Fuzzy Logic based Automated Transient Identification for Plant Monitoring

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Abstract: Plant monitoring and diagnosis are usually integrated as one process to detect and isolate suspicious symptoms and use these to identify the root cause of the failure [1, 2]. The research reported here enables a new plant monitoring and diagnosis framework that employs multiple fuzzy rule-based decision-support system at different diagnosing stages. By employing fuzzy sets and by constructing a decision concerning the normalcy of system behavior in stages, we are able to exploit far more detailed hierarchical information contained in the signals. The fuzzy rule based transient identification system is implemented in MATLAB© using its fuzzy logic toolbox. The paper describes in detail a new fuzzified transient behavior identification scheme. The experiments results demonstrate how traditional features such as those used in wavelet online pre-processing (WOLP) [10] and highly autonomous sensor (HAS) [19] for transient behavior identification can be fuzzified to improve the efficiency and performance of traditional monitoring and diagnosis used for the same purpose.

I. Introduction and Literature Review

Plant monitoring and diagnosis are usually integrated as one process to detect and isolate **suspicious** symptoms and use these to identify the root cause of the failure [1, 2]. There are several phrases that have similar meanings such as *failure detection*, *failure prediction*, *in-process evaluation*, *on-line inspection*, *identification and estimation*. Most current plant monitoring systems only check a few critical variables against their individual upper and lower limits, and trigger the alarm when a variable moves out of its range [3]. Some more sophisticated systems use redundant sensors to provide more data, but still follow the same route of independently checking measurements from redundant sensor sets against range limits.

The research reported here enables a new plant monitoring and diagnosis framework, which employs fuzzy rule-based algorithms to exploit far more detailed information contained in the signals. The computational complexity remains quite reasonable for time constraints of most real-time systems, especially after the rule-based model is constructed.

Diagnosis systems are usually used to identify certain pre-defined behavior patterns associated with known problems of the system. The most common approach for diagnosis in an industrial system is the use of experts. Experts observe the current values of the critical and measurable variables of the system and their recent history to identify the current behavior pattern correctly within time limit. Correction actions will then be issued by a control algorithm whenever it is necessary.

Many industrial processes are characterized by long periods of steady-state conditions with intercalated dynamic responses that last only a short time. These transient behavior patterns may corresponds to normal conditions such as planned interruptions or operation transitions to another steady state, or minor disturbances (noise to the system or the sensing element). They can also represent abnormal behaviors such as major external disturbances, actuator or sensor failures. Since these dynamic transient behavior patterns are critical in determining the normalcy of working condition of a system, a lot of researches have been done to model and classify them for diagnostic purposes. General approaches of diagnosis include rule-based expert systems[4-5], model-based state-estimation and prediction[6-7], fuzzy logic [8-9], fuzzy-fractal rule-based system [10], static and dynamic pattern recognition techniques such as neural networks [11-14], adaptive template matching [15], and *HMM* (Hidden Markov Models) [16-18].

In this paper, a new transient identification scheme using fuzzy logic is presented. Signal features based on wavelet decomposition and control theory are fuzzified and used in fuzzy rule-based classifiers (*FRBC*) to identify the behavior patterns. If the system is in transient (normal or abnormal) state, the signals picked up by each sensor monitoring different aspects of the system should be correlated since they should all react to the same system-wide conditions. The decision fusion based monitoring and diagnosis architecture integrates the low level and high level decisions. In the low level decision fusion, output from sensor fusion algorithm is used to validate the feature signals of each sensor. In the high level fusion, the decision about the transient behavior is made by fusing decisions from different diagnosis algorithms, or from different sensors that monitor the same system. For example, the wavelet decomposition provides information about the changing point of the transient pattern, but the more traditional running standard deviation (for real-time process) often gives better discrimination of the noise level of the data.

The paper is organized as follows: Section II describes and defines the fuzzy rule based plant monitoring and diagnosis problem and the system architecture used in the paper. Section III describes the algorithm details for wavelet online pre-processing (WOLP) [10] and highly autonomous sensor (HAS) [19] based fuzzy feature extraction algorithms and the fuzzy rule based classifier used for diagnosing. Section IV presents the system implementation and simulation results. We conclude the paper in Section V.

