# Fault Diagnosis For Gearbox Based On Deep Belief Network

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***Abstract*— As equipment becomes more and more complex, it is increasingly difficult to manually extract and select fault features manually based on expert experience or signal processing techniques. In addition, the shallow model such as BP neural network and SVM have trouble to deal with the complex mapping relationship with respect to the measured signal and the health condition of the equipment, who faces the problem of dimensional disaster. Combined with the advantages of deep confidence network (DBN) in features extraction and deal with high-dimensional and nonlinear samples, a fault feature extraction and diagnosis method based on deep confidence network for gearbox is investigated in this framework. The method uses the original time domain signal to train the deep confidence network and completes the intelligent diagnosis through deep learning. The preponderance is that it can take out the dependence on a great quantity of signal processing techniques and diagnostic experience, and accomplish the extraction of fault features and the intelligent diagnosis of health status with the characteristic of self-adaption. The method has no periodic requirements for time domain signals, and has strong versatility and adaptability. The experimental results of the fault diagnosis for the planetary gearbox demonstrated the feasibility and superiority of the presented method.**

***Keywords-deep confidence network (DBN); gearbox; fault diagnosis; feature extraction***

## I. INTRODUCTION

As a key part of the mechanical transmission system, it will easily lead to the break down of the entire mechanical system if a fault occurs, thus affecting the normal production activities. As the most common form of transmission in rotating machinery, gear transmission systems are also the most prone to failure and failure. Massive Data is acquired due to the large amount of equipment, the great many measuring points, the high data sampling frequency, and the long service life of the equipment, thus promoting the field of fault diagnosis into the era of “big data”[1]. Aiming at the characteristics of diversity, non-linearity and high-dimensionality for big data of fault diagnosis, it becomes a new problem big data health monitoring for mechanical equipment to use advanced theoretical methods to mine information from big data, and identify equipment health status efficiently and accurately

In 2006, Hinton et al. [2] first explored deep learning theory who has opened up a wave of deep learning in academia and industry. Since then, many companies and research institutes at home and abroad have conducted extensive research on deep learning and have achieved remarkable results in practical applications [3-6].

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Nowadays, the deep learning model has achieved great success in image processing, speech recognition and hardware implementation [7-12]. Simultaneously, the field of deep learning applications is gradually increasing, such as predicting drug activity, cancer detection, and time series prediction. Obviously, deep learning has become a significant means of big data analysis. It has become a mainstream trend of current mechanical intelligent fault diagnosis to researching and using advanced deep learning theory to efficiently and accurately mine fault information from mechanical fault big data.

Tran et al. merged Deep Belief Net (DBN) and TKEO algorithm into fault diagnosis of reciprocating compressor valves, and achieved higher accuracy [13]. Li et al. proposed a multi-mode MDSVC classification method and was applied to the fault diagnosis of gears, which effectively improved the accuracy of gear fault diagnosis and solved the problem of low diagnostic accuracy under a single vibration source [14]. Li Yanfeng et al used the singular value decomposition (SVD) to extract the corresponding characteristics of the rolling bearing, and deep learning method are used to identify the health condition of rolling bearing, which improved the recognition accuracy of the rolling bearing fault mode and fault degree.

Deep learning theory has the following advantages over traditional diagnostic methods： (1) By combining low-level features to form more abstract deep features, features can be automatically extracted from big data which can reduce the dependence on professional knowledge and prior knowledge; (1) Simulating the deep tissue structure of the brain, establishing a deep model, and efficiently characterizing signals and health conditions by construct complex mapping. Based on the deep learning theory, a gear fault diagnosis method on the basis of deep belief network (DBN) is devised in this paper.

