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Study on Fault Diagnosis of Dynamometer Card Based on Multi-scale Convolution Neural Network

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Abstract

Fault diagnosis of dynamometer card has great significance to the condition analysis of sucker rod pumps. At present, the recognition accuracy of dynamometer diagnosis method is not high, and it needs complex feature extraction process. To solve this problem, this paper proposes a fault diagnosis method for dynamometer card based on multi-scale convolution neural network. Multi-scale convolution neural network extracts features independently, and convolution kernels of different sizes can extract more comprehensive and effective features of dynamometer card. Finally, the extracted feature vectors are classified by using softmax function. The method is validated by real oilfield data. Experiments show that the recognition accuracy of this method is 99.44% for 8 working conditions, such as traveling valve leakage, gas influence, insufficient liquid supply, standing valve leakage, sand production, oil rod break off and normal operation.

Keywords

Deep learning, multi-scale convolution, dynamometer card, fault diagnosis.

1. Introduction

Rod pumping units are widely used in China's petroleum industry. At present, the most widely used fault diagnosis method of rod pumps is to use dynamometer data for analysis. The dynamometer is a two-dimensional curve drawn based on the sampling data of the suspended point load and displacement. The curve shape and curve data can effectively and intuitively reflect the working condition of the pump.

At present, the main dynamometer diagnosis method is to extract feature vectors that can effectively reflect the operating conditions of the pump, and use the diagnostic model to diagnose.Li Kun et al. used the invariant moment to analyze the power diagram[1].Wang Xiufang et al. described the power diagram by mapping the power diagram curve to a gray correlation matrix[2].Li Kun et al. used freeman chain codes to describe the outline of the dynamometer diagram to extract dynamometer features[3], and Zheng Boyuan et al. extracted seven geometric features such as the valve's working position and area to analyze the dynamometer diagram[4].These methods first extract the eigenvector feature vectors. Then using BP neural network, support vector machine (SVM), clustering, extreme learning machine (ELM) and other diagnostic models for fault identification.These fault diagnosis methods rely on manual selection of features, calculation is complex, and the results are uncertain, and there is still much room for improvement in fault diagnosis rate.

In recent years, deep learning methods have achieved breakthrough research results in face recognition, medical image classification, etc.and their powerful feature learning capabilities have attracted widespread attention.The development of deep learning provides new ideas for fault diagnosis of dynamometers.

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Zhong Zhidan et al. introduced a deep belief network to perform automatic feature extraction on dynamometer images, avoiding complex manual feature extraction processes, and improving the recognition rate and speed[5,6].Duan Youxiang et al. applied the improved Alexnet model to fault diagnosis of dynamometer diagrams, and achieved good recognition results in four operating conditions: normal, unsatisfactory, gas influence, and sucker rod broken[7]. Zhong Zhidan et al. proposed to use Convolutional Neural Network (CNN) for feature extraction of dynamometer diagrams and use SVM as a classifier for fault recognition[8].Fan Haojie et al. used sparse autoencoders[9] and stack sparse autoencoders[10] to extract the separability characteristics of dynamometer data. Using deep learning networks to perform dynamometer fault diagnosis, the diagnostic performance shows superiority compared to traditional diagnostic methods that rely on manual feature extraction.

Existing deep neural networks used for fault diagnosis of dynamometer diagrams are completed in a single path, and the size of the filter is individually set in each layer, which limits the flexibility of the parameters.Song Qingsong et al. used a multiscale convolutional neural network to extract the combined multiscale features of traffic signs, which improved the accuracy of the algorithm[11].Multi-scale convolutional neural networks have also achieved good results in plant leaf recognition[12] and face recognition[13]. Multi-scale convolutional neural network has not been used in dynamometer fault diagnosis methods. Therefore, this paper proposes a multi-scale convolutional neural network-based fault diagnosis method for dynamometer diagrams.Using multi-scale convolution to extract richer and more effective features of the power diagram, which improves the accuracy of fault identification.