II. Fuzzy Rule based Plant Monitoring and Diagnosis System

Assume a system, S, can be described by n measurable variables $\{x_1, x_2\ldots,x_n\}$ (state variables) and each variable has m possible values/patterns. The number of the possible system behaviors $b\in \{b_1,b_2,\ldots,b_l\}$ is $l = m^n$. When the system complexity increases, l increases **exponentially**. However, it is often not necessary to explore all possible combinations of state variables because not all behaviors are physically feasible.

In general, the system's behaviors $b\in \{b_1,b_2,\ldots,b_m\}$ are defined with respect to various system conditions, including normal behaviors such as *monotonic increase* and *decrease*, *step change*, *noise at acceptable level*, as well as abnormal behaviors that trigger alarms. All these behaviors can be fully represented by the state variables of the system. By definition [20], state variables of a system are the minimum set of independent variables that completely describe a system. In reality, however, not all state variables are measurable. Either another measurable property that has a functional relationship with the immeasurable variable is used or several semi-redundant measurable variables with overlap coverage are used. Instead of using the numerical values of the state variables directly, feature vectors are usually extracted to represent the pattern of the signal.

The transient behavior identification problem is to identify transient behavior of the individual state/measurable variables and classify the combination of concurrent transient patterns as different system state behaviors. The diagnostic reasoning process will be triggered by unacceptable behaviors at either individual sensor or at system level. Abduction inference algorithms such as Bayesian networks and fuzzy influence diagram can be used to pin point the root cause of the abnormality. The success of finding the root causes depends heavily on correct transient behavior identification. For example, assume each variable has three possible states, namely, *normal*, *high noise*, and *disturbance*. If these transient behaviors can be isolated and identified correctly, it would be straightforward to find the abnormal state variable.

More formally, assume the input measurable signals from the sensing units are $X = \{x_1, x_2, \ldots, x_n\}$, the corresponding feature signals are $f = \{f_1, f_2, \ldots, f_n\}$. The *transient behavior identification* is to use the feature signal, f, to determine whether the system behavior is acceptable or not, $b \in \{b_1, b_2, \ldots, b_m\}$. The goal of the inverse problem, *system diagnosis*, usually triggered by detection of abnormal system behaviors, is to use behavior, b, and feature signal, f, to determine which measurable variable x_i and the corresponding sensing unit se_i causes the abnormality.

Figure 1 shows some typical transient behavior for a process in a plant [11, 15, 16-18]. The signals were generated in Matlab. All the plots were also generated in Matlab. In specific, the membership function plots (as shown in Figure 2, 4, and 5) were generated in Matlab using its Fuzzy Logic Toolbox. Figure 1 illustrates how a transient identification and diagnosis scheme

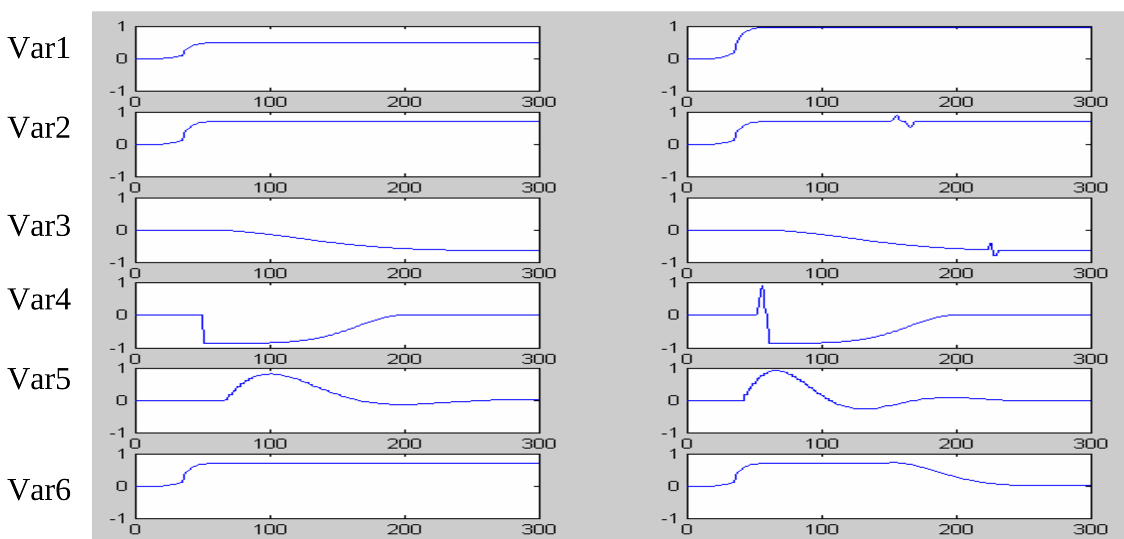
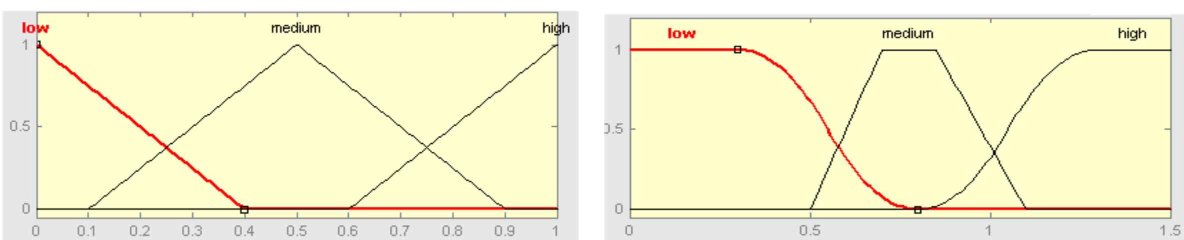


