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Pumping unit fault analysis method based on wavelet transform time-frequency diagram and CNN

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Abstract

According to the characteristics of the signal of the pumping unit, the processing result of the wavelet packet threshold de-drying algorithm is not good, so this paper proposes a new method to improve the algorithm. Experiments show that the improved algorithm improves the signal-to-noise ratio by 2.2 dB compared to the traditional algorithm, and the root mean square error decreases. Then the signal of the pumping unit is (CWT), the time-frequency diagram is obtained, and it is displayed in the form of grayscale image. Then the time-frequency diagram is input as the feature map, and the CNN classifier model is established to realize the intelligent fault of the pumping unit. diagnosis. The results show that the method can effectively identify the fault type of the pumping unit and has a high recognition rate.

Keywords

Wavelet Transform; Convolutional Neural Network; Signal Processing.

1. Introduction

According to the characteristics of the pumping unit signal, the wavelet packet denoising can adaptively select the frequency band corresponding to the signal according to the characteristics of the signal to be analyzed, so as to be able to match the spectrum of the signal to be analyzed. The improved wavelet packet threshold algorithm proposed in the literature determines the corresponding threshold by determining different threshold parameters. This method is similar to most traditional wavelet packet denoising methods.

In order to solve the above problems, an improved algorithm based on wavelet packet coefficient threshold denoising is proposed. The pumping unit's signal is a typical non-stationary signal, and continuous wavelet transform (CWT), as a time-frequency analysis method, can effectively extract the time-frequency characteristics of non-stationary signals, and is one of the important methods for analyzing and processing non-stationary signals. The time-frequency analysis results of CWT are presented in the form of time-frequency diagrams. The time-frequency diagram is essentially a two-dimensional map reflecting the energy intensity of signals at different times and frequencies. It can display the details of signals from multiple angles, thus effectively describing the signals. Subtle fault characteristics! Therefore, the wavelet time-frequency diagram can be used as a characteristic map to characterize the running state of the rolling bearing to realize the fault diagnosis of the pumping unit! For example, Zhang Meijun can use the gray-scale time-frequency map generated by CWT to distinguish the normality of the gearbox. And the fault state, and can further distinguish two fault characteristics of the same frequency occurring at different times in the fault, but the judgment and recognition of the gray time-frequency map depends on experienced professionals, and the judgment

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result includes the person's Subjective factors, and the complexity of the fault makes it difficult for human judgment to meet the accuracy and efficiency requirements of the identification.

Convolutional Neural Network (CNN) is a multilayer perceptron (MLP) designed to identify two-dimensional feature maps. It is a deep learning network model with multiple hidden layers. It can transform low-level features to high-level features through layer-by-layer feature transfer, to achieve feature learning and expression compared to shallow networks compared to CNN for complex features. The ability to learn expression is stronger, the operation speed is faster, and the problem of training falling into local extremum is avoided.

Aiming at the above problems, this paper proposes an intelligent fault diagnosis method for rolling bearings based on wavelet time-frequency diagram and CNN, which is to generate CWT generated time-frequency map of the pumping unit vibration signal, and then input it as a feature map to CNN to realize pumping. Diagnostic identification of oil machine failures.

2. Data processing

2.1 Improved wavelet packet threshold denoising algorithm

First, the first decomposition reconstruction is performed. The processed signal f(t) is decomposed by N-layer wavelet packet (this paper selects the db5 wavelet basis function), and the threshold filtering of the 1~N layer wavelet coefficients is performed to remove the noise n(t) to obtain n1(t)g(t). Expressed as:

$$f(t) = n(t) + n_1(t)g(t) \xrightarrow{\text{阀值去噪}} n_1(t)g(t) \tag{1}$$

The threshold-filtered wavelet packet coefficients are reconstructed. The signal f1(t) is obtained. Since the signal f1(t) and the noise are statistically independent of each other, the logarithm operation is performed on f1(t). The expression is as follows:

$$lb(n_1(t)g(t)) = lb(n_1(t)) + lb(g(t)) \tag{2}$$

Then, a second decomposition and reconstruction is performed. Perform N-layer wavelet packet decomposition on lb(n1(t)g(t)) (this paper selects db7 wavelet basis function), and threshold the 1~N layer wavelet packet coefficients to remove the noise lb(n1(t) corresponding The wavelet packet coefficients are obtained, and the wavelet packet coefficients corresponding to lb(g(t)) are obtained. Finally, the wavelet packet coefficients after the second denoising are reconstructed to obtain lb(g(t)), and the expression is as follows:

$$\delta_\lambda(\omega) = \begin{cases} \omega - a\lambda + \dfrac{2a\lambda}{1+\exp(\omega)} & |\omega| \geq \lambda (0 \leq a \leq 1) \\ 0 & |\omega| < \lambda \end{cases} \tag{3}$$

