

Fault Diagnosis of Multi-Information Fusion in Train Intelligent Control System Based on Fuzzy Neural Network and Evidential Theory

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Abstract

Aiming at the becoming, uncertainty and space distributing of input multi-fault characteristic information in train intelligent control system fault diagnosis, a system structure for fault diagnosis of multi-information fusion in train intelligent control system is presented. The method of fault diagnosis of multi-information fusion in train intelligent control system based on fuzzy neural network and D-S evidential theory is discussed. Result of example indicates that this method can effectively improve the probability and reduce the uncertainty of diagnosis.

Keywords: *Fault diagnosis, Information fusion, Fuzzy neural network, Evidential theory*

1. Introduction

Reliable intelligent control system is needed in the operation of the train. Disaster would happen if any part of the system fails, so fault diagnosis in the train intelligent control system is one of the most important technologies to secure operation of the train, and the research about it is meaningful in both theory and practice. Fault diagnosis is to evaluate system operation and fault condition by comprehensively processing status information and existing knowledge. As the control system becomes more intelligent and complicated, the type and number of the sensor quickly increase, and these sensors form sensor groups. So only when these uncertain characteristics information are comprehensively used by multi-information fusion technology in the fault diagnosis, could faults be diagnosed and then separated timely, so as to secure the safe operation of the train.

Greatly different with common industry process, the operation of train is a complicated process combining qualitative and quantitative information, time and space, partial linearity and integral non-linearity, human and machine. The train intelligent control system has multiple input and output variables, most of which are nonlinear, time-varying, redundant, uncertain and space distributed[1]. Therefore, multi-information fusion technology should be used to fuse multi-sensor data and other information in order to improve precision and reliability of fault diagnosis, and then make the right decision.

Single multi-information fusion method has defects in the practice, so this thesis combines fuzzy neural network and evidential theory in fault diagnosis of train intelligent control system, which could resolve problems caused by the single method.

2. Fuzzy Neutral Network, Evidential Theory & Multi-information Fusion

2.1 Fuzzy Neutral Network and Multi-information Fusion

It is becoming a new technology to combine fuzzy theory and neutral network technology into fuzzy neutral network. Its essence is to put input fuzzy signal or weight into common neutral network. It expresses complementarity of fuzzy system and neutral network, because it integrates the calculation of language, logical inference, step by step processing and non-linear mapping, which could meet requirements of multi-sensor information fusion.

In the fault diagnosis, parallel handling ability of fuzzy neutral network speed up the recognizing and judging of the fault, and its robustness and tolerance could greatly improve ability of anti-inference and fault tolerance, so as to improve safety, reliability and stableness of the fault diagnosis system.

2.2 Evidential Theory and Multi-information Fusion

Evidential theory is used to make decision by fusion inference of all evidences in the same recognition frame, which belongs to decision input/output process [2]. It could greatly solve the problem of uncertainty in the fault diagnosis.

Definition 1 : assume U as recognition frame, then when function $m: 2^U \rightarrow [0,1]$ (2^U is power assume of U) meets 2 following conditions :

$$(a) \quad m(\Phi) = 0,$$

$$(b) \quad \sum_{A \subset U} m(A) = 1$$

m is basic probability assignment in the frame U ; $\forall A \subset U, m(A)$ is referred to as basic probability assignment function of A .

Belief function meeting conditions could be formed with basic probability assignment function :

$$Bel(A) = \sum_{B \subset A} m(B)$$

Definition 2 : assume U as recognition frame, $A \in 2^U$, $Bel(A)$ is belief function of A . $1 - Bel(A)$ is referred to as plausibility function of A . The function value is referred to as plausible value $PL(A)$,

$$PL(A) = 1 - Bel(\bar{A}) = \sum_{B \subset U} m(B) - \sum_{B \subset A} m(B) = \sum_{B \cap A \neq \Phi} m(\bar{B})$$

Definition 3: assume $Bel(A)$ and $PL(A)$ as belief value and plausible value of A respectively, binary group $[Bel(A), PL(A)]$ as uncertain interval of A , $[0, Bel(A)]$ as reliable interval, $[0, PL(A)]$ as no-doubt interval of proposition "A is true"[3].