Figure 1 Typical transient behaviors of a simple system with six variables.

might be for a simple system having six measurable variables, each variable having two possible transient patterns. There are 64 (2^6) system behaviors in total for the system. These transient behaviors are organized to demonstrate the normal and abnormal (with external or internal disturbance) behavior of the system. The signals shown in the first column of the six variables are considered normal behaviors. The signals in the second column show the signal approaching its limit (the second column for *var1*), external disturbance imposed on the component (the second signal for *var2* to *var4*), and possible new normal behaviors (the second signal for *var5* – response higher order system and *var6* – step change down). The abnormal behaviors usually are caused by external or internal disturbances superimposed on normal behavior (such as the signals shown in the second column for *var2* to *var4*). They could also be new behaviors, such as power loss of a sensor (flat signal after the sensor loses the power) or of a mechanical component (such as second signal for '*var6*' with or without ripples due to unavoidable inertia). The abnormal behavior can be further classified into either *acceptable* behavior (such as spikes or external disturbances) or *unacceptable* (such as power loss or saturation caused by exceeding limit, which usually triggers warnings or alarms).

In reality, these incoming signals from sensors are usually corrupted with various noise and uncertainty (associated with sensor or system state). Thus, it is natural to introduce fuzzy sets to represent the different features of the signal as well as the membership that the signal belongs to any of the transient behavior patterns.

Figure 2(a) shows the fuzzy membership functions for transient pattern *step changes*, representing the possibility that the signal is a step change, i.e., *low*, *medium*, and *high.* Triangular membership functions shown in equation 1 are suitable for these linguistic variables. The membership functions shown in Figure 2(b) are for the feature linguistic variable *Maximum Coefficient for Wavelet Decomposition*. The *sigmoidal* membership function (equation 2) is suitable for these feature linguistic variables. Depending on the sign of parameter a, the



(a) (b)

Figure 2 The membership functions of (a) state variable *Step Change* and (b) signal features *maximum coefficient of wavelet decomposition*

sigmoidal function is inherently open to the left (*very low*) or right (*very high*).

The *medium* or *normal* state for a corresponding linguistic variable of a system state can be modeled by the *trapezoidal* membership function (equation 3).

$$\textit{triangular membership function}:$$

$$f(x;a,b,c)=\begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{cases}$$

$$\textit{or} \qquad (1)$$

$$f(x;a,b,c)=\max(\min(\frac{x-a}{b-a},\frac{c-x}{c-b}),0)$$

$$\textit{sigmoidal membership function}:$$

$$f(x,a,c)=\frac{1}{1+e^{-a(x-c)}} \qquad (2)$$

$$\textit{trapezoidal membership function}:$$

$$f(x;a,b,c,d)=\begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \dfrac{d-x}{d-c}, & c \le x \le d \\ 0, & d \le x \end{cases}$$

$$\textit{or} \qquad (3)$$

$$f(x;a,b,c,d)=\max(\min(\frac{x-a}{b-a},1,\frac{d-x}{d-c}),0)$$

Figure 3 shows the system architecture for fuzzy transient behavior identification. The Fuzzy transient identification (*FTI*) block includes a fuzzy feature extraction algorithm (FFEA) and a fuzzy rule-based inference engine (*FRBIE*). The input to the *FTI* is the raw signals. The fuzzy feature extraction algorithms include fuzzified wavelet online pre-processing (WOLP) and highly autonomous sensors (HAS). The feature vectors from these are fed into the fuzzy rule based inference engine with fuzzy membership value of the input signal as the output.

Using a simple system with six variables as an example. As shown in Figure 1, twelve transient patterns are identified for the system, two for each variable. These six variables are monitored simultaneously in order to get a complete understanding of the system condition. Thus, the system has 36 conditions in total ($C_6^1 C_6^1$). The fuzzy transient behavior identification decision fusion algorithm fuses the transient behavior decisions from different FTI algorithms to maximize the confidence of assigning each input signal to one of the eleven transient patterns. The membership value for 64 possible system scenarios are output from the fusion algorithm. Afterwards, another *FRBIE* is used to decide the system condition based on the transient identification results and output the one with maximum confidence.

The confidence of each feature extraction algorithm is initialized by the identification accuracy in the learning phase. When the system is deployed for online monitoring and diagnosis, the fused identification results are used as truth values. The confidence of each feature extraction algorithm is adjusted based on the error rate of its identification with respect to the fused identification.

III. Fuzzified Feature Extraction and Transient Identification

The fuzzy feature extraction algorithm for the *FTI* can be any feature extraction algorithm with fuzzified features. Fuzzified *WOLP* (Wavelet On-Line Preprocessing) [10] and *HAS* (Highly Autonomous Sensor) [19] feature extraction algorithms were studied here.

For a signal with *n* samples, using a sliding window size *w* with overlap of *o* between windows,

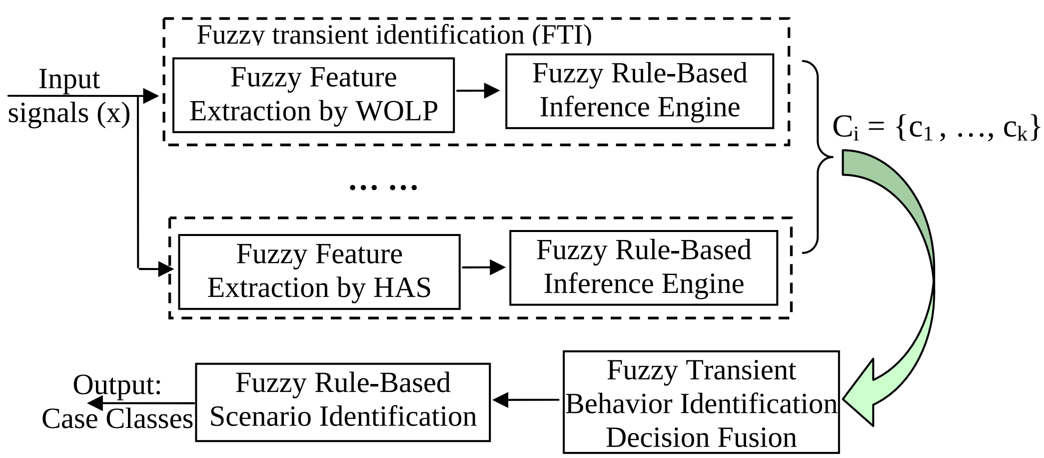


Figure 3 System architectures for fuzzy transient behavior identification by decision fusion of different fuzzy feature extraction and classification

there will be a set of $t = (n\text{-}w)/(w\text{-}o)$ features. To deal with temporal information, the fuzzy rule-based transient classifier (*FRBTC*) has $k * t$ inputs, where k is the number of features. Each input has membership functions representing the linguistic values *low*, *medium*, and *high* for the particular parameter. The *FTI* block has one output in this case. When dealing with m types of transient patterns, the ($m+1$)-dimensional output has $m+1$ membership values, each representing the possibility of the signal belonging to one of the corresponding $m+1$ transient types. (The additional transient type is *unknown.*)

The *WOLP* feature extraction algorithm is based on the Haar multi-scale wavelet decomposition [22]. Three features are extracted from a sliding window on the actual signal time-series. They are denoted as (mr, mh, ml), where $mr \in R$ is the mean residual at the coarsest scale, mh and ml are the maximum and minimum coefficients of the wavelet decomposition over all scales. Roverso [10] shows that these three features capture the trend of the signal as well as important discontinuities such as step changes, spikes, and disturbances. He also shows that a *large* absolute value of the minimum coefficient corresponds to a *large* increase in the signal value and a *large* value of the maximum coefficient corresponds to a *large* decrease in the signal value. Furthermore, mh and ml maintain nearly linear relation with respect to changes in the signal. That is, the value of mh or ml is roughly doubled when the change rate of the signal is doubled. The fuzzy rule-based transient identification algorithm depends on membership functions (e.g., the aforementioned triangle, sigmoid, and trapezoidal function that defines *low*, *medium*, and *high*) for the set of linguistic variables $\{mh, ml, mr\}$. The simulation results show that fuzzified features improved the robustness to noise and small variations and generalization capability of the transient identification algorithm.

The feature extraction algorithm based on *HAS* [19] is modified in two ways to fit to the transient identification problem. First, instead of extracting features for each sample, we only extract features for the sliding window with overlap as defined above. This reduces significantly the number of inputs for the fuzzy rule-based classifier, from $k * n$ to $k * t$. For a signal with 300 samples, the number of input is reduced from $3 * 300 = 900$ to $3 * 9 = 27$. Second, only four features that capture the rough trend of the signal are used. These are “Measurand Time Constant Check”, “Sensor Time Constant Check”, “Mean Residual” (*MR*), and “Deviation Check” (*DC*). A local model for the signal within the sliding window is learned for non-periodic signal (i.e., the periodic component is negligible) by six-degree polynomial curve-fitting. The model for periodic signal is learned by FFT, where predominant frequency, DC components, and the coefficients for *sine* and *cosine* components are extracted.

- The *MR* feature is the difference between the prediction value from these models and the real input signal. It captures the trend of the signal and has membership functions over such linguistic values as *large*, *medium* and *smal*.

- The “Deviation Check” is based on the statistical properties of the signal such as running standard deviation and the given system noise level. When the running standard deviation of the input signal is higher than those obtained from the prediction value by those models with given system noise level, the “Deviation Check” is high.

- Based on control theory, the membership functions designed for “Time Constant Check” include “Electronic Disturbance”, “External Disturbance”, and “System Behavior”. The

"Electronic Disturbance" membership function represents transients with short duration caused by electronic disturbances within the sensing unit. The "External Disturbance" membership function defines transients with longer duration, usually caused by an external disturbance to the system that is monitored by the sensor. The "System Behavior" membership function defines normal system transients, with duration even longer than those of "External Disturbance". The membership functions for "Deviation Check" include *high*, "*low*, and *normal*, representing the noise level of the signal.

The output of the modified feature extraction algorithm is in the format $([fm_{i1}, fm_{i2}, \ldots, fm_{ik}])$, where fm_{ik} is the membership value for the k^{th} membership function of feature i.

IV. System Implementation and Simulation Results

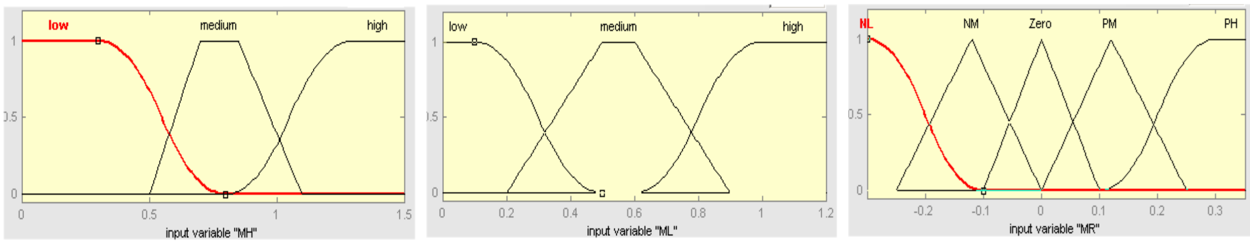
4.1 Data Sets:

As shown in Figure 1, there are 6 variables in the system, each with two possible transient patterns. Close observation shows that the normal transient pattern for var2 and var6 are the same, i.e., it is the "Step Change with Normal Amplitude". As the result, we have in effect eleven independent transient patterns shown in Figure 1. Training and testing data set were generated based on these eleven independent transient patterns. The first eight patterns are used to train the system to get the initial confidence of each algorithm. The remaining three patterns are used as the base for *unknown* type transients during the test.

