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Bearing Fault Diagnosis Based on Auto-Encoder Combined with CNN

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Abstract. To address the problem that traditional bearing fault diagnosis methods rely on professional knowledge and are tedious, this paper proposes an end-to-end CNN-based bearing fault diagnosis model to achieve automatic fault recognition. In addition, considering the problem that noise exists in the actual working conditions, a bearing fault diagnosis model based on Auto-encoder(AE) combined with CNN is proposed(AE-CNN). The noisy signal is coded and decoded by the designed AE, and the de-noised result is used as the input of the designed CNN to achieve the bearing fault diagnosis under noisy conditions. Experiments on CWRU have proved the effectiveness of the designed CNN and AE-CNN. The designed CNN achieves 99.83% fault diagnosis accuracy under noise-free condition. The AE-CNN achieves 97.14% fault diagnosis accuracy under - 4db signal-to-noise ratio(SNR) noise condition, which is 2.31% higher than the CNN with the same noise, and compared with the results of other advanced methods, it has achieved competitive results.

Keywords. bearing, auto-encoder, noise, fault diagnosis, signal processing

1. Introduction

During the service of a certain naval gun, it relies on various mechanical equipment. Conducting research on mechanical equipment fault diagnosis can help maintain the safe operation of mechanical equipment, improve its reliability and stability. As an essential component, bearings account for a large proportion of mechanical equipment failures[1]. This paper focuses on the key components of mechanical equipment, bearings, and conducts research on bearing fault diagnosis methods based on vibration signal analysis.

Traditional methods heavily rely on professional knowledge to process raw signals and extract features. The bearing fault diagnosis method based on deep learning can automatically obtain the bearing vibration features of the original vibration signal to achieve end-to-end bearing fault diagnosis, without the need for professional domain knowledge to manually design and extract features. In [2-6], CNN, Long Short Term Memory, attention mechanism and a series of deep learning methods were applied to bearing fault diagnosis and achieved good results.

These methods have made some progress, but have not taken into account the noise issues in actual working conditions. Some researchers have shifted their focus to the

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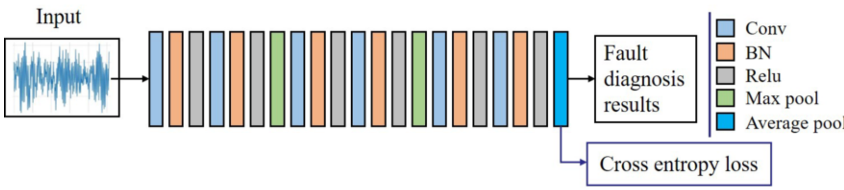

Figure 1. Structure of CNN-based bearing fault diagnosis model.

problem of bearing fault diagnosis under noisy conditions. Li et al. [7] proposed a new Transfer learning method based on domain confrontation training to achieve bearing fault diagnosis under -4dB 8dB SNR. The multi-scale noise-modulated SR method based on wavelet packet transform is studied in [8] and in the data reconstruction stage of [9], noise is reduced and the useful information hidden in the raw data is extracted. Although there have been studies focusing on bearing fault diagnosis in noisy environments, there is relatively little research available, and there is still significant room for improvement in diagnostic accuracy.

In response to the problem of traditional bearing fault diagnosis methods relying on professional knowledge and being cumbersome, this paper first takes the vibration signals of rolling bearings as the object, establishes an end-to-end fault diagnosis model based on CNN, and considers the problem of noise in actual working conditions, a bearing fault diagnosis model based on AE-CNN is proposed. The original vibration signals with added noise are encoded and decoded through AE, and the obtained denoised signal is used as the input of the designed CNN for feature extraction to achieve end-to-end bearing fault recognition and achieve bearing fault diagnosis under noisy conditions.

2. Methodology

This paper first establishes a bearing diagnosis model based on CNN, and the details are introduced in section 2.1. Afterwards, considering the actual working conditions of noise, a bearing diagnosis model based on AE-CNN is established, and the details are introduced in section 2.2.

