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Building Intelligence Into an Autopilot -- Using Qualitative Simulation to Support Global Decision Making*

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This paper represents an addendum to an earlier paper published by the same research group in SIMULATION in 1989. In the earlier paper, a crisp inductive reasoner had been employed to qualitatively reason about the behavior of a quantitatively simulated B-747 aircraft, to determine when a structural malfunction occurs, to hypothesize about the nature of this malfunction, and to decide upon a global strategy that allows operation of the quantitative aircraft model under the modified flying conditions.

In the addendum, the formerly crisp inductive reasoner has been replaced by a fuzzy inductive reasoner. The paper demonstrates the enhanced discriminatory power and the improved forecasting capability of the modified reasoning scheme. In addition, the fuzzy inductive reasoner allows prediction of a quasi-continuous response spectrum, whereas the crisp inductive reasoner was able to predict discrete (class) values only.

Keywords: Qualitative simulation, inductive reasoning, fault detection, fault characterization, decision-making

1. Introduction

An important objective of our research is the development of a methodology combining the quantitative simulation of a continuous process with the qualitative simulation of an automated supervisory control system. In this paper, qualitative simulation is applied to inductively reason about the behavior of a quantitative simulation model representing a B-747 airplane in high-altitude horizontal flight. The qualitative model must be capable of mimicking the human situation assessment process, to learn how the system behaves, to identify specific events, and to come up with a new control strategy for the system once it has been structurally modified.

A previous research effort at the University of Arizona resulted in a crisp inductive reasoner that was able to recognize within a few seconds after a simulated malfunction had taken place that the aircraft had qualitatively changed its behavior, which then triggered a diagnostic engine that enabled the reasoner to distinguish between 10 different types of malfunctions after stimulating the aircraft by adding a small amount of binary noise to the input signals and examining the aircraft's reaction. The results of this study were reported in this same journal in 1989[14].

The current research effort extends the previous investigation by incorporating fuzzy measures into the

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inductive reasoning process, and by modifying the algorithm for the evaluation of the quality factor of the qualitative (structural) relationships found by the inductive reasoner. In this paper, the enhancement of the discriminatory power of a fuzzy inductive reasoner over a crisp inductive reasoner will be demonstrated. As a consequence, the number of errors in the qualitatively predicted states has been reduced from one third to less than one tenth, and the error chains produced by those errors have almost vanished. Also, it will be shown that, while the previously used reasoner had sometimes difficulties to discriminate between different types of malfunctions, the fuzzy inductive reasoner is able to discriminate clearly and unambiguously between different types of malfunctions that make the aircraft react in similar ways. Also, the fuzzy inductive reasoner is able to identify malfunctions in a shorter span of simulated time of the quantitative model than its crisp counterpart. In addition, the fuzzy inductive reasoner allows prediction of a quasi-continuous response spectrum, whereas the crisp inductive reasoner is able to predict discrete (class) values only.

2. Description of the Application

A number of publications on inductive reasoning have previously been published by the same research group. The earliest paper describing the method can be found in[3]. Details on the numerical aircraft model and the application of the crisp inductive reasoner to it can be found in[13]. A compressed version of[13] was published in[14]. The fuzzy extension of the inductive reasoning methodology was first discussed in [7], and was elaborated upon in[4]. The application of fuzzy inductive reasoning to the aircraft model was presented in[1]. Different defuzzification methods were compared in[11]. Finally, the combination of quantitative and qualitative simulations involving a differential equation model for the quantitative subsystem and a fuzzy inductive reasoner for the qualitative subsystem were first presented in[5]; the construction of a qualitative model itself is also described in the same reference. In the interest of saving space, the results that were presented in the aforementioned earlier publications will not be repeated here. The interested reader is invited to consult the earlier publications to familiarize him or herself with the details of the methodology.

2.1. The Quantitative Model

The ACSL[9] numerical aircraft model used in this research effort is exactly the same that was reported in the previously published paper[14]. This model, named B4, corresponds to a Boeing 747 airplane at cruise flight. The original aerodynamic parameters of this model were modified to obtain four different models, with which a library was constructed. These models represent structural changes of the original plane, and were thought to be sufficiently representative to be considered as transients/accidents. The main characteristics of these models are:[13]

- Model B4 is the original model that represents a Boeing 747 in cruise flight at high altitude. Its aerodynamic parameters are considered as reference values for the other models.
- Model 747 represents an enlarged Boeing 747 in cruise flight. The values for the Lift L, Drag D, aerodynamic momentum M, and the pitch angle θ are changed in comparison with the B4 model.
- Model B5 represents a change of the original B4 model, in which the aerodynamic parameters L and D are increased, whereas M and θ are decreased.
- Model B13 represents another change of the B4 model. Here L, D, and θ are increased, whereas M is decreased.
- Model B14 is very similar to the B4 Model. The only difference is that M and θ are slightly increased.

