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Fault diagnosis of high-speed train bogie based on LSTM neural network

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Dear editor,

With the extensive implementation of high-speed railway acceleration, higher requirements for safety and stability are put forward. In order to guarantee the safety of the high-speed train (HST), it is critical to detect the abnormal state in operation. Bogie that plays an important role in reducing vehicle vibration is connected to the track and the train body, and its health condition directly affects the safe operation of train.

There is a correlation between the vibration of train body and the state of the bogie. With the deterioration of mechanical components in the whole system, the vibration signal also changes. Many sensors are installed on the HST which is tracked and monitored for a while. Then a considerable amount of train data will be obtained, normally containing abundant fault information. Because the principle of bogie failure is complex and the fault features are difficult to visualize, it is hard to extract fault information using traditional signal processing methods. As such, a new and effective method in dealing with fault diagnosis of train bogies is of significance.

A lot of studies have been conducted for the fault diagnosis of HST. In [1], the fault detection filter design of the dynamics of HST was proposed. In [2], for the input disturbance with random noise, the sensor fault detection of the suspension system with orbital regularity and noise was studied. Yuan et al. [3] proposed an adaptive fault compensation scheme for HSTs and traction system actuators with longitudinal dynamics, and their simulation results demonstrated the effectiveness of the theoretical achievement.

In this study, an artificial recurrent neural network (RNN) called LSTM [4] network approach is proposed for fault diagnosis of train bogies. The task of fault diagnosis is to identify different types of failures. LSTM network can analyze the inherent correlation of vibration signals in the processing of time series data, so it is increasingly used in data-driven fault diagnosis. To the best of the authors' knowledge, it is the first time to apply LSTM for fault diagnosis of HST bogies.

High-speed train bogie. Train motion and braking heavily depend on the bogie that carrise the body of the train. The HST uses a two-stage suspension system to assure the stable operation. The study mainly focuses on the secondary suspension system that consists of air springs, lateral damper, and anti-yaw damper. Horizontal and vertical disturbances between the train body and the track can be eliminated or compensated partially by the bogie system.

It is worth pointing out that failure data of bogies could not be generated in actual engineering environment because bogie failure may result in serious accidents. The experimental data adopted in this study is generated by the dynamic model built by the State Key Laboratory of Traction Power in Southwest Jiaotong University. The HST dynamic model (CRH380A) is simulated by SIMPACK, consisting of a train body, four wheelsets, two frames, a secondary damper, and a secondary spring. The track spectrum used for simulation is built by real data from Wuhan-Guangzhou railway. The bogie mode simulates the LMA wheel tread and fully considers the wheel-rail geometry, interaction force, and suspension force.

The dataset acquired from SIMPACK simulation consists of 58 channels, which correspond to different directions' data collected from sensors installed on different positions of bogie, e.g, train-body accelerations, train structure accelerations, etc. The data are recorded with the sampling frequency of 243 Hz, and the operation time of HST is about 3.5 min at the speed of 200 km/h. Hence, there are 51000 data points collected in each health condition. Then, 357000 sampling points are achieved in total for 7 health conditions, including one normal state and six fault types, as summarized in Figure 1(e). Before conducting fault diagnosis, every 290 points are regarded as a training sample, so the dataset has 1225 samples. Among them, 1032 samples are used as the training data.

Neural networks. In recent years, RNNs have been frequently applied to dealing with time-series data. As a special structure of RNNs, the LSTM network is adopted for fault diagnosis of HST bogie in this study, where the input of the network is the time-series signals obtained from 58 independent sensors.

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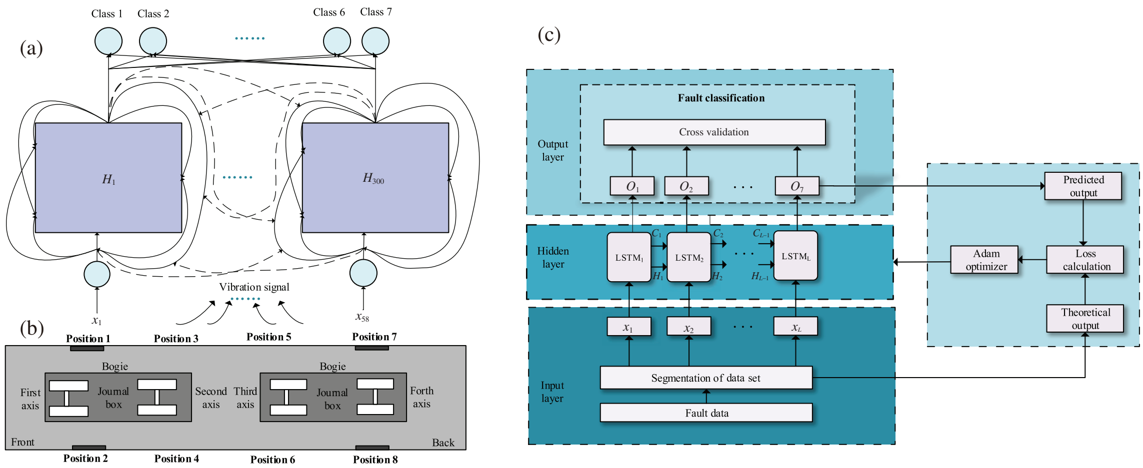

