DOI:10.18686/ahe.v7i36.12686

Bearing Fault Diagnosis Based on Improved one-dimensional Convolutional Neural Network

Yiguang Wang, Ronaldo Juanatas*, Jasmin Niguidula, Jonathan Caballero, Deye Jiang, Tao Ning
Technological University of the Philippines

Abstract: Traditional bearing fault diagnosis mainly combines the characteristics of non-periodic, nonlinear and non-stationary vibration signals of bearing machinery, and uses one-dimensional convolutional neural network model for fault identification and diagnosis. However, it relies too much on data collection, and has problems such as low diagnostic accuracy, poor diagnostic effectiveness and overfitting of model, which urgently needs to be improved and optimized. Based on the classical one-dimensional convolutional neural network fault diagnosis method, this paper designs a new one-dimensional convolutional neural network model using Dropout technology. After adding the Dropout layer to the convolutional layer, the generalization ability of the bearing fault diagnosis model is greatly enhanced, and the probability of fault error diagnosis is reduced.
Keywords: One-dimensional convolutional neural network; Batch normalization layer; Bearing failure; Fault diagnosis

The stable operation of rotating machinery depends on the bearing, the bearing in different working conditions of the load, speed is different, easy to appear damage failure, there is a large security risks, but also produce significant economic losses. At present, deep learning models have been widely used in the field of intelligent bearing fault diagnosis. Many scholars have explored deep confidence networks, long and short term memory neural networks, recurrent neural networks and convolutional neural networks, and integrated them with discrete wavelet transform, shallow learning machine, synchronous compression transform, etc., so as to extract bearing vibration signal features. Although these diagnostic methods extract and distribute bearing fault characteristics, there are also deficiencies such as too large number of network parameters, complex extraction process and low diagnostic accuracy. In this study, a bearing fault diagnosis method based on an improved one-dimensional convolutional neural network uses Dropout to improve generalization ability, optimize model performance, and ensure the accuracy of fault diagnosis results.

1. Theoretical overview

1.1 One-dimensional convolutional neural network

Combined with the differences in the input data, the convolutional neural network can be divided into one, two and three dimensions. Among them, one-dimensional convolutional neural network (1DCNN) is suitable for processing one-dimensional time series data, while the data used for mechanical bearing fault diagnosis is collected by acceleration sensors and belongs to one-dimensional vibration signals. Therefore, a fault diagnosis model framework can be designed based on one-dimensional convolutional neural network [1]. The one-dimensional convolutional neural network consists of four modules: input layer, convolutional layer, pooling layer, activation layer and full connection layer. It covers a number of neural networks with filtering functions, which can screen fault signals, smooth signals, and classify fault types with the help of Softmax classifier.

1.2 Batch normalization layer

In order to avoid the risk of overfitting, after the batch normalization layer is added to the convolution layer of the one-dimensional convolutional neural network in the bearing fault diagnosis model, the output of the neural network can be adjusted to speed up the training speed, enhance the stability of the output value of the network, and improve the overall performance of the network. The specific steps for batch normalization of small batch data are as follows:

（1）Calculate the mean value of each dimension: $\mu_\beta = \frac{1}{m}\sum_{i=1}^{1} x_i$, Where, the dimensional mean is expressed as μ_β .

(2) Calculate the dimensional variance: $\sigma_\beta^2 = \frac{1}{m}\sum_{i=1}^{1} x_i (x_i - \mu_\beta)^2$, Where, the dimensional mean is expressed as σ_β^2 .

(3) Normalized processing of one-dimensional data: $\hat{x}_i = \frac{x_i - \mu_\beta}{\sqrt{\sigma_\beta^2 + \varepsilon}}$, Where, the normalized processing value is expressed as $\hat{x}_i$,The initialization parameter value is ε .

(4) Translation and reduction processing, γ 、 β learning parameters are introduced into the batch normalization layer: $\hat{\gamma}_i = \gamma \hat{x}_i + \beta$, Among them, the input after normalization is $\hat{x}_i$, and the output of the batch normalization layer is $\hat{\gamma}_i$.

