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# Imbalanced Fault Classification of Industrial Bearings based on Generative Adversarial Network with An Improved Structure

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**Abstract.** With the development of modern industry, data collection is becoming heterogeneous with very huge amount, thus data-driven technology has become increasingly important in process monitoring. At present, the pattern recognition method based on Artificial Neural Network (ANN) has been widely used in fault classification of rotating machinery. However, they require a large amount of sample data to participate in training models to ensure the accuracy, while sample data is extremely lacking in engineering practice. Therefore, a suitable method is needed for fault classification of rotating machinery in the case of small samples and imbalanced data. This paper proposed a fault classification framework for small sample data, which can be used to generate fault data through GAN for fault classification. First, GAN generates different types of fault data with the same distribution as the original data, and then compares the generated time series data and the real time series data with various degree of difference evaluation indicators to obtain the fault classification results, which can verify the effectiveness of GAN in fault data classification.

**Keywords:** GAN, Fault classification, Difference comparison, Imbalanced sample

## 1. Introduction

With the rapid development of science and technology in modern society, in order to improve productivity, various industrial equipment has been widely used in all aspects of social production, such as machinery, chemical, energy, and petrochemical industries that are closely related to the economy. When there is a problem with key industrial equipment, it can cause economic losses to the slightest, and serious accidents with casualties. Among many machinery and equipment, industrial bearings are the most widely used[1]. Therefore, it is very necessary to classify the faults of industrial bearings. In the operating state of the equipment, accurately identifying the fault categories of industrial bearings is of great significance for social production and avoiding safety accidents[2].

Traditional fault classification starts from the data. First, the vibration acceleration signal of the bearing is collected in the laboratory or industrial site, and then the signal is analyzed in the time domain, frequency domain, and time-frequency domain. These methods include short-time Fourier transform and wavelet transform and Hilbert-Huang transform and so on. Finally, specific classifiers such as Artificial Neural Network (ANN) are used for pattern recognition, so as to achieve the purpose of fault classification for industrial bearings. In recent years, many data-driven classification methods have been proposed, such as naive Bayes, Fisher discriminant analysis, support vector machine (SVM), random forest, etc [3][4][5]. These existing classification algorithms perform well on relatively balanced data and can accurately detect fault types. However, compared with conventional data, fault data in modern industrial processes is usually more difficult to obtain, which results in the number of fault samples being much smaller than the number of conventional samples. Regardless of the classic fault classification method or the deep learning method, the field of industrial bearing fault classification still faces some challenging problems. In actual production, the occurrence of faults is often random, the collection of fault signals is more difficult and the amount of data is small, which causes The occurrence of insufficient samples and data imbalance during fault diagnosis. How to perform fault diagnosis of rotating machinery with small samples and unbalanced data has gradually attracted the attention and discussion of the scientific research community, which is also the focus of our research [6][7][8].In recent years, in the field of small sample generation, the hottest model in deep learning is undoubtedly Generative Adversarial Networks (GAN). Generative Adversarial Networks (GAN) is a deep generative model proposed by Goodfellow et al. in 2014 [9]. The main purpose of GAN is to learn the distribution of real data, and then generate new data with similar characteristics to the real data. Generative adversarial network has good generalization ability [10]. At present, GAN has been widely used in the field of image and vision [11][12], a large number of researches based on GAN, most of which are oriented to image data, such as image generation, image denoising, etc. Now, GAN has made considerable progress in the field of image processing [13][14][15].

The goal of this article is to build a model that can generate a large number of new samples that have a similar overall distribution to the real samples. The model can balance existing samples and generate an expanded data set based on the original data set. The expanded data set helps to improve the fault tolerance rate of fault classification, thereby improving the accuracy of fault classification. Most scholars who study GAN data generation focus on the generation of image data, and rarely generate specific time series data. In the field of fault classification, the fault data obtained is rarely picture data under normal circumstances. In this paper, the original GAN model is also adjusted to directly generate time series data, and the fault classification is finally completed by comparing the difference between the generated time series data and the real data, which can prove the important role of GAN in small sample fault classification.

