Construction of Fault Diagnosis Model of Metro Wheel Speed Box System Based on Convolution Neural Network

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Abstract. This research focuses on a fault detection method apply on the subway wheelsets. This fault diagnosis method is mainly aimed at the vibration signal to distinguish the fault and abnormal situation. At the same time, the vibration signal incorporated with the deep learning method to establish the diagnosis mechanism. Reliable online data of subway in a city of China and CNN (Convolutional Neural Network) are applied in the web training process. The degradation of vibration signal of rolling functional unit (wheelset) was summarized, and the difference between normal and fault signals of rolling functional unit (wheelset) was studied. The feedback learning mechanism makes it possible to update the neural network in real time.

1. Introduction
Wheelsets play a significant important role in the current application of transports [1]. The performance of subways, vehicles, airplanes and other machines installed with wheels will be affected by the performance of the wheel pairs [2]. Once wheelsets faults occur they may cause machines to malfunction and even fail, which leads to financial losses and even fatal incidents [3]. Currently, people have paid much attention on the wheel maintaining and fault detection [4]. However, due to the strict standard of precision to the wheel pairs, manual maintenance and fault detection are extremely difficult, some minor fault marks such as slight tread stripping, wheel angle deviation and rim wear are disabled to be discovered in time [5]. Luckily, people focus on the digital fault diagnose methods, such as image fault identification, noise fault identification, vibration fault identification, etc [6].

Focus on the mechanical fault detection, vibration signals are considered to contain more detectable fault information as a result of being collected by the acceleration sensors which are directly attached on the equipment [7]. In order to analyze these signals and extract the useful information involved in the original noise, many signal processing methods like FastICA (Fast Independent Component Analysis) and CPW (Cepstrum pre-whitening) are proposed [8]. However, these data processing methods are incapable of extracting deep features automatically and also shows the weakness of low efficiency and low accuracy [9].

In recent years, machine learning is widely used in the mechanical fault detection. In addition, Deep Learning shows the strong advantages in the efficiency and accuracy under the support of the amount data [10]. Moreover, the data form could be diversiform. The neural network could realize the in time detection even Omitting tedious data processing steps. Common machine learning methods include: linear model, neural network model (the difference from the lower neural network method is that this refers to simple neural network method, such as multi-layer perceptron: MLP), support vector machine model, decision tree model, Bayesian classifier, clustering, dimension reduction. The basic technique of
deep learning is to use the distance value between label value and forward propagation value as feedback signal to fine-tune the weight value to reduce the loss value corresponding to the current example. Commonly used neural network models include: CNN (Convolutional Neural Network), RNN (Recurrent Neural Network), GAN (Generation of Antagonistic Model), GNN (Diagram Neural Network), RL (Reinforcement Learning) and multiple variants of the model.

Convolutional neural network (CNN) is a kind of feed-forward neural network. Its artificial neurons can respond to a part of the surrounding units in the coverage area, which has excellent performance for large-scale image processing. It includes convolutional layer and pooling layer.

In short, convolutional neural network is a deep learning model or multi-layer perceptron similar to artificial neural network, which is often used to analyze and process visual data.

Convolutional neural network is a kind of neural network algorithm which can classify data effectively, convolution neural network includes one-dimensional, two-dimensional and three-dimensional convolution neural network. One-dimensional convolution neural network is often used for data processing of sequence class; two-dimensional convolution neural network is often used for text recognition of image class; three-dimensional convolution neural network is mainly used for data recognition of medical image and video class.

In the 1960s, Hubel and Wiesel found that their unique network structure can effectively reduce the complexity of the feedback neural network when they studied the neurons used for local sensitivity and direction selection in the cat's cerebral cortex. Then they proposed the convolutional neural network (CNN for short). Now, CNN has become one of the research hotspots in many scientific fields, especially in the field of pattern classification. Because the network avoids the complex pre-processing of the image and can directly input the original image, it has been widely used. K. The new recognition machine proposed by Fukushima in 1980 is the first implementation network of convolutional neural network. Subsequently, more researchers improved the network. Among them, the representative research achievement is the "improved cognitive machine" proposed by Alexander and Taylor, which combines the advantages of various improved methods and avoids the time-consuming error back propagation.

Luckily, real-time vibration sampling technique has been more mature. The vibration signal could be sampled in the real time and upload to the host database and the cloud. According this condition, CNN (Convolutional Neural Network) shows the great potential in fault feature extraction to support decision making for maintenance management. In this research, real data from a Chinese city’s subway line will be applied. According to the original record, normal, warning, and fault data are recorded and had been well classified, provided an excellent source of data for subsequent neural network applications. These labeled data are always available to train a well working intelligent detection model. This research could be separated into two parts:

1. By running vibration data on subway wheel line, the performance fault diagnosis method of rolling functional parts was established and optimized, and the performance degradation vibration diagnosis theory of wheels was studied according to the diagnosis method and diagnosis results.

2. The degradation of vibration signal of rolling functional unit (wheelset) was summarized, and the difference between normal and fault signals of rolling functional unit (wheelset) was studied.