The test set has 450 transient patterns, 50 for each of the nine transient patterns (eight *known* patterns and one *unknown* pattern). The signals is generated by adding to the eight transient patterns a combination of random amplitude warping (stretching or shrinking the signal amplitude up to ± 30%), delay (up to ± 20%), time warping (stretching or shrinking the signal in the time dimension, up to ± 20%), and Gaussian noise (± 1%). The unknown transient patterns were generated by randomly selecting one of the four patterns (one of them is actually a "known" pattern) five times and generate ten signals with variation described above. The resulting test transient signals have from 200 to 400 samples. Finally, all signals are normalized to contain 300 samples. The sliding window size chosen is 32 samples ($w = 32$), with a five-sample overlap between windows ($o=5$), resulting in nine sets of feature vectors for each signal. Thus, the number of inputs for the fuzzy rule-based transient identification algorithm is 27 since both feature extraction algorithms use 3 different features. The output of the fuzzy inference classifier has nine Gaussian type membership functions (equation 4), each corresponding to one of the nine patterns. The rules for the system are assigned manually now based on the feature membership values for the "original" patterns. Obviously, learning methods such as neural network, nearest neighbor or decision tree and optimization method such as genetic algorithm can be used to improve the rule assignment.

4.2 System Design and Implementation:

For the feature extraction algorithm based on wavelet decomposition, the membership functions for three linguistic variables (*mh*, *ml*, and *mr*) are shown in Figure 4. Similar shaped membership functions are used for the three linguistic variables (*TC*, *DC*, and *MR*) of HAS based feature extraction algorithm. The output membership functions are the same for both feature extraction algorithm, shown in Figure 5.



(a) (b) (c)

Figure 4 Membership functions of the input features (a) MH, or TC; (b) ML or DC; (c) MR

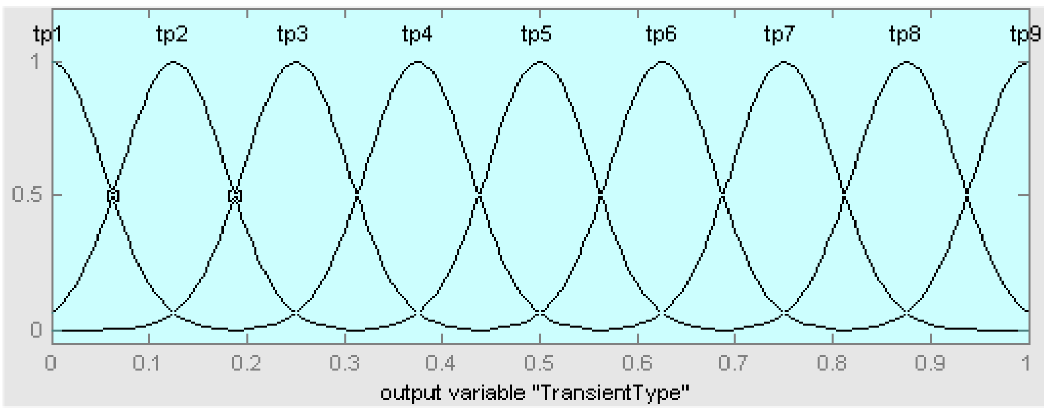


Figure 5 membership functions of the output variable – transient patterns.

4.3 Classification Rules and Classification Result:

Based on the feature values extracted for those *original* patterns, eleven rules are created for each feature extraction algorithm, including the rule for identifying the "Unknown" type. If the features f_i $(i=1,\ldots,27)$ have membership value P_m (m∈[1,5] for feature *MR* or m∈[1,3] for other features)for input data S_j, $(j\in R)$, then all these fuzzy classification rules have the general format:

$$R^{(i)}: \text{IF } f_1 \text{ is } P_{1m} \text{ AND } f_2 \text{ is } P_{2m} \text{ AND} \ldots \text{AND } f_{27} \text{ is } P_{27m} \text{ THEN } y \text{ is } C_{i.}$$

Figure 6 shows part of the rule list with configuration for six variables.

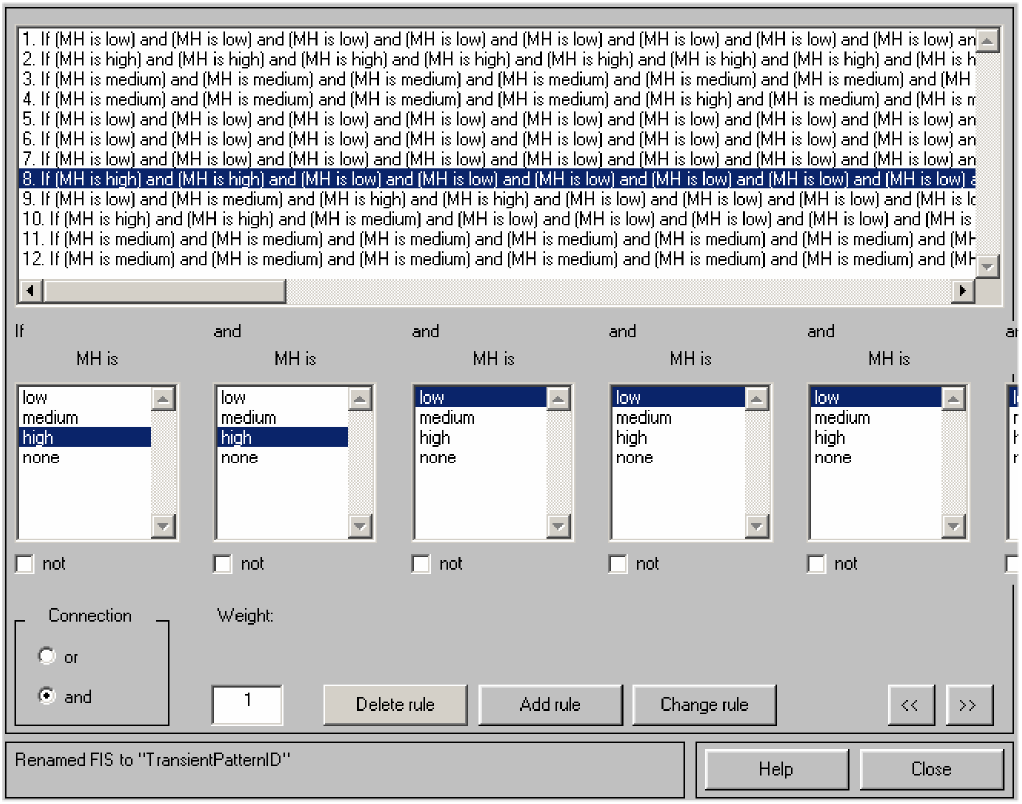


Figure 6 Fuzzy rule base for transient identification

Table I shows the transient pattern classification results for each feature extraction algorithm. The results are very satisfactory considering the simple fuzzy rule base inference system being used. The feature extraction algorithms give comparative performance, which is not surprising since the selected feature set captures well the tendencies of the signals. Because we introduce the *unknown* type here, the misclassification rate is a bit better than those reported in [11]. That study includes a *non-classification* rate. (That is, the system does not classify the transient or it classifies the transient pattern as belonging to more than one class.)

TABLE I TRANSIENT IDENTIFICATION (ID) RESULTS

	Correct ID Rate	Misclassification
WOLP based Fuzzy Transient ID	96.7 %	3.3%
HAS based Fuzzy Transient ID	92.8%	7.2%
WOLP based Transient ID	86.3%	13.7%

In order to compare the results of the transient identification with and without fuzzy logic, we use pruned decision-tree (C4.5 [23]) to classify the non-fuzzified feature set from WOLP based feature extraction algorithm. The training set and testing set each has 250 signals randomly selected from the 450 test signals generated. The classification rate is average over ten runs. The comparison shows that using fuzzy logic in transient identification can improve performance with simpler system. However, there’s not much difference between the performances of the two fuzzified feature based transient identification algorithms. More experiments are necessary to fine tune the fuzzy rule base, to compare the performance of different transient identification algorithm using more patterns, etc.

V. Conclusions

In this paper, fuzzified transient pattern identification algorithm is proposed based on different fuzzified feature extraction algorithms. An implementation in MATLAB has been used to study in more detail the advantages of the fuzzified feature extraction for transient identification problem. Two feature extraction algorithms, based on *WOLP* and *HAS*, respectively, are fuzzified so that they output fuzzy membership of the features for each input signal. Comparison between the two feature extraction algorithms shows that WOLP and HAS based feature extraction are comparable. Comparison between numerical feature sets and the fuzzified linguistic feature membership value set shows that the fuzzified version improves transient identification performance even though we only use a very simple fuzzy rule-based classifier.

VI. References

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