# 2. Method

In this section, the method of fault classification of industrial bearings based on generative adversarial network is mainly discussed. In order to address the imbalance problem in the fault classification of industrial bearings and the lack of diversity and robustness of traditional fault classification methods. A fault classification methods are introduced. For industrial unbalanced data, GAN can be used as a means of data expansion, thereby improving the accuracy and robustness of fault classification. This method integrates the generation characteristics of GAN, improves and expands the industrial bearing data set, so that it has a better performance in the classification accuracy of industrial bearing fault data.

## 2.1. GAN

The main idea of GAN is the two-players game in game theory. There are two sets of networks inside, one is called generator G, and the other is called discriminator D. Simply put, the generator G is responsible for fabricating data out of thin air. The discriminator D is responsible for judging whether the data is true or not. GAN uses an unsupervised learning method for training, which can be widely used in the fields of unsupervised and semi-supervised learning. In the training process of the model, they continue to compete with each other, the discriminator is updated by ascending its stochastic gradient, the generator is updated by descending its stochastic gradient. The discriminator parameters are updated by ascending its stochastic gradient SG_D as in formula (1). The generator parameters are updated by descending its stochastic gradient SG_G as in formula (2). The generator can generate almost real samples, especially in the image field, the image generated by the well-trained generator is usually difficult to be recognized by the human eye. The structure of GAN is shown in the right half of Fig. 1, the role of GAN is to generate data with the same distribution as the original data, so that small sample data can be expanded.

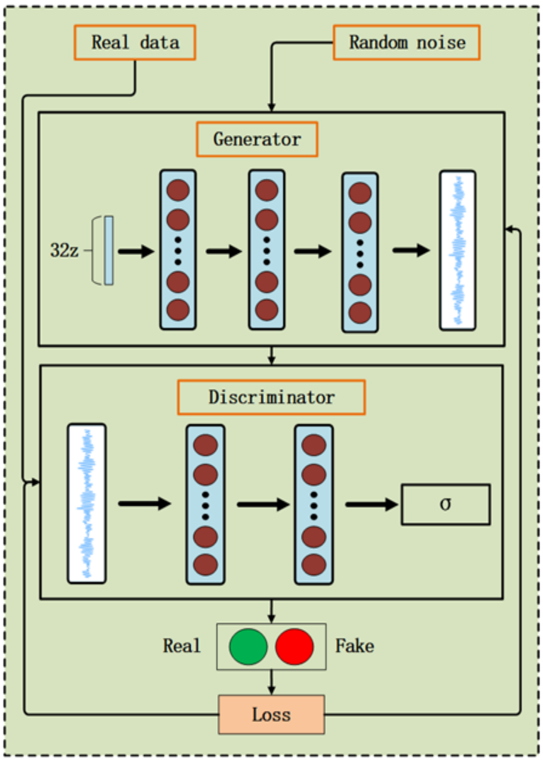


Fig. 1: Framework of GAN.

$$SG_D = \frac{1}{m}\sum_{i=1}^{m}\left[log\, D\left(x^{(i)}\right) + log(1 - D(G(z^{(i)}))\right] \tag{1}$$

$$SD_G = \frac{1}{m}\sum_{i=1}^{m} log(1 - D(G(z^{(i)})) \tag{2}$$

## 2.2. Time-series evaluation index

For the generated time series data, there are three time-series evaluation index ($TEI$) selected: $MSE$, $RMSE$, $MAE$. By comparing the TEIs of the generated data and the original data, the result of the fault classification is obtained. The smaller the value of these three TEIs, the smaller the error between the generated data and the real data, witch means the classification accuracy is higher. Next, the calculation methods of these 3 TEIs will be introduced one by one.

