The Fourteenth International Symposium on Artificial Life and Robotics 2009 (AROB 14th '09),
B-Con Plaza, Beppu, Oita, Japan, February 5 - 7, 2009

Intelligent Diagnosis System for Transmission Line: Fuzzy-Bayesian Classifier Approach

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Abstract: We develop an intelligent diagnosis system which is based on fuzzy-classifier. The term of intelligent diagnosis system (IDS) is a real-time fault monitoring system for transmission line. Based on the Time-Frequency Domain Reflectometry (TFDR) algorithm, we implement the wire detecting system which shows the condition of the wires. The concrete processes are represented as follows: 1) the reflected signals which are sent from the fault of wires are obtained and saved in main server; 2) IDS classifies the fault type of the wires into damage and normal. For classifying the fault type efficiently, we use the fuzzy-Bayesian classifier which is merged the IF-THEN rules with Bayesian algorithms. Simulation results convincingly validate the effectiveness of our algorithms.

Keywords: Intelligent diagnosis system (IDS), fuzzy-Bayesian classifier, time-frequency domain reflectometry (TFDR).

I. INTRODUCTION

Detecting fault for transmission lines is very important because the main origins of electric accidents are faults of wires. In [1], the importance of aging electrical wiring and associated faults in aircraft has been highlighted. Generally, there become known to three kinds of the fault detection algorithm – time domain reflectometry (TDR), frequency domain reflectometry (FDR) and time-frequency domain reflectometry (TFDR). However, the resolution and accuracy of the TDR and FDR are limited by the rise/fall time and frequency sweep bandwidth, respectively.

In order to supplement the weak points of TDR and FDR, Shin *et. al.* propose a new high-resolution reflectometry technique that operates simultaneously in both the time and frequency domains [1]. The TFDR algorithms have shown better accuracy in fault localization than the TDR in the same experimental conditions. However, each fault detecting experiment has performed respectively so that it is hard to recognize the fault types of real-used wires. In other words, it is necessary to group the each type of faults for electric wires.

The conventional classifiers are needed for the classification of the highly complex real data such as the sensory data and the signal data. Among the many classifiers, a fuzzy classifier which is to translate domain expert's knowledge in a linguistic form into discriminant function is very popular because of its usefulness [2-5]. However, fuzzy methods are cumbersome to use in high dimensions problems. For solving that, some researchers attempted to merge the fuzzy classifier and others, especially statistical ones, and improve the capability of the pattern classification problem [7], [9-11]. Among them, Bayesian decision theory is a fundamental statistical technique. The main idea of the Bayes classifier is to capture all information about class membership available from the set of conditional probability densities. Reference [2] introduces the new fuzzy rule-based classifier equipped with a Bayes rule consequent which is known as fuzzy-bayesian classifier.

Generally, the result of the detecting signals which are sent from the faults of transmission lines is represented as highly nonlinear appearance. For classifying these complex signals, we propose an intelligent diagnosis system (IDS) [8]. When unknown faults are detected by TFDR algorithm, we are able to recognize the kinds of faults through the IDS. For classifying the faults efficiently, we use the fuzzy-Bayesian classifier which is represented as IF-THEN rule. Finally, to show the feasibility of the proposed algorithm, computer simulations are provided.

This paper is organized as follows: Section 2 fuzzy-Bayesian algorithms are developed. In Section 3, we formulate the IDS. An example is shown in Section 4. This paper concludes with Section 5

