^2 = \varnothing$, then the second sensor is found to be faulty.

5.3 Comparison

Having extended the application range of the both schemes to the qualitative models of systems with QOB, here we analyze the capability and costs of these schemes. The case of single observer in fig. 4 is shown as a comparison. In fig. 4,

$$\hat{X}^3 = \hat{X}^0 - X_{y_1 y_2 y_3} = \hat{X}^0 \cap \overline{X}_{y_1 y_2 y_3} \quad (22)$$

$$X_{y_1 y_2 y_3} = X_{y_1} \cup X_{y_2} \cup X_{y_3} \quad (23)$$

where $X_{y_1 y_2 y_3}$ is the set of behaviors removed from $\hat{X}^0$ after the consistency check by all three outputs y_1, y_2 and y_3, $\hat{X}^3$ is the resultant of the single observer and hence the complement of $X_{y_1 y_2 y_3}$ in $\hat{X}^0$.

We also define $\hat{X}^3{}_I$ and $\hat{X}^3{}_U$ are the intersection and union of behavior sets after observation filtering driven by all three outputs, respectively, which are here equal to each other.

The same to the case of analytical observer banks, QDOS can here deal with multiple faults; while QGOS can detect multiple faults and isolate only a single fault. A single QOB can only detect faults.

By calculation, we have

$$\hat{X}^0 \supseteq \hat{X}^1{}_I = \hat{X}^2{}_I = \hat{X}^3{}_I \quad (24)$$

this demonstrates that the three methods are equivalent in predicting qualitative behaviors and detecting faults. Furthermore,

$$\hat{X}^0 \supseteq \hat{X}^1{}_U \supseteq \hat{X}^2{}_U \supseteq \hat{X}^3{}_U \quad (25)$$

This shows that as the cost of acquiring the isolation of faults by observer bank one has to store more possible behaviors, and QDOS, being able to isolate multiple faults needs the most storage among them.

6. Discussion and Future Work

In many applications such as control and fault detection, on the one hand measurement are reachable, on the other hand only a general description of a family of systems excluding specific information of the concrete system seems to make little sense. The presented QOB provides a framework, in which this kind of information can be utilized to reduce accumulated ambiguity and to avoid spurious solution as much as possible. It is meaningful, specially for continuous-time systems, to narrow continually their predicted temporal intervals of qualitative states with measurements, which is just the second advantage of QOB over previous methods. The more sampled values are available, the more accurate the predictions are.

The simple example in section 4 showed that, on the one hand, the observation filtering can greatly reduce the possible behavioral branches; on the other hand, the number of behaviors remains to be very large and increase dramatically with respect to the simulation steps. As a matter of fact, it seems that, we are facing a dilemmatic situation. On the one hand, the practical applications require the explicit temporal information about the estimated behaviors; on the other hand, the introduction of specific time measure results in the lowering of the level of abstraction and, therefore, the multiplication of the number of distinct behaviors. In fact, a large number of behaviors in table 1 are similar to each other and may be classified (abstracted) into a single one.

An application of the *Qualitative Observer* to Instrument fault detection and isolation problems has been preliminary discussed. An interesting result similar to analytical observer was acquired.

Concerning the possibility of applications, it is also worthwhile to notice that the introduction of fuzzy set and possibility theory to quantity space (Shen & Leitch 1993) and constraints (Zhuang & Frank 1996) has intensified the power of QDE in modeling, because many problems in real world are difficult to be modeled by physical laws; instead, empirical knowledge can go a long way in describing such systems. With the aid of fuzzy theory this kind of information can be integrated into models. The fuzzy QOB bas been developed (Zhuang & Frank 1996) to extend the application domains of original QOB and to provide an evaluation to the estimated behaviors.

Next we are interested in seeking the answers for following questions:

- After observation filtering, is the all behaviors left complete? Under which conditions?
- Can the initial state be unknown as with classical observers?
- How to reduce further the qualitative behaviors/states to be stored by clustering?
- Which advantages and disadvantages QOB has compared to parameter identification methods, which apply inputs and outputs to determine the model first and then give the behaviors of systems?

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