1.3 Dropout technology

The basic idea of Dropout technology is to combine the activation of some neurons with a specific probability during training to simplify the network model, get rid of the disadvantage of relying on some local features, and make the model more robust and have stronger generalization ability [2]. In this process, each batch training network model is different, they are all subsets of the original network, and the subset network shares the weight, which is consistent with the parameter number and layer number of the original network. The application of the Dropout method realizes the independence of each neuron in the network, and more subnetworks can be obtained with different batch training. The overfitting phenomenon is effectively avoided.

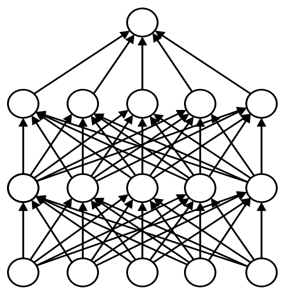

Figure 1: Neural network training results with Dropout technology

2. Bearing fault diagnosis based on improved one-dimensional convolutional neural network

Aiming at the shortcomings of the traditional one-dimensional convolutional neural network, by applying the batch Dropout method to the network model construction, we can create an improved one-dimensional convolutional neural network model and better carry out bearing fault diagnosis operation. The optimized network model is applied to TensorFlow and Keras toolbox, including input layer, feature extraction layer, full connection layer and output layer. The feature extraction layer is subdivided into convolution layer, batch normalization layer, Sigmoid activation layer and maximum pooled task layer. The fully connected layer is responsible for deleting the neural units in the network by applying Dropout technology and updating the parameters in the remaining neural units according to stochastic gradient descent method, continuously repeating the operation [3].

In the diagnosis of bearing faults, the original vibration signal of bearings should be input into the improved network model. After entering the feature extraction layer, since the lower convolution layer is subdivided into six layers, and the size of convolution kernel of each layer is directly related to the size of the receptive field of the convolution layer, large convolution kernel should be used in the first convolution kernel to ensure that the receptive field is large enough. The remaining five layers need to use small convolution kernel to reduce the number of parameters and thus shorten the operation time [4]. After completing the convolution operation, in the batch planning layer, we need to improve the generalization ability of the network model and use the advantage of Dropout technology to avoid overfitting of the model in the full connection layer. In order to improve the computing power of the bearing fault diagnosis network model, it is necessary to rely on Adam optimizer to update the weight.

3. Experimental results and comparative analysis

3.1 Experimental data

In order to verify the bearing fault diagnosis capability based on the improved one-dimensional convolutional neural network, the bearing data of Case Western Reserve University in the United States was selected to carry out simulation test analysis for three types of faults of rolling element, inner ring set and outer ring [5]. The four sets of data used correspond to the vibration acceleration signals of mechanical bearings under various working conditions in turn, and the working conditions are expressed as 0, 1, 2 and 3, respectively, and the bearing damage diameters caused by the three types of faults also have certain differences. In this document, there are 1000 data sets, including one normal state data and three fault data. Labels are named in the order of 0 to 9.The Settings are described in the following table.

Table 1: Experimental data sets

Signal type	Sample number	Sample length	Damage diameter (inch)	Tag
normal	1000	1024	0	0
Inner ring damage	1000	1024	0.007、0.014、0.021	1、2、3
Outer ring damage	1000	1024	0.007、0.014、0.021	4、5、6
Rolling body damage	1000	1024	0.007、0.014、0.021	7、8、9

During the experiment, data sets should be scrambled, 7 as training sets, 2 as validation sets, and 1 as test set, and batch normalization operations should be completed after unified processing. Moreover, one-dimensional convolutional neural network training courses should be carried out to evaluate the performance of the one-dimensional convolutional neural network optimization model by comparing the test results and training results [6].

3.2 Setting of relevant parameters

When setting the parameters, the improved one-dimensional convolutional neural network model with Dropout technology can set the parameters to 0.2, 0.3, and 0.5 in order to carry out three sets of experiments, control the number of iterations to 50 times, and obtain the fault diagnosis rate of the training set [7]. The results show that when the Dropout parameter is 0.5, the fault diagnosis accuracy of the training set is about 94%, and when the Dropout parameter is 0.2 or 0.3, the fault diagnosis accuracy of the training set is > 99%. The accuracy rate is relatively stable when the parameter is 0.3. Therefore, the optimal Dropout parameter value of the improved network model is 0.3. At the same time, the model also sets the pooling layer into six layers. The convolution kernel sizes of the first layer and the remaining layers are 64×1, 3×1, and the pooling size is 2×1, respectively. Under Adam algorithm, the optimizer learning rate is 0.001, the Dropout is 30%, and the number of iterations is 200. [8]

