Fault Diagnosis for Brake System in High-Speed Trains Using the Phased Features and Multi-layer Perceptron

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Abstract. Recently, High-Speed Train (HST) has been developing quickly. The brake system is the most important part in HST. Therefore its safety and reliability have attracted much attention from both academic and industrial community. Many data-driven methods are introduced to handle the fault diagnosis problem for brake system. However, the existing data-driven methods barely analyse the brake system. The used features lack of interpretability. In this paper, a fault diagnosis model using the phased features and multi-layer perceptron (MLP) is proposed for brake system. The proposed model is divided into two stages: offline and online stages. In the offline stage, after the analysis of brake system, the phased features are extracted. Then the MLP model is trained based on the phased features. In the online stage, the model learned in the offline stage is used to diagnosis the fault. The experimental platform for brake fault is constructed to validate the proposed model. The results shows the superiorities compared with other diagnosis methods in terms of precision, recall and F1-score.

1. Introduction

In recent years, High-Speed Train (HST) has been developing quickly in China [1]. In 2017, HSR extended to 29 of the country’s 33 provincial-level administrative divisions and exceeded 25,000 km in total length, accounting for about two-thirds of the world's high-speed rail tracks in commercial service. According to China’s Mid-to-Long Term Railway Network Plan, by 2030, the HST would link all provincial capitals (excluding Lhasa) and cities with more than half million people [2]. With the fast development of HST, its safety and reliability has attracted more and more attention.

Brake system is the most critical control components for the safety and reliability of the train operating at high speed. The efficient brake system is a guarantee that the train would decelerate within a reasonable distance even under the most adverse conditions [3]. If fault is diagnosed timely, maintenance decision can prevent serious damages to the HST. Therefore accurate and timely fault diagnosis in the brake system is clearly an important issue.

Because of the increasing installation of monitoring systems on various industrial systems, data-driven fault diagnosis have become more popular [4]. The data-driven fault diagnosis consists of feature extraction, feature selection, and feature classification. Firstly, features are extracted from huge amounts of the monitor process data. Secondly, features are selected by the statistical methods. Finally,
fault are classified based on the features. In [3], decision tree (DT) were used as classifiers for classifying brake faults using the statistical features extracted from the vibration signals. In [5], for fault diagnosis of brake system, descriptive statistical features were extracted from the vibration signals and the feature selection was carried out using the C4.5 DT algorithm. The selected features were classified into different faults by support vector machine (SVM). In [6], an automated fault detection method using SVM and AE parameters is proposed to diagnosis the valve condition in reciprocating compressor. It employs the SVM for AE parameters analysis in an attempt to reduce human intervention in the analysis process. However, these methods don’t analyse the brake system deeply enough. The features lack of interpretability. It is bad for industrial fault diagnosis.

In this paper, a fault diagnosis model using the phased features and MLP for brake system is proposed. The phased features are extracted according to the structure of the brake system. Then the MLP is used for fault diagnosis. Section 2 analyses the brake system and proposes the phased features based on the analysis. Then the fault diagnosis model using the phased feature and MLP is introduced. In Section 3, the experiment platform is constructed to demonstrate the proposed fault diagnosis model. Finally, the conclusions are described in Section 4.

2. The proposed fault diagnosis model

A fault diagnosis model using the phased features and MLP for brake system is proposed in this paper. The proposed model is divided into two stages: offline and online stage. In the offline stage, the phased features is extracted according to the structure of brake system. Then the MLP model is trained for diagnosis. In the online stage, the model learned in the offline stage is used to diagnosis the fault.

2.1. The brake system

First, the structure of brake system is analysed in this subsection. In HST, the electro-pneumatic (EP) brake system is the most common brake system. The brake system applies air pressure to the train line to realizes the locomotive braking function based on driver’s instruction. In this process, air pressure is regulated by air-filled and air-bled with control the valves opening and closing, such as relay valve, relief valve, air-filled valve and air-bled valve. During the braking process, the solenoid valve is in the state of switching frequently. Therefore, the solenoid valves become the main fault element of the brake system.

Table 1. The phased features of sensor signals

| Driving current | Stage                  | phased features                      |
|-----------------|------------------------|--------------------------------------|
| Driving current | Absorption touch       | Peak current, maximum current change rate |
|                 | Actuation movement     | Bottom current, minimum current change rate, Opening time |
|                 | Electrified holding    | Maximum current change rate          |
|                 | Release touch          | Stable voltage                        |
|                 | Release motion         | Minimum current change rate          |

2.2. Data processing and the phased features extraction

The current and voltage of solenoid valve are changing in the process of braking. The trend of the sensor signals is studied in this paper to realize the fault diagnosis of valve.