2.2. The Qualitative Model

In this section, only a brief description will be given in order to show the differences between the crisp and the fuzzy inductive reasoner, since these differences will be elaborated upon later in the paper.

The data extracted from the numerical ACSL simulation constitute the "measurement data" of the qualitative model. The execution of the quantitative model, and the extraction of the measurement data matrix were now done under the control of Matlab[8] instead of CTRL-C[12] as used before, but this is without further concern, since the two versions of SAPS are identical in their behavior.

The discretization needed to enable the qualitative reasoning process is done by means of fuzzy recoding instead of crisp recoding[6]. In the fuzzy recoding module, a fuzzy membership value is appended to the recoded (class) value, so this process can be referred to as "fuzzification"[10]. The discretized variables are used to find the most plausible qualitative relationship among them, which is called the fuzzy optimal mask. This optimal mask will in turn be used to qualitatively forecast the behavior of other variables. This process is called qualitative simulation through fuzzy inductive reasoning. The main difference between the crisp forecast and the fuzzy forecast is that the former predicts not only the class value but also the values corresponding to the membership function.

From the resulting qualitative variables, continuous signals can then be "regenerated" that can subsequently be used as inputs to other quantitative or qualitative submodels. In the context of fuzzy systems, the regeneration process is known as "defuzzification." Figure 1 shows the fuzzy inductive reasoning process. The inference engine has both a crisp part, where the qualitative class and side values are computed, and a fuzzy part where the fuzzy membership values are computed.

2.3 Differences Between a Crisp and a Fuzzy Inductive Reasoner

There exist two main differences between the previously reported crisp inductive reasoning methodology and the currently employed fuzzy inductive reasoning approach. The first lies in the computation of the quality measure of the masks, and the second lies in the utilization of the available fuzzy measures in the inductive reasoning process.

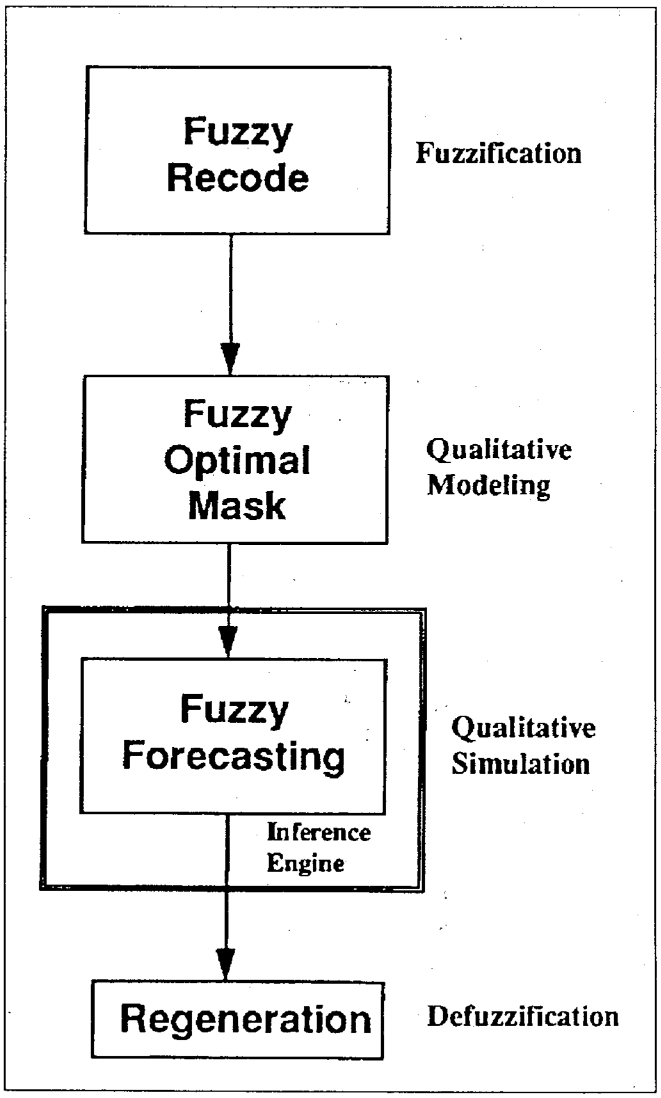

Figure 1. Fuzzy inductive reasoning process.

