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Diagnosis of Sliding Bearing Lubrication State Based on SC-ResNet

Yimei Zeng*, Yang Yu

[1]Faculty of Information Engineering, Shenyang University of Technology, Shengyang, China
*Corresponding Author: 2667102665@qq.com

ABSTRACT

In response to the issue of poor diagnostic performance of models due to the scarcity of samples for lubrication failure states in sliding bearings in practical engineering applications, this thesis proposes a fault diagnosis method for the lubrication state of sliding bearings based on a Self-Calibrated Residual Network (SC-ResNet). By leveraging the self-calibrated convolution, which significantly enhances the network's receptive field and feature extraction capabilities without increasing the number of parameters and complexity, a self-calibrated residual block is designed to construct the SC-ResNet model. This model is capable of diagnosing the lubrication state of bearings using a small number of samples inputted into a pre-trained model. Experimental results indicate that this method performs exceptionally well under conditions with a limited number of samples, achieving higher Recall and F1-score values compared to other methods.

KEYWORDS

Sliding bearing; Acoustic emission; Lubrication state; Self-calibrated convolution; Fault identification

1. INTRODUCTION

Sliding bearings are crucial support components for large rotating machinery such as steam turbines, typically operating under high loads and in harsh environments. Prolonged operation can easily lead to the deterioration of lubrication conditions, triggering various faults and causing significant safety incidents[1]. Therefore, effective monitoring of the lubrication state of sliding bearings is of great significance.

Common methods for condition monitoring of sliding bearings include center trajectory measurement, oil analysis, noise monitoring, infrared temperature measurement, and vibration analysis, et[2]. However, these techniques have considerable limitations in identifying subtle changes in lubrication state, predicting early fault characteristics, and accurately correlating the monitored signals with the actual operational condition of the bearing. Acoustic Emission (AE) is a physical phenomenon where transient elastic waves are generated due to the rapid release of energy within an object or material[3]. Currently, as an emerging technology, AE detection technology has been widely applied in the field of equipment condition monitoring. In the context of diagnosing the lubrication state of sliding bearings, scholars have long confirmed the feasibility and unique advantages of AE technology[4]. Lu Xu Xiang[5] and others proposed a method for recognizing the lubrication state of sliding bearings by combining wavelet scattering transformation and convolutional neural networks, achieving a recognition rate of 95.28%. Tan Hao Yu[6] and others proposed a method for diagnosing the lubrication state of sliding bearings based on AE signals and information entropy distance, effectively distinguishing different lubrication states of sliding bearings and improving diagnostic accuracy. Towsyfyan H et al[7]used time-frequency domain analysis methods to analyze AE signals under different lubrication states, achieving diagnosis of the lubrication state of sliding bearings. König et al[8] utilized deep learning methods of convolutional neural networks to monitor and classify wear failure modes of sliding bearings, achieving high precision. Babu et al[9]used wavelet transform to decompose signals and combined them with artificial neural networks (ANN) for multi-condition fault diagnosis of sliding bearings, reaching a classification accuracy of 85.7%.

Through research, it has been found that the diagnosis of the lubrication state of sliding bearings mainly employs traditional signal processing and machine learning methods, which depend on expert experience and knowledge of signal processing, and have limitations in feature extraction and complex adaptability. Although deep learning methods have potential, they are limited by the amount of data, especially the difficulty in obtaining sufficient data on poor lubrication states in actual production. In response to this issue, this paper proposes the SC-ResNet model, aiming to address the reliable diagnosis of the lubrication state of sliding bearings under conditions of small samples.

2. INTRODUCTION TO RELEVANT PRINCIPLES

2.1. Residual neural networks

Residual Networks (ResNet) utilize the technique of residual mapping, training the network by connecting multiple residual blocks in series. The purpose of this design is to simplify the training of deep learning models. This approach allows the network to directly optimize the error in mapping from input to output, rather than the original mapping itself, thereby enhancing the learning capability of deep networks[10]. The structure is depicted in Figure 1.

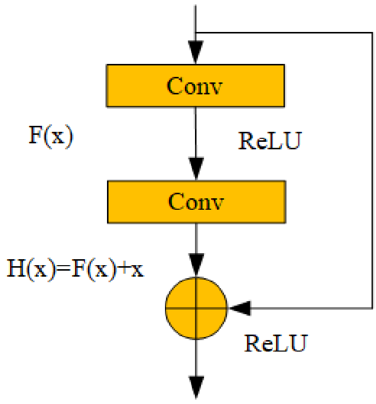


Figure 1: Residual Unit

The residual unit F(x) can be represented as follows:

$$F(x) = H(x) - x \tag{1}$$

In the formula: x is the input to the residual neural network, $H(x)$ is the feature learned from the input x. Residual neural networks are not only easy to optimize, but they also prevent overfitting as the number of layers increases. They mitigate the issues of vanishing gradients and address the problem of network degradation.

2.2. Self-Calibrated convolution

To address the limitations of traditional residual neural networks in feature extraction and receptive field expansion, Self-Calibrated Convolution (abbreviated as SCConv) optimizes the convolution operation. SCConv successfully broadens the receptive range of the convolutional layer without increasing the number of model parameters or affecting the existing network architecture. This improvement significantly enhances the model's efficiency in capturing critical fault features, thereby strengthening the overall performance of the model[11].

The operation of Self-Calibrated Convolution is divided into two main parts: one part is the self-calibrated scale space processing, and the other part is the original scale space processing. The specific steps can be divided into five:

Step 1: The input features are evenly divided into two equal parts, each containing half of the channel information, denoted as A1, A2;

Step 2: The convolution kernel Z is split into four sub-kernels of the same dimensions, each carrying a portion of the parameters of the original convolution kernel, denoted as Z1, Z2, Z3, Z4;

Step 3: The input features undergo self-calibration processing, Feature A1 is first sent into two channels with different resolutions for processing. Through an average pooling layer, feature A2 is downscaled to construct a low-resolution latent feature space, which helps to expand the model's perceptual domain. Subsequently, the downscaled features are deeply explored and their resolution is restored using convolution layer Z2 and up sampling techniques to capture subtle fault signals in the original data. After being activated by a Sigmoid function, these features are used to calibrate and enhance the key information captured by the convolution layer Z3. Ultimately, after further processing by the convolution layer Z4, a series of refined featuresY1 is output. This strategy aims to enhance the model's accuracy and sensitivity in identifying and extracting key fault features by refining features at a low-resolution level and filtering out redundant information. The operation is as follows:

$$\mathrm{T} = \mathrm{avgpool}_{\mathrm{r}}(A_1) \tag{2}$$

$$\bar{\mathrm{X}}_1 = up(\mathrm{T} * \mathrm{Z}_2) \tag{3}$$

$$\bar{\mathrm{Y}}_1 = A_1 * Z_3 \cdot \sigma(A_1 + \bar{\mathrm{A}}_1) = \frac{A_1 * Z_3}{1 + \exp\left(-(A_1 + \overline{\mathrm{AA}}_1)\right)} \tag{4}$$

$$\mathrm{Y}_1 = \bar{\mathrm{Y}}_1 * Z_4 \tag{5}$$

In the formula: $avgpool()$ represents the average pooling operation; r is the down sampling rate; up() denotes up sampling;σ is the Sigmoid function, which enhances the model's nonlinearity.

Step 4: Within the feature space at the original resolution, the input feature A2 is sent into the convolution layer Z1, which then produces a new feature representation Y2;

Step 5: A Concatenation operation is performed, merging the feature outputs Y1 and Y2 from different scales to form a comprehensive set of features Y.

SCConv (Self-Calibrated Convolution), through its adaptive mechanism, focuses on the neighboring information at each spatial position and filters out peripheral interference, thereby improving the accuracy of information processing. This allows SCConv to expand the receptive field of the convolutional layer and significantly enhance the model's ability to capture and analyze data features.

3. DIAGNOSIS OF SLIDING BEARING LUBRICATION STATE BASED ON SC-RESNET

3.1. Self-Calibrated residual blocks

To address the issue that traditional residual modules may overlook important contextual information due to the limitations of the convolutional kernel's receptive field when handling classification tasks, a self-adaptive residual unit—known as the Self-Calibrated Residual Block—has been designed. By replacing the regular convolutional kernels within the residual block with Self-Calibrated Convolution (SCConv) kernels, the newly designed residual block can automatically establish long-distance spatial and channel dependencies at various spatial positions. This approach significantly enhances the network's ability to generate highly discriminative features while maintaining the network architecture and parameter scale, thereby strengthening the network's feature extraction and learning capabilities. The structural design of the Self-Calibrated Residual Block is illustrated in Figure 2.

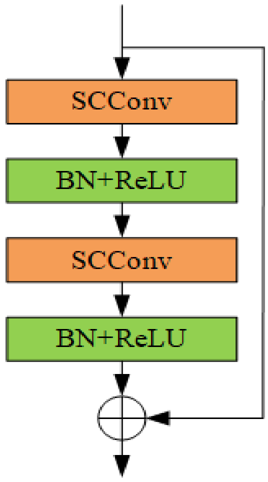


Figure 2: Self-Calibrated residual block

3.2. SC-ResNet model structure and diagnostic process

The network is composed of five residual modules connected in sequence, as shown in Figure 3. The input raw signal is first preliminarily processed by a wide-kernel convolutional unit, which aims to reduce the interference of environmental noise on the feature extraction process. Subsequently, the signal passes through five residual blocks sequentially, with the first and third residual blocks designed as self-calibrated residual blocks to enhance the network's ability to learn feature information. Each residual module consists of two convolutional layers, followed by a ReLU activation layer and a batch normalization layer. This configuration not only accelerates the convergence rate of the network but also strengthens the model's generalization performance. Ultimately, the processed data is dimensionally reduced through a global average pooling layer and then processed through a fully connected layer and a dropout layer to accurately identify and classify the different working states of the bearing.

The basic process for diagnosing the lubrication state of sliding bearings using the SC-ResNet is as follows: Initially, during the model training phase, a set of training samples with clear state labels is introduced. These samples are input into the SC-ResNet model for preliminary training. Thereafter, a Softmax classifier is used for error backpropagation, and the Adam optimization algorithm is employed to optimize and adjust the network parameters, with the goal of minimizing the loss function. This process is iterated until the model training is complete. Subsequently, during the state recognition phase, untrained test samples are fed into the well-trained SC-ResNet model for feature extraction. The extracted features are then passed to the Softmax classifier for state classification, and the accurate recognition rate of the test samples is ultimately calculated and output.

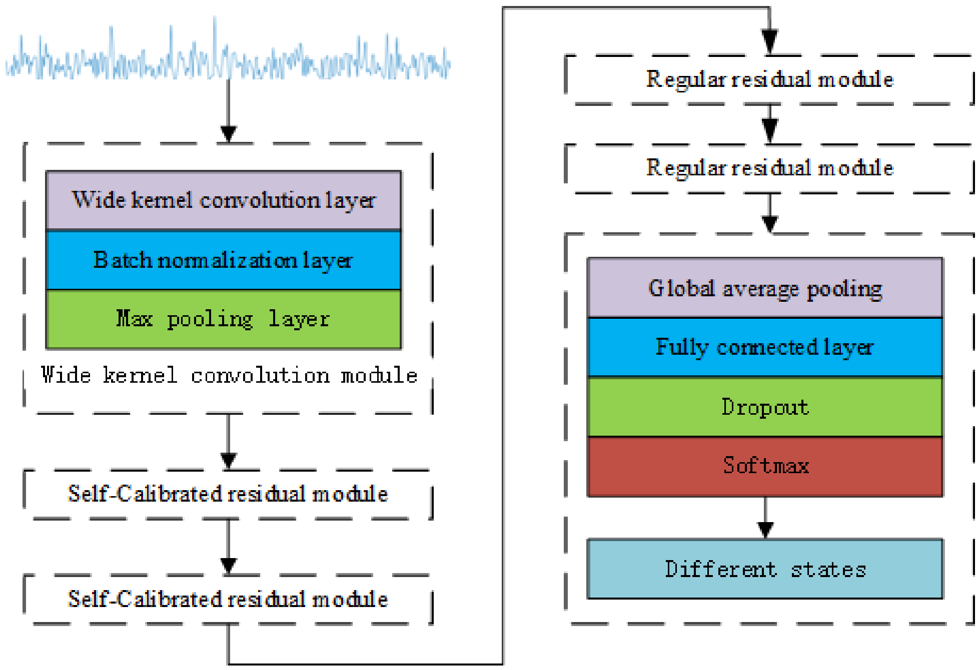


Figure 3: Network structure diagram

4. EXPERIMENTS AND ANALYSIS

4.1. Experimental data and parameter settings

The experimental platform used in this study is a sliding bearing rotor test rig, which is utilized to simulate the lubrication state experiments of sliding bearings. The structure of the experimental platform is shown in Figure 4.

Figure 4: Sliding bearing rotor test rig

Acoustic emission signals of the bearing under three lubrication states—normal lubrication, oil scarcity, and oil breakage—were collected using an acoustic emission acquisition system. A total of 300 samples were collected from the bearing, with each sample being 1000 in length and a sampling frequency of 1MHz, containing 100 samples for each state. To study the state diagnostic performance of SC-ResNet under different small sample scenarios, the dataset was used to construct five different training sets with 5, 10, 40, 80, and 100 samples for each state, respectively, while the test set contained 100 samples for each state. The small sample experimental dataset is shown in Table 1. The network was constructed under PyTorch, with the weight loss function using cross-entropy loss, 'same' as the padding method, the wide convolutional kernel size set to 8x8, the pooling layer size to 2x2, and the number of kernels to 64. In the residual blocks, the convolutional kernel size was uniformly set to 3x3, with the number of kernels being 32, and the convolutional stride was set to 1. The batch size was 64, and the dropout rate was 0.5. The Adam optimizer was used, with a learning rate of 0.0001. Each sample was adjusted to a two-dimensional array form of 100x10 for model training, and the network model was trained for 500 epochs.

Table 1. Small sample experimental dataset

Dataset	State Types and Sample Quantities		
	Normal Lubrication	Oil Scarcity	Oil Breakage
Training Set A	5	5	5
Training Set B	10	10	10
Training Set C	40	40	40
Training Set D	80	80	80
Training Set E	100	100	100
Test Set	100	100	100

4.2. Analysis of diagnostic performance under small sample conditions

In engineering practice, sliding bearings often operate under normal lubrication conditions for extended periods, while data on poor lubrication states is typically limited. To explore the model's diagnostic performance under small sample conditions, a series of experiments were designed in this chapter. Specifically, we used the five different training datasets with varying sample sizes listed in Table 1 to train the model separately. A unified test set containing 100 samples was used to evaluate the model's diagnostic performance. To investigate the impact of the number of training samples containing lubrication insufficiency information on the diagnostic efficacy of the method proposed in this study, the performance results of the model on the same test set are detailed in Table 2.

Table 2. Comparison of accuracy rates for different sample sizes

Sample Set	Accuracy%	Precision%	Recall%	F1 score
5	94.67	94.66	94.67	0.9465
10	96.58	96.64	96.58	0.9667
40	99.33	99.34	99.33	0.9933
80	99.33	99.34	99.33	0.9933
100	99.33	99.34	99.33	0.9933

Observing Table 3, it can be seen that when the number of samples for each state in the training set is only 5, the accuracy rate has already reached 94.67%. As the number of samples increases, the performance metrics of the model continue to improve and eventually stabilize. When the number of samples for each state increases to 40, the accuracy rate has reached 99.33%. This indicates that even with a small sample size, the SC-ResNet model can effectively distinguish between different states. Therefore, in subsequent experiments, the number of samples in the training set is determined to be 40, while the number of samples in the test set is uniformly set to 100. The test results of SC-ResNet are shown in Figures 5 and 6, respectively. The performance of the SC-ResNet network model on the test set is displayed using a confusion matrix, which is shown in Figure 7.

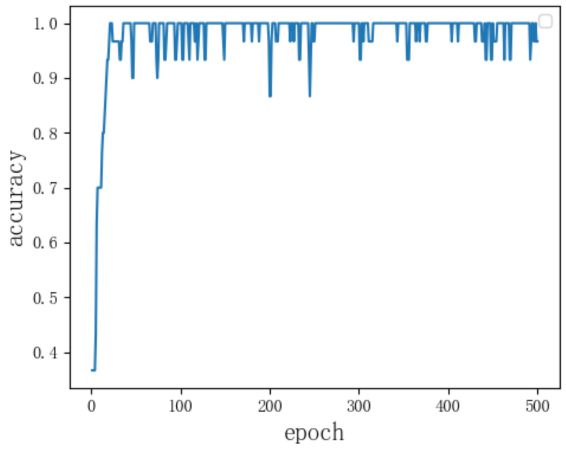


Figure 5. SC-ResNet accuracy on the test set

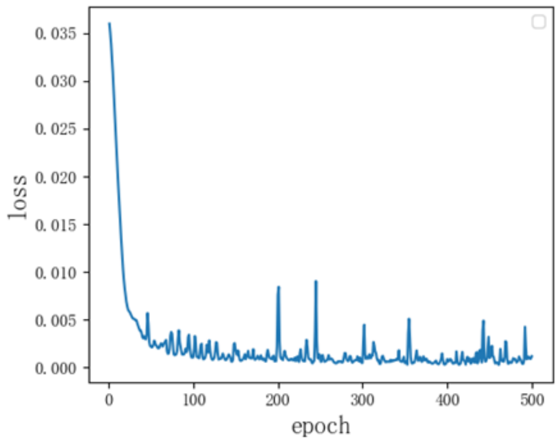


Figure 6. SC-ResNet loss value on the test set

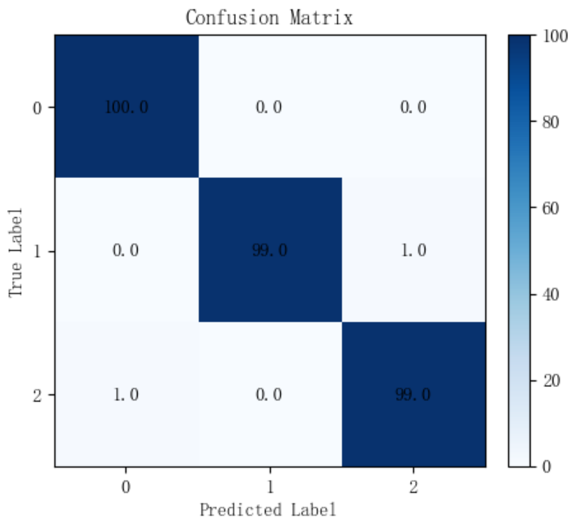


Figure 7. SC-ResNet confusion matrix

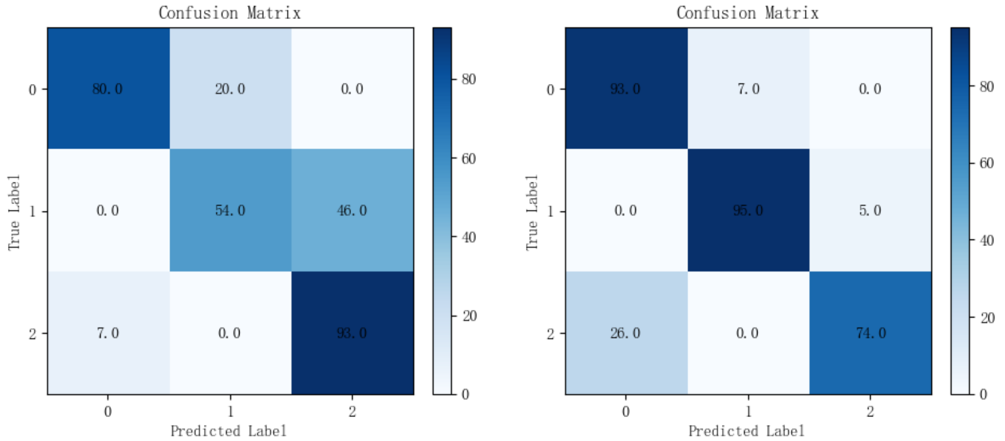
4.3. Comparative analysis with other methods