Finally, an exponential operation is performed on lb(g(t)) to obtain a signal g(t) after the reactivation. The operation method is as follows:

$$lb(g(t)) \xrightarrow{\text{指数运算}} g(t) \tag{4}$$

In the above steps, the selection of the threshold function is more critical. The commonly used threshold functions have a hard threshold function and a soft threshold function. The hard threshold function is defined as:

$$\delta_\lambda(\omega) = \begin{cases} \omega & |\omega| \geq \lambda \\ 0 & |\omega| \geq \lambda \end{cases} \tag{5}$$

The soft threshold function is defined as:

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$$\delta_\lambda(\omega)=\begin{cases}\operatorname{sgn}(\omega)(|\omega|-\lambda) & |\omega|\geq\lambda\\ 0 & |\omega|\leq\lambda\end{cases} \tag{6}$$

In the above formula, w is a wavelet coefficient and is a threshold. It can be seen from the above equation that the hard threshold method is easy to make the signal oscillate because the wavelet coefficient value is discontinuous. The reason for this is that the method is based on the selected threshold value, and all points where the |w| value is less than the selected threshold after the signal is decomposed become 0, and all points greater than or equal to the threshold are still w. As can be seen from equation (6), the soft threshold function tries to make the processed estimated wavelet coefficient values overall continuous, but since the continuity of the threshold function is achieved by left and right movement.

Based on the above analysis, the absolute value of the wavelet coefficient estimated by the soft threshold function always has a constant difference from w, which greatly reduces the accuracy of reconstruction, so it is necessary to reduce this deviation, but if it is reduced to zero, it becomes hard. The threshold function, and our purpose is to minimize the error between the estimated value and the original wavelet coefficient. Based on this idea, the following new threshold function is constructed.

$$\delta_\lambda(\omega)=\begin{cases}\omega-a\lambda+\dfrac{2a\lambda}{1+\exp(\omega)} & |\omega|\geq\lambda(0\leq a\leq 1)\\ 0 & |\omega|<\lambda\end{cases} \tag{7}$$

When a is 0, the above formula becomes a hard threshold function; when a is 1, the above equation is equivalent to a soft threshold function; that is, as the || increases, the absolute value of the deviation gradually decreases to The constant deviation occurring in the soft threshold method is greatly reduced, the reconstruction precision is obviously improved, and the denoising effect is enhanced. So we only need to choose the appropriate value between 0 and 1, which will get better denoising effect.

2.2 Continuous wavelet transform

For functions in any space, the definition of CWT is:

$$CWT_f(a,\tau)=[f(t),\varphi_{a,\tau}(t)]=\frac{1}{\sqrt{a}}\int f(t)\varphi^*(\frac{t-\tau}{a})dt(l) \tag{8}$$

Where: the mother wavelet is obtained by stretching and translating:

$$\varphi_{a,\tau}(t)=\frac{1}{\sqrt{a}}\varphi\ (\frac{t-\tau}{a}),\ a,\tau\in R, a\neq 0 \tag{9}$$

Where: is a scale factor, indicating frequency-dependent scaling; is a translation factor; is a wavelet basis function! When I takes a large value, it is beneficial to extract low-frequency features in the signal. When the value is small, it is beneficial to extract the signal. High frequency characteristics in the middle.

The key to CWT is the selection of wavelet basis functions. The selected wavelet basis function waveform should be similar to the fault characteristics of the signal. The Morlet wavelet (morl wavelet) waveform is similar to the impact characteristics of the pumping unit fault, while the ComplexMorlet wavelet (cmor wavelet) is the complex form of the Morlet wavelet and has better adaptive performance. Therefore, this paper chooses cmor wavelet as the wavelet basis function of CWT.

Figure 1 is the signal waveform diagram of the pumping unit under different conditions, which are the time domain waveforms of the vibration signal of the pumping unit normal, 143V, 380V, 420V, locked and stopped. It can be seen from the figure that there are certain differences in the time domain

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waveforms of different states, but the identification of the signal states cannot be completed for non-professionals, and these signals are only individual ideal signals. In fact, the signal waveforms of some states are very similar. Hard to distinguish. Therefore, state recognition based on the time domain waveform of the signal alone is not reliable.

The normal condition is 220V, 143V is the low pressure condition, 380 is the high pressure condition, 420V is the higher pressure condition, and the blocking rotation is a case where the motor stalling motor still outputs the torque when the rotation speed is 0 rotation. jobs.

