Deep Convolution Neural Network Motor Fault Identification Based on Generative Adversarial Network under Unbalanced Sample

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Abstract. Based on the problem that the traditional motor fault diagnosis method relies on the signal processing power and the model generalization ability is poor, this paper proposes a fault diagnosis method based on generative adversarial network under unbalanced data sets. It builds a small sample training set to train generative adversarial network, and adds the generated sample to the original small sample training set. A deep convolutional neural network (DCNN) model that is suitable for motor fault diagnosis is proposed, and the fault characteristics are learned from the original data layer by layer, so as to realize the identification of different faults. After a lot of experimental analysis, the method is better than the existing depth model in terms of detection rate and error rate.

Introduction

As the most important driving equipment in modern social industrial system, it is important to ensure the safe and efficient operation of the motor. Therefore, it is of great significance to monitor the condition of the motor and to diagnose the fault [1].

The traditional fault diagnosis mainly deals with the data, through a series of time domain and frequency domain analysis of the current and vibration data of the motor, and obtains the characteristics containing fault information, and then evaluates it, such as multi-scale entropy analysis, empirical modal decomposition, morphological filtering and wavelet transformation [2]. It needs sufficient accurate hardware acquisition equipment and complex troubleshooting methods, which has some cost problems and algorithmic difficulty [3].

With the development of intelligent algorithms such as machine learning and pattern recognition, these intelligent algorithms are used to extract data characteristics. It finally fed into a specific classifier, and motor fault and recognition can be completed. The classic classification algorithms have Support Vector Machine (SVM), Artificial Neural Network (ANN), Random forest (RF), K Nuclear Methods (KMs), Machine Learning (ML), and so on [4]. In the massive device monitoring data, the difference of different category characteristic data samples leads to the data generally unbalanced [5]. There is a small sample size of fault categories. The accuracy of this unbalanced data classification is difficult to guarantee by traditional methods. In this paper, an unbalanced data fault identification method based on generative adversarial network (GAN) is proposed, which first builds the GAN of small sample data categories, and generates data that conforms to the characteristics of small categories and adds it to the original small sample training set, so as to ensure the balance of the different categories of sample training sets [6].

Data Sample Generation Algorithm Based on Generative Adversarial Network

Generative Adversarial Network

At present, the classical neural network method can do a good job of fault identification of large data categories, while ignoring the small data categories. But in the actual fault data, the samples of small categories have more valuable information.

In this paper, a category unbalanced fault classification based on the generative adversarial
network is proposed. In 2014, Goodfellow proposed GAN and quickly set off a research boom in deep learning [7]. GAN’s idea comes from the zero-sum game. When the interests of one side increase, the interests of the other side decrease. GAN is a kind of deep generation model that utilizes each other, mainly consisting of generating network G and discrimination network D [8]. The final generation model can learn the real sample distribution law, and generate enough to mess up the sample [9]. The GAN’s training process can be defined as the following Eq. 1.

$$\min_G \max_D V(D, G) = E_{x \sim P_{\text{data}}(x)}[\log D(x)] + E_{z \sim P_z(z)}[\log(1 - D(G(z)))]$$

(1)

\(x\) represents the real sample, \(z\) represents the random noise in the input generation model, \(D(x)\) indicates the probability that the input sample is determined by the discrimination model, \(G(z)\) indicates the sample generated after the generated model accepts random noise, \(P_{\text{data}}(x)\) represents the real data distribution, and \(P_z(z)\) indicates the generated data distribution. In this paper, a solution combining DCNN with generating confrontation networks is proposed for these two problems to improve the quality of generated samples. As shown in Fig. 1.

As shown in Fig. 2, the black dotted line is the Gaussian distribution of the real data, the green line is the forged distribution learned by the generated network, the blue line is the probability, and the horizontal line of the standard \(x\) represents the Gaussian distribution. The space of \(x\), the horizontal line of the standard \(z\) represents the sampling space obeying the evenly distributed \(z\). It can be seen that the mapping relationship from the space of \(z\) to the space of \(x\) is learned.

![Generative adversarial network structure diagram](image1)

![Probability distribution map when running GAN](image2)

**Generative Adversarial Network Structure Design and Parameter Settings**

In this paper, the deep convolution neural network is combined with the generation of the adversarial network, and the deep convolution is introduced into the generative adversarial network for unsupervised training. The powerful feature extraction ability of the deep convolution network is used to improve GAN’s learning effect, and make the training process more stable, and obtain higher quality sample data. However, the generation network and the discrimination network are still different in terms of the design of the specific network structure. For building network \(G\) as shown in Fig. 3. The convolution core size of the anti-convolution is 4x4, and the step length is set to 2. The map of the resulting model network structure is shown in the following diagram.

In this deep network, batch training is used, with a training size of 10 samples per batch, so batch-norm is required between two layers of anti-convolution. In the network structure, the other layers of the generated model use ReLU activation function to solve the problem of gradient disappearance and speed up the training convergence. As shown in Eq. 2.

$$\text{ReLU}(x) = \begin{cases} 
  x, & x > 0 \\
  0, & x \leq 0
\end{cases}$$

(2)

The output layer uses the Tanh instead of the ReLU activation function. As shown in Eq. 3.

$$\text{Tanh}(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

(3)

The network structure of the discrimination model is shown in the figure below. The discrimination model \(D\) is a DCNN. The use of the right and wrong probability produce loss values,
and the loss value back to the generation network, to improve the generation network parameters, for the next round of training to generate a more realistic false sample. Finally, a closed-loop feedback generation adversary network is formed, knowing that the network reaches Nash equilibrium and generating false data that is infinitely approximate to real data. As shown in Fig. 4.

The LeakyReLU is used in D model except for the output layer. As shown in Eq. 4.

\[
\text{Leaky ReLU}(x) = \begin{cases} 
  x, & x > 0 \\
  0.2x, & x \leq 0 
\end{cases}
\]

The output layer of the D model uses the Sigmoid activation function. As shown in Eq. 5.

\[
\text{Sigmoid}(x) = \frac{1}{1 + e^{-x}}
\]

The generation model and the discrimination model are added to batch standardization at each layer. This method can solve the problem of poor initialization effect, and help the gradient spread to each layer of the network, and accelerate the convergence of the model. Batch standardization processing can also effectively alleviate the problem of model overfitting, avoiding generation model crash, and prevent the resulting samples from converging to the same point. This method uses the first-order moment estimation of gradient and second-order moment estimation to dynamically adjust the learning rate of each parameter. In the reverse propagation stage, it updates weight to obtain the global optimal solution, so that the Loss function reaches the minimum.

**Motor Fault Diagnosis Model Overall Design based on DCNN**

In order to realize the diagnosis of early weak faults and the accurate identification of different fault, this paper proposes a fault diagnosis method based on the deep convolution neural network model, which first uses the generative adversarial network to achieve the equalization of different categories of samples. Finally, it realizes the diagnostic identification of small sample fault categories. As shown in Fig. 5.

The input data is flattened, and the input convolution network is a sample of 20x20. The final output is the result of classification, i.e. the result of motor fault recognition. The network consists of three convolution layers, each with a pooled layer after each, and finally through two fully connected layers, using the softmax function for final classification.

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**Figure 3. Structure of the generative model.**

**Figure 4. Structure of the discriminative model.**

**Figure 5. Motor fault diagnosis structure diagram.**
Study Implementation and Analysis

The experimental environment for this article is Intel(R) Core (TM) i5-3230M CPU s2.6GHz processor, 12.0GHz running memory (RAM), GeForce GT 740M GPU. The overall model is implemented using the TensorFlow platform in Python's framework.

Processing of Experimental Data Sets

This paper uses the open motor bearing data set provided by the laboratory of Western Reserve University as a training set, which includes motor normal bearing data, drive end bearing fault data and fan end bearing fault data [11]. In the bearing fault data, it includes rolling fault, inner ring fault and outer ring fault. To present the bearing state as fully as possible, the experiment takes the time domain data as a sample, and the length of a single sample is 400. The experimental data set as shown in Table 1.

| Data set | Motor speed [r/min] | Fault Type | Fault Diameter [inch] | Total sample size | Category |
|----------|---------------------|------------|------------------------|-------------------|----------|
| A, B, C, D | 1797, 1772, 1750, 1730 | Ball Fault | 0.007 | 2000/2000/2000/6000 | 0 |
|          |                     | Ball Fault | 0.014 | 2000/2000/2000/6000 | 1 |
|          |                     | Ball Fault | 0.021 | 2000/2000/2000/6000 | 2 |
|          |                     | Inner Race Fault | 0.007 | 2000/2000/2000/6000 | 3 |
|          |                     | Inner Race Fault | 0.014 | 2000/2000/2000/6000 | 4 |
|          |                     | Inner Race Fault | 0.021 | 2000/2000/2000/6000 | 5 |
|          |                     | Normal | 0.000 | 2000/2000/2000/6000 | 6 |
|          |                     | Outer Race Fault | 0.007 | 2000/2000/2000/6000 | 7 |
|          |                     | Outer Race Fault | 0.014 | 2000/2000/2000/6000 | 8 |
|          |                     | Outer Race Fault | 0.021 | 2000/2000/2000/6000 | 9 |

Experimental Verification

The experiment uses the Adam optimizer, which can iteratively update the neural network weight based on the training data, minimizing the loss value of the differential and the generator. The learning rates for the build model and the adversarial model are set at 0.0001 and 0.00001, respectively, and the remaining parameters are set to the default values. 10 samples are read per batch. The GAN eventually generates a fake sample close to the real data. In order to verify the performance of the network, two verification methods are selected, and one is to generate the training loss value of D model against the network. As shown in Fig. 6.

The data is identified by the DCNN designed in this article. This solves the problem of data imbalance and greatly improves the fault recognition rate of small sample categories. The fault identification rate change graph is shown in Figure 7. This train a total of 2500 cycles. The figure can be seen that the recognition rate is only 20%, but with the increase in the number of training, the network parameters are also optimized, so the recognition rate is also constantly improved. Network completes 500 training sessions when the recognition rate can reach 90%, and the final recognition rate remains at about 95%.

Four case verifications are set, namely, fault identification with raw data, fault identification using ANN method, fault identification using SVM method and fault identification in combination with GAN and DCNN [12]. The final recognition rate is shown in Table 2. It can be seen from the table that the fault identification rate is not high with the original data directly, while the recognition rate is improved by the ANN and SVM methods, but there is still a certain gap with the recognition rate of the method used in this paper.

Another method of verification selected is to observe the spectral comparison of real data and generated data, because the bearing vibration data used in this paper. The real samples and the resulting samples are transformed through FFT to generate their spectrogram. As shown in Figure 8. As can be seen from the graph, the real data is still some gap, but from the overall trend point of view, 50Hz, 100Hz and 300Hz are both obvious characteristics, so it can be considered that the data generated by the network has the main characteristics of the original data.
Figure 6. Training errors of generative adversarial network.  Figure 7. Curve of accuracy change.

Table 2. Different methods of recognition accuracy (%).

| Methods    | Test-A | Test-B | Test-C | Test-D |
|------------|--------|--------|--------|--------|
| Primitive Data set | 93.15  | 93.20  | 93.25  | 94.54  |
| ANN        | 95.45  | 95.57  | 96.66  | 97.01  |
| SVM        | 96.31  | 96.43  | 95.24  | 96.76  |
| GAN-DCNN   | 96.56  | 96.76  | 97.23  | 97.13  |

Figure 8. Spectrum comparison of real data and fake data.

Conclusion

In this paper, based on the current data imbalance of small sample categories in motor fault diagnosis, a motor fault diagnosis of deep learning based on generative adversarial network is proposed [13-15]. It can be seen that the new sample generated by the GAN model is not a simple copying and splicing of the original sample, but a real sample distribution law is learned, and a new and effective new sample is generated. Combined with the current development of deep learning technology in motor failure, considering that motor fault anomaly detection and analysis is becoming more and more important in industrial development.

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