During the process of data generation, the sensor data is mixed with noise which from various environmental factors. So the data processing is necessary to eliminate the noise. Median filtering as a non-linear noise processing method is used in the proposed model. It has better characteristic on edge preservation and depression of the noise. The basic principle of median filtering algorithm is to replace
the value of any point in the digital sequence with the median value of the neighbourhood of each point.

Assuming the signal sequence is \( x = \{ x_1, x_2, \cdots, x_n \} \) and sorting the \( N \) numbers by size, then the median filtering is used to smooth the sequence. After smoothing data, the phased features are extracted from sensor data to represent effective information for fault diagnosis. The working process of the solenoid valve is divided into five stages: the absorption touch stage, the actuation movement stage, the electrified holding stage, the release touch stage, and the release motion stage. Based on different stages, the phased features are extracted as Table 1.

Each phased feature contains the effective diagnosis information of sensor data. In order to enhance generalization by reducing overfitting and reduce the computational complexity, wrapper algorithm is used to select feature in this paper.

In wrapper feature selection algorithm, the performance of the final learner is regard as the evaluation criterion of the feature subset as follows.

1) Setting the initial optimal error \( E \) to infinity. The best feature subset is the complete set of attributes \( A \), and the number of repetitions \( t \) is 0.

2) A set of characteristic subset \( A' \) is generated randomly and calculating the error of the classifier is \( E' \) when using the subset of the feature.

3) If \( E' \) is smaller than \( E \), then \( A' = A, E' = E \) and repeat 2); otherwise \( t = t + 1 \) and jump out of the loop when \( t \) is greater than the stop control parameter \( T \).

In this process, feature selection requires multiple training of the learner and select the best feature subset for the given learner.

2.3. Fault diagnosis based on MLP

Based on wrapper algorithm, the phased features are reduced for dimension reduction. After that, the Multi-layer Perceptron is used to diagnose the fault of brake system.

MLP is a supervised learning algorithm, and can learn a non-linear function approximator [7]. It is different from other algorithm, in that between the input and the output layer, there can be one or more non-linear layers, called hidden layers as Figure 2 shown.

At first, preparing the training dataset \( D = \{ (x_i, y_i) \}_{i=1}^{n}, x_i \in \mathbb{R}^m, y_i \in \mathbb{R} \). Where, \( n \) is the number of samples. \( x_i (i=1,2,\cdots,n) \) is \( m \)-dimensional phased feature vector \( I_i (i=1,2,\cdots,m) \) as the input of MLP. \( y_i \) is the label of fault. And the weighted input of \( j \) node in the hidden layer can be expressed as:

\[
  h_j = \sum_{i=1}^{m} W_{ij} \times I_i + b_j
\]  

where \( W_{ij} \) is the connection weight which from the input layer \( i \) node to the hidden layer \( j \) node, \( b_j \) is bias for the corresponding node, the output of the \( j \) node in the hidden layer is \( H_j \):

\[
  H_j = \tanh(h_j)
\]  

After several iterations, the input \( o_k \) of output layer \( k \) note from hidden layers is

\[
  o_k = \sum_{j=1}^{J} W_{jk} \times H_j + b_k
\]  

where output layer contains \( K \) notes \( (k=1,2,\cdots,K) \). The output \( O_k \) of the \( k \) node in the output layer corresponding to different activation functions.

Then, the mean square error minimization method is used to adjust the weights between layers and the mean square error \( E_k \) and gradient \( g_{sk} \) of the \( n \) training sample for the \( k \) node in the MLP output layer is
In the training process, it is necessary to judge that $E_k$ is less than the given error or not. If $E_k$ is less than the given error, the training of this node is completed, otherwise the next step weight is carried out as follows.

$$W_{jk} = W_{jk} + l \times g_{jk}$$

(6)

where $l$ is the learning factor which determined by the experience value. Heavy gradient calculation and weight updating until network convergence. Based on this process, we can get the fault diagnosis model which learned from offline data.

3. Experimental study

3.1. Experiment platform

The BCU and PID control algorithms are used in the experimental platform. High-speed solenoid valves, sensors and equalizing reservoir are basically the same with the train loading components, which can simulate real vehicle condition very well. Among them, the model of high-speed solenoid valve (supply valve and exhaust valve) is MAC 35A-ACA-DDFA-1BA, and the model of pressure sensor is Keller PA-21Y (two-wire connection is adopted and the output signal is the current with 4-20MA) and the volume of equalizing reservoir is 1.2L. The pneumatic triplex contains desiccant, filter and pressure reducing valve to effectively filter the water in the wind source and achieve a reduced pressure output.