2. Multi-Scale Convolutional Neural Network

This paper presents a multi-scale convolutional neural network model for fault diagnosis of dynamometer diagrams. The multi-scale convolutional neural network includes an input layer, a multi-scale convolutional layer, a pooling layer, a fully connected layer, and an output layer. Convolution kernels of different sizes can extract different features. Convolution kernels of small size are convoluted to obtain features that better reflect local characteristics. Convolution kernels of large sizes are convoluted to obtain features that better reflect global characteristics, so the resulting features can better reflect the characteristics of the input image, and ultimately achieve better classification results.

In the multi-scale convolutional layer, three different sizes of convolution kernels are used to extract the features of the input feature map, and the feature extraction results are stitched as the output features of the multi-scale convolution block. Figure 1 shows a multi-scale convolution structure.

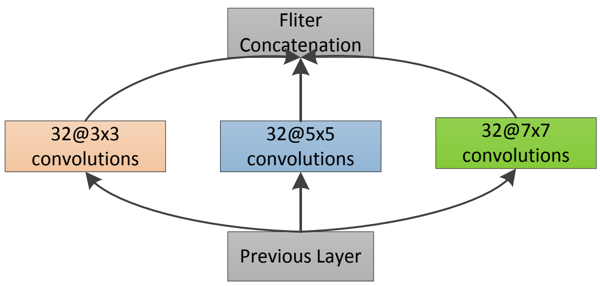

Figure 1. Multiscale convolution block

The multi-scale convolutional neural network model proposed in this paper includes a total of 8 layers. The model includes 2 multi-scale convolutional layers, 2 maximum pooling layers, 1 convolution layer, 1 average pooling layer, and input and output. The multi-scale convolutional neural network structure is shown in Figure 2.

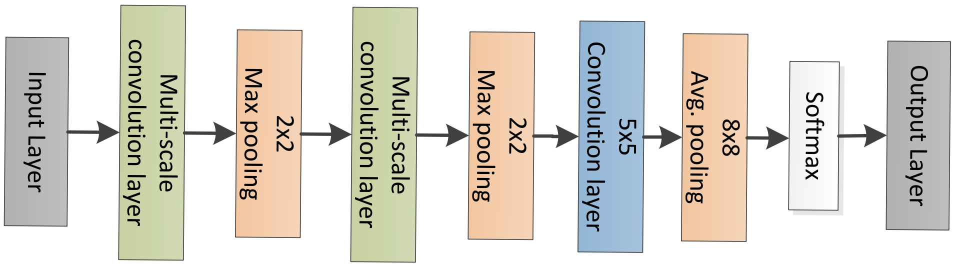

Figure 2. Multiscale CNN structure

The activation function can improve the non-linear characterization ability of the network model and it has a significant impact on the performance of the neural network. The activation function after the convolutional layer of the model used is Swish activation function in this paper , and its formula is as shown in equation (1).The Swish function has the characteristics of no upper bound, lower bound, smoothness, and non-monotonicity. The Swish function has the characteristics of no upper bound, lower bound, smoothness, and non-monotonicity.

$$f(x) = x \cdot \frac{1}{1+e^{-x}} \tag{1}$$

3. Experiment and Result Analysis

3.1. Experimental Data

The data used in the experiments in this paper are from the real data collected in the oilfield, with a total of 3184 dynamometer data. This article mainly identifies seven types of pump failures such as sand production, disconnection, gas impact, insufficient liquid supply, fixed valve leakage, swimming valve leakage, and air lock, as well as normal operating conditions. Figure 3 shows eight typical operating conditions.

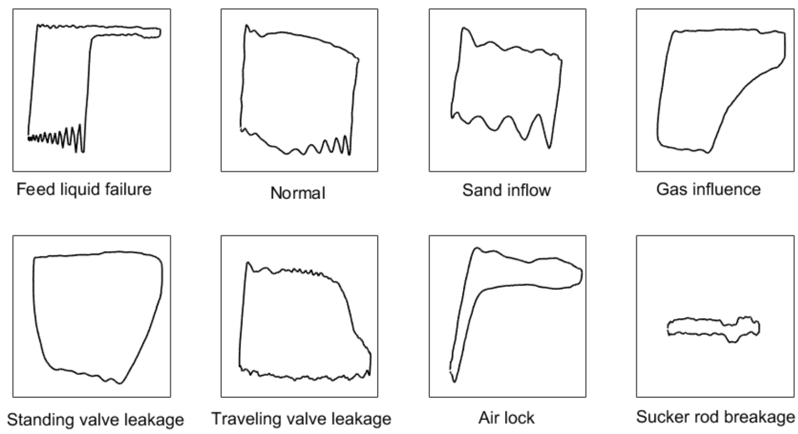

Figure 3. Eight typical working condition indicator diagrams

According to the input size of the network structure, the dynamometer data is pre-processed into normalized, smoothed and other pre-processed pictures of size 32 * 32. Randomly select 2/3 of the dynamometer data for various working conditions as the training set, and the remaining 1/3 as the test set. The training set has a total of 1932 pieces of data and the test set

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has 1,252 pieces of data. There are 8 types of power diagram data in this article. The eight types of data samples are represented by numbers 0-7. The model in this paper uses the softmax classifier to classify. Therefore, the One-hot coding label of the power diagram data is added. The distribution and labels of different types of dynamometer data are shown in Table 1.

Table 1. Indicator diagram data and labels

Fault description	No. of train samples	No. of test samples	label	One-hot label
Normal	300	200	0	[1 0 0 0 0 0 0 0]
Traveling valve leakage	300	200	1	[0 1 0 0 0 0 0 0]
Sand inflow	300	200	2	[0 0 1 0 0 0 0 0]
Gas influence	300	200	3	[0 0 0 1 0 0 0 0]
Feed liquid failure	240	120	4	[0 0 0 0 1 0 0 0]
Standing valve leakage	300	200	5	[0 0 0 0 0 1 0 0]
Air lock	110	76	6	[0 0 0 0 0 0 1 0]
Sucker rod breakage	82	56	7	[0 0 0 0 0 0 0 1]

3.2. Comparative Experiment of Different Network Models

In order to verify the fault recognition performance of the model in this paper. Compare the model in this paper with the PSO-SVM model in the literature[1], the CNN-SVM model in the literature[8], and the improved Alexnet network model in the literature[7].The analysis is performed from the aspects of feature extraction and accuracy on the test set. The experimental results are shown in Table 2.

Table 2. Three Scheme comparing

Method	Testing accuracy(%)
PSO-SVM[1]	92.19
MiniAlex[7]	97.69
CNN-SVM[8]	98.24
Method of this article	99.44

As can be seen from Table 3, the test accuracy of the deep neural network model is much higher than that of the PSO-SVM model. The PSO-SVM model manually selects the classification features to be extracted, and then uses the extracted features for fault diagnosis. These features can't express the differences between the dynamometers, and this fault diagnosis model is very dependent on the selected features, and has a certain degree of uncertainty. The deep learning model automatically extracts features through neural networks, avoiding the tediousness and uncertainty of artificially selecting features, and the extracted features can better reflect the differences between the power maps. Compared with other deep learning models, the model in this paper has the highest test accuracy, which indicates that the model in this paper has better feature extraction capabilities, and the extracted features contain more comprehensive and effective identification information, which can get better fault diagnosis results.

4. Conclusion and Suggestion

This paper proposes a fault diagnosis method based on multi-scale convolutional neural network for the seven fault working conditions and normal working conditions of sucker rod pump. A multi-scale convolution block is composed of convolution kernels of three sizes: 3 * 3, 5 * 5, 7 * 7. The model uses two multi-scale convolution blocks to perform multi-scale feature extraction on the dynamometer, and finally uses softmax function to classify. Experiments show

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that compared with the traditional indicator diagram fault diagnosis model, the proposed model avoids the complex feature engineering and reduces the dependence of fault recognition accuracy on the selected features. At the same time, compared with the traditional convolution neural network, the proposed model uses convolution kernels of different sizes to extract more effective global and local features and improves the recognition performance of the model. This model has a high recognition rate in the fault diagnosis of indicator diagram. It has a good application value to apply the idea of artificial intelligence to the fault identification of indicator diagram.

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