2.3 D-S Rule of Combination

D-S rule of combination reflects combined effect of evidences. Assume some belief functions based on different evidences in the same frame, if these evidences are not completely conflicting, then this rule could be used to calculate one belief function, which is considered to be produced by combination of these evidences.

Assume Bel_1 and Bel_2 as 2 belief functions in the same recognition frame U , and m_1 and m_2 are its basic probability assignment functions, if $A \subseteq U$ and $m(A) > 0$, A is focal element; focal elements are A_1, A_2, \dots, A_K and B_1, B_2, \dots, B_r respectively. And assume

$$k_1 = \sum_{A_i \cap B_j = \Phi} m_1(A_i)m_2(B_j) < 1$$

then

$$m(C) = \begin{cases} \frac{\sum_{A_i \cap B_j = C} m_1(A_i)m_2(B_j)}{1 - k_1} & \forall C \subset U, C \neq \Phi \\ 0, & C = \Phi \end{cases}$$

In this formula, if $k_1 \neq 1$, then m determines one basic probability assignment function; if $k_1 = 1$, then m_1 and m_2 are considered to be conflicting, and basic probability assignment functions could not be combined.

3. Hierarchical Structure and Model of Fusion System

Train intelligent control system has functions of traction control, braking control, assistant control, adhesion control, logic control, network management, information processing, etc. According to structure of train intelligent control system, the fault could be classified into software (computer diagnosis and control program) fault and hardware (control organ, sensor and computer interface) fault. Fault diagnosis system acquires information of train control system in real time, monitor faults by rules of estimation and diagnosis, and give warning when there are hidden faults and abnormalities. If any fault happens, it would find position of the fault, and provide countermeasures.

3.1 Hierarchical Structure of Multi-information Fusion of Fault Diagnosis in Train Intelligent Control System

According to characteristics and requirements of fault diagnosis in train intelligent control system, one suitable information fusion structure is used-hierarchical structure. As multi-information processing technology, it classifies common system structure into 4 layers: detection, time & space, attribute, symbol[4]; and classifies information fusion into 3 layers: data, characteristic and decision making. DFS model is popularized into more general conditions. The following Figure 1 indicates the hierarchical structure of fault monitoring, warning and diagnosis.

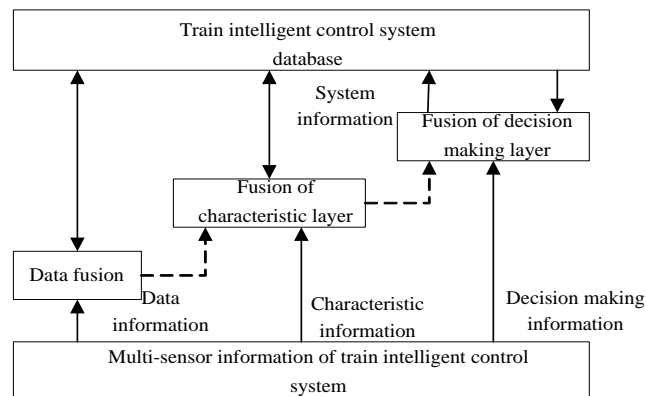


Figure 1. Hierarchical Structure of Multi-Information Fusion of Fault Diagnosis in Train Intelligent Control System

Data fusion includes data directly reflected in multi-sensor system, and pre-processing or analysis of these data, etc. i.e. signal filtering, spectrum analysis, wavelet analysis, etc.; characteristic fusion includes making effective decision about data fusion results, which basically corresponds fault diagnosis methods; decision making layer corresponds measures on fault separation, derating, etc. These 3 layers of structure respectively meet requirements of monitoring & warning, fault diagnosis and fault separation measures in fault diagnosis system.