2.1. CNN based bearing fault diagnosis model

This paper takes the vibration signal of rolling bearings as the object and establishes a bearing fault diagnosis model based on CNN, as shown in figure 1. Utilizing the powerful feature extraction ability of CNN, useful information is automatically extracted from the original bearing vibration signal, thereby achieving end-to-end bearing fault diagnosis.

The specific parameters of the CNN network model are shown in Table 1. The CNN model constructed in this paper has a total of three convolution modules, each of which uses the form of splitting the 3×3 convolution into 1×3 and 3×1 for convolution operations. There are two convolution layers, and each convolution layer passes through a batch normalization layer(BN) and a Relu layer, which can reduce the number of parameters and increase the nonlinear layer. And the first two convolutional modules end up using max pool, while the last convolutional module ends up using average pool, as can be seen in some classic networks [10].

Table 1. Parameter values of CNN-based bearing fault diagnosis model

Network layer	Kernel size	Padding	Stride	Output size
Conv	(3,1,16)	(1,0)	1	(32,32,16)
BN	(-,-,16)	-	-	(32,32,16)
Relu	-	-	-	(32,32,16)
Conv	(1,3,16)	(0,1)	1	(32,32,16)
BN	(-,-,16)	-	-	(32,32,16)
Relu	-	-	-	(32,32,16)
Maxpool	(2,2)	-	2	(16,16,16)
Conv	(3,1,32)	(1,0)	1	(16,16,32)
BN	(-,-,32)	-	-	(16,16,32)
Relu	-	-	-	(16,16,32)
Conv	(1,3,32)	(0,1)	1	(16,16,32)
BN	(-,-,32)	-	-	(16,16,32)
Relu	-	-	-	(16,16,32)
Maxpool	(2,2)	-	2	(8,8,32)
Conv	(3,1,64)	(1,0)	1	(8,8,64)
BN	(-,-,64)	-	-	(8,8,64)
Relu	-	-	-	(8,8,64)
Conv	(1,3,64)	(0,1)	1	(8,8,64)
BN	(-,-,64)	-	-	(8,8,64)
Relu	-	-	-	(8,8,64)
Averagepool	-	-	-	(1,1,64)

2.2. Bearing Fault Diagnosis Model Based on AE-CNN

Under real working conditions, noise is inevitable, and its source and size are uncertain, which will affect the model's extraction of bearing vibration signal features and ultimately affect the diagnostic results. To address this problem, this paper proposes a bearing fault diagnosis model based on AE-CNN. The original vibration signal with added noise is encoded and decoded by AE. The denoised signal is used as the input of the designed CNN for feature extraction to realize bearing fault identification. The network structure is shown in figure 2.

AE is an unsupervised neural network that first extracts data into higher dimensions through feature extraction, and then reconstructs the input. Based on the encoding and decoding structure, the encoder encodes low dimensional data into high dimensional data. The decoder receives high dimensional data and attempts to reconstruct the original low dimensional data, learning by changing the original input data from one representation to another. Some researchers applied AE to bearing fault diagnosis[11-13], but there is still room for improvement. In the fault diagnosis model based on AE-CNN constructed in this paper, AE is used to encode and decode the original vibration signal with added noise, and the denoised signal obtained is used as the input of the designed CNN for feature extraction.

For the details of the encoding and decoding process of the original vibration signal with added noise through AE: firstly, signal x is input into the encoder for feature extraction, and the signal undergoes downsampling, reducing spatial features; afterwards, the feature $y = f(x)$ after passing through the encoder is input into the decoder, and up-

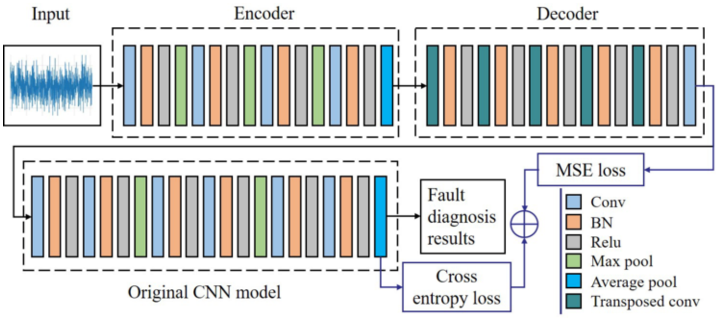

Figure 2. Structure of AE-CNN-based bearing fault diagnosis model.