## II. PRINCIPLE OF FAULT DIAGNOSIS BASED ON DEEP CONFIDENCE NETWORK

### A. *The structure of DBNs and its training process*

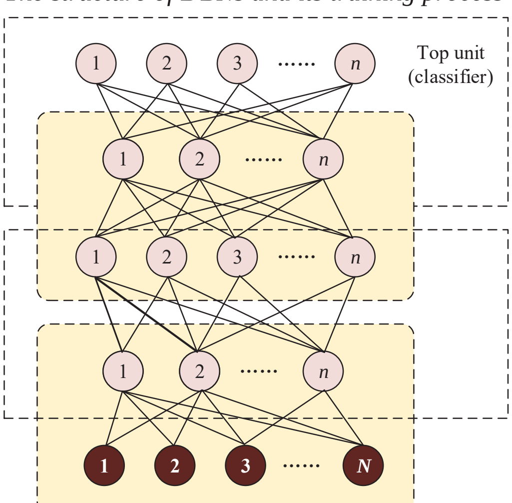


Figure 1. DBNs network structure

The deep confidence network can be seen as a stack of multiple RBMs. By stacking multiple RBMs, deep features can be extracted from complex data. However, stacking RBM can only obtain high-level features from complex raw data, who cannot directly classify the data. To obtain a complete DBN model, a traditional supervision classifier should be added at the top of the stacked RBM. The basic structure of a complete deep confidence network is shown in Fig. 1.

Figure 1 shows a 4-layer DBNs network. The network architecture can be easily expressed as $N-n_1-n_2-n_3$, and the number of points of the input layer is N, that is the neurons of the first, the second and the third input layer is $n_1$, $n_2$, $n_3$.

RBM is an energy-based model whose energy of the joint configuration of the visible variable *v* and the hidden variable *h* is:

$$E\left(v,h|\theta\right)=-\sum_{i=1}^{n}\sum_{j=1}^{m}v_jW_{ij}h_i-\sum_{j=1}^{m}b_lv_j-\sum_{i=1}^{n}c_ih_i \tag{1}$$

Where *w* is the weight between the visible units and hidden units, *b* and *c* are the offsets of visible and hidden units respectively. *n* is the number of visible layer units; *m* is the number of hidden layer units.

In RBM, the KL distance between the true distribution of the samples and the edge distribution represented by the RBM network is the differences between the two. The KL distance is:

$$KL\left(q\|p\right)=\sum_{X\in\Omega}q\left(x\right)\ln\frac{q\left(x\right)}{p\left(x\right)}=$$
$$\sum_{X\in\Omega}q\left(x\right)\ln q\left(x\right)-\sum_{X\in\Omega}p\left(x\right)\ln p\left(x\right) \tag{2}$$

When the KL distance is the smallest, that is, the value of *lnp(x)* is the largest, that is, the maximum likelihood estimate of the input sample is the largest:

$$\frac{\partial\ln L\left(\theta|\bar{v}\right)}{\partial\theta}=\frac{\partial}{\partial\theta}\left(\ln\sum_{\bar{h}}e^{-E\left(\bar{v},\bar{h}\right)}\right)-\frac{\partial}{\partial\theta}\left(\ln\sum_{\bar{v},\bar{h}}e^{-E\left(\bar{v},\bar{h}\right)}\right)=$$
$$-\sum_{\bar{h}}p\left(\bar{h}|\bar{v}\right)\frac{\partial E\left(\bar{v},\bar{h}\right)}{\partial\theta}+\sum_{\bar{h}}p\left(\bar{v},\bar{h}\right)\frac{\partial E\left(\bar{v},\bar{h}\right)}{\partial\theta}$$

According to the calculation result, deriving a, b, and c respectively:

$$\frac{\partial ln\left(\theta|\bar{v}\right)}{\partial w_{ij}}\infty\left\langle v_ih_i\right\rangle_{data}-\left\langle v_ih_i\right\rangle_{model} \tag{3}$$

$$\frac{\partial ln\left(\theta|\bar{v}\right)}{\partial b_j}=v_j-\sum p\left(\bar{v}\right)v_j \tag{4}$$

$$\frac{\partial ln\left(\theta|\bar{v}\right)}{\partial c_j}=p\left(H_i=1|\bar{v}\right)-\sum_{\bar{v}}p\left(\bar{v}\right)p\left(H_i=1|\bar{v}\right) \tag{5}$$

The feature extraction process of DBNs is shown in Fig 2.