- The $MSE$ value is a measure that reflects the degree of difference between the estimator and the estimator, in other words, the expected value of the square of the difference between the generated data and the real data. MSE can evaluate the degree of data change. The smaller the value of $MSE$, it means that the data generated by the generative model is closer to the real data. The $MSE$ between the real data and the generated data can be calculated by Formula (3).The ISBN assigned: 978-1-84626-xxx-x, etc.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

- The $RMSE$ value between the two sets of data is equal to the square root of their $MSE$ value. The $RMSE$ value between the real data and the generated data can be calculated by Formula (4).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4}$$

- The $MAE$ value represents mean absolute error, if the value is smaller, it means that the generated model has better accuracy. The $MAE$ between the real data and the generated data can be calculated by Formula (5).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y_i}| \tag{5}$$

# 3. Comparison and classification

Since a lot of data have been obtained through GAN, a lot of comparison results can be obtained by comparing the TEIs between the generated data and the real data. To a certain extent, the selected TEI can reflect the difference between the generated data and the real data. Generally, there are big differences between data of different categories, and small differences between data of the same category. Thus, the criterion for classifying every kind of real data is the difference between it and a large amount of generated data. Data of unknown type will be classified into the category, which has the least difference with it.

In order to make the experimental data more convincing, 100 sets of data in each category are selected to get lots of TEIs, the average value of TEIs is considered as the criterion. Finally, the classification result of the time series can be obtained by Formula (6) .

$$I_{sequence} = MSE + RMSE + MAE \tag{6}$$

Table 1: Networks Structure of Gan

| TYPE | GAN |
|---|---|
| Generator | 1x32<br>Linear<br>1x128<br>ReLU<br>Linear<br>1x128<br>ReLU<br>Linear<br>1x1000 |
| Discraminator | 1x1000<br>Linear<br>1x128<br>ReLU<br>Linear<br>1x1<br>Sigmoid<br>Probability value |

# 4. Experiments

## 4.1. Modelling framework

In this section, the proposed fault classification of industrial bearings based on generative adversarial network framework is given in Fig. 1 The framework contains two processes for different input situations. Different $GANs$ are used for data expansion according to different input conditions, then the massively generated data and the original data are compared to get $TEIs$, and finally the fault classification is obtained according to the comparison result. In the experiment, the network structure of $GAN$ is adjusted for better performance in generation, and the parameters of the $DCGAN$ layer and the GAN layer in this paper are shown in Table 1.

## 4.2. Data analysis

In order to illustrate the proposed fault classification method, a large number of vibration data should be generated to compare with the original data. The experimental data comes from the bearing data set of Case Western Reserve University (CWRU) in the United States [16]. The signal collected in this experiment contains 10 types of Fan-End bearing data, which are a set of normal state data and the inner ring fault bearing data, outer ring fault bearing data, and rolling element fault bearing data generated by bearings of three different sizes. The bearing fault data of the Fan-End at a sampling frequency of 48K is selected for the experiment.

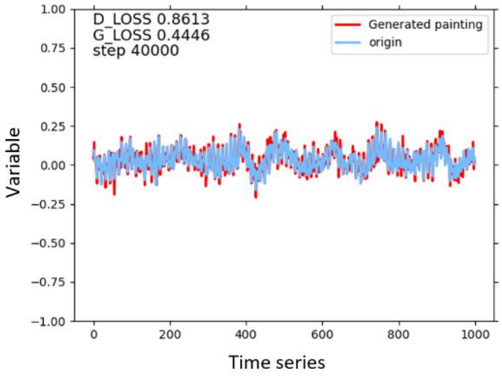


Fig. 2: The generated data and the original data in the normal state category after 40000 steps.