II. Fuzzy-Bayesian Classifier

2. 1 Fuzzy Classifier

Generally, the fuzzy rule-based classifier is

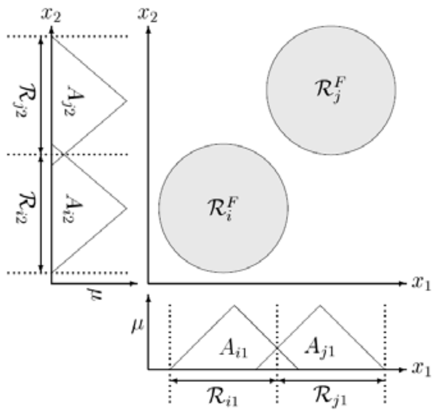

Fig. 1. The decision regions R_1 and R_2 of the fuzzy classifier

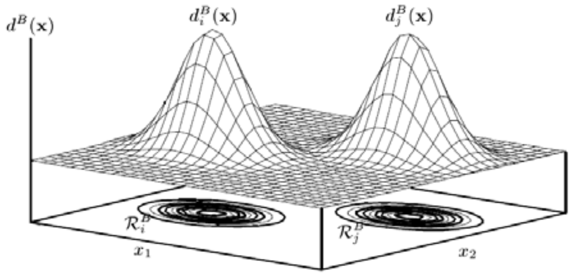

Fig. 2. The decision regions R_1 and R_2 of the Bayesian classifier

represented as following form:

$$R_i : \text{If } x_1(t) \text{ is } A_{i1} \text{ and} \ldots \text{and } x_n(t) \text{ is } A_{in} \quad \text{the class is } i, \tag{1}$$

where R_i is the i th fuzzy rule, x_j is the j th feature variable, and A_{ij} is the fuzzy set. The output of (1) is obtained as

$$Y(x(t)) = \frac{\sum_{i=1}^{p} h_i(x(t)) y_i}{\sum_{i=1}^{p} h_i(x(t))} \tag{2}$$

where $h_i(x(t)) = \prod_{j=1}^{m} \mu_{M_{ij}}(x_j)$, $\mu_{M_{ij}} \in [0, 1]$. The conjunction rule to transform the fuzzy sets into a discriminant function is

$$w_i = \mu_{A_{i1}} \times \cdots \times \mu_{A_{in}} \tag{3}$$

where w_i perform to divide the feature space R^n into the decision regions $R_1, \ldots, R_m$. Therefore, the fuzzy classifier is to assign a feature variable vector x to class C_{i1} , if

$$w_{i_1} > w_{i_2}, \quad \forall i_2 \neq i_1, \quad i_2 \in I_m \tag{4}$$

Fig. 2 shows the decision regions of the fuzzy classifier.

2.2 Bayesian Classifier

Using the prior probabilities $P(x)$ and the conditional densities $P(x \mid C_i)$, especially, the multivariate Gaussian model, the Bayesian classifier is designed by the following discriminant functions [2]:

$$d_i(x) = \frac{1}{(2\pi)^{\frac{2}{n}} \mid \Sigma_i \mid^{\frac{1}{2}}} e^{-\frac{1}{2}(x-m_i)^T \Sigma_i^{-1} (x-m_i)} P(C_i) \tag{5}$$

where x is n-component column vector, m_i is the n-component mean vector, Σ_i is the $n \times n$ covariance matrix, C_i, is the i th class, and $|\Sigma_i|$ and Σ_i^{-1} are its determinant and inverse, respectively. As shown in Fig. 3, the Bayesian classifier is said to assign a feature vector x to class C_{i_1} , if

$$d_{i_1}(x) > d_{i_2}(x), \quad \forall i_2 \neq i_1, \quad i_2 \in I_m . \tag{6}$$

2.3 Fuzzy-Bayesian Classifier

Despite of the existence of good point of previous researches, it is necessary to develop new algorithm. In spite of the many advantages, the fuzzy classifier has the following limitations: fuzzy methods are cumbersome the use in high dimensions or on complex problems or in problems with dozens of hundreds of features. Also, Bayesian classifier has the following drawbacks: it is drawback to determine and compute $P(x \mid C_i)$. Specifically, in the design of Bayesian classifiers, particularly in the design of Gaussian normal classifiers, a frequently made assumption about the normal form of $P(x \mid C_i)$ governing of patterns is not necessarily true for real data.

Motivated by above observation, we suggest a method to identify the fuzzy classifier and to effectively reduce the dimension of Bayesian classifier for implementing the intelligent diagnosis system. The concrete algorithms are represented as following three steps:

Step 1: Construct the initial fuzzy-Bayesian classifier by using the MIMO fuzzy model.
Step 2: Through the fuzzy set analysis, prune the feature variables.
Step 3: Finely tune the premise parameters for the misclassified feature vectors.

III. Intelligent Diagnosis System

IDS is the classification system which is based on the fuzzy-Bayesian classifier. Generally, it is difficult to classify the result of the detecting signals which are sent from the faults of transmission lines. See the following two TFDR results:

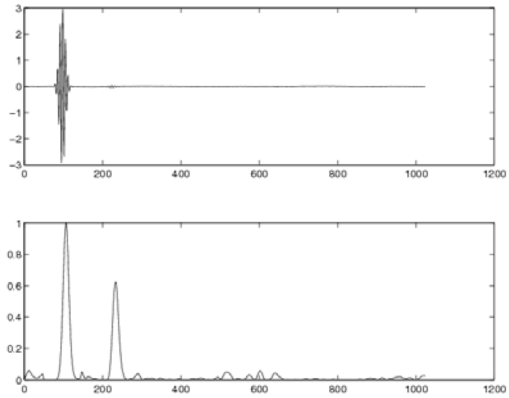

Fig. 3. TFDR result signal (normal)

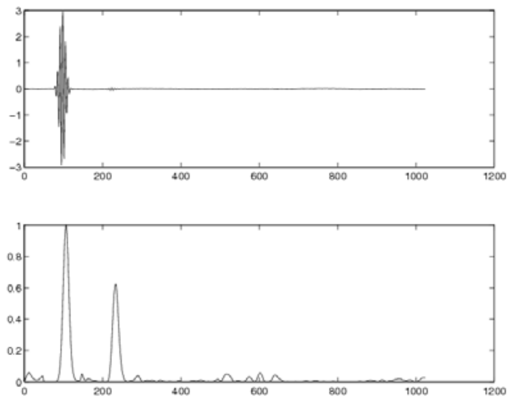

Fig. 4. TFDR result signal (fault)

Figure 3 and 4 are represented as the TFDR result signal, the one is normal condition and the other has the fault in the transmission line. As you shown these two figures, it is very difficult to classify the condition of the transmission line. In order to solve this problem, we propose the IDS which is based on the fuzzy-Bayesian classifier.

VI. Simulation Result

The purpose of the intelligent diagnosis system is to classify the condition of 220V transmission line. As shown in Fig 3 and 4, the magnitude of the reflected signal is very small so that it is too difficult to classify the each condition.

In this paper, we classify the condition of transmission line. The simulation process is represented as follows:

Cable Type: VCTF 1.5
Input Signal: linearly modulated chirp signal with a Gaussian envelope
Time Duration: 50*ns*
Frequency Bandwidth: 100 *MHz (*400*MHz* ~ 500*MHz)*
Frequency Sweep: Linearly increasing
($\beta / 2\pi = 100$ *MHZ/*50*ns*)