In the closed-loop control mode, the brake control unit (BCU) receives the equalizing reservoir target value command issued by the upper computer, and compares the target value with the real-time pressure value of the equalizing reservoir fed back by the pressure sensor. If the pressure of equalizing reservoir is lower than the target pressure, then the main air reservoir inflates the equalizing reservoir through the supply valve. Conversely, the equalizing reservoir is exhausted to the atmosphere through the exhaust valve. The BCU issues a PWM control for the supply valve and exhaust valve. By precisely controlling the pressure of the equalizing reservoir, the train tube is controlled to achieve the braking of the train. Figure 1 is a schematic diagram of the experimental platform in closed loop control mode, Figure 2 is the experiment platform.
In the equalizing reservoir control system, according to the engineer's experience, in the normal case of the BCU, common faults include electric air valve failure, sensor failure, and air leakage. The existing fault diagnosis system is unrecognizable for the slight delay of the spool and the slight change of the return spring. Therefore, the stuck of the solenoid valve is studied in this paper.

3.2. Data acquisition and filtering
An external PXI box for data acquisition is used in this paper. PXI (PCI extensions for Instrumentation) is a rugged PC-based measurement and automation platform released by National Instruments. The collected signals include the voltage and current signals of the supply valve and the exhaust valve, the pressure of the equalizing reservoir, the pressure of main air reservoir. The sampling frequency is 10,000 Hz because the response time of the high-speed solenoid valve is generally within 10ms. The median filter window size used for the current is 7, for the voltage and the pressure of equalizing reservoir are 13, and for the pressure of total wind is 31.

3.3. Feature processing
The experiment used a total process of charge and exhaust to the equalizing reservoir as a sample, and the brake pressure was set to 300 KPa. In the experiment, the BCU uses the PI algorithm to control the switch of the high-speed valve in a closed loop, which leads to the process of multiple switching of the air charging and exhaust valve. Under normal circumstances, it can be stabilized by adjusting about 10 times. Due to noise interference, a precise extraction for the time domain characteristics of the current and voltage is challenging. Therefore, average and median processing are adopted to the valve's operating characteristics in a sample, reflecting the relevant characteristics of the valve as much as possible. Thus the proposed phased features mentioned before are used as input. In addition, the air filling time, maintenance time and exhaust time of the equalizing reservoir also used as input. The range of these features may be very different, which will have a great impact on the model training. Therefore, features need to be standardized.

3.4. Performance analysis
In this paper, the precision, recall and F1-score are used to evaluate the accuracy of the method. When the output of the algorithm is 1, indicates that the supply valve is stuck, while the output is 0, indicates that the supply valve is normal.

This section discusses the influence of the number of features on prediction accuracy and the comparison between different methods. The comparisons with other methods including Decision Tree (DT) and Support Vector Machines (SVM) are carried out to show the superiority of MLP. The parameters of other methods are optimized by grid search. A total of 28 sample data are obtained from the experimental platform. Among them, 18 samples are normal for the supply valve, 10 samples are stuck, and the exhaust valves used in the experiment are normal. Samples for training and prediction are randomly divided into portion of seven and three. The experimental results are taken the average of 10 trials to exclude the effects of random disturbances. The optimizer of MLP is Adam, the hidden layer is 2, the neurons in each layer is (64, 32), the learning rate is 0.05, the activation is sigmoid.

The Figure 3 shows the influence of the number of features selected by the Wrapper on the prediction precision. It can be seen that the precision of the MLP is almost higher than that of the other two methods. That means that selected features can well reflect the fault characteristics. When the number of features is 12, 14, 18, 19, 20, 21, 23, 26, 29, 30, the precision reaches 1, indicating that the fault can be judged 100%. And DT does not have 100% precision. The precision of the SVM is lower than the other two methods. When 12 features are selected, the precision of the three methods is relatively high, under which the other evaluation methods are used for comparison. The experimental results are shown in the Table 2. As can be seen from the Table 2, MLP has the highest precision, recall, F-score, indicating that MLP can accurately determine faults and no faults. DT is superior to SVM in accuracy, recall and F1-score.
4. Conclusion
In this paper, for fault diagnosis in brake system, a model using the phased features and MLP is proposed. The phased features are proposed based on the analysis of brake system. The proposed phased feature is interpretable. The MLP is used as the classifier to classify the faults of brake system. We verified the effectiveness of this model by the experimental platform which is constructed for brake fault. The results shows the proposed model is able to diagnosis fault and has better performance compared with other diagnosis methods.

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