sampling is carried out through transposed convolution to increase the width and height of the input, in order to achieve the purpose of noise reduction and signal recovery. The signal is restored to the original signal data $\widetilde{x} = g(y) = g(f(x))$ that is close to no noise, allowing $\widetilde{x}$ to replicate the input x as much as possible. During the signal recovery process, the number of channels decreases and the spatial scale increases. The encoding of the middle layer here is the most important mapping from the input signal to the encoder, which is to achieve automatic feature extraction of the signal. It can be expressed as follows:

$$
\begin{aligned}
y &= f(x) = A(wx+b) \\
\widetilde{x} &= g(y) = A(w^{'}x+b^{'}) \\
L_{AE}(x,\widetilde{x}) &= L_{AE}(x, g(f(x)))
\end{aligned} \tag{1}
$$

Where, A represents the activation function Relu, L_{AE} represents the loss function mean squared error(MSE).

The whole model is trained end-to-end, and the total loss L is the sum of the MSE after AE and the cross entropy loss after the original model.

$$
L = -\frac{1}{N}\sum_{i=1}^{N} log \frac{e^{W_{y_i}^T x_i + b_{y_i}}}{\sum_{j=1}^{n} e^{W_j^T x_i + b_j}} + \frac{1}{2}\sum_{k}(y_k^{'} - y_k)^2 \tag{2}
$$

Among them, n represents the number of fault categories; N represents the size of the batch size; $x_i \in \mathbf{R}^d$, which represents the feature vector of the $i-th$ sample, with an d -dimension; y_i represents the category label of the $i-th$ sample; $W \in \mathbf{R}^{d\times n}$ is the weight matrix, and W_j represents the $j-th$ column of W; $b_j \in \mathbf{R}^n$ is offset; $y_k^{'}$ represents data prediction output, i.e. decoder output; y_k represents the true label of the fault data; k represents the dimensionality of the data.

As the parameters of the original CNN model are already described in the previous section, the specific parameters of the encoder and decoder parts in the model are listed here, as shown in Table 2 and Table 3, respectively. The formula for calculating the size of the feature map after transposed convolution operation is:

$$
\begin{aligned}
H_{out} =&(H_{in}-1)\times stride[0]-2\times padding[0]+\\
&dialation[0]\times(kernel_size[0]-1)+\\
&out_padding[0]+1\\
W_{out} =&(W_{in}-1)\times stride[1]-2\times padding[1]+\\
&dialation[1]\times(kernel_size[1]-1)\\
&+out_padding[1]+1
\end{aligned} \tag{3}
$$

Among them, index [0] represents the data in the height direction, index [1] represents the data in the width direction, and *dialation* is a parameter that uses empty convolution. In this paper, the default is 1.

Table 2. Encoder parameter values of AE-CNN-based bearing fault diagnosis model

Network layer	Kernel size	Padding	Stride	Output size
Conv	(3,3,64)	1	1	(32,32,64)
BN	(-,-,64)	-	-	(32,32,64)
Relu	-	-	-	(32,32,64)
Maxpool	(2,2)	-	2	(16,16,64)
Conv	(3,3,128)	1	1	(16,16,128)
BN	(-,-,128)	-	-	(16,16,128)
Relu	-	-	-	(16,16,128)
Maxpool	(2,2)	-	2	(8,8,128)
Conv	(3,3,128)	1	1	(8,8,128)
BN	(-,-,128)	-	-	(8,8,128)
Relu	-	-	-	(8,8,128)
Maxpool	(2,2)	-	2	(4,4,128)
Conv	(3,3,128)	1	1	(4,4,128)
BN	(-,-,128)	-	-	(4,4,128)
Relu	-	-	-	(4,4,128)
Averagepool	-	-	-	(1,1,128)

3. Experiment

3.1. Dataset

The experiment uses the open dataset CWRU bearing vibration database of Case Western Reserve University in the United States to verify the proposed algorithm [14]. There are three types of bearing faults in this database, and a total of 10 different bearing health status data, corresponding to labels 0-9.

