Z. J. CHEN, J. ZHAO, M. A. LIU

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METALLURGICAL PRODUCTIONS FAULT DETECTION METHOD BASED ON RESLSTM-CNN MODEL

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Timely detection of abnormal working conditions and accurate diagnosis of abnormal working conditions are of great research significance to ensure the safe and stable operation of metallurgical production processes and to avoid losses caused by faults. In this paper, it propose a residual long and short-term memory network and convolutional neural network (RESLSTM-CNN) model for fault detection in metallurgical production processes bearing fault detection with an accuracy of 98,92 %.

Keywords: metallurgical production, fault, detection, bearing, method network model

INTRODUCTION

Due to the high-dimensional, non-linear, non-Gaussian and time-varying nature of metallurgical production process data, it is effective for fault detection in metallurgical production processes to reduce property damage and can reduce personal safety. Optimal monitoring of mechanical signals can more effectively help analyze machine performance, which in turn can improve metallurgical production efficiency and more importantly give us insights into machine health. Bearing failures are one of the main causes of industrial machine downtime, and it is important to address this issue with high reliability to reduce machine failures.

Fault detection and diagnosis methods are generally classified into three categories: expert experience-based methods, model-based methods, and data-driven methods. The rapid development of deep neural networks based on shallow learning detection methods can no longer meet the needs of contemporary mechanical fault detection in metallurgy. In order to comprehensively analyze the signal data, this paper proposes a mechanical fault detection method (RESLSTM-CNN) using a classical deep neural network model. To evaluate the performance of the RESLSTM-CNN model for bearing fault classification, this paper evaluates our deep learning method on Prognostics and Health Management (PHM) challenge datasets.

RELATED WORK

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In order to comprehensively analyze the signal data, this paper proposes a mechanical fault detection method (RESLSTM-CNN) using a classical deep neural network model. To evaluate the performance of the RESLSTM-CNN model for bearing fault classification, this paper evaluates our deep learning method on Prognostics and Health Management (PHM) challenge datasets.

Deep learning techniques are developing rapidly, and the trend of bearing fault detection has shifted from traditional methods to deep learning-based methods. Since the original signal collected from the gas pedal is one-dimensional data, convolutional neural networks (CNN) [1] are widely used by many researchers for bearing fault diagnosis. In 2020, Li et al [2] proposed a method based on Long Short Term Memory Network for motor bearing fault identification method, which uses Long Short Term Memory Neural Network with Peephole (LSTMWP) for feature extraction, combined with Softmax classifier, to achieve motor fault diagnosis. In 2020 Chen et al [3] proposed a combined model of multi-scale CNN and LSTM (MCNN-LSTM) to automatically extract signal features at different frequencies from the original data using two CNNs with different kernel sizes. Lu et al [4] used an efficient and reliable deep learning method based on convolutional neural networks and trained deep hierarchical structures in a robust way that was trained using greedy layer-by-layer transmission rules established.

Z. J. Chen, J. Zhao, M. A. Liu, School of Computer Science and Software Engineering, University of Science and Technology Liaoning, China. Corresponding author: J. Zhao (zhaoji_1974@126.com)

The researchers found that by simulating the cognitive process, the advantages of image recognition and visual perception for load-bearing fault diagnosis are introduced, and a novel feature representation of load-bearing data using supervised deep learning is discussed to be effective. In order to minimize the safety accidents such as economic losses due to mechanical failures accidents. Therefore we propose a residual long and short-term memory network and convolutional neural network, the RESLSTM-CNN model for metallurgical production process fault detection.

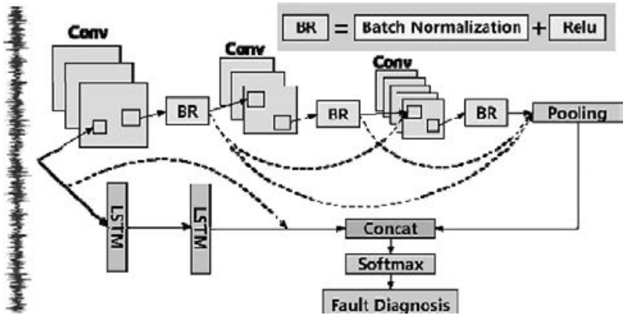

Figure 1 The structure of RESLSTM-CNN

RESLSTM-CNN MODEL

The RESLSTM-CNN model is shown in Figure 1. The RESLSTM-CNN model is divided into two parts: one is the RESLSTM module and the other is the convolutional module for feature extraction. The main difference between the LSTM and the original RNN is that the LSTM uses a more complex recurrent layer with many more components than the original recurrent layer, and the LSTM model is shown in Figure 2.