a)The Quality Factor

The quality of a structural relationship, i.e., a mask, is primarily determined through the *Shannon entropy* of its state transition matrix, which determines its forecasting power over a single step. The Shannon entropy relative to one input is calculated from the equation

$$H_i = \sum_{\forall o} p(o|i) \cdot \log_2 p(o|i) \tag{1}$$

where $p(o \mid i)$ is the conditional probability of a certain output state o to occur, given that the input state i has already occurred. The term probability is meant in a statistical rather than in a true probabilistic sense. It denotes the quotient of the observed frequency of a particular state divided by the highest possible frequency of that state. The overall entropy of the mask is then calculated as the sum:

$$H_m = -\sum_{\forall i} p(i) \cdot H_i \tag{2}$$

where $p(i)$ is the probability of that input to occur. The highest possible entropy H_{max} is obtained when all probabilities are equal, and a zero entropy is encountered for relationships that are totally deterministic. A normalized overall entropy reduction H_r is defined as:

$$H_r = 1.0 - \frac{H_m}{H_{max}} \tag{3}$$

It is not practical to use the Shannon entropy exclusively in the performance index that evaluates the quality of a mask. The reason is that, with growing mask complexity, the number of discrete states the system can be in grows. Since the total number of observations remains constant, the observation frequencies of the observed states become smaller and smaller, until eventually every state that has ever been observed has been observed precisely once. Thus, all observed state transitions are totally deterministic, and the forecasting power over a single step is maximized. However, the predictiveness of the model over several steps will nevertheless be poor, since already the next predicted state will, in all likelihood, have never been observed before, which will bring the forecasting process to an immediate halt.

The previously employed methodology used the complexity of the mask, that is, the number of relationships among variables, in the performance index. However, the mask complexity is only an indirect measure of the number of legal states. The currently employed methodology uses the *observation ratio*, a quality measure that reduces the mask quality if there exist states that have been observed less often than five times. Thus the observation ratio, O_r, is introduced as an additional contributor to the overall quality measure for a better selection of the optimal mask:

$$O_r = \frac{5 \cdot n_{5x} + 4 \cdot n_{4x} + 3 \cdot n_{3x} + 2 \cdot n_{2x} + n_{1x}}{5 \cdot n_{leg}} \quad (4)$$

where:

n_{leg} = number of legal input states;
n_{1x} = number of input states observed only once;
n_{2x} = number of input states observed twice;
n_{2x} = number of input states observed thrice;
n_{4x} = number of input states observed four times;
n_{5x} = number of input states observed five times or more.

If every legal input state has been observed at least five times, O_r is equal to 1.0. If no input state has been observed at all (no data are available), O_r is equal to 0.0. Thus, O_r can also be used as a quality measure. The overall *quality of a mask*, Q_m, is then defined as the product of its uncertainty reduction measure, H_r, and its observation ratio, O_r:

$$Q_m = H_r \cdot O_r \quad (5)$$

The *optimal mask* is the mask with the largest Q_m value.

b) Fuzzy Measures

The crisp inductive reasoner worked with crisp landmarks in the recoding of the measurement data. These "rigid" landmarks were responsible for a loss of valuable information about the system that could no longer be exploited by the qualitative model, and this in turn led to a reduction in its forecasting capabilities, which diminishes the discriminatory power of the tool in the application at hand. Fuzzy measures were introduced as a technique to deal with the uncertainty of landmarks.

Figure 2 depicts the fuzzy membership functions used by SAPS-II, the inductive reasoner employed in this research. They are normal distributions with values 1.0 at the arithmetic mean of any two neighboring landmarks, and 0.5 at the landmarks themselves.

The fuzzy membership functions allow recoding each numerical value into a qualitative triple composed of the *class value* (as in the previous methodology), the *fuzzy membership value*, which is a measure of the likelihood of the class value, and the *side value* which indicates whether the quantitative value is to the left or to the right of the maximum of the fuzzy membership function. The membership functions can be easily calculated using the equation:

$$Memb_i = \exp(-\tau_i \cdot (x - \mu_i)^2) \quad (6)$$

where x is the continuous variable to be recoded, μ_i is the algebraic mean between two neighboring landmarks, and τ_i is determined such that the membership function, $Memb_i$, degrades to a value of 0.5 at the landmarks.

No information is lost in the recoding process. The original real-valued measurement data can be regenerated exactly from the qualitative triple. The fuzzy forecasting process must now predict, for a given set of inputs, not only the class value of the output, but also its membership and side values, thus, fuzzy forecasting predicts an entire qualitative triple. Thereby, the numerical information is indirectly preserved, which in turn makes it possible to regenerate real-valued output

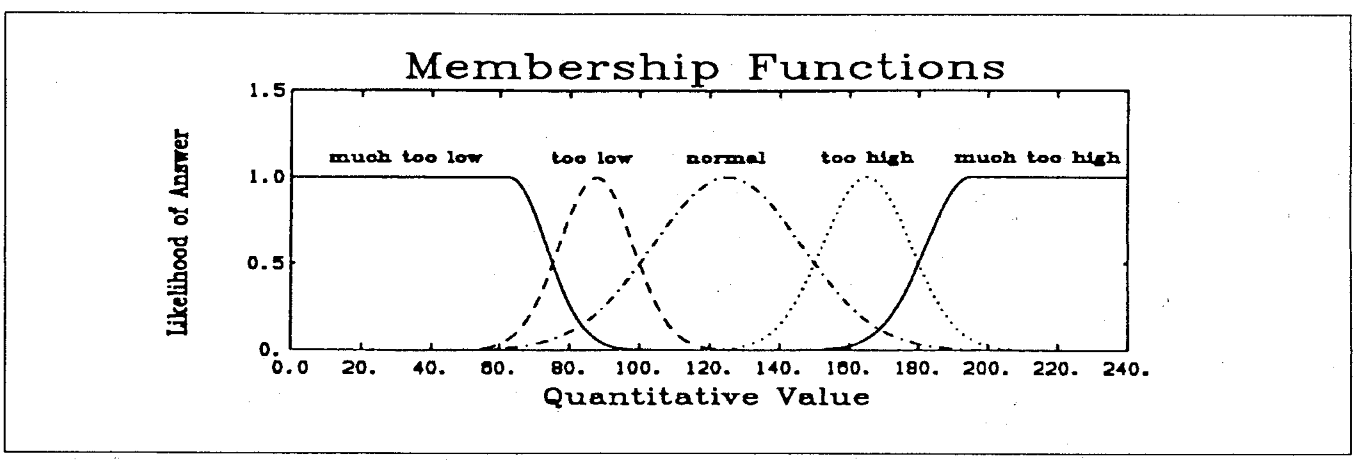

Figure 2. Typical membership functions used by SAPS-II.

signals from the qualitative model with surprisingly good accuracy.

In fuzzy forecasting, the membership and side functions of the new input are compared with those of all previous recordings of the same qualitative input contained in the behavior matrix. The one input with the most similar membership and side functions is identified. For this purpose, a cheap approximation of the regenerated quantitative signal

$$d_i = 1 + side_i * (1 - Memb_i) \tag{7}$$

is computed for every input variable of the new input set, and the regenerated d_i values are stored in a vector. This reconstruction is then repeated for all previous recordings of the same input set. Finally, the L_2 norms of the difference between the d vector of the new input and the d vectors of all previous recordings of the same input are computed, and the previous recording with the smallest L_2 norm is identified. Its *output* and *side* values are then used as forecasts for the *output* and *side* values of the current state.

Forecasting of the new membership function is done a little differently. Here, the five previous recordings with the smallest L_2 norms are used (if at least five such recordings are found in the behavior matrix), and a distance-weighted average of their fuzzy membership functions is computed and used as the forecast for the fuzzy membership function of the current state. Absolute weights are computed as follows:

$$w_{\mathrm{abs}_k} = \frac{d_{\max} - d_k}{d_{\max}} \tag{8}$$

where the index k loops over the five closest neighbors, and $d_i \leq d_j$, $i < j$; $d_{max} = d_5$. The absolute weights are numbers between 0.0 and 1.0. Using the sum of the five absolute weights:

$$s_w = \sum_{\forall k} w_{\mathrm{abs}_k} \tag{9}$$

it is possible to compute relative weights:

$$w_{\mathrm{rel}_k} = \frac{w_{\mathrm{abs}_k}}{s_w} \tag{10}$$

Also the relative weights are numbers between 0.0 and 1.0. However, their sum is always equal to 1.0. It is therefore possible to interpret the relative weights as percentages. Using this idea, the membership function of the new output can be computed as a weighted sum of the membership functions of the outputs of the previously observed five nearest neighbors:

$$Memb_{out_{new}} = \sum_{\forall k} w_{rel_k} \cdot Memb_{out_k} \tag{11}$$

The fuzzy forecasting function will usually give a more accurate forecast than the probabilistic forecasting function. The fuzzy membership functions allow preserving more quantitative information in the reasoning process, whereas the class values can still be used to process the available information in a qualitative fashion. Thus, the qualitative analysis allows us to generate quickly a rough qualitative response, while the fuzzy membership functions can then be used to smoothly interpolate between the qualitative class values to obtain a quasi-continuous response spectrum. In the application at hand, the fuzzy membership functions also serve to enhance the discriminatory power of the event classifier.

3. Comparison of Results

The inductive reasoning functions are used to qualitatively and inductively reason about the measurement data taken from the ACSL simulation run. The quantitative data will be used to build a qualitative model that represents the behavior of the airplane in the vicinity of a steady-state trajectory. Figure 3 compares the qualitative simulation results obtained using crisp and fuzzy forecasting. Notice in the error matrix that the crisp methodology produced a reiterative error on the *drag D* variable that the fuzzy methodology avoids. Both simulations correspond to the B4 model excited with harmonic functions of long periods. Figure 4 shows the real and forecast *drag* signals from the B4 model.

When a sudden structural change occurs, the qualitative model will receive inputs that have never been seen before, which means that it will no longer be able to predict the future behavior of the system, which, in turn, trips off an alarm indicating that an accident has happened.

In a separate library, other qualitative models are stored that represent a variety of structural changes of the aircraft. Once the original model is no longer able to predict the system behavior, these models are consulted in order to identify the one that best predicts the new behavior of the aircraft. As each of these models represents a particular type of accident, this information can then be used to conclude what type of accident has happened, i.e., to discriminate between different types of accidents. In the very moment when a library model has become capable of correctly predicting the behavior of the structurally modified system, the continuous monitor is able to know what accident has taken place, and with this information, it can decide upon an appropriate corrective action or a new control strategy

Real values | Forecast values | Error matrix

Crisp Methodology

$$
\begin{array}{c}
\text{step}\backslash\text{var} \\ 2501 \\ 2502 \\ 2503 \\ 2504 \\ 2505 \\ 2506 \\ 2507 \\ 2508 \\ 2509 \\ 2510
\end{array}
\begin{array}{c}
L\quad D\quad \gamma \\
\begin{pmatrix} 3 & 3 & 3 \\ 2 & 3 & 3 \\ 2 & 2 & 3 \\ 1 & 1 & 3 \\ 1 & 1 & 3 \\ 1 & 1 & 2 \\ 1 & 1 & 1 \\ 2 & 1 & 1 \\ 2 & 2 & 1 \\ 1 & 2 & 1 \end{pmatrix}
\end{array}
\qquad
\begin{array}{c}
L\quad D\quad \gamma \\
\begin{pmatrix} 3 & 3 & 3 \\ 2 & 3 & 3 \\ 2 & 3 & 3 \\ 1 & 1 & 3 \\ 1 & 1 & 3 \\ 1 & 1 & 2 \\ 1 & 1 & 1 \\ 2 & 1 & 1 \\ 2 & 1 & 1 \\ 1 & 3 & 1 \end{pmatrix}
\end{array}
\qquad
\begin{array}{c}
error_L\quad error_D\quad error_\gamma \\
\begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 1 & 0 \end{pmatrix}
\end{array}
$$

Fuzzy Methodology

$$
\begin{array}{c}
\text{step}\backslash\text{var} \\ 2501 \\ 2502 \\ 2503 \\ 2504 \\ 2505 \\ 2506 \\ 2507 \\ 2508 \\ 2509 \\ 2510
\end{array}
\begin{array}{c}
L\quad D\quad \gamma \\
\begin{pmatrix} 3 & 3 & 3 \\ 2 & 3 & 3 \\ 2 & 2 & 3 \\ 1 & 1 & 3 \\ 1 & 1 & 3 \\ 1 & 1 & 2 \\ 1 & 1 & 1 \\ 2 & 1 & 1 \\ 2 & 2 & 1 \\ 1 & 2 & 1 \end{pmatrix}
\end{array}
\qquad
\begin{array}{c}
L\quad D\quad \gamma \\
\begin{pmatrix} 3 & 3 & 3 \\ 2 & 3 & 3 \\ 2 & 2 & 3 \\ 1 & 1 & 3 \\ 1 & 1 & 3 \\ 1 & 1 & 2 \\ 1 & 1 & 1 \\ 2 & 1 & 1 \\ 2 & 2 & 1 \\ 1 & 2 & 1 \end{pmatrix}
\end{array}
\qquad
\begin{array}{c}
error_L\quad error_D\quad error_\gamma \\
\begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}
\end{array}
$$

Figure 3. Differences between the same forecast points without and with fuzzy measures.

