Application of Projection Pursuit Analysis Method Based on Kernel Function in Fault Diagnosis for Rolling Bearing

Cheng Jing¹,², Su Le¹, Wang Weiqing¹,², He Shan¹,²

¹ XinJiang University School of Electrical Engineering Urumqi, China
² Engineering Research Center of Education Ministry For Renewable Energy Power Generation and Grid Technology Urumqi, China

Abstract. In view of nonlinear and non-Gaussian characteristics of fault feature for rolling bearing of wind turbine, the projection pursuit analysis method based on kernel function is put forward to make pattern recognition for all bearing running states. It elaborates the principle of projection pursuit method, and plan and steps for pattern recognition, then has a simulation and test by MATLAB software. The test results show that the projection pursuit analysis method based on kernel function is an effective method for fault diagnosis, and it can quickly and efficiently identify rolling bearing running states.

1. Introduction
Rolling bearing is the precision and vulnerable core part of wind turbine transmission system. It will be affected by vibration, heat, force and other factors during long-term operation, resulting in corrosion, gluing, wear and other damage, causing major safety problems and huge economic losses. Therefore, the accurate fault diagnosis of rolling bearing is a major problem to ensure the safety and economic operation of the unit.

At present, statistical pattern recognition and neural network pattern recognition are widely used in the field of mechanical fault diagnosis, such as Bayesian classification, linear classification, cluster analysis, BP neural network, wavelet neural network analysis [1-8]. However, the pattern recognition method based on statistical theory can only deal with linear relations effectively, and the fault characteristics and fault categories of rolling bearings are often nonlinear relations. The neural network method can be used to solve nonlinear and fault-tolerant problems, but it needs to train samples first. The setting and selection of parameters such as input and output layer, hidden layer and number of neurons in the training process is a difficult problem, which has a great influence on the training results. As a bridge of linear to nonlinear relation, kernel function can extend many linear analysis methods to nonlinear field through kernel technique. Therefore, in this paper, the vibration monitoring of the rolling bearing parts of the fan is carried out, and the kernel based projection pursuit analysis method is used to further realize the fault pattern recognition and diagnosis.

2. Projection pursuit analysis based on kernel
The kernel function method is a series of nonlinear data processing methods which have applied "kernel mapping". Firstly, the original data is mapped from data space to feature space by nonlinear mapping, and the corresponding linear processing is carried out in feature space. Thus, the processing
ability of nonlinear data is greatly enhanced, and the nonlinear transformation between data space, feature space and category space is realized.

The kernel function based method has principal component analysis method (PCA), Fisher discriminated method, Projection pursuit analysis (PP) and so on.

2.1. Projection pursuit analysis
Most of the traditional statistical analysis methods are based on normal distribution, but many actual measurement sample data do not meet the normal distribution. Projection pursuit analysis is an effective method to analyze and process high-dimensional data, especially non-normal distribution data. According to the concrete situation of the practical problem, it determines a criterion function and projects the high-dimensional data into the low-dimensional subspace, so that the projected data can be classified and recognized well [9]. The process consists of the following steps:

Data preprocessing. In order to eliminate the dimension of each index value and unify its variation range, the original data is normalized.

Constructing projection index function. In order to classify and identify well, it is necessary to construct a projection index function so that the projected data is as dense as possible, and it is best to condense into several groups, and each group should be dispersed as much as possible.

Optimizing projection function. The projection index function varies with the direction of projection, and different projection directions reflect different data structure characteristics. The projection function is optimized to find the best projection direction to reflect the structural characteristics of the data to the greatest extent.

Classification. Two orthogonal projection directions are determined by the projection function, and the coordinate system is established to obtain the projection value of the feature space sample data in the coordinate system, so as to compare and classify.

Therefore, projection pursuit analysis mainly includes two aspects: finding projection mode and selecting projection index.

2.2. Projection pursuit analysis based on kernel
Two sets of samples for n (n>2) dimension $\Phi_1 = \{X_1, X_2, ..., X_{M1}\}$ and $\Phi_2 = \{X_{M1+1}, X_{M1+2}, ..., X_{M1+M2}\}$ exist:

$$\bar{X}_i = \frac{1}{M_i} \sum_{x \in \Phi_i} X \quad (i=1,2)$$

$$S_i = \sum_{x \in \Phi_i} (X - \bar{X}_i)(X - \bar{X}_i)^T \quad (i=1,2)$$

$$S_o = \sum_{x \in \Phi} (\bar{X}_1 - \bar{X}_2)(\bar{X}_1 - \bar{X}_2)^T$$

In which, $\bar{X}_i$ is the mean vector of two types of samples, $S_i$ is the dispersion matrix within the sample class, $S_o$ is the sample interclass dispersion matrix.

In case of $\Phi = \Phi_1 + \Phi_2$, $M = M_1 + M_2$, $S = S_1 + S_2$, suppose there are two orthogonal projection directions $a_1$ and $a_2$. Bring

$$y_{i1} = a_1^T \cdot X_i, \quad y_{i2} = a_2^T \cdot X_i \quad (i=1,2,\ldots,M)$$

To make the sample set $\{ (y_{i1}, y_{i2})^T \}$ $(i=1,2,\ldots,M)$ with minimal classification error, the projection index is set to:

$$\min J(a_1, a_2) = C \sum_{i=1}^{M} \xi_i$$
In which, $C$ is the penalty coefficient, $\xi_i$ is a relaxation factor due to misclassification. When correctly classified, $\xi_i = 0$.

The next step is to optimize the projection function. In order to simplify the process, the projection and classification processes are carried out independently because there are many optimization parameters. Two orthogonal projection directions are obtained by Fisher method [10] and principal component analysis in the projection process. The projection index is:

$$\frac{a_i^T S a_i}{a_i^T S a_i} = \max\left(\frac{a_i^T S a_i}{a_i^T S a_i} \right) \quad (|a| = 1)$$

(6)

### 3. Fault Pattern Recognition Scheme and Measure

The essential work of rolling bearing running state monitoring and fault diagnosis is how to obtain the correct information of its characteristic parameters through the monitoring of the external characteristics of the bearing so as to analyze and identify its running state. As a result, the condition monitoring and fault diagnosis of the equipment is the application process [11] of pattern recognition. The problems of rolling bearing pattern identification and fault diagnosis of wind turbine have the following characteristics:

There are many samples of normal operation state and few samples of fault operation state; there are three main types of fault operation mode: outer ring fault, inner ring fault and rolling body fault.

Two types of miscalculations in the normal state and the fault state can result in different degrees of loss: the loss caused by the missing judgment (that is, the fault state is judged to be the normal state) is more serious than the loss caused by the wrong judgment (that is, the normal state is judged to be the fault state).

At the beginning of the operation of the equipment, it is generally in a normal state of operation, and various fault states will occur one after another over time. With the increase of service time and the influence of environmental factors, the operating parameters will change, and the classification criteria between various states will change.

Therefore, when the general pattern recognition theory and method are applied to meet the requirements of pattern recognition and fault diagnosis when applied to specific examples of fault diagnosis. The flow chart of fault pattern recognition scheme used in this paper is shown in Figure 1.

![Figure 1. Pattern recognition flow chart for rolling bearing](image-url)

There are four main stages in the whole pattern recognition process: data acquisition, data preprocessing, feature extraction and feature selection, pattern recognition. The fault diagnosis of rolling bearing based on kernel projection pursuit analysis is as follows:

Data acquisition. The vibration signal of the bearing is measured by multiple acceleration sensors installed in different positions.
Data preprocessing. