Fault diagnosis method of rare earth extraction production line based on wavelet packet and alexnet transfer learning

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Abstract: In rare earth production, improving the fault detection of extraction equipment has a key impact on improving extraction efficiency and product quality. The traditional method is based on the observation of the liquid level, the efficiency and accuracy can’t be guaranteed. In this paper, a fault diagnosis and recognition method for rare earth extraction production line based on wavelet packet and alexnet transfer learning is proposed. Taking six fault states of rare earth extraction production line as the research object, the fault signal is extracted by wavelet packet decomposition, and the corresponding target data set of time-frequency diagram is generated. Then, the pre trained alexnet model is trained and fine tuned on the generated target data set, and finally applied to fault diagnosis of rare earth extraction production line. The results show that the proposed method is more accurate than the traditional convolution neural network, which verifies the effectiveness of the method.

1. Introduction
Rare earth elements (REEs) have attracted wide attention and attention of the world's scientific and technological circles due to their unique properties and extensive uses, which have led to the development of many related high-tech industries. The emergence and breakthrough of new rare earth materials have greatly promoted the development of production technology. In the rare earth smelting process, extraction technology determines the level of rare earth production efficiency of enterprises, but also seriously affects the quality of products. The quality of extraction equipment and the degree of automation of equipment control restrict the operation efficiency of extraction production line. Therefore, it is very important to detect the status of rare earth extraction production line online in actual production to ensure the stable and safe operation of equipment Important.

At present, scholars have done a lot of research on fault diagnosis and online detection of rare earth extraction production line. Hu Qingzhong [3] proposed to use the Internet of things technology for online fault detection of rare earth extraction production line. Wang Zhantao [4] proposed a fault diagnosis method for rare earth extraction production line based on Bayesian quadric discrimination. In this paper, the fault diagnosis method based on BP neural network and neural network is proposed. Wang Xia [5] and others put forward an intelligent control system for rare earth extraction process, which is composed of intelligent optimization setting and process loop control.
In order to identify the fault status of rare earth extraction production line and improve the fault diagnosis accuracy of rare earth extraction production line, a fault diagnosis method of rare earth extraction production line based on wavelet packet decomposition and migration learning is proposed. Firstly, wavelet packet decomposition with high time-frequency resolution is selected to carry out time-frequency analysis on the collected fault signals and establish time-frequency image data set. Then, based on the deep learning framework, the time-frequency image data set is taken as the research object, and the alexnet network is used to classify the time-frequency image data set. The falling speed of loss function and the accuracy of verification set are used as evaluation criteria, and compared with the traditional convolution neural network recognition. The results show that the accuracy of alexnet is high and the decline rate is slower. The diagnosis mode of rare earth extraction production line based on time-frequency analysis and deep learning framework is established.

2. Wavelet packet decomposition

The traditional wavelet transform discretizes the scale parameters and translation parameters. It can extract the characteristics of the signal in different frequency bands and observe the time domain characteristics of the signal at different scales. However, this method can only decompose the low-frequency part of the signal, that is, the approximate part, while the high-frequency part, i.e., the detail part, is not decomposed, which means that the resolution of the high-frequency part of the signal is very low. The wavelet packet transform optimizes the method and decomposes the detail part of the signal. It divides the frequency band into several levels, adaptively selects the corresponding frequency band to analyze the signal characteristics, and the corresponding signal spectrum improves the time-frequency analysis ability. Figure 1 is a wavelet packet decomposition tree formed by three-level wavelet packet decomposition.

![Wavelet packet decomposition tree.](image)

Figure 1  Wavelet packet decomposition tree.

\( X_1 \) Represents the high frequency part of the signal, \( X_2 \) represents the low frequency part of the signal. Its resolution is determined by the frequency of wavelet packet decomposition. The more times of decomposition, the lower the resolution. So wavelet packet decomposition is widely used in non-stationary signal. The decomposition algorithm is as follows:

\[
P_{j+1}^{2i-1}(t) = H P_{j}^{i-1}(t) \\
P_{j+1}^{2i}(t) = G P_{j}^{i-1}(t)
\]

(1)

(2)

Where \( H \) is a low-pass filter, \( G \) is a high-pass filter, and \( P_j^i \) is a high-pass filter is the i-th wavelet packet obtained from the j-level wavelet packet decomposition. The number of wavelet packets in each layer is twice that in the previous layer. The data length of each wavelet packet is half of that of the previous layer, and the time domain resolution of each wavelet packet is halved. The frequency bands of wavelet packets are adjacent and the bandwidth is equal. The more levels of decomposition, the finer the frequency band.

In order to extract the correlation signals of a certain frequency band or some frequency bands, it is necessary to adopt the wavelet packet reconstruction algorithm. The reconstruction formula is as follows:

\[
P_j^i(t) = G^* P_{j+1}^{2i}(t) + H^* P_{j+1}^{2i-1}(t)
\]

(3)

\( G^* \) and \( H^* \) is the dual operator of \( G \) and \( H \), and also the conjugate transposition matrix of \( H \) and \( G \). Suppose that the original signal is decomposed by j-level wavelet packet to get 2j wavelet packets. If the 2i wavelet packet is to be reconstructed, the data of other wavelet packets in this layer should be set to zero. The processed data is substituted into the reconstruction formula to reconstruct layer by layer.
The meaning of the above expression is that the signal is reconstructed by wavelet packet decomposition low-frequency coefficient and high-frequency coefficient obtained by threshold quantization.[6]

3. Alexnet migration learning network
Alexnet is a kind of transfer learning network, which is composed of five layers of convolution layer, three layers of pooling layer and three layers of full connection layer. The pooling layer is behind the convolution layer, and the activation function of linear rectification function is used for nonlinear operation. The back-propagation algorithm is used to update the network parameters.

The input of the network is 224 * 224 * 3 pictures. The number of cores in the first layer of convolution layer is 96, and the size is 11 * 11 * 3. After input, convolution is used. Here, the nonlinear relu function is used as the neuron activation function, which can accelerate the convergence speed of the network. The expression of the relu function is as follows:

\[ f(x) = \max\{0, x\} \] (4)

When using the relu activation function and the gradient descent method, the convergence speed is faster. Only one threshold value is needed to get the activation value, and the calculation speed is faster. Alexnet also has a special computing layer, LRN layer, which smoothes the output of the current layer. Its calculation formula is as follows:

\[ b_{k,y} = a_{k,y} / (k + \alpha \sum_{j=\max(0,i-\frac{n}{2})}^{\min(N-1,i+\frac{n}{2})} (a_{j,y}^l)^2)^\beta \] (5)

\( N \) is the number of convolution kernels, \( k, \alpha, \beta, n \) is a super parameter, \( b_{k,y} \) and \( a_{k,y}^l \) represents a position in the output structure, and their superscript indicates the channel where the current value is located, indicating that the direction of stacking is along the channel.

4. Fault diagnosis of rare earth extraction production line
The production process of rare earth extraction mainly includes extraction and washing stages. After the solution enters the extraction workshop, it flows through the extraction tank and is continuously stirred by the stirring device to make the solution containing rare earth elements fully contact with the organic solvent. The mixing device mainly consists of motor, mixing shaft, belt and fault monitoring equipment. The fault monitoring system mainly monitors the speed of belt and the voltage of motor.

Generally, one motor drives several stirring tanks, and the relevant fault data are collected through sensors. So far, several common faults of rare earth extraction production line are selected for analysis. The common faults and measured fault data are shown in Table 1.

| Serial number | fault type                        | data type     |
|---------------|----------------------------------|---------------|
| 1             | Fracture of mixing shaft         | Vibration signal |
| 2             | Drive shaft slipping             | Vibration signal |
| 3             | Motor coil short circuit         | Speed signal  |
| 4             | Cracks on outer shaft of mixing bearing | Vibration signal |
| 5             | Voltage fault                    | Voltage signal |
| 6             | Current fault                    | Current signal |

According to the inquiry data, the rated voltage, current and speed of the rare earth extraction line are 380V, 9.9A and 720rad/min respectively. When the voltage works normally, the voltage fluctuation range is between -5% and 10%, and the normal current is not more than 10% of the average three-phase current. The vibration signal, speed signal, voltage signal and current signal under different working
faults are measured. The working frequency is 12khz. In the first class, 400 data points are taken as a data set, and 300 data sets are selected and randomly divided into training set and test set. The number of training set and test set is 200 and 100. After grouping, wavelet packet is used to decompose these signals to extract fault features. The time-frequency diagram produced by wavelet packet decomposition is shown in Figure 2.

![Figure 2 Wavelet packet time frequency chart](image)

Through the time-frequency diagram, different fault signals can be clearly seen. After wavelet packet decomposition, the high-frequency part can be expressed in the time-frequency diagram. The dark color represents the higher energy characteristics. It is proved that the time-frequency diagram after wavelet packet decomposition can express the fault characteristics obviously.

The generated time-frequency chart is brought into the migration learning network for training and learning. The CPU is i5-8625 of Intel, the frequency is 1.8GHz, and the memory is 8G. The training is based on MATLAB 2019a platform. Set the maximum number of iterations to 504, the default value of the solver is 0.01, and the maximum number of training cycles is 8. The confusion matrix is obtained as shown in Figure 3, and the serial numbers in the figure correspond to those in Table 1.

![Figure 3 confusion matrix](image)
From Figure 3, it can be clearly seen that, in addition to the identification error of 2% in the mixing shaft fault, other faults can be identified accurately.

![Figure 4 alexnet training curve](image)

The accuracy and loss function is shown in Figure 4, in which the abscissa represents the number of iterations, the ordinate represents the discrimination error, the red curve represents the training sample data error, the blue curve represents the accuracy discrimination rate of the training sample data, and the zigzag curve represents the training curve with the learning rate of 0.01. It can be seen from the figure that if the iteration is more than 180 times, the error rapidly decreases to less than 0.5. The transformation of the accuracy curve corresponds to that of the loss function curve one by one. Finally, the training accuracy is 99.44% and the data loss is less.

Compared with the traditional convolution neural network, the accuracy of the traditional neural network can only reach 80.49%, which proves that the proposed method has higher accuracy than the traditional convolution neural network.

5. Conclusion
According to the development of rare earth production industry, combined with the development of artificial intelligence detection technology, a fault diagnosis method of rare earth extraction production line based on wavelet packet and alexnet migration learning is proposed in this paper. Combining with the actual production status of extraction production line of a rare earth production company, the expected effect is achieved. Alexnet is suitable for learning convolution network with small sample size, and can greatly shorten the time of calculating the fitness function value in the optimization process. It can solve the problem of multi state fault diagnosis with small samples, and greatly improve the fault diagnosis performance of rare earth extraction production line.

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