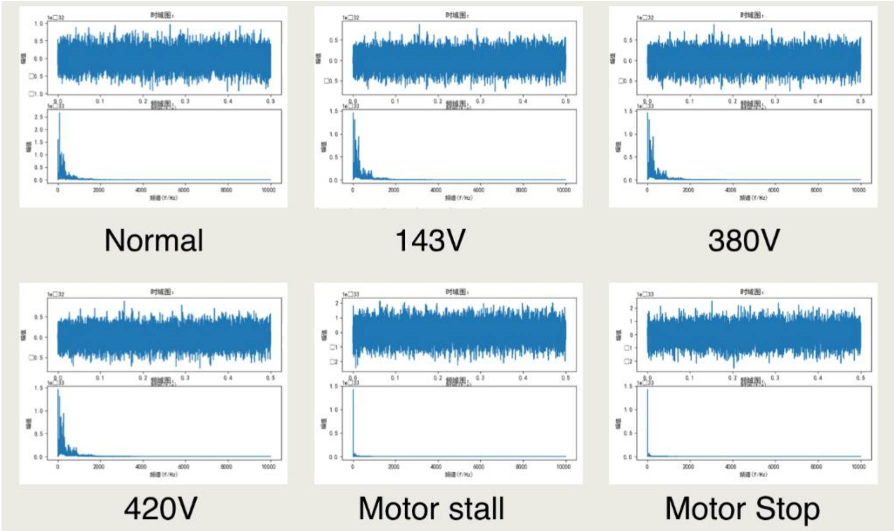

Figure 1 Signal waveform diagram of the pumping unit under different conditions

The CWT is generated by using the cmor3-3 wavelet base on the signals in the bearing sample data set to generate a time-frequency map. The six signals in the above figure are taken as an example, and the time-frequency diagram is shown in the figure below.

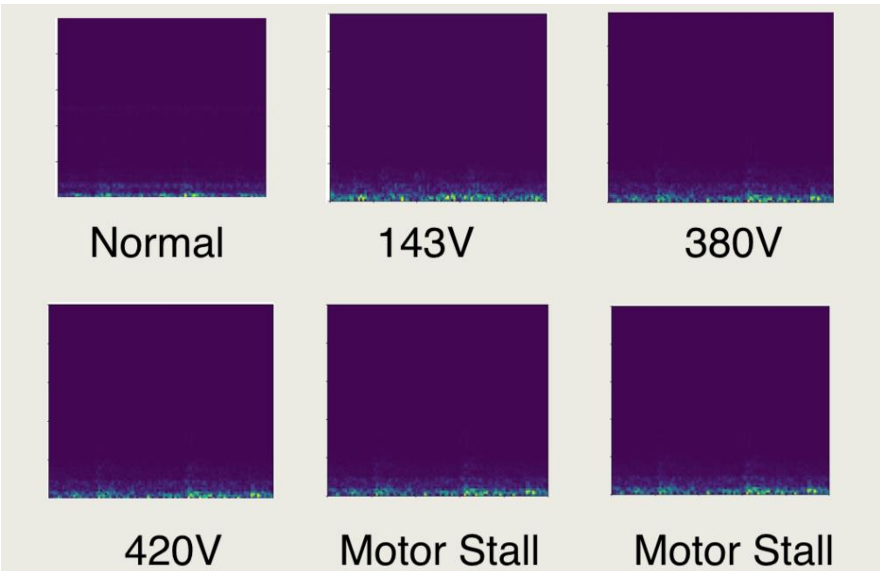

Figure 2 Time-frequency diagram of the pumping unit in different states

Then, the time-frequency map is compressed, and the compressed time-frequency map size is set to 28×28.

Finally, 1400 feature map samples of different states of the bearing were obtained, and 900 of them were selected as training samples, and the remaining 500 were used as test samples. The table below shows the number of different fault samples and the label configuration.

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Table 1 Sample size and label configuration for different faults

Signal type	training sample	Test samples	Sample label
Normal signal	900	500	[1 0 0 0 0 0] T
Motor 143V	900	500	[0 1 0 0 0 0] T
Motor 380V	900	500	[0 0 1 0 0 0] T
Motor 420V	900	500	[0 0 0 1 0 0] T
Motor shutdown	900	500	[0 0 0 0 1 0] T
Motor blockage	900	500	[0 0 0 0 0 1] T
Total	5400	3000	

3. Convolutional neural network

3.1 Structure of the network

The CNN is composed of an input layer, a hidden layer, a fully connected layer and an output layer. The hidden layer is composed of a plurality of convolution layers and sampling layers, and the full connection layer and the output layer form a classifier, and the classifier can be a logistic regression. Softmax regression, SVM. Wherein, the convolution layer is convolved with a feature map of the input layer by a specific convolution kernel plus an offset, and then an output function is obtained by an activation function; the sampling layer is characterized by the output feature map of the convolution layer. filter.

The structure of CNN used in this paper is shown in Figure 1: The size of the input feature map is 28X28, the hidden layer is composed of two layers of convolution and two layers of sampling, and the convolution kernels of the first and second convolution layers The numbers are 6 and 12 respectively, the size of the convolution kernel is taken as 5X5, and the activation function selects the sigmoid function. The sampling mode of the sampling layer selects the mean sampling, that is, the average value in the pxp region is obtained for the feature map, and the region size is 2X2 and the region is Do not overlap; the classifier chooses the softmax classifier.

3.2 Network construction and training tests and optimization and results

The structure of the CNN is the same as that of the above figure. In addition, since the state of the pumping unit to be identified is six, the number of output layer nodes of the network is taken to be six according to the setting of the sample label.

After the network structure is determined, the training samples are used to train the network. The training parameters are set as follows: batch=30, epoch=30, a=1. The configuration of the experimental platform is as follows: Windows 7 32-bit operating system, CPU is i5-3470@3.20Ghz, the program running environment is Matlab2011. The error convergence curve of the network in the training process is shown in Figure 7. The abscissa indicates the process of iterating 30 times for all batch sample sets in the network training process, and the ordinate indicates the network model in the training process to a batch sample set. Iterate 1 error value. It can be seen from the figure that after the network training iteration 30 times, the error value tends to a small value and remains stable, indicating that the network has been trained to converge.

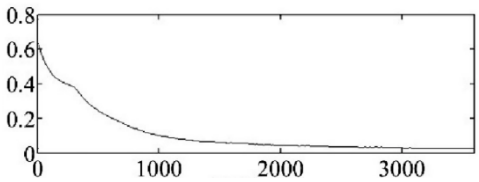

Figure 4 Iterative process

In order to improve the network's recognition performance of faults, optimization and improvement are made from the structural parameters and training parameters of the network.

The 10 structural schemes of the design network are trained and tested separately using the feature map sample set, and the training parameters are the same as 2.2. In order to test the stability of network performance and eliminate the influence of random factors, each experiment is repeated 10 times. The learning rate is adaptively adjusted and the training error is used as the stopping condition. The specific method is as follows: The learning rate is set to 0.9, the minimum learning rate is set to 0.6, and the learning rate is adjusted once every five iterations. The attenuation factor of the learning rate is set to 0.97; the training error limit value is 5 X. The experiment was repeated 10 times under the same conditions, and the results are shown in Table 5. It can be seen from the table that the method can effectively improve the correct recognition rate of the network and the stability of the recognition performance.

Table 2 Training Optimization Results

Number of experiments	1	2	3	4	5	6	7	8	9	10
Correct recognition of percentage	82.3	81.5	83.4	84.5	81.9	82.4	82.3	81.4	84.6	82.6
Number of iterations	71	68	72	72	69	70	69	68	72	70

Tested networks were tested using test samples. The final correct recognition rate was 96%, and the average time taken for iteration was 6.14 s. Table 3 shows the recognition results for different signal types.

Table 3 Identification rate of different faults

Signal type	Normal signal	Motor 143V	Motor 380V	Motor 420V	Motor shutdown	Motor blockage
Correct recognition of percentage	90	98	97	96	95	96.3

4. Conclusion

For the first time, the time-frequency diagram is directly used as the basis for fault diagnosis identification. Based on wavelet time-frequency diagram and CNN, the experimental research on intelligent fault diagnosis of pumping unit is carried out, and the following conclusions are drawn:

(1) The intelligent fault diagnosis method of pumping unit based on wavelet time-frequency diagram and CNN is feasible and effective. The time-frequency diagram generated by CWT can effectively reflect the time-frequency characteristics of the signal and accurately characterize the operating state of the pumping unit. Using CNN, the characteristics of the wavelet time-frequency map can be fully learned and expressed to realize the pumping unit. The intelligent diagnosis and identification of faults avoids the lack of feature expression caused by human participation and the lack of recognition accuracy and efficiency.

(2) By optimizing and improving the structural parameters and training parameters of CNN, it can effectively improve the correct recognition rate of faults and the stability of recognition performance.

(3) CNN can successfully identify similar fault samples with large difference in time-frequency diagram as one class, which reflects its strong generalization ability and clustering ability; CNN can successfully distinguish heterogeneous fault samples with similar time-frequency maps. Its strong feature extraction and recognition capabilities.

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