Intelligent fault diagnosis system design and implementation of diaphragm pump based on artificial intelligence

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Abstract. This article designs and implements a fault diagnosis system for diaphragm pump. The key components of the diaphragm pump are equipped with three-axis vibration intelligent sensor to collect vibration data, the edge side completes the data pre-processing, and then transmits it to the cloud platform through NB-IoT. For the non-linear, non-smooth complex system, the time frequency representation is obtained by continuous wavelet transformation, after compressing the time frequency representation as the input of the two-dimensional neural network model, using the two-dimensional convolutional neural network model for training and monitoring, to complete the identification and positioning of diaphragm pump fault.

1. Introduction
Diaphragm pump is a large equipment of water conservancy and hydropower. Regular inspection, spot inspection, patrol inspection, overhaul and minor repair are carried out according to relevant national standards. Due to the high reliability requirements of water conservancy and hydropower projects, the relevant standards are mostly conservative. With the improvement of equipment design and manufacturing technology, material technology and operation scheduling technology, the relevant specifications and standards seriously do not adapt to the actual situation. The implementation of the specifications leads to a large number of "over maintenance" problems in the industry. A large number of non-must be disassembled, not only destroyed the dynamic and static running clearance, affecting the life of the diaphragm pump. At the same time, the cost of diaphragm pump equipment has increased significantly. Therefore, it is of technical significance and economic value to establish fault diagnosis model for the key components of diaphragm pump to realize fault warning and diagnosis.

2. Overall framework design for intelligent failure systems
The intelligent fault system is shown in Figure 1, it consists of the perception layer, the transmission layer, the cloud platform and the application software from the bottom to top. After collecting the vibration data and completing some pre-processing, the three-axis vibration intelligent sensor transmits the data to the cloud platform through the NB-IoT module, which is analyzed and processed by industrial big data and artificial intelligence algorithms, thus completing the fault alarm and diagnosis.
2.1. Intelligent sensor installation
A factory motor spindle speed is $n = 1490 \text{rpm}$, the rotation frequency of the spindle is $f_r = n/60 = 24.8 \text{Hz}$, and the number of gear teeth carried by the spindle is 30, the gear swing frequency is $f_s = 24.8 \text{Hz}$, meshing frequency is $f_m = 30 \times 24.8 = 744 \text{Hz}$, therefore, the base frequency sampling frequency is $f_s = 744 \times 2.56 = 1905 \text{Hz}$. The article does not use traditional sensors, but intelligent sensors AIC8641-20, is to take into account the complex industrial field wiring and overall cost. Its installation diagram is shown in Figure 2.

2.2. Convolutional neural network data processing
The characteristics of one-dimensional vibration data are relatively single, and the network model may ignore some valuable information in the signal. In this paper, the one-dimensional vibration data is enhanced sampling, a small section of vibration data is obtained, and then this small segment of discrete vibration data is analyzed by time-frequency-domain to obtain a time frequency representation[1].

2.2.1. Data enhanced sampling
The original vibration data shall be overlapped and sampled[2], and the samples collected each time have a part of overlap. If the data of 120000 discrete points are sampled, 1000 adjacent discrete points shall be collected for each sample in a step of 100, so that there will be an overlapping part of 900 points between each two adjacent samples. In this way, a vibration data with 120000 points can obtain 1190 samples, although there are 900 duplicate data points between adjacent samples, they are completely different inputs for neural network.

2.2.2. Time-frequency representation of vibration data
The time-frequency representation of the time-domain data samples obtained by enhanced sampling is obtained through time-frequency-domain analysis. At present, there are mainly two time-frequency-domain analysis methods for obtaining time-frequency diagrams, one is based on short-time Fourier transform (STFT) and the other is based on continuous wavelet transform (CWT). The zoom function of CWT has obvious advantages in the analysis of non-stable signals of water conservancy and hydropower. The larger the number of sampling points in the scale domain of CWT, the higher the analysis accuracy, and higher quality TFR images can be obtained.

Based on the time-domain analysis of continuous wavelet transformation, if equation (1) is a small wave fundamental function, the continuous wavelet transformation can be defined as the inner product of signal $f(t)$ and wavelet base, such as equation (2)[3].
\[ \psi_{ab}(t) = \frac{1}{\sqrt{|a|}} \psi \left( \frac{t-b}{a} \right) \]  

(1)

\[ W_{\psi f}(a,b) = [f(t), \psi_{a,b}(t)] = \frac{a}{\sqrt{|a|}} \int_{-\infty}^{+\infty} f(t) \psi \left( \frac{t-b}{a} \right) dt \]  

(2)

Where a is a scale factor, representing frequency-related scaling, b is a time translation factor.

2.2.3. Time-frequency representation zoom

The data sampling frequency is 2560Hz, in order to obtain all the frequency information in the conversion process, the TFR image obtained by continuous wavelet transformation is a huge image data. In order to better train the network, the image must be compressed. In this paper, the nearest neighbor interpolation method[4], bilinear interpolation method and bicubic interpolation method are tested and compared. The closest neighbor interpolation method is to assign the grayscale value of the pixel closest to the pixel to be sought in the four adjacent pixels to the pixel to be sought. The nearest neighbor interpolation method compresses the image in small amount, but will cause discontinuity in the grayscale of the resulting image, there may be obvious jaggedness in the grayscale change, and the use of bilinear interpolation method to compress the image can meet the requirements of the algorithm for data. Bilinear interpolation is a linear interpolation operation in two directions, which makes full use of the real pixel values in the source graph to jointly determine a pixel in the target graph.

2.3. Structure and training of two-dimensional convolutional neural networks

The convolutional neural network structure used in this paper is improved on the basis of LeNet, and the structure is shown in Figure 4, using the deep convolutional neural network structure of five convolution layers, of which the convolution core size of the first convolution layer is 7x7, and the convolutional core size of the remaining convolution layer is 3x3. After extracting the features through the convolution core with larger size in the first convolution layer, then the small convolution kernel is used to extract detailed features, which can enhance the expression ability of the network. Because there are few convolution kernel parameters and a batch normalization layer is added between the first bad convolution layer and the pool layer, it is helpful to reduce the possibility of over fitting.

2.3.1. Batch Normalization Layer

Batch normalization can improve the training efficiency of deep neural network and enhance the robustness of network. Batch normalization[5] is a method of data normalization, and for data from any output in training, the data is regulated to a central area, which is a good way to combat gradients disappearing. If the effect on each layer of the network, you can control the distribution of data with the input changes sensitive areas, equivalent to regardless of the change in data distribution, the efficiency of this training is improved.
2.3.2. *Training of two-dimensional convolutional neural networks*

The training process is as follows, because two-dimensional picture data is different from one-dimensional data, it is not realistic to write a large amount of data to memory, so the way to transfer data to the network by feed. TensorFlow supports placeholders, so the training network uses a combination of feed_dict() and feed(), which is equivalent to building a pipeline between the network models between data sets, and then providing data to the network model by setting the size of the batch, which can save memory and improve training efficiency.

3. *Experimental results and conclusions*

In this paper, the proposed method is verified by the bearing data of Jiangsu Aerospace Hydraulic Equipment Co., Ltd, the various faults are identified, and the two-dimensional convolutional neural network of the Figure 4 deep learning architecture is used, and the three-layer convolution is used. Using the TFR image data after wavelet transformation as input to train the network, and using Tensorboard to monitor the training and testing process, after training 11,000 steps, the model accuracy stabilized and the accuracy reached 90%.

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**References**

[1] Li, H.K., Zhou S, Huang W.Z. (2010) Research and application of state recognition method based on time-frequency image feature extraction. Vibration and shock, 29(7):5.

[2] Zhang, W., Li, C., Peng, G. (2017) A deep convolutional neural network with new training methods for bearing fault diagnosis under noisy environment and different working load. Mechanical Systems & Signal Processing, 100: 439-453.

[3] Liang, R., Ran, W.F., Yu C.L., Chen W.F. (2021) Fault state identification of gearbox operation based on CWT - CNN. Aerodynamics Journal: 1-9.

[4] Liu, Y.T., Yu, Q.S., Li, S.K., Liu, X.Y. (2021) Research on multi model fusion image intelligent detection method based on deep learning. http://kns.cnki.net/kcms/detail/11.2175.TN.20211125.1028.022.html.

[5] Zhao, K. Jiang, H.K., Lu, T.F. (2019) Fault diagnosis of rotating machinery based on enhanced batch normalized convolution neural network. In: The 13th National Conference on vibration theory and Application. Xi'an.