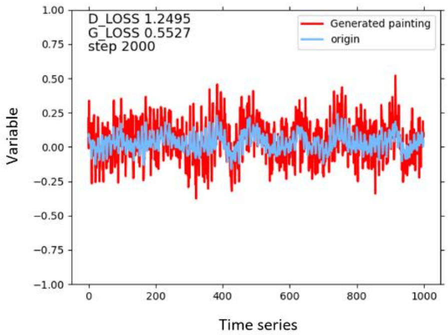


Fig. 3: The generated data and the original data in the normal state category after 2000 steps.

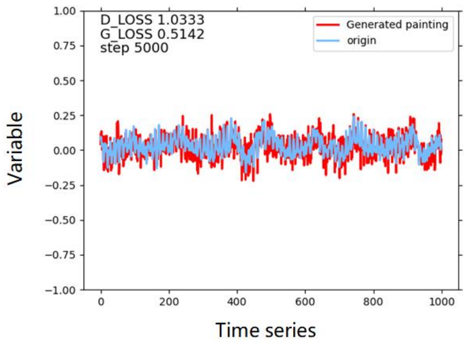


Fig. 4: The generated data and the original data in the normal state category after 5000 steps.

## 4.3. Method of GAN

When using GAN to process time series data, the data will be directly generated based on the original real data. Of course, what will be generated is also time series data with the same length as the original data. As the Fig. 2 shows, the blue curve is the real data, and the red curve is the generated data. After 40000 steps of training, the GAN model can generate data similar to the original data, which can well expand the original sample data. The difference from the traditional neural network is that the loss of GAN is always changing, because the two neural networks contained in GAN have been in a state of confrontation, and eventually they will reach a state of equilibrium, and at that time, the quality of the generated data will also tend to be stable. Fig. 6 shows the change of the loss curve when using GAN to train normal state data. The generative network and the discriminant network are in constant confrontation, and eventually stabilize.

As Fig. 3 shows, it is a comparison diagram of the real data and the generated data that have been trained for 2000 steps, and there is a visual difference. Comparison diagram of the real data and the generated data that have been trained for 5000 and 10000 steps are shown in Fig. 4 and Fig. 5, in which some differences can still be seen. Therefore, the generated data after training for 40,000 steps are selected as the experimental object, and the selected 100 generated data for each category are set as comparison candidates. The result of the difference comparison between the real data in normal state and the generated data in 10 different states is shown in Table 2. The selected TEIs are MSE, MAE, RMSE. The smaller these values, the smaller the difference between the data and this type of data, that is, the data should be classified into this type. The result is expressed as a stacked histogram as shown in Fig. 7. As Fig. 7 shows, the ordinate value is the smallest in the normal column, so the difference is the smallest. In the same way, by comparing the real data in B007 state with the generated data in 10 different states, the TEIs are obtained and the result of the difference comparison between the real data in normal state and the generated data in 10 different states is shown in Table 3. The result of the difference comparison between the real data in B007 state and the generated data in 10 different states is expressed as a stacked histogram as shown in Fig. 8. As Fig. 8 shows, the ordinate value is the smallest in the BOO7 column, so the difference is the smallest. This shows that the real data in B007 state should be classified into the category of B007, that is, the fault classification is successful.

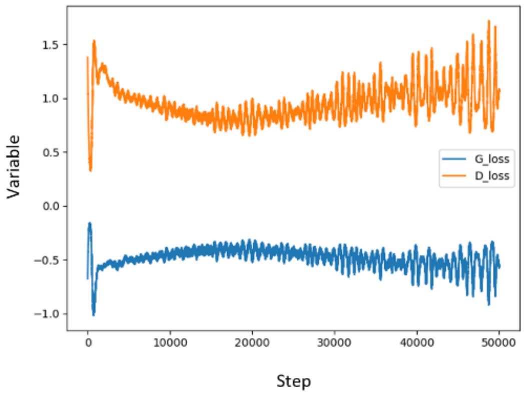


Fig. 6: Changes in generator loss and discriminator loss when training data under normal state.

Table 2: The result of the difference comparison between the real data in normal state and the generated data in 10 different states

| NAME | MSE | RMSE | MAE | TOTAL |
|---|---|---|---|---|
| B007 | 1.477 | 12.134 | 9.676 | 23.286 |
| B014 | 1.219 | 11.028 | 8.73 | 20.977 |
| B021 | 1.348 | 11.601 | 9.213 | 22.162 |
| IR007 | 6.038 | 24.517 | 19.466 | 50.022 |
| IR014 | 1.457 | 12.05 | 9.388 | 22.895 |
| IR021 | 3.557 | 18.819 | 14.604 | 36.98 |
| OR007 | 4.862 | 21.992 | 17.314 | 44.168 |
| OR014 | 1.648 | 12.819 | 10.382 | 24.849 |
| OR021 | 1.485 | 12.169 | 9.681 | 23.335 |
| normal | 0.075 | 2.707 | 2.16 | 4.941 |

Table 3: The result of the difference comparison between the real data in B007 state and the generated data in 10 different states

| NAME | MSE | RMSE | MAE | TOTAL |
|---|---|---|---|---|
| B007 | 0.088 | 2.942 | 2.341 | 5.371 |
| B014 | 1.887 | 13.726 | 11.039 | 26.651 |
| B021 | 1.655 | 12.86 | 10.295 | 24.81 |
| IR007 | 5.34 | 23.054 | 18.442 | 46.836 |
| IR014 | 1.927 | 13.871 | 11.074 | 26.872 |
| IR021 | 4.173 | 20.392 | 16.071 | 40.636 |
| OR007 | 5.961 | 24.366 | 18.944 | 49.271 |

| | | | | |
|---|---|---|---|---|
| OR014 | 1.922 | 13.854 | 11.056 | 26.832 |
| OR021 | 2.168 | 14.713 | 11.748 | 28.629 |
| normal | 1.463 | 12.088 | 9.656 | 23.207 |

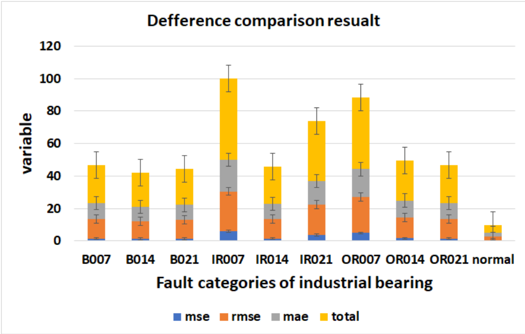


Fig. 7: The result of the difference comparison between the real data in normal state and the generated data in 10 different states.

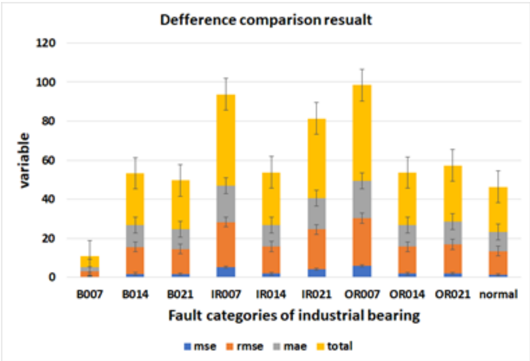


Fig. 8: The result of the difference comparison between the real data in B007 state and the generated data in 10 different states.

## 5. Conclusion

In this paper, an imbalanced data fault classification method for industrial bearings based on GAN is proposed to generate sufficient fault data, with improved structure to improve the accuracy of fault classification model. This method has the versatility and robustness that traditional methods do not have, and to a certain extent solves the problem of insufficient data in traditional fault classification. This method expands the original data, especially the faulty data, to obtain fault classification results through computations of evaluation index of generated data and the real data. Therefore, the effectiveness of this method on imbalanced fault classification is verified by evaluation results. From the perspective of practical application, this method can not only improve the classification accuracy, but also expand the original data, which can effectively solve the problem of insufficient data, and greatly improve the fault detection and classification model accuracy.

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