Table 3. Decoder parameter values of AE-CNN-based bearing fault diagnosis model

Network layer	Kernel size	Padding	Out padding	Stride	Output size
Transposed conv	(3,3,128)	1	1	2	(2,2,128)
BN	(-,-,128)	-	-	-	(2,2,128)
Relu	-	-	-	-	(2,2,128)
Transposed conv	(3,3,64)	1	1	2	(4,4,64)
BN	(-,-,64)	-	-	-	(4,4,64)
Relu	-	-	-	-	(4,4,64)
Transposed conv	(3,3,64)	1	1	2	(8,8,64)
BN	(-,-,64)	-	-	-	(8,8,64)
Relu	-	-	-	-	(8,8,64)
Transposed conv	(3,3,64)	1	1	2	(16,16,64)
BN	(-,-,64)	-	-	-	(16,16,64)
Relu	-	-	-	-	(16,16,64)
Transposed conv	(3,3,64)	1	1	2	(32,32,64)
BN	(-,-,64)	-	-	-	(32,32,64)
Relu	-	-	-	-	(32,32,64)
Conv	(1,1,1)	0	-	1	(32,32,1)

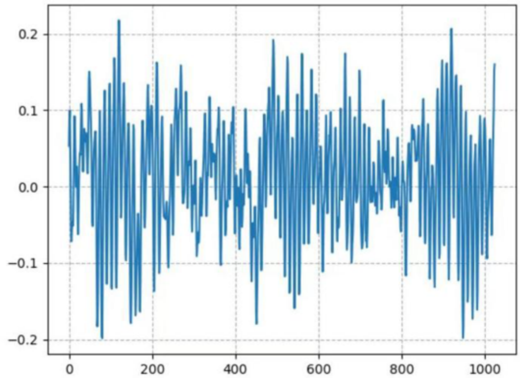

Figure 3. Image of original signal.

3.2. *Data preprocessing*

Adding noise to the original signal. Noise is widely present in various environments, among which additive white Gaussian noise (AWGN) is one of the most representative and easily quantifiable noises. This paper uses AWGN as additional noise to study the impact of noise on bearing fault signal classification. Five types of SNR are added, from strong to weak: -4dB, -2dB, 0dB, 2dB, and 4dB. Figure 3 and figure 4 shows the normal time-domain signal without noise added and the signal with noise added when the load state is 0. The SNR added is -4db. It is evident in figure 4 that the noise signal will seriously interfere with the original signal feature extraction.

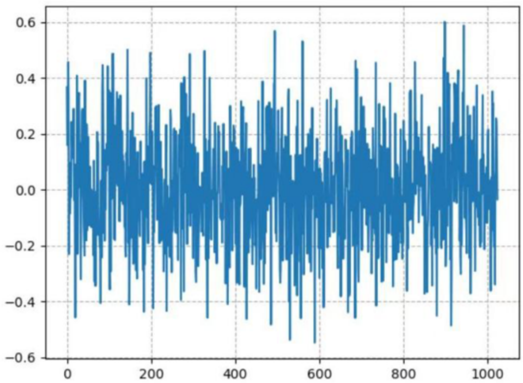

Figure 4. Image of signal after adding noise.

Data segmentation. This paper uses the data processing method where each segment has partial overlap to expand the effective data, and sets the length of a single data sample for overlapping sampling to 1024. During the experimental process of this paper, 70% of the sample data is randomly selected from each type of health status data as training data, 10% of the sample data is selected as validation data, and the remaining 20% of the sample data is selected as testing data.

Data rearrangement. This paper performs a rearrangement operation on one-dimensional time-domain signal, elevating it to a two-dimensional image. To obtain an image of N^2 size, the original vibration signal is randomly truncated with a length of $N \times N$ signal. Let $Q(i), i = 1,2,3...,N$ represent the numerical value of the original one-dimensional vibration signal, and $P(j,k), j,k = 1,2,3...,N$ represent the pixel intensity of the image. This paper rearranges the shape of 1024 one-dimensional data to a two-dimensional 32×32 image as the input.