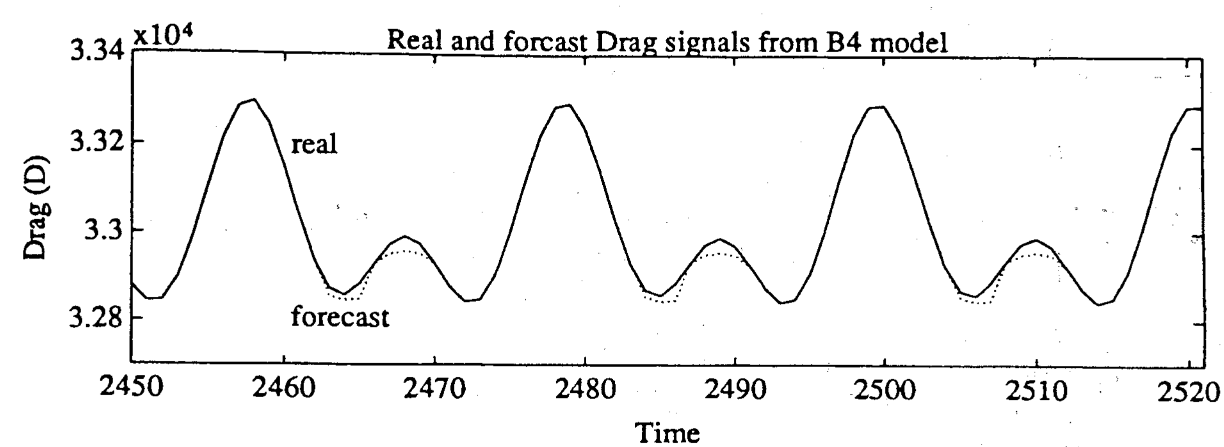

Figure 4. Real and forecast (then regenerated) drag signals from B4 model.

to be taken. Figure 5 shows the process of continuously and qualitatively monitoring the aircraft.

3.1 Detection of the Accident

The detection of accidents proceeds as follows: the failure detector implemented in the qualitative model forecasts the future behavior of the system and then compares this forecast with the actual measured data. As the forecast is based on past behavior of the system, it is somewhat adaptive to slow changes in the system parameters or a slow drift in the steady-state, but a sudden structural change is immediately detected since the behavior of the system can no longer be forecast with the optimal masks that have been evaluated for the system under observation.

The failure detector works through a threshold error alarm that counts the incorrect forecasts within a given period of time, and trips the alarm whenever the accumulated number of incorrectly predicted future states surpasses a threshold that is built into the detector.

Figure 6 shows the differences between the detection processes corresponding to each methodology. The data corresponds to a B4 to B747 structural change in normal