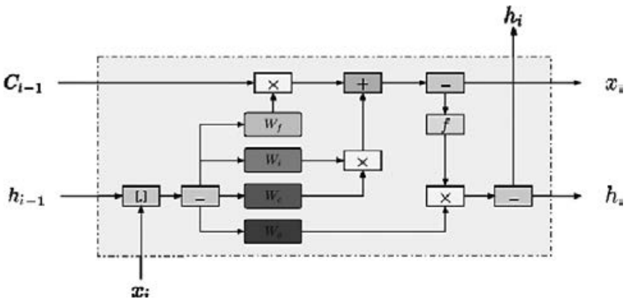

Figure 2 The network structure of LSTM

$$f_i = \sigma(W_f[x_i, h_{i-1}] + b_f) \tag{1}$$

$$i_i = \sigma(W_i[x_i, h_{i-1}] + b_i) \tag{2}$$

$$o_i = \sigma(W_o[x_i, h_{i-1}] + b_o) \tag{3}$$

$$\widetilde{c_i} = \tanh(W_c[x_i, h_{i-1}] + b_c) \tag{4}$$

$$C_i = f_i \odot C_{i-1} + i_i \odot \widetilde{c_i} \tag{5}$$

$$h_i = o_i \odot \tanh(C_i) \tag{6}$$

f_i is the forgetting gate, i_i is the input gate, and o_i is the output gate. The output result after the “forgetting” selected by the forgetting gate is dotted with C_{i-1}, the input gate is dotted with $\widetilde{c_i}$, and then the above two parts are summed to obtain the C_i of the current moment. The output gate is the final control means of the whole LSTM output. The output gate first shunts C_i to pass the data stream to the next moment (i.e., C_{i-1} moment); on the other hand, the output gate controls the data stream through the tanh activation function and then performs the dot-multiplication operation with the output gate to get the hidden state h_i at the current moment. The structure of the residuals is shown in Figure 3.

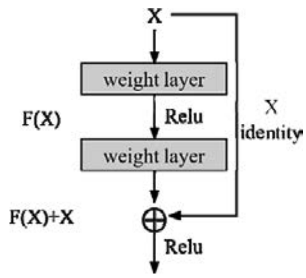

Figure 3 The network structure of residuals

$$H(x) = F(x) + x \Rightarrow F(x) = H(x) - x \tag{7}$$

The residual structure provides two ways to solve the degeneracy problem: identity mapping and residual mapping. The identity mapping refers to the “curved” part of the graph, and residual mapping refers to the remaining part of the non identity mapping refers to the “curved” part of the graph, and residual mapping refers to the remaining part of the non-”curved” part. F(x) is the pre-summing network mapping, and $H(x)$ is the input to the post-summing network mapping.

The convolution module builds multiple filters capable of extracting features from the input data, and mines the fault features hidden in the data layer by layer to achieve a high-dimensional representation of the data. The mathematical expression of the convolution layer is shown as follows.

$$o_j^l = \sigma(\sum_{i \in M_j} o_i^{l-1} \times \varpi_{ij}^l + b_j^l) \tag{8}$$

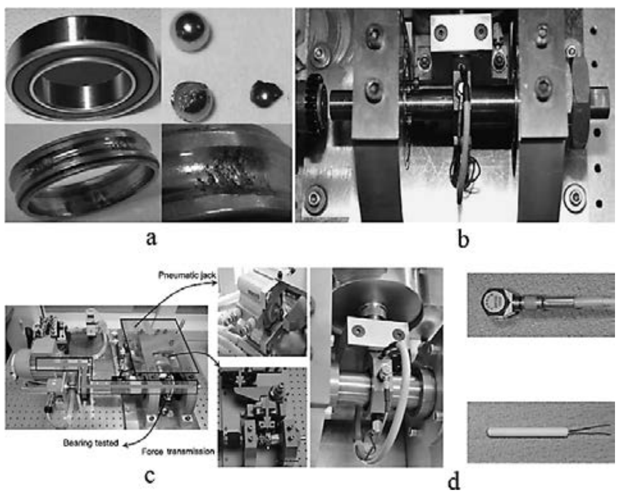

Figure 4 PRONOSTIA sample

where o_j^l is the output of the j-th neuron at layer l, o_i^{l-1} is the input of the i-th neuron at layer l-1, M_j is the input feature map, l is the network at layer l, ϖ is the weight matrix, i.e., the filter, b_j^l is the network bias of the j-th neuron at layer l, σ is the activation function.

EXPERIMENT AND ANALYSIS

The PHM challenge dataset [5] is performed on a laboratory experimental platform (PRONOSTIA) that accelerates bearing degradation under constant and/or variable operating conditions while collecting online health monitoring data (speed, load, temperature, vibration).