2. The frontal working mechanism of convolutional neural network

First of all, several parameters are listed as follow:
Table 1. Parameters description

| Symbol | Meaning |
|--------|---------|
| \(a_n\) | Output of neurons in layer n |
| \(z_n\) | Input of neurons in layer n |
| \(W_n\) | Weight matrix of mapping in layer n-1 to layer n |
| \(b_n\) | Offset value correspondingly |
| \(x\) | Input of train data |
| \(y\) | Label of train data |

Set output layer as layer n, corresponding to output \(a_n\), and use the mean square deviation to measure the loss \(L\):

\[
L(W, b, x, y) = \frac{1}{2} ||a_n - y||^2_2
\]  

(1)

And the output is:

\[a_n = \sigma(z_n) = \sigma(W_n a_n^{-1} + b_n)\]  

(2)

Substitution (2) into (1):

\[
L(W, b, x, y) = \frac{1}{2} ||a_n - y||^2_2 = \frac{1}{2} ||\sigma(W_n a_n^{-1} + b_n) - y||^2_2
\]  

(3)

Derivation by chain rule:

\[
\frac{\partial L(W, b, x, y)}{\partial W_n} = \frac{\partial L(W, b, x, y)}{\partial z_n} \frac{\partial z_n}{\partial W_n} = (a_n - y) \odot \sigma'(z_n)(a_n^{-1})^T
\]  

(4)

\[
\frac{\partial L(W, b, x, y)}{\partial b_n} = \frac{\partial L(W, b, x, y)}{\partial z_n} \frac{\partial z_n}{\partial b_n} = (a_n - y) \odot \sigma'(z_n)
\]  

(5)

where \(\odot\) is the transvection of the two vectors.

Let:

\[
\delta_n = \frac{\partial L(W, b, x, y)}{\partial z_n} = (a_n - y) \odot \sigma'(z_n)
\]  

(6)

Substitution (6) into (4) and (5):

\[
\frac{\partial L(W, b, x, y)}{\partial W_n} = \frac{\partial L(W, b, x, y)}{\partial z_n} \frac{\partial z_n}{\partial W_n} = \delta_n (a_n^{-1})^T
\]  

(7)

\[
\frac{\partial L(W, b, x, y)}{\partial b_n} = \frac{\partial L(W, b, x, y)}{\partial z_n} \frac{\partial z_n}{\partial b_n} = \delta_n
\]  

(8)

Derivation by chain rule:

\[
\delta_n = \frac{\partial L(W, b, x, y)}{\partial z_n} = \frac{\partial L(W, b, x, y)}{\partial z^{n+1}} \frac{\partial z^{n+1}}{\partial z_n} = \delta_n \frac{\partial z^{n+1}}{\partial z_n}
\]  

(9)

From equation (2):

\[z^{n+1} = W_n^{n+1} a_n + b^{n+1} = W_n^{n+1} \sigma(z^n) + b^{n+1}\]  

(10)
Then

\[
\frac{\partial z^{n+1}}{\partial z^n} = (W^{n+1})^T \odot \sigma'(z^n)
\]  

(11)

Substitute (11) into (9)

\[
\delta^n = \delta^{n+1} \frac{\partial z^{n+1}}{\partial z^n} = (W^{n+1})^T \delta^{n+1} \odot \sigma'(z^n)
\]  

(12)

3. Diagnostic model construction

The convolution neural network model is usually based on the feed-forward neural network model, only the hidden layer is replaced by the convolution layer, the pooling layer and the full connection layer.

Due to the large scale and close correlation of wheel group vibration data in the operation of subway, two-dimensional convolution neural network is selected to analyze the characteristics of vibration data. In practice, the sensor measured data can be real-time learned by using neural network during Subway operation, which makes the neural network suitable for vibration signal identification under various practical and complex conditions.

The experimental data are from the vibration data and fault information of wheel groups generated by the actual operation of the subway. The data set consists of 250 groups, 200 of which are selected as training set and 50 as test set. The flow chart for model building is shown below.

![Flow chart for model building](image)

**Figure 1.** the flow chart for model building

3.1. Running Condition Coding

Operating conditions are mainly divided into three categories: normal, early warning and failure. Use integer coding for classification, as shown in the table below:
| No. | Type   |
|-----|--------|
| 1   | Normal |
| 2   | Warning|
| 3   | Fault  |

3.2. Data Processing
In actual operation, the data obtained by the subway vibration sensor is $1 \times 4096$ one-dimensional array. To be used in 2-D convolution neural network, the array is reformulated into $64 \times 64$ 2-D array.

3.3. Construct CNN Model Structure Diagram
Based on the convolution neural network model in image processing, the following neural network model can be built:

The input data is $64 \times 64$ two-dimensional data. Considering the number, size, sampling width (step) and the relationship between data characteristics and accuracy, the parameters of each convolution layer are set as follows:

![Figure 2](image)

Figure 2. The parameters of each convolution layer

In the figure, four layers of net had been established. Rectangles symbolizes input information, and the circle means output results.