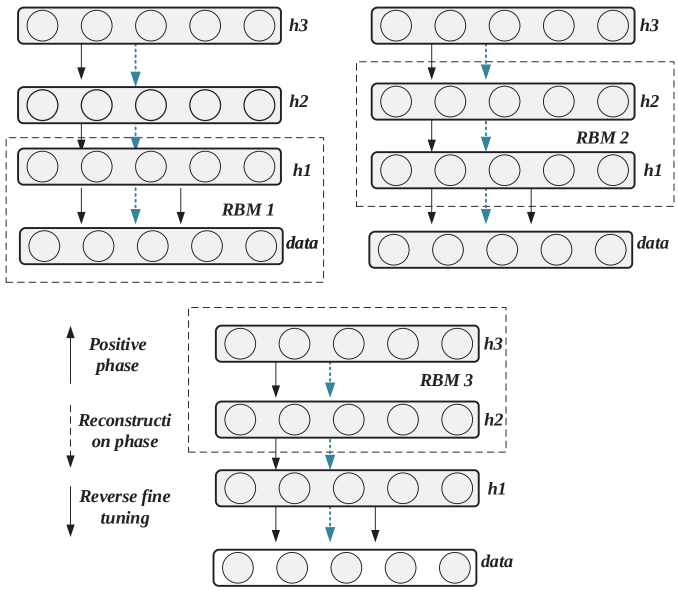


Figure 2. DBNs feature extraction process layer by layer

## B. *Fault diagnoisis based on DBNs*

This paper investigated a fault diagnosis method for Gearbox Based on DBN under different working conditions. The flow chart of the project is shown in Figure 3.

The exposition of this method is described as follows.

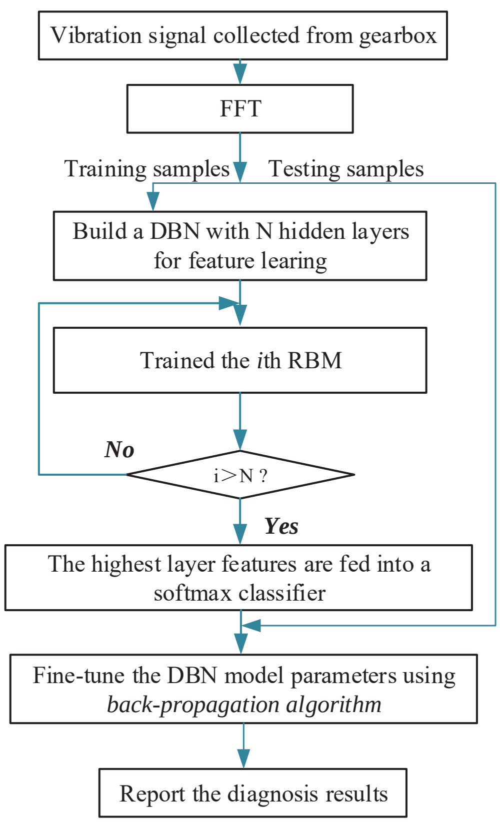


Figure 3. The flowchart of the proposed method

- The vibration signals collected from gearbox are measured and preprocessed by sensors and data acquisition system.
- FFT is applied for raw data to convert the raw data from time domain to frequency domain. And then the feature dataset into training and testing samples are selected separately.
- DBN model is built on the premise of a series of pre-trained RBM. The highest level functions are input into the software Max classifier solve the problem of fault diagnosis. BP algorithm is utilized to fine-tune parameters of depth models to enhance fault diagnosis.
- Test samples to certificate the performance of the proposed DBN model. The diagnostic accuracy was calculated and the results were reported.

## III. CASE STUDY

From the DBNs-based feature extraction process, as we can see that the first layer of DBNs network is the data layer, so it is crucial to build a reasonable data set for improving fault identification accuracy.

The experimental samples coms from PHM Data Challenge Competition in 2009 are adopted for this work. Data come are collected from a two-stage standard cylinder spur gear reducer. The reducer are composed of input shaft, idler shaft and output shaft. The first stage deceleration ratio is 1.5 and the second stage deceleration ratio is 1.667. The input shaft includes 32 teeth and the output shaft includes 80 teeth. There are 96 teeth and 48 teeth in the two gears on the idle axle.

Fig. 5 are used to illustrate the physical and schematic diagram of the two-stage reducer.

