A Multi-Sensor Data Fusion Fault Diagnosis Method for Rail Vehicle Transmission System

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Abstract—The transmission system is a critical part of the rail vehicle bogie, mainly responsible for power drive and transmission. The performance of the transmission system directly affects the safe operation of trains. This paper proposes a multi-sensor data fusion method combined with deep belief nets (DBN) and fuzzy integral algorithm (FI) to improve the accuracy and reliability of fault diagnosis for rail vehicle transmission systems. First, multi DBN classifiers are established for the vibration signals collected from the key components of transmission systems to carry out preliminary fault diagnosis. Then, FI is applied to fuse the preliminary diagnosis results of DBNs to obtain comprehensive judgment. The effectiveness of the approach is verified by the bearing dataset collected in lab. This method is simple and practicable, and possesses certain applicability.

1. Introduction

The rapid development of rail vehicles, in recent years, has garnered more and more attention to the safe operation of trains. The main assembly of the rail vehicle power bogie, the transmission system, is responsible for transmitting the torque output from the motor to the wheel by gears and driving the train along the track. However, the harsh working environmental factors such as track irregularity excitation, high speed, heavy load, and high-frequency vibration during operation can damage transmission systems. Therefore, improving the accuracy and reliability of fault diagnosis for transmission system will effectively prevent interruptions and even casualties [1, 2].

Traditional intelligent fault diagnosis researches need help of advanced signal processing technology and shallow machine learning algorithm. The recognition accuracy depends on feature extraction. In order to reduce the dependence on expert experience, some scholars apply deep learning algorithms to railway train bogies fault diagnosis [3, 4]. As a classic model of deep learning, DBN has been widely studied in application and algorithm improvement because of its strong feature extraction advantages. Gan proposed a two-layer hierarchical diagnosis model based on DBN, which could identify bearing fault type and the damage degree at the same time [5]. Shao used PSO to optimize the parameters of DBN for rotating bearing fault diagnosis, and achieved high recognition accuracy [6].

Although these methods can effectively improve the accuracy of fault diagnosis, they are not considering the combination of multi-sensor data fusion technology with deep learning algorithm. Due to the complex structure of rail vehicle transmission system, the signals among different components are interrelated seriously. Single sensor cannot reflect the running state of transmission system, so it is...
necessary to combine the idea of multi-sensor data fusion with deep learning. Multi-sensor data fusion has three levels, namely data level, feature level, and decision level. Among these, decision level fusion has a strong anti-interference ability and can draw relatively reliable conclusions for conflict conditions. D-S evidence theory is a common method used in decision level. Since D-S evidence theory may draw wrong conclusions dealing with conflict problems, some scholars proposed a fuzzy integral (FI) fusion algorithm. Because fuzzy theory uses fuzzy membership to adjust the weights of evidence sources, the fusion result has high fault tolerance, which was widely used in multi classifier fusion. Aydin proposed a fusion detection method for pantograph arc based on SVM and FI, and the accuracy was verified higher than a single classifier [7].

A multi-sensor data fusion method based on DBN and FI for fault diagnosis of rail vehicle transmission system is proposed in this paper. Firstly, the vibration signals collected from the key components of transmission systems are normalized after FFT. Secondly, multi DBN classifiers are established for multi sensors to carry out preliminary fault diagnosis. Finally, the membership matrix is determined according to the output of DBNs, and FI is used for fusion diagnosis to obtain comprehensive judgment.

Following is the outline of the paper: Section 2 describes DBN; Section 3 introduces the fuzzy theory; Section 4 describes the fusion fault diagnosis steps; Section 5 is experimental verification; and Section 6 draws a conclusion.

2. DBN

DBN is composed of several restricted boltzmann machines (RBMs). Each RBM is composed of a visible layer \( v \) and a hidden layer \( h \). DBN is to achieve the purpose of mining the essential characteristics of data by training RBMs layer by layer. A softmax classifier is added to the top layer of the DBN to give the probability output of the fault type. Figure 1 shows the structure of DBN.