To further verify the advantages of the SC-ResNet model proposed in this paper under small sample conditions, two methods, ResNet and CNN, were selected for comparative analysis. The training results are shown in Table 3. It can be observed that the model presented in this paper significantly outperforms the other methods in terms of performance. Whether it is accuracy, recall, or the F1 score, our model achieves the highest values, indicating better identification effects.

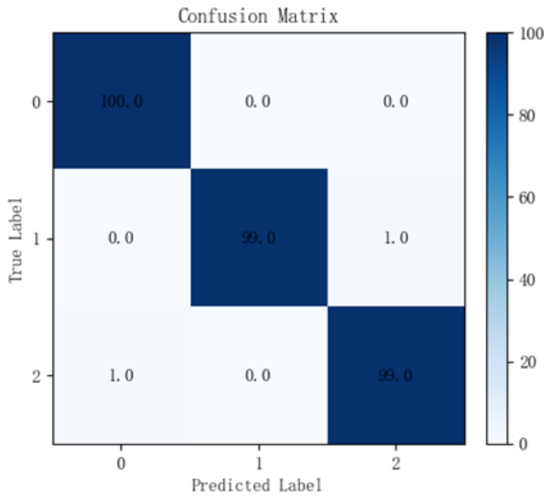
Table 3. Performance comparison with other networks

Method	Accuracy%	Precision%	Recall%	F1 score
CNN	75.67	77.28	75.67	0.7647
ResNet	87.33	88.32	88.33	0.8832
SC-ResNet	99.33	99.34	99.33	0.9933

To thoroughly evaluate the performance advantages of the SC-ResNet model in recognizing samples of lubrication insufficiency states, this study introduces three different methods for a quantitative analysis of the confusion matrix on the test set. The relevant results can be seen in Figure 8. It is evident that only the model proposed in this paper can essentially achieve complete differentiation between different bearing states, while other models exhibit varying degrees of misclassification. In particular, the misclassification phenomenon of the CNN model is more pronounced. Only 80 normal state samples were correctly classified, only 54 oil scarcity state samples were correctly classified, and only 93 oil breakage state samples were correctly classified. It can be seen that the CNN model has a significant misclassification when distinguishing between different lubrication states and cannot effectively complete the state diagnosis work. Regarding the improved ResNet model before the enhancement, 93 normal state samples were correctly classified, only 95 oil scarcity state samples were correctly classified, and only 74 oil breakage state samples were correctly classified. It can be seen that the ResNet model exhibited a significant misclassification with oil breakage lubrication state samples, resulting in poor diagnostic effectiveness. This phenomenon further confirms that the SC-ResNet model possesses excellent identification and classification capabilities for various lubrication states of sliding bearings under small sample conditions.



a CNN b ResNet



c SC-ResNet

Figure 8. Confusion matrices of different methods

5. SUMMARY

This paper presents a diagnostic method for the lubrication state of sliding bearings based on Self-Calibrated Convolutional Residual Neural Networks (SC-ResNet). Experimental results show that this method exhibits excellent diagnostic performance under various small sample conditions. When there are only five training samples per state, it achieves an accuracy rate of 94.67%. When there are only 40 training samples per state, the accuracy rate can reach 99.33%. Furthermore, compared to the recognition accuracy rate of 87.33% for the pre-modified ResNet network, the accuracy rate has been improved by 12%. Compared with other methods, the method proposed in this paper has a higher identification accuracy rate, as well as higher Recall and F1-score values in fault mode recognition.

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