Data are obtained by 30 Hz input shaft speed and high load. The sampling frequency is 66.7 kHz and the sampling time is set to 4 s. The fault mode was illustrated in Table 3.

In order to test the diagnosis results of DBNs of different data conditions, two types of data are set in the case. The first one is to intercept the original time domain signal to construct a time domain data set; the second type is a spectrum data set constructed by FFT transforming the time domain signal (the number of points is 1024, wherein the training set sample number is 600 and the testing set is 1000. Before importing the experimental dataset into the DBNs network, the dataset needs to be normalized.

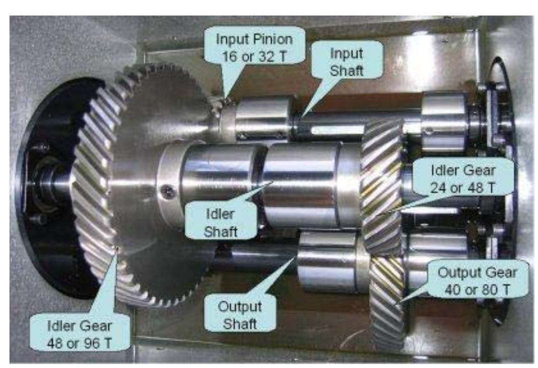

Figure 5. Detailed information of the gearbox

TABLE I. TABLE 1 FAULT PATTERNS OF THE GEARBOX

| ***Fault pattern*** | | ***A*** | ***B*** | ***C*** | ***D*** | ***E*** | ***F*** | ***G*** | ***H*** |
|---|---|---|---|---|---|---|---|---|---|
| **Gear** | 32T | Good | Chipped | Good | Good | Chipped | Good | Good | Good |
| | 96T | Good | Good | Good | Good | Good | Good | Good | Good |
| | 48T | Good | Eccentric | Eccentric | Eccentric | Eccentric | Good | Good | Good |
| | 80T | Good | Good | Good | Broken | Broken | Broken | Good | Good |
| **Bearing** | IS:IS | Good | Good | Good | Ball | Inner | Inner | Inner | Good |
| | ID:IS | Good | Good | Good | Good | Ball | Ball | Good | Ball |
| | OS:IS | Good | Good | Good | Good | Outer | Outer | Good | Outer |
| **Shaft** | Input | Good | Good | Good | Good | Good | Imbalance | Good | Imbalance |
| | Output | Good | Good | Good | Good | Good | Good | Keyway sheared | Good |

IS-Input Shaft, ID-Idler Shaft, OS-Output Shaft, :IS-Input Side

When constructing a DBNs network, the depth L of the network (the number of RBM layers), the number of neurons n per layer of RBM, the learning rate ε, and the corresponding weights W and b. All of the parameters are fixed except the weights are continuously updated. Therefore, it is necessary to select the appropriate network depth L, the number of hidden layer neurons n and the learning rate ε in the process of constructing the DBNs network, who can improve the fault recognition accuracy rate as much as possible.

### *A. The impact of the number of network layers on accuracy*

This case studies the effect of different network layers on the accuracy. In this case, the number of hidden layer neurons is 200. Fig.6 shows the corresponding fault identification accuracy of different network layers. The abscissa represents the number of network layers, and the ordinate represents the accuracy of fault identification.

It can be clearly seen from Fig.6 that when the number of DBNs network layers is 3 (that is, the number of hidden layers is 2), the correct rate of fault identification is the highest, and as the number of hidden layers increases, the correct rate of fault identification of DBNs decreases.

TABLE II. CORRESPONDING FAULT IDENTIFICATION ACCURACY OF DIFFERENT NETWORK LAYERS

| ***Network layers*** | ***MLP layer=0*** | ***MLP layer=256*** | ***MLP layer=1024*** |
|---|---|---|---|
| ***1*** | 0.9995 | 1 | 1 |
| ***2*** | 0.9998 | 0.9989 | 0.9985 |
| ***3*** | 1 | 1 | 1 |
| ***4*** | 0.9999 | 1 | 1 |
| ***5*** | 1 | 0.9999 | 1 |
| ***6*** | 0.9987 | 1 | 0.125 |
| ***7*** | 1 | 1 | 0.1245 |
| ***8*** | 0.125 | 0.125 | 0.1245 |
| ***9*** | 0.125 | 0.125 | 0.1245 |

This means that under the certain data condition, when the number of network layers is 3, the data can be fully learned. When the number of network layers continues to increase, the phenomenal of over fitting will occur, which result in a lower accuracy of fault identification. The number of network layer exceeds eight，the accuracy is no more than 0.125. For further research, we did an experiment on the impact of different MLP layers on accuracy.