3.2 Fusion Model of Fuzzy Neutral Network

Train intelligent control system fault diagnosis is a process of multi-information fusion, including fault detection, separation, estimation, classification, evaluation and decision making. The system continuously produces all kinds of information in the operation, which indirectly reflects operation status of the diagnosis object, so these information could be acquired by sensor. Besides, the information also could be obtained from existing knowledge and indirect results. They may be identical, similar or different, which are called redundant information, cross information and complementary information respectively. Fault characteristics, sensitive to operation status of the diagnosis object, could be found by these information, and then these characteristics are respectively transferred to sub fuzzy neutral network as input signals [5]. All sub fuzzy neutral networks are parallel and there is not connection among each other. Outputs of all sub fuzzy neutral networks, as inputs of fusion neutral networks, could reduce the uncertainty of decision making and increase correct diagnosis rate. Finally diagnosis conclusion is made by specific rules of decision making, i.e. operation status of the object. Basing on above knowledge, this thesis proposes multi-information fusion fault diagnosis model in train intelligent control system based on fuzzy neutral network and evidential theory, showed in Figure 2.

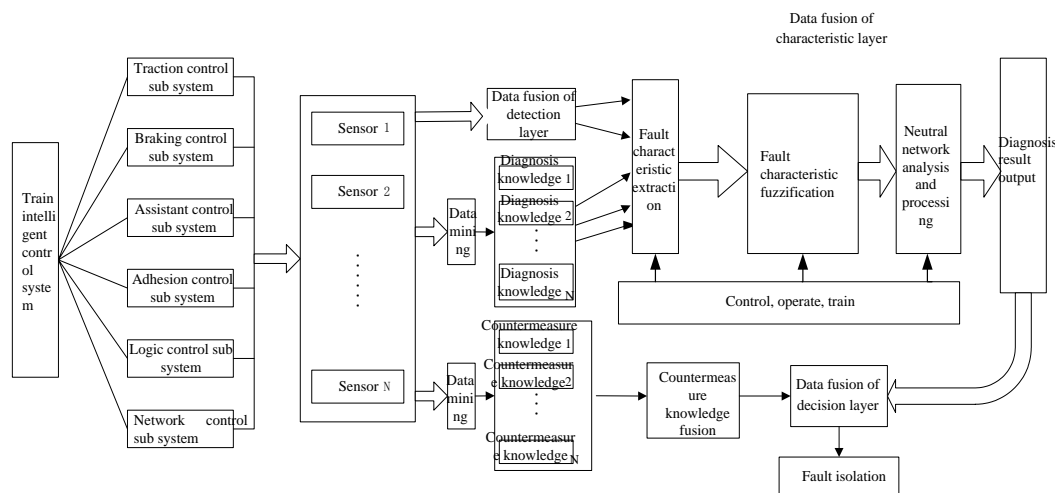


Figure 2. Multi-Information Fusion Fault Diagnosis Model in Train Intelligent Control System Based on Fuzzy Neutral Network and Evidential Theory

4. Multi-information Fusion Fault Diagnosis Model in Train Intelligent Control System Based on Fuzzy Neutral Network and Evidential Theory

With the development of railway transportation, the importance of train intelligent control system in the safe operation of the train is more realized. The operation of train intelligent control system is mainly dependent on fault diagnosis, including fault detection, recognition, estimation, decision making and separation. Fault recognition

and information fusion is the basis of multi-information fusion fault diagnosis in train intelligent control system based on D-S evidential theory.

4.1 Recognition Frame U

Common faults in control system lie in computer diagnosis program, control program, control organ, sensor, computer interface, etc. And these faults could also be classified into urgent fault and slow fault.

4.2 Selection of Sensor

Detection technology is becoming more and more advanced, so is the sensor technology. Common fault diagnosis sensors include infrared sensor, speed sensor, acceleration sensor, displacement sensor, temperature sensor and pressure sensor, etc.

4.3 Fuzzy Neutral Network Fusion

Fault recognition is a complicated process in fault diagnosis, because one fault may has different characteristics in different conditions. We use sensor to detect information and comprehensively analyze them with existing knowledge, and then we acquire characteristics of faults which are sensitive to the change of operation status of train intelligent control system. After fuzzification, these characteristics are transferred to input terminal of neutral network. Then the network uses knowledge learned in training to conduct inferential analysis and give fault diagnosis results, and then sends them to higher layer for fusion.