![Figure 1 The structure of DBN](image)

Assuming the visible layer element is \( v = \{v_1, v_2, v_3, ..., v_I\} \in \{0,1\}^I \), the hidden layer element is \( h = \{h_1, h_2, h_3, ..., h_J\} \in \{0,1\}^J \), and the internal parameters are \( \theta = \{w, a, b\} \). Then the energy function between \( v \) and \( h \) can be expressed as

\[
E(v, h; \theta) = -\sum_{i=1}^{I} a_i v_i - \sum_{j=1}^{J} b_j h_j - \sum_{i=1}^{I} \sum_{j=1}^{J} w_{ij} v_i h_j
\]  

(1)

where \( I \) is the number of neurons in the visible layer; \( J \) is the number of neurons in the hidden layer; \( a \) is the bias of neurons in the visible layer; \( b \) is the bias of neurons in the hidden layer; and \( w \) is the connection weight between the hidden layer and the visible layer.

Then, the joint probability distribution of \( v \) and \( h \) can be obtained,

\[
p(v, h; \theta) = \frac{e^{-E(v, h; \theta)}}{Z(\theta)}
\]  

(2)

where \( Z(\theta) \) is obtained by summing the energy values between all visible and hidden layers.
The independent probability distribution of $v$ can be expressed as

$$
\begin{align*}
P(v; \theta) &= \frac{1}{Z(\theta)} \sum_{v} e^{-\mathcal{X}(v, \phi)} \\
&= \frac{1}{Z(\theta)} \sum_{v} \exp(v^T w h + b^T v + a^T h) \\
&= \frac{1}{Z(\theta)} e^{(v^T e)} \prod_{j=1}^{d} \left[ 1 + \exp \left( a_i + \sum_{j=1}^{d} w_{ij} v_j \right) \right] 
\end{align*}
$$

The essence of RBM is to train RBMs to have the highest probability of conforming to the input sample distribution. To solve this problem, logarithm is taken from both sides of (3), and maximum likelihood estimation is adopted. $\theta = \{a_i, b_j, w_{ij}\}$ is learned by random gradient descent method. When the training process of RBMs is over, the parameters of DBN are fine-tuned by the back propagation neural network to further reduce the training error.

### 3. Fuzzy Integral

Fuzzy integral (FI) fusion algorithm is based on fuzzy set theory and developed from fuzzy density. It measures the relative importance of each information source to the final classification result by fuzzy measure.

#### 3.1. Fuzzy measure

Fuzzy measure is the key of FI algorithm, which has a great influence on the performance of fusion system. Sugeno introduced $\lambda$ as an additional condition, which was called $g_\lambda$ fuzzy measures.

Given $E, F \subset Q, E \cap F = \emptyset$, there exists $\lambda > -1$ such that (4) holds, this is called $g_\lambda$ fuzzy measure.

$$
g(E \cup F) = g(E) + g(F) + \lambda g(E) g(F) \tag{4}
$$

Fuzzy density measures the importance of each classifier.

$$
g_\lambda(H) = g' + g_{\lambda}(\{q_1, q_2, \cdots, q_n\}) + \lambda g' g_{\lambda}(\{q_1, q_2, \cdots, q_n\})
= \sum_{r=1}^{\lambda} g_r + \sum_{r=1}^{\lambda} \sum_{r=1}^{\lambda} g_{r'} g_{r'}^k + \lambda \sum_{r=1}^{\lambda} g_{r'} g_{r'}^k \cdots g_{r'}^k \tag{5}
$$

Here the set $Q = \{q_1, q_2, \cdots, q_r\}$ represents the fuzzy density of each classifier. With the regularity condition $g_\lambda(Q) = 1$, we can obtain the following result.

$$
\lambda + 1 = \prod_{r=1}^{\lambda} (1 + \lambda g') \tag{6}
$$

#### 3.2. Fuzzy integral

Given a finite set $Q = \{q_1, q_2, \cdots, q_r\}$, and a function $h: Q \rightarrow [0, 1]$, the fuzzy integral of $h$ on $Q$ with respect to $g$ is defined as

$$
\int_{Q} h(Q) \circ g() = \sup_{\alpha \in (0,1]} \min[\alpha, g(\{q \mid h(q) \geq \alpha\})] \tag{7}
$$

where $g$ are $g_\lambda$ fuzzy measures defined on $Q$, $h()$ is arranged in ascending order $h(q_1) \geq h(q_2) \geq \cdots \geq h(q_r)$, and $h(q_i)(i = 1, 2, \cdots, r)$ is the credibility of the source $q_i$.

On this basis, Choquet integral is proposed, which is defined as

$$
\int_{Q} h(q) \circ g() = \sum_{i=1}^{r} (h(q_i) - h(q_{i-1})) g(A_i) \tag{8}
$$
where \( A = \{q_1, q_2, \cdots, q_i\} \) is a subset of universe, and recursion solves the fuzzy measure \( g(A) \).

\[
g(A) = g(\{q_i\}) = g^1
\]

\[
g(A) = g^i + g(A_{-i}) + \lambda g^i g(A_{-i}), (i = 1, 2, \cdots, r)
\]

4. Multi-Sensor Data Fusion Fault Diagnosis for Rail Vehicle Transmission System Based on DBN-FI

The flowchart of the proposed framework is shown in Figure 2, and the specific implementation steps are as follows:

1. The vibration signals from the key components of transmission system under different fault conditions are collected synchronously.
2. Establishing DBN1, DBN2, and DBNL classifiers for multiple sensors, respectively.
3. Vibration signals are normalized after fast Fourier transform and input into DBNs.
4. Determining fuzzy measure according to the recognition rate of DBNs and composing the matrix \( D^L \). where \( D^L = \{d_{11}, d_{12}, \cdots, d_{1n}\} \) is the output of the \( i \)th classifier, \( L \) is the number of classifiers.
5. Combining the fuzzy measure with the membership matrix \( D \) and using Choquet integral to fuse the diagnosis results.

![Figure 2: The multi-sensor data fusion fault diagnosis framework](image)

5. Experiment validation

5.1. Data description

In view of the confidentiality of domestic rail vehicles fault data and the difficulty of obtaining all the different fault modes of transmission systems, the bearing dataset provided by the Case Western Reserve University (CWRU) is used to verify the proposed approach [8]. The experimental platform is shown in Figure 3: including a motor (1.5KW), a torque sensor and a power tester. The drive end bearing is SKF6205 and the fan end bearing is SKF6203. In the experiment, the vibration acceleration of drive end (DE), fan end (FE) and base (BA) are collected. The vibration signal is collected by 16 channel data recorder, and the sampling frequency is 12KHz. This paper includes two conditions: (1) the speed is 1797rpm, and the torque is 0; (2) the speed is 1772rpm, and the torque is 0.7457kw.

There are six fault types in the dataset, including drive end bearing inner ring fault (DE_IR), drive end bearing ball fault (DE_ball), drive end bearing outer ring fault (DE_OR), fan end bearing inner ring fault (FE_IR), fan end bearing ball fault (FE_ball), and fan end bearing outer ring fault (FE_OR). In this paper, three channel signals (DE, FE, BA) are used. Each sample is divided into 50 groups with 2048 points, and a total of 600 groups are obtained. In order to simulate the strong noise in the actual
operation of rail vehicles, we add Gaussian white noise with SNR-12.

Figure 3 The rolling bearing experimental setup

5.2. Preliminary diagnosis of DBN
Considering that the speed and load always changing in practical operation, this paper uses the mixed samples of two conditions to train and test the DBN model. In the experiment, the samples of the same fault type under different working conditions are regarded as one class, and a total of 600 groups of samples are obtained. Randomly selected 60×6 groups for training, and the remaining 40×6 groups for testing. After many trials, the parameters setting of DBN is determined. DBN adopts five layers, in which the input layer is 1024 and the output layer is 6. The number of units in the first hidden layer, the second hidden layer and the third hidden layer are 600, 300, and 100 respectively. The learning rate is 0.1, and the number of iterations is set 150. The accuracy of BA, DE and FE is shown in Table 1, which is 93.33%, 96.25%, and 94.17% respectively.

5.3. Fusion diagnosis based on DBN-FI
According to the average probability of DBNs for each fault type, the fuzzy measure \(g' = g(x_i),i = 1,2,\cdots,n\) is determined, and the measure values on the subset are calculated recursively according to (9) and (10). After fusion, the accuracy has been significantly improved, which is shown in Table 1. The accuracy of fusion diagnosis under the mixed condition is 98.83%. In comparison, it can be found that the accuracy of fusion diagnosis is significantly higher than that of single classifier.

| Working condition | Classifiers | Accuracy(%) |
|-------------------|-------------|-------------|
| Mixed conditions  | DBN1 93.33  | DBN-FI 98.83 | DBN-DS 97.5  |
|                   | DBN2 96.25  |             |             |
|                   | DBN3 94.17  |             |             |

5.4. Comparative analysis
In order to verify the superiority of the proposed method, DBN-DS and SVM-FI diagnostic frameworks are constructed respectively to compare the accuracy of different fusion methods. Table 1 depicts the diagnostic results of DBN-DS. In comparison, it can be found that the accuracy of FI is higher than that of D-S evidence theory, which is mainly because D-S evidence theory is easy to reach wrong judgment when dealing with conflict problems. However, FI fusion algorithm not only considers the importance of each classifier, but also considers the interaction between classifiers in the fusion process, so the fusion diagnosis results are more accurate and reliable.

The SVM adopts radial basis function (RBF), and the parameter is set as \([-C,-g]=256, 2\]. Time domain features: root mean square value, kurtosis, crest factor, shape factor, standard deviation, and frequency domain features: average frequency, frequency center, root mean square frequency, standard deviation frequency are manually extracted as the input of SVMs. The preliminary diagnosis of SVMs and the fusion diagnosis of SVM-FI are shown in Table 2.
Table 2  The Accuracy of SVM and SVM-FI

| Working condition | Classifiers | Accuracy(%) | SVM-FI |
|-------------------|------------|-------------|--------|
| Mixed conditions  | SVM1       | 87.5        |        |
|                   | SVM2       | 85          |        |
|                   | SVM3       | 79.17       |        |
|                   | SVM-FI     | 93.33       |        |

Compared with Table 1 and Table 2, the recognition rate of DBNs is much higher than that of SVMs. DBN1 is 5.83% higher than SVM1, DBN2 is 11.25% higher than SVM2, and DBN3 is 15% higher than SVM3. The accuracy of DBN-FI is 5.5% higher than that of SVM-FI. Besides, DBN adopts automatic feature extraction, which improves the intelligence of fault diagnosis.

6. Conclusions
This paper proposes a multi-sensor data fusion fault diagnosis method based on DBN-FI for fault diagnosis of rail vehicle transmission system. This method is simple and practicable, and possesses certain applicability. By the experimental verification, the following conclusions are drawn:
1) The results of DBN-FI fusion diagnosis are better than other fusion methods. Its accuracy is 1.33% higher than DBN-DE and 5.5% higher than SVM-FI.
2) DBN adopts automatic feature extraction, which reduces the dependence of expert experience, and improves the intelligence of fault diagnosis.
3) The accuracy of multi-sensor data fusion fault diagnosis is higher than that of single sensor, whether using traditional intelligent methods or deep learning.
Although the multi-sensor data fusion fault diagnosis method proposed in this paper effectively improves the accuracy of fault diagnosis, FI fusion integral still needs human participation. In the future, the adaptive fusion function of deep learning algorithm will be studied to realize multi-level and multi-scale fusion diagnosis, and realize intelligent fault diagnosis.

Acknowledgments
This work was supported by the Scientific Research Projects of Tianjin Municipal Education Commission (Grant 2020KJ121), and the Tianjin Science and Technology Plan (Grant 20KPHDRC00030).

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