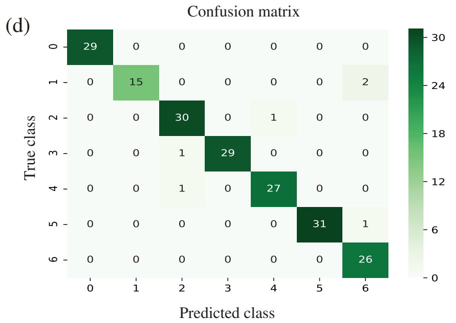

(e)

Label	Health condition
0	Normal state
1	Failure of anti-yaw damper
2	Failure of air springs
3	Failure of lateral damper
4	Failure of air springs and lateral damper
5	Failure of air springs and anti-yaw damper
6	Failure of lateral damper and anti-yaw damper

Figure 1 (Color online) (a) The workflow of LSTM network. (b) The location of sensors in the simulation model. The samples which generated by (b) are inputs to neural network (a). (c) The algorithm flow based on LSTM network. (d) Confusion martix for the fault diagnosis on the test set. The labels of true and predicted class are given in (e).

The main difference between the LSTM network and the traditional RNN is the structure of the cell. In the LSTM network, each neuron is a memory cell including an input gate, a forget gate and an output gate. The forget gate is used to control the impact of historical information on the weight of the current unit. The input gate is used to control the effect of current input data on the weight of the unit. The calculation of the gate is influenced by the input data x_t at time t, the output value h_{t-1} and the memory value c_{t-1} of LSTM unit at time $t-1$. The output gate is used to control the export of the state value of the memory unit. Mathematically, each neuron can be expressed as follows:

$$\begin{aligned} i_t &= \sigma(W_{xi} \cdot x_t + W_{hi} \cdot h_{t-1} + W_{ci} \cdot c_{t-1} + b_i), \\ f_t &= \sigma(W_{xf} \cdot x_t + W_{hf} \cdot h_{t-1} + W_{cf} \cdot c_{t-1} + b_f), \\ o_t &= \sigma(W_{xo} \cdot x_t + W_{ho} \cdot h_{t-1} + W_{co} \cdot c_t + b_o), \\ c_t &= f_t \times c_{t-1} + i_t \times \tanh(W_{xc} \cdot x_t + W_{hc} \cdot h_{t-1} \\ &\quad + b_c), \\ h_t &= o_t \times \tanh(c_t), \end{aligned}$$

where i_t, f_t, c_t and o_t represent the outputs of input gate, forget gate, cell state as well as output gate, respectively, and W, h and b denote the input weight, recurrent weight as well as bias of each gate respectively. In addtion, σ denotes the sigmoid function and the operator $\cdot$ means matrix multiplication.

The dynamic simulation model of the train body is associated with 58 sensors, which are located in Positions 1, 4, 5, 8, and the first to fourth axes in wheel-set and axle box, as demonstrated in Figure 1(b). The data for training and test in neural network can be obtained from these sensors, which are actually the inputs to the hidden layer: $x^1 = \{x_1, x_2, \ldots, x_{58}\}$.

Consequently, the LSTM network has an input layer, which contains 58 neurons, and each neuron corresponds to a particular channel. Meanwhile, it contains a hidden layer of 300 cells, and an output layer with 7 neurons. The architecture of the LSTM network is given in Figure 1(a).

Experimental results. In experiment, the number of training epoches is set as 155, and the learning rate decreases along the iteration axis, where the initial learning rate is 0.003. Moreover, the number of random seeds is assumed to be 10. The adaptive moment estimation (Adam) algorithm [5] is used to update all the weights of the network. The workflow of the whole algorithm is shown in Figure 1(c).

To confirm the performance of the network, the test data set is applied to the network. The accuracy of the fault classification is up to 96.6%. Among the 193 samples in test data set, 187 samples are correctly classified. The confusion martix is given in Figure 1(d).

From the confusion matrix, we can find that (1) for health conditions 2 and 4, both faults have similar vibration characteristics when the train is operated with high speed; (2) one sample of health condition 1 is wrongly divided into the class of health condition 6, which indicates that the effectivity of anti-yaw damper is stronger than the lateral damper; (3) the confusion of health conditions 3 and 5 implies that the LSTM network cannot effectively memorize the features of long-term relevance.

Conclusion. In this study, a method of fault diagnosis of HST bogie using LSTM network is presented. The multi-body simulation software SIMPACK is used to generate fault data, which is utilized to train and test the network. The experimental results show that the proposed method can learn the spatial and temporal correlation of fault features in vibration signals, without data preprocessing and prior knowledge. The accuracy of the fault classification is up to 96.6%, implying that the proposed method has good performance in HST bogie fault diagnosis.

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