4.3.1 Fuzzy Neutral Network Structure

Fuzzy neutral network in this thesis applies four-layer structure (see diagram 3). The 1st one is input; the 2nd one is fuzzification of input signals; the 3rd one is hidden layer, which is the result of repeated debugging and optimization; the 4th one is output.

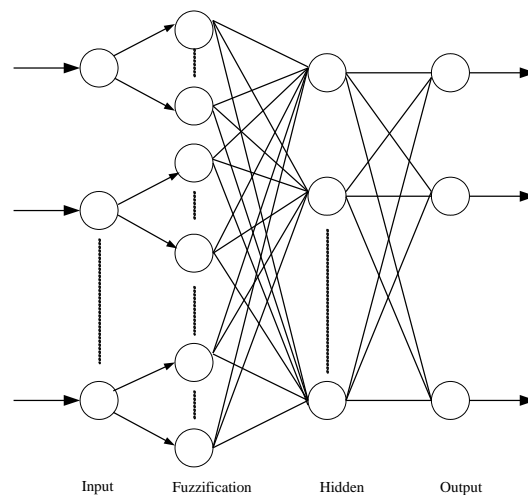


Figure 3. Fuzzy Neutral Network Structure

4.3.2 Determination of Fuzzy Membership Function

The 2nd layer is fuzzification. Its first function is to fuzzify input signals and transfer accurate variables into sub space of fuzzy variable domain; the second function is to standardize input variables for network processing. Every value of input signal group has 3 sub fuzzy sets (large, middle, small), i.e. every value of input signal has 3

membership functions, which is normal distributed. Fuzzification is showed in following formula:

$$IN_{ij}^k = \exp \left| \frac{(IN_i^k - \alpha_{ij})^2}{\delta_{ij}^2} \right|$$

In this formula, α_{ij} is the average of its sub set, describing the position of reference point of membership function; δ_{ij} is variance of its sub set, describing degree of closeness between variable and reference point, i.e. width of membership function.

4.3.3 Network Learning Algorithm

Because traditional BP has defects of slow convergence speed and local minima, this system makes following improvement to it:

a. Dynamically change learning rate and trend factor of the network according to variation trend of error in the sample training, so as to improve convergence speed. Assume η α E as learning rate, trend factor and error respectively, and the formula is as follows:

$$\eta(t+1) = \eta(t) + \alpha \eta(t)$$

$$\alpha \eta(t) = -\beta \alpha E(t) = -\beta [E(t) - E(t-1)] \quad \beta \in (0,1)$$

when $\alpha E(t) \geq 0, \alpha = 0$

when $\alpha E(t) < 0, \alpha = 0.7$

b. In order to prevent overall error caused by some neuron, value of neuron with small error is not revised.

c. In order to prevent saturation of the network caused by too big input vector, input vector is normalized by membership function before being input into neural network.

d. The judgment of local minimum is added into the algorithm. The weight could be adjusted when local minimum happens, and then the training is resumed.

4.4 Fusion Process

In the fault recognition of train intelligent control system, we use multiple sensors at the same time, and measure every sensor in multiple periods, and then fuse these information of multiple sensors in multiple periods. This thesis proposes distributed fusion algorithm according to above fusion methods of time domain and space domain, showed in diagram 4. Its main process is: firstly conduct fusion of time domain on revised measure information of every sensor, and then the results are conducted fusion of space domain using evidential theory, and finally make decision according to corresponding rules, i.e. firstly calculate fault probability assignment after information fusion of every sensor in all periods, and then use this result to calculate overall fault probability assignment after fusion, and finally use the overall result to make decision based on corresponding rules.

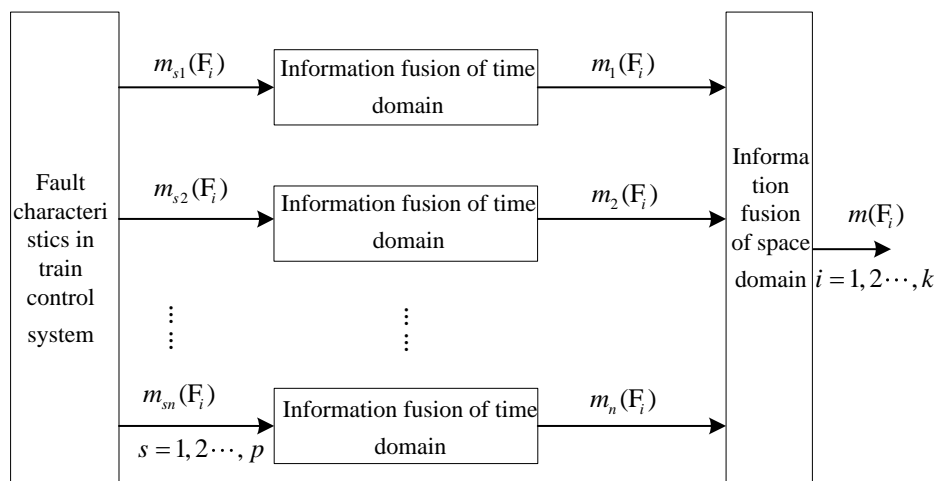


Figure 4. Distributed Fusion Algorithm of Fault Recognition in Train Intelligent Control System

5. Cases of Fault Diagnosis

We assume that 3 independent sensors are used to detect 4 probable faults in train intelligent control system F1、 F2、 F3 and F4, and the process is as follows: firstly, train fuzzy neural network using 30 groups of representative samples in the database until the error $E = 0.0001$. Then, input 3 groups of sensor data into the network, and output 3 fault probability assignments after time fusion of 3 sensors in 3 measure periods m_1, m_2 and m_3 , showed in following table 1.

Table 1. Fault probability assignment

| | Fault F1 | Fault F2 | Fault F3 | Fault F4 | Uncertain θ |
|-------|----------|----------|----------|----------|--------------------|
| m_1 | 0.6188 | 0.2563 | 0.1123 | 0.0000 | 0.0126 |
| m_2 | 0.5792 | 0.3621 | 0.0536 | 0.0000 | 0.0051 |
| m_3 | 0.6294 | 0.2547 | 0.0987 | 0.0000 | 0.0172 |

The second step is fusion of space domain, i.e. calculate all sensors' fault probability assignment after fusion of 3 periods by using fault probability assignment of every above sensor, which means fusing m_1, m_2 and m_3 . The results after fusion are showed in Table2.

Table 2. Fault Probability Assignment of All Sensors

| | Fault F1 | Fault F2 | Fault F3 | Fault F4 | Uncertain θ |
|-----|----------|----------|----------|----------|--------------------|
| m | 0.9113 | 0.0862 | 0.0025 | 0.0000 | 5.3e-8 |

The final step is making decision, i.e. make decision based on basic probability assignment after fusion of time domain-space domain. We assume $\varepsilon_1 = \varepsilon_2 = 0.1$, the decision is F1, i.e. the fault is F1. Compared with the single use of evidential theory in Reference 6, the fusion method is more advanced, i.e. probability of F1 is improved, so that of other faults is decreased; and the uncertainty is greatly decreased. Therefore, precision of fault diagnosis is improved.

6. Conclusion

In the fault diagnosis of train intelligent control system, information from multiple types of sensors is greatly complementary. More accurate and complete information could be acquired after information fusion of sensors. Besides, diagnosis system could

be more reliable, because it could still operate normally when one or some sensors fail. However, it is common that characteristic information of faults will be variable, uncertain and redundant when they are inputted. Therefore, different fusion system structures and fusion algorithms should be used in different conditions. So this thesis combines fuzzy neural network and D-S evidential theory and proposes hierarchical structure and model of multi-information fusion fault diagnosis of train intelligent control system. It also discusses multi-information fusion fault diagnosis method and distribution fusion algorithm of train intelligent control system based on neural network and D-S evidential theory. Results of cases indicate this method could greatly improve probability of the diagnosis, reduce noise, and decrease uncertainty, so as to ensure safety of the train intelligent control system.

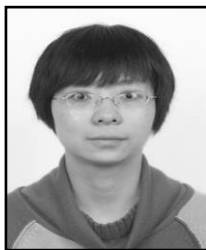
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