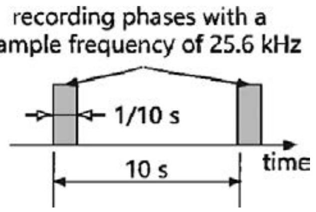

Figure 5 Vibration signal acquisition parameters description

The main goal of PRONOSTIA is to provide realistic experimental data describing the ball bearing degradation throughout its service life (until complete failure). PRONOSTIA consists of three main parts (e.g. Figure 4): the rotating part, the degradation generating part (radial forces applied to the bearing under test) and the measuring part. In Figure 4, (a) representative bearings, (b) representative Shaft support bearings, (c) representative Details of the loading section, and (d) representative Measuring part (including accelerometer and temperature sensor). In this paper, the PRONOSTIA platform vibration signal with an amplitude below 20 g was selected. The sampling rate is 25,6 kHz and 2 560 samples are recorded every 10 seconds (as shown in Figure 5). The PHM challenge dataset has a bearing anode as shown in Figure 6. The bearing is equipped with two synthetic rubber seals to prevent the leakage of lubricant and the entry of dust, water and other harmful substances. The bearing is set at a rated load of 2 470 N statically and a rated load of 4 000 N dynamically: 4 000 N.

To reduce the impact of classification accuracy by randomness, each baseline model was run 20 independent experiments each, the models were written using the tensorflow=1,16 framework, and all experiments were run on a GTX3 080Ti machine. The learning rate (lr) was set to 0,001, and the optimizer was Adam, using a cross-entropy loss function (cross-entropy). The batch training size is 256 and the epoch is set to 300. To prevent overfitting during training we use the Early Stopping method and end the training when the loss value of the validation set does not decrease for 10 consecutive times. In this paper, *ACC* is chosen as the evaluation metric for RESLSTM-CNN, and *ACC* is mathematically defined as follows.

$$Acc = \frac{TP + TN}{TP + FP + FN + TN} \tag{9}$$

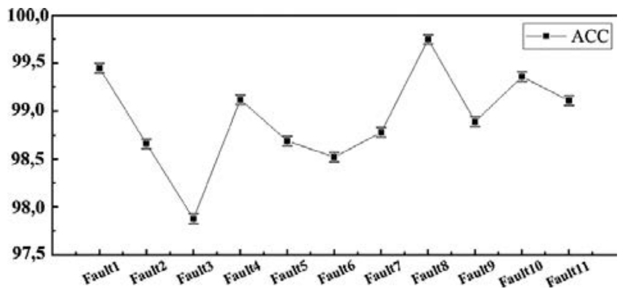

Figure 7 Comparison of accuracy on the PHM challenge dataset

In Figure 7, this paper compares the accuracy of the RESLSTM-CNN model in the PHM challenge dataset for 11 fault categories. The RESLSTM-CNN model performs the best in Fault 8 detection with 99,75 % and the worst in Fault 3 with 97,88 %. Throughout the PHM challenge dataset, in order to make the experimental data more convincing, five rounds of cross-validation are conducted in this paper, and the point-line error plots are drawn by experimental comparison. Overall, the model designed in this paper achieves an average accuracy of 98,92 % ±0,05 in 11 categories.

In Figure 8, this paper also compares CNN, RNN-CNN, LSTM and LSTM-CNN classical models, respectively, and finds that the RESLSTM-CNN proposed

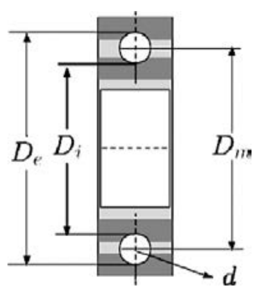

Figure 6 Bearing Characteristics

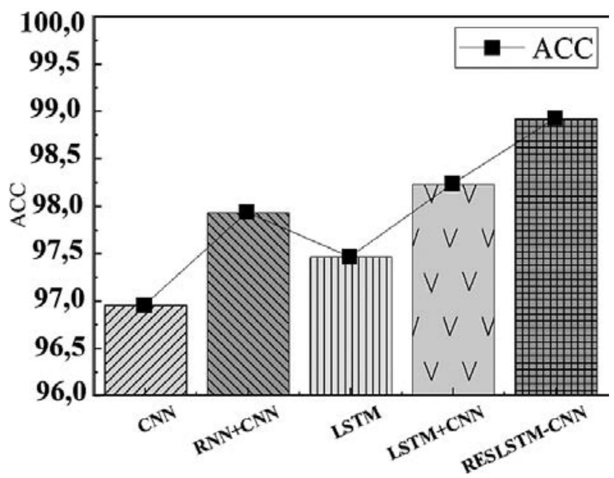

Figure 8 Baseline model comparison

in this paper ensures high accuracy in metallurgical machinery fault detection and effectively reduces the inaccuracy rate of manual fault detection.

CONCLUSION

This paper proposes a method of chemical process fault detection based on RESSTM-CNN network model, which can effectively extract the local and global features of metallurgical machinery fault data; this paper pairs four baseline models and conducts comparison experiments on the PHM challenge dataset 11 fault categories to verify that the RESSTM-CNN metallurgical fault diagnosis method proposed in this paper has high fault diagnosis accuracy and easily distinguishes different fault types.

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Note: The responsible translators for English language is Z. J. Chen – University of Science and Technology Liaoning, China