The first convolution layer has 32 convolution cores with the size of $5 \times 5$. When the sampling width and length are both 1, 32 characteristic maps of $60 \times 60$ can be extracted; then the pool layer with the filter size of $2 \times 2$ can be reduced to 32 characteristic maps of $30 \times 30$.

The second convolution layer has 64 convolution cores with the size of $5 \times 5$ and the sampling width and length of 1. 32 characteristic maps of $26 \times 26$ can be extracted, followed by the pool layer and the filter size of $2 \times 2$. 64 characteristic maps of $13 \times 13$ can be further extracted.

The third convolution layer employs 64 $5 \times 5$ convolution cores with sampling width and length of 1, and 64 $9 \times 9$ characteristic maps can be extracted. A $3 \times 3$ filter is used in the pool layer and reduced to 64 $3 \times 3$ feature maps.

The fourth convolution layer employs 128 $3 \times 3$ convolution cores with 1 sampling width and 1 sampling length. 128 $1 \times 1$ characteristic maps can be further extracted and 2-dimensional data can be compressed into 1-dimensional data to provide data for the final full connection layer. In the full connection layer, the Softmax function is used to diagnose whether there is a failure of the subway.
Each pooling layer uses Average Pooling, which represents the average of all the values of each window as the values of the corresponding elements of the output matrix. In addition, after each convolution layer is processed, its output is normalized. This will speed up learning and avoid overfitting.

4. Model simulation
Based on the neural network constructed above, the learning rate is set at 0.01 and the number of iterations is 50. The accuracy changes with the iterations as follows:

![Figure 3. Accuracy varies with iteration](image)

For the 50 test sets given, the trained neural network can completely and accurately determine the category of vibration signal. The results are satisfactory. Because the deep learning algorithm adopts the layer by layer greedy learning method, its training time is longer than other neural networks, but after the network training, the diagnosis results can be given according to the data quickly, which can be used for real-time online diagnosis.

5. Conclusion and discussion
This research focuses on the fault detective based on the combination application of existing database and machine learning. In this paper, the real operation data of subway provided valuable original resources for the research. Therefore, the results of this study will be applicable to the multi motion mode, load size, load action mode, wheel speed, contact angle, environmental temperature and lubrication state. The CNN (Convolutional Neural Network) plays an important role in the analysis process. This application of CNN (Convolutional Neural Network) can labeled the data and report the real time running state of Metro wheels. This method enhanced the efficiency and accuracy of the fault detective process since the original real time vibration signal could be used as the input directly and without any processing. Furthermore, the output data in normal state will be classified and labeled again as "input" of Convolutional Neural Network, so that the Convolutional Neural Network can be updated after a period of use. To achieve the effect of self-upgrading. This self-upgrading step allows CNN automatic fault diagnostic mechanism to be used for a long time in a changing mechanical motion environment and working conditions.

References
[1] Du Mengxing, Wang Yanwei. Design and Implementation of Emergency Warning System Based on CNN [J]. Journal of Wuhan Institute of Technology, 2019, 12(23): 1-6.
[2] Song Yunbo, Chen Dongyan, Yun Hao, Fu Fuping. An Efficient Target Detection Method Based on Cascaded Convolution Neural Network [J]. Computer Engineering and Application, 2018,
45(12): 1-12.

[3] Li Jian, Wang Xiaoming, Zhang Yinghai, Wang Weidong, Shang Jie, Gailei. Research on Seismic Phase Pickup Method Based on Deep Convolution Neural Network [J]. Geophysical Journal, 2020, 63(04): 1591-1606.

[4] Wei li, Zhang Jun, Zhang Zhifu, Ma Xingyu, Zong Liming. On-line Detection of Bearing Failure of Subway Vehicles [J]. Modern Urban Rail Transit, 2019(12): 16-21.

[5] Zhang Xu. Research on Application of Fault Monitoring and Intelligent Diagnosis System for Metro Electromechanical Equipment [J]. Value Engineering, 2019, 38(35): 172-173.

[6] Liu Jianqiang, Zhao Dongming, zhaonan. An improved fault diagnosis method for bogie bearings of metro vehicles [J]. Journal of Railways, 2018, 40(11): 55-61.

[7] Wang Fengtao, Ao Yinhui. Fault diagnosis of flat wheels of subway vehicles based on multifractal theory [J]. Mechanical Engineering and Automation, 2018, 23(05): 12-14.

[8] Feng Shuai. Research on Fault Diagnosis and Residual Life Prediction of Rolling Bearings in Subway Train Running Parts [D]. Beijing Jiaotong University, 2016.

[9] Wang Fumin. Experimental Study on Simulation Fault Diagnosis of Metro Gear Transmission [D]. Taiyuan University of Science and Technology, 2016.

[10] Ceng Qi. Fault Diagnosis Method for Bearing of Metro Bogie [J]. Residential and Real Estate, 2015, 34(11): 162.