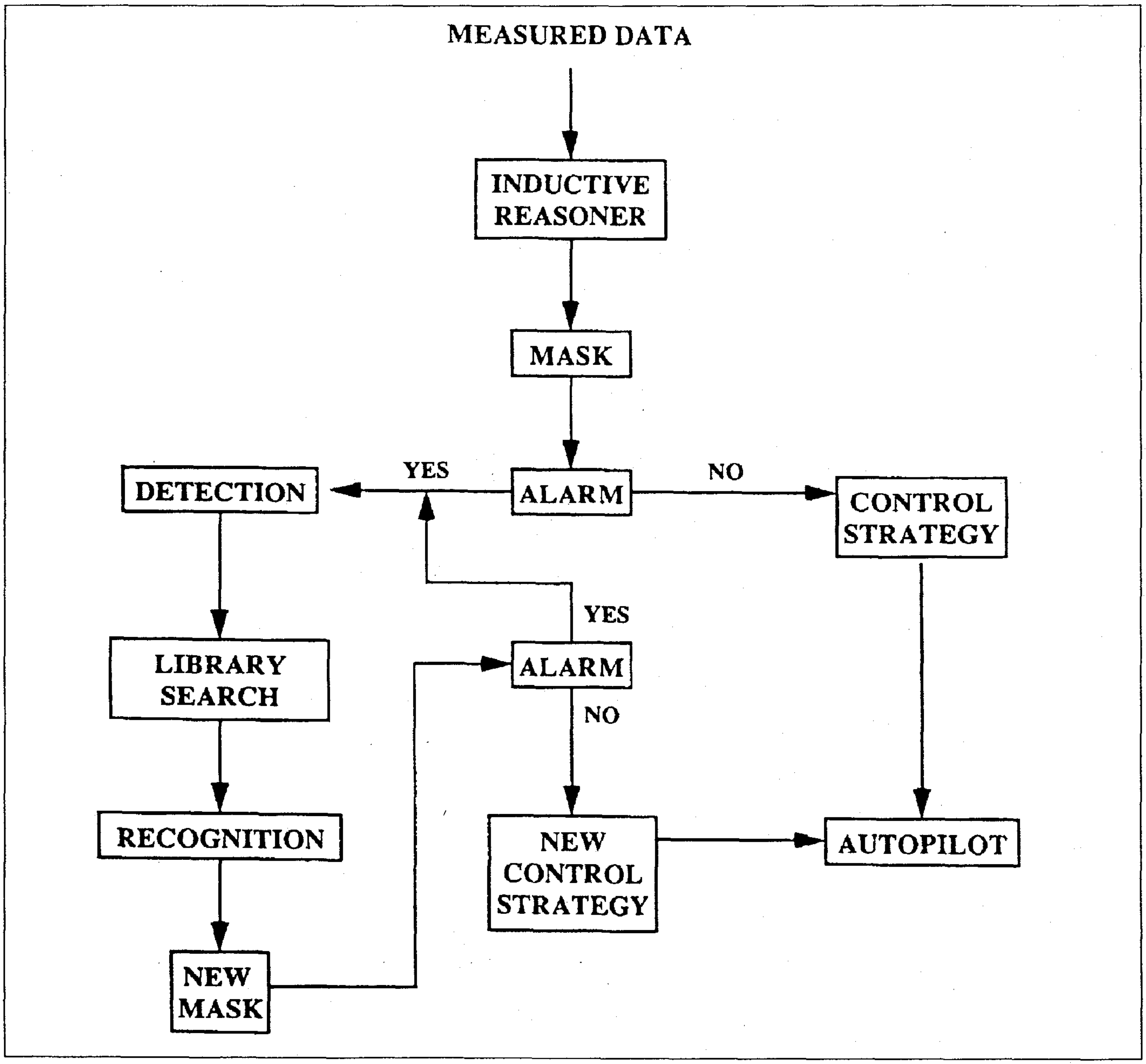

Figure 5. Continuous monitoring process.

Error matrix | **Alarm matrix**

Crisp Methodology

step\var	$error_L$	$error_D$	$error_Y$	alarm
995	0	0	1	0
996	0	0	0	0
997	0	0	0	0
998	0	0	0	0
999	0	0	0	0
1000	0	0	0	0
1001	0	0	−1	0
1002	0	0	0	0
1003	0	0	0	0
1004	−2	3	−1	1
1005	−3	1	−1	1
1006	1	0	0	1
1007	0	0	0	1
1008	0	0	3	1
1009	−3	2	2	1
1010	−1	3	0	1

Fuzzy Methodology

step\var	$error_L$	$error_D$	$error_Y$	alarm
995	0	0	0	0
996	0	0	0	0
997	0	0	0	0
998	0	0	0	0
999	0	0	0	0
1000	0	0	0	0
1001	1	0	−2	0
1002	−3	−1	1	1
1003	0	−2	1	1
1004	−2	1	−1	1
1005	−1	2	0	1
1006	2	−1	1	1
1007	−1	1	0	1
1008	−3	0	−2	1
1009	−3	2	0	1
1010	0	3	0	1

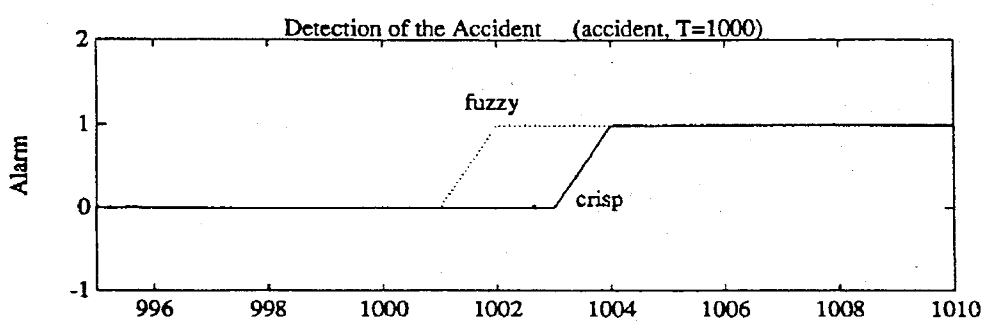

Figure 6. Differences between crisp and fuzzy threshold error alarms for the detection of the accident.

horizontal flight (referred in the previous investigation as the"Broken Model"). Notice that the detection of the accident is made faster than before due to the reduction in the number of forecast errors when the correct model is used, which permits reducing the threshold value of the alarm matrices.

3.2 Recognition of the Type of Accident

The new methodology has also improved the recognition process. Figure 7 shows the differences between the old and the new methodologies when trying to recognize a B4 to B14 transition in normal horizontal flight, that is, when trying to discriminate between two very similar qualitative models. Notice that the crisp inductive reasoner has more difficulties than the fuzzy inductive reasoner in recognizing the right qualitative model from the library.

4. Conclusions

The main advantage of the improved methodology is a significant reduction of the number of forecasting errors. The previously used system as described in[14] had between 25% and 33% errors in the forecasting points, while with the new system the percentage of errors varies consistently between 3% and 12% when the correct qualitative model is being used. This permits a reduction in the threshold value used by the detection

Error matrix / **Alarm matrix**

Crisp Methodology

step\var	$error_L$	$error_D$	$error_T$	alarm
201	0	−1	0	0
202	0	0	−2	0
203	0	0	−1	0
204	−1	0	−1	1
205	−1	0	0	0
206	0	0	0	0
207	1	0	−1	0
208	0	−1	0	0
209	−1	0	−1	1
210	0	0	0	0

Fuzzy Methodology

step\var	$error_L$	$error_D$	$error_T$	alarm
201	0	0	0	0
202	0	0	−1	0
203	0	0	0	0
204	0	0	−1	0
205	0	0	0	0
206	0	0	0	0
207	0	0	0	0
208	0	0	0	0
209	2	0	−1	1
210	0	0	0	0

Figure 7. Differences between crisp and fuzzy threshold error alarm for the recognition of the type of accident.

and recognition processes. Furthermore, an incorrect forecast often led to an entire chain of consequence errors, which would immediately trip the alarm if the accumulation window was selected too narrowly. The new system doesn't exhibit this problem any longer. False alarms are no longer caused by error chains, and therefore, the accumulation window of the threshold error alarm can be made much shorter, which allows the structural change to be detected several points earlier than when using the old system.

With respect to the recognition of the accident itself, the B4 to B747 transition is identified seven sampling intervals earlier than before, and the B4 to B13 transition is identified three sampling intervals earlier.

The other main advantage is the unambiguous identification of the post-accident steady state, i.e., the new set of optimal masks that correctly describe the post-accident behavior. Using the new algorithm, the former confusion between the B5 and B13 post-accident states[13] is completely avoided, in spite of their exhibiting very similar post-accident behaviors.

The purpose of the application shown here is just to demonstrate the enhancement of the discriminatory power and the forecasting capability of the fuzzy inductive reasoning methodology. The approach was used to provide a human plant operator with additional information that might prove useful when dealing with a developing emergency[1]. In a real-time environment, this approach has a severe drawback because it requires time after a structural change has taken place for determining the new qualitative model to be used. During this time period, the supervisory control is disabled for all practical purposes. However, it is exactly this time period when the transition takes place, and when knowledge of what is going on would be most valuable to dampen out the transition shock and to steer the system smoothly into its new mode of operation. If the transition from one structural mode to another is not an emergency but a normal event that will happen regularly during system operation, the mode transition must be both detected and discriminated almost immediately. In[2], a new method for dealing with variable structure systems based on fuzzy inductive reasoning is proposed that addresses this problem.

In this paper, it was shown that including the observation ratio in the quality factor of the qualitative relationships and adding fuzzy measures to the inductive reasoning process can significantly improve its qualitative simulation accuracy, and thereby its discrimination power.

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