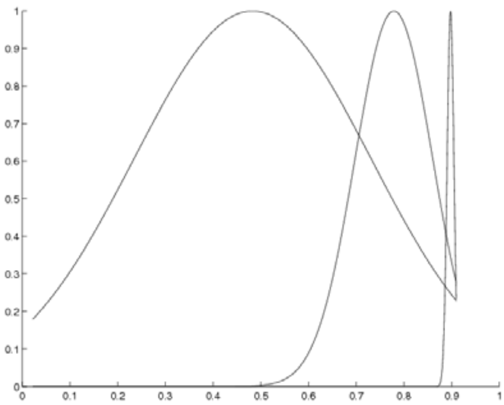

Fig. 5. Membership function of R_1

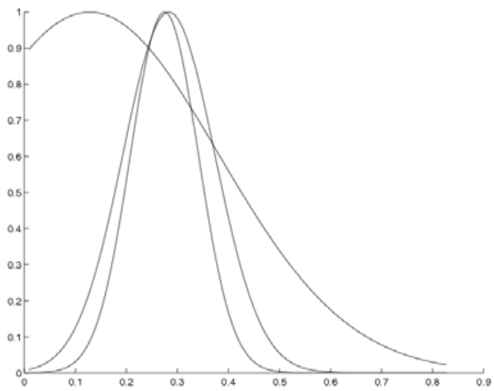

Fig. 6. Membership function of R_2

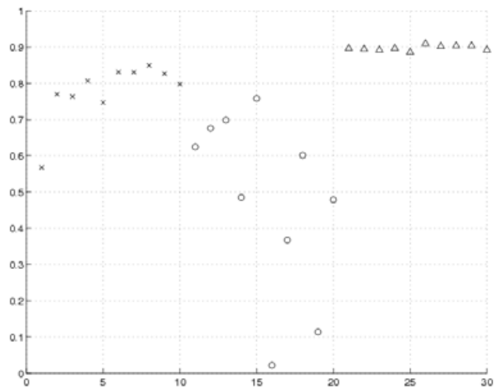

Fig. 7. The classification result

Figure 5 and 6 are the membership function of each fuzzy rule and Figure 7 represents the classification result of TFDR signal. A symbol 'x' means the normal condition, 'o' means the connected with fan, '△' means the fault of transmission line.

V. Conclusion

We have proposed IDS which is based on the fuzzy-Bayesian classifier for transmission. Based on the TFDR algorithm, the wire detecting system shows the condition of the cable and transmission line. We analyze the reflected signal which is sent from the wire detecting system and classify the fault type of the wires by using intelligent diagnosis system. For classifying the fault type efficiently, we use the fuzzy-Bayesian classifier. The simulation results for the transmission line (VCTF 1.5) are shown the excellence of the proposed algorithm.

ACKNOWLEDGMENT

This research was funded by the Korea Electrical Safety Corporation (KESCO), Project #R-2006-1-229, "Implementation of real-time fault monitoring system for transmission line."

REFERENCES

[1] Y. J. Shin, T. S. Choe, C. Y. Hong, E. S. Song, J. G. Yook, and J. B. Park, "Application of time-frequency domain reflectometry for detection and localization fault on a coaxial cable," IEEE Trans. Instrumentation and measurement, vol 54, no. 6, Dec. 2005. .
[2] M. H. Kim, J. B. Park, W. G. Kim, and Y. H. Joo, "Identification of T-S fuzzy classifier via linear matrix inequalities," LNAI 3809, pp. 1134-1137, 2005.
[3] M. Setnes, and H. Roubos "GA fuzzy modeling and classification: complexity and performance," IEEE Trans. Fuzzy Syst., vol. 8, pp. 509-522, 2000.
[4] Y. H. Joo, H. S. Hwang, K. B. Kim, and K. B. Woo, "Linguistic model identification for fuzzy system," Electron. Letter. vol. 31, pp. 330-331, 1995.
[5] T. P. Wu and S. M. Chen, "A new method for constructing membership functions and fuzzy rules from training examples," IEEE Trans. Syst., Man, Cybern. B. , vol. 29, pp. 25-40, 1999.
[6] H. Roubos and M. Setnes, "Compact transparent fuzzy models and classifiers through iterative complexity reduction," IEEE Trans. Fuzzy Syst., vol. 9, no. 4, pp. 516-524, 2001.
[7] Y. Shi, R. Eberhart, and Y. Chen, "Implementation of evolutionary fuzzy systems," IEEE Trans. Fuzzy Syst,, vol. 7, pp. 109-119, 1999.
[8] H. C. Sung, J. B. Park, and Y. H. Joo, "Implementation of intelligent diagnosis system based on fuzzy-Bayesian classifier," SCIS & ISIS 2008, pp. 570-573, 2008.