3.3 Result analysis and discussion

For the first dataset, the accuracy of the improved model and the classical model is 99.93% and 95.7%, respectively. In the second dataset, the accuracy of the improved model and the classical model is 99.96% and 97.1% respectively. In the third dataset, the accuracy of the improved model and the classical model is 99.2% and 88.08%, respectively. In the fourth dataset, the accuracy of the improved model and the classical model is 99.86% and 98.3%, respectively [9]. This shows that the improved one-dimensional convolutional neural network model basically converges after 70 iterations, and the average accuracy rate of the verification set is 99.6% and the average accuracy rate of the training set is > 99%, which indicates that the model is superior and has high diagnostic accuracy for bearing faults. In addition, compared with the classical one-dimensional convolutional neural network model, the accuracy difference of test sets on each data set is significantly reduced, and the optimization model shows strong generalization ability and stability ability [10].

4. Conclusion

The bearing fault diagnosis model built in this research based on improved one-dimensional convolutional neural network has been significantly improved in practicality, stability and generalization ability with the support of ropout technology. It has achieved end-to-end fault detection, greatly improved diagnostic accuracy and suppressed the problem of model overfitting, and has good practical engineering application value.

References:

[1] YU Miao. Application and Research of Improved Convolutional Neural Network in Bearing Fault diagnosis [D]. Dalian Jiaotong University, 2023.

[2] Wu Jigang, Wen Gang, Yang Kang. Aero engine fault diagnosis based on improved one-dimensional Convolutional neural Network [J]. Journal of Electronic Measurement and Instrumentation, 2023, 37 (03): 179-186. (in Chinese)
[3] HU Yu. Research on Bearing Fault Diagnosis Algorithm Based on one-dimensional Convolutional Neural Network [D]. Beijing University of Chemical Technology, 2022.
[4] Pan Yihao, Xiao Hong, Zhou Yubin, et al. Fault Diagnosis of Multi-axis Industrial Robot Based on Improved One-dimensional Convolutional Neural Network [J]. Modular Machine Tool & Automatic Processing Technology, 2021, (12): 10-14+18.
[5] Yang Yun, Ding Lei, ZHANG Haoyu. Research on Bearing Fault Diagnosis based on Improved one-dimensional Convolutional Neural Network and Bidirectional Gated cycle Unit [J]. Mechanical Science and Technology for Aerospace Engineering, 2023, 42 (04): 538-545.
[6] Cheng Liang, Dong Zijian, Wang Shumin, et al. Fault Diagnosis of Rolling Bearing Based on Improved One-dimensional Convolutional Neural Network [J]. Machine Design and Research, 2023, 39(3):126-130.
[7] Dong Shao-Jiang, PEI Xue-Wu, WU Wen-liang, et al. Rolling bearing fault Diagnosis Method Based on multi-layer noise reduction technology and improved Convolutional Neural Network [J]. Journal of Mechanical Engineering, 2021, 57(1):9.
[8] Meng Zhiqiang, Dong Shaojiang, Pan Xuejiao, et al. Fault Diagnosis of Rolling Bearing Based on Improved Convolutional Neural Network [J]. Modular Machine Tool & Automatic Machining Technology, 2020(2):5.
[9] Wang Qi, Deng Linfeng, Zhao Rongzhen. Fault Identification of Rolling Bearing based on improved one-dimensional Convolutional Neural Network [J]. Journal of Vibration and Shock, 2022, 41(3):8.
[10] Zhang Yuanxu, Cheng Changxin, Song Shengjian. Fault Diagnosis of Rolling Bearing Based on Improved RBF Neural Network [J]. Industrial Instrumentation & Automation, 2018(6):4.

About the author:

Yiguang Wang(1987.8-), male, Han nationality, Pubei Guangxi, PhD candidate, experimentalist, artificial intelligence fault diagnosis.

Contact: Ronaldo Juanatas, Email: rjuanatas@yahoo.com.