From the result, we can conclude that the recognition rate is not only have relation with the number of network layers, but also related to the number of network layers.

### *B. The impact of the number of hidden layer neurous on accuracy*

In order to study the influence of the number of hidden neurons on the correct rate of DBN fault identification, the following analysis will analyze the influence of the number of hidden layer neurons on the correct rate of fault identification when the number of DBNs network layers is 3. Set the number of two hidden layer neurons to an equal number for analysis.

TABLE III. CORRESPONDING FAULT IDENTIFICATION ACCURACY OF DIFFERENT HIDDEN LAYER NEURONS

| ***Numbers of hidden layers*** | ***MLP layer=256*** | ***MLP layer=1024*** |
|---|---|---|
| ***50*** | 0.9995 | 1 |
| ***100*** | 0.9989 | 0.9985 |
| ***150*** | 1 | 1 |
| ***200*** | 1 | 0.9989 |
| ***250*** | 0.9999 | 1 |
| ***300*** | 0.9987 | 0.125 |
| ***350*** | 1 | 0.1245 |

We can conclude from Figure 7 that when the number of hidden layer neurons varies between 50 and 300, the correct rate of DBN fault identification is stable between 95% and 98%, and there is no obvious increase or decrease trend. It can be seen that the number of hidden layer neurons has little effect on the correct rate of network fault identification.

### *C. Comparison of the accuracy of different diagnostic methods*

In order to highlight the advantages of the DBNs method, compare the DBNs-based fault diagnosis method with other pattern recognition methods. The fault diagnosis result of the eight kinds of fault data by various diagnostic models are shown in Table 1.

TABLE IV. FAULT DIAGNOSIS RESULT OF DIFFERENT MODEL

| Diagnostic models | Fault diagnosis result |
|---|---|

| | |
|---|---|
| Time-domain signals-DBN | 0.7889 |
| FFT-PNN | 0.8565 |
| EMD-SVD-PNN | 0.8996 |
| FFT-DBNs | 0.9989 |

The first method in Table 1 is to diagnose the original time domain vibration signal of the gear by using the DBN directly. The DBNs network framework used is 2048-100-100, and the learning rate ε=0.2. The second method is to perform FFT transformation on the vibration signal to obtain the signal spectrum, and then SVM is applied to fault diagnosis. The third one is to perform empirical mode decomposition (EMD) first, SVD is extracted as feature vector, and SVM is used for fault recognition. The last method is the proposed method in this paper, the DBNs network framework used is 1024-100-100, and the learning rate ε=0.2.

It can be seen from Table 2 that when the original time domain signal is directly diagnosed by the DBN network, the accuracy of fault identification is obviously low. The maximum accuracy is not more than 78%, which does not meet the requirements of fault diagnosis. When the original signal transformed by FFT and then the DBN fault diagnosis is performed, the fault discrimination effect is qualitatively improved, whose accuracy rate is up to 100%. We can also conclude that the fault recognition capability of the proposed method is significantly better than the other three machine learning methods.

## IV. CONCLUTION

This paper proposed a fault diagnosis method based on DBNs, and experiment result shows outstanding performance of fault recognition. (1) In network framework parameters, network layer is the main factor to affect the diagnosis performance. (2) The diagnostic accuracy is significantly improved after FFT transformation. (3) After parameter adjustment, the diagnostic accuracy of DBNs is higher than that of machine learning. This is because traditional machine learning methods always combined with manual features, while deep learning can automatically extract fault features, which improves the accuracy of diagnosis accuracy to some extent.

Future work includes applying the proposed approach to fault diagnosis in multiple operating conditions.

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