3.3. Implementation detail

The adam optimizer is used for training. The initial learning rate and weight factor are set to 10^{-3} and 10^{-4} respectively, and the batch size used is 16. There are 25 periods in the training phase, and the learning rate of the 15th and 20th dropped by 90%. The graphics card used in this experiment is GTX1660Ti, with a dedicated GPU memory size of 6GB.

3.4. Experimental results and analysis

3.4.1. Experimental results of bearing fault diagnosis model based on CNN

This paper first conducted experiments on CRWU using the constructed CNN based bearing fault diagnosis model to verify the effectiveness of it. The accuracy of the validation and testing sets at each epoch is shown in the figure 5. It can be seen that at the 25th epoch, the accuracy rates are 100% and 99.83% respectively. Starting from the 15th epoch, the curves obtained on the three datasets tended to be stable and close to 1, proving the stability and accuracy of the model.

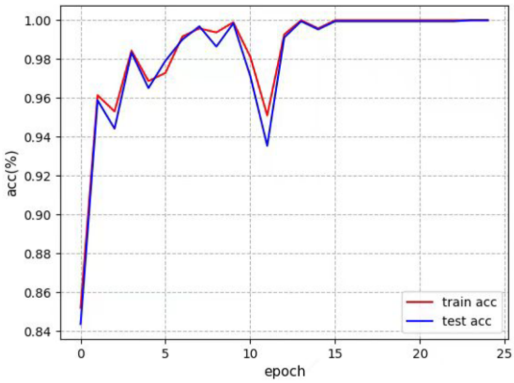

Figure 5. Accuracy of CNN-based bearing fault diagnosis model in the absence of noise.

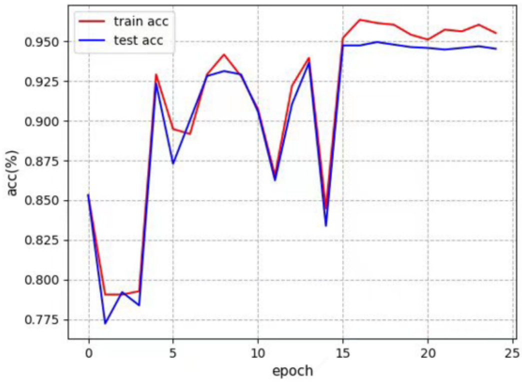

Figure 6. Accuracy of CNN-based bearing fault diagnosis model in the presence of noise.

Considering the noise under actual working conditions, this paper conduct experiments on the CNN based bearing fault diagnosis model with added noise. The experimental results are shown in figure 6. When adding noise of -4db, at the 25th epoch, the accuracy obtained by the validation and test sets are 96.35% and 94.95% respectively, which are 3.65% and 5.04% lower than those without noise. It can be seen that noise interferes with the model's extraction of signal features, which affects the fault diagnosis results.

3.4.2. Experimental results of bearing fault diagnosis model based on AE-CNN

According to the above experimental results, it can be seen that noise will reduce the accuracy of the model. Therefore, this paper proposes a bearing fault diagnosis model based on AE-CNN. The constructed model is tested on CRWU with added noise, and the accuracy obtained on the validation and test sets under different SNR noise conditions

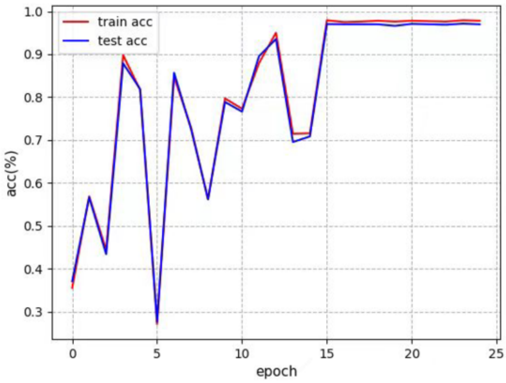

Figure 7. Accuracy of AE-CNN-based bearing fault diagnosis model in the presence of noise.

is shown in Table 4. The curves of the validation and test sets with SNR of -4db noise added are shown in figure 7. Figure 8 shows the confusion matrix, showing the details of AE-CNN fault diagnosis results. Compare the accuracy obtained with some advanced methods, and the experimental results are shown in Table 5.

Table 4. Comparison of fault diagnosis accuracy of AE-CNN model with different SNR

SNR(dB)	-4	-2	0	2	4
Validation set accuracy(%)	97.92	99.14	99.58	99.90	1.00
Test set accuracy(%)	97.14	98.49	99.32	99.64	99.79

From Table 4, it can be seen that the fault diagnosis accuracy of the AE-CNN is at a high level under various SNR conditions, indicating that the method proposed has strong noise suppression ability.

From figure 7, it can be seen that at the 25th epoch, the accuracy rates obtained by the validation and test set of AE-CNN are 97.92% and 97.14% respectively, which are 1.63% and 2.31% higher than the original CNN model, demonstrating the robustness of AE-CNN under noise conditions.

From the Confusion matrix in figure 8, we can see that AE-CNN has a high diagnostic accuracy rate for various bearing fault types. Except for rolling element fault B14 with fault size of 14mil, the diagnostic accuracy rate is 89.30%, the recognition rate for other fault types is higher than 90%, and the recognition rate for eight fault types is higher than 95%, and the recognition rate for three fault types is 100%. The rolling element fault B14 with a fault size of 14mil is easily confused with the rolling element fault B7 with a fault size of 7mil and the outer ring fault OR14 with a fault size of 14mil because their fault features are similar under noise conditions, leading to severe misjudgment by the model.

From Table 5, it can be seen that the AE-CNN has obtained competitive results compared with the experimental results of advanced methods. Compared to the siamese network [9], the AANN[15] and MCNN[16], it has increased by 0.91%, 4.03%, and 8.90% respectively, proving the effectiveness of the proposed AE-CNN model. The model presented in paper [17] [18] is relatively complex and achieves slightly higher accuracy than

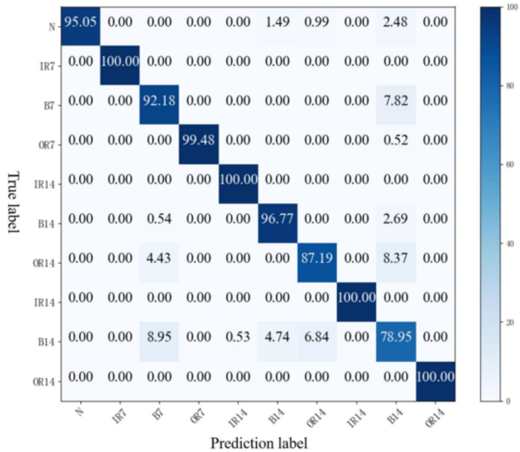

Figure 8. Accuracy of AE-CNN-based bearing fault diagnosis model in the presence of noise.

Table 5. Comparison of fault diagnosis accuracy of different methods under noise situation

Methods	Fault diagnosis accuracy(%)
The designed CNN	94.95
Siamese network[9]	96.26
AANN[15]	93.38
MCNN[16]	89.2
DLSTM[17]	97.21
CORAL[18]	97.85
AE-CNN[This paper]	97.14

our method. Our model is simple and easy to implement, capable of achieving good fault diagnosis accuracy, and has practical engineering significance.

4. Conclusion

This paper is based on deep learning methods for bearing fault diagnosis. Firstly, a CNN model is designed for end-to-end bearing fault diagnosis. Then, considering the presence of strong noise in actual working conditions, a bearing fault diagnosis model based on AE-CNN is proposed to achieve bearing fault diagnosis under noisy conditions. The experiment results on the CWRU demonstrate the effectiveness of the proposed model. The method proposed in this paper can be used for fault diagnosis of bearings under noise conditions, and has engineering practical value. However, due to the simplicity of the model, it still has a certain degree of scalability. On the one hand, the latest methods such as attention mechanism can be added to improve feature extraction capabilities, thereby improving the accuracy of fault diagnosis. On the other hand, the method proposed in this paper is to denoise the data before feature extraction and classification. In future research, we can improve the progressiveness of the model, which can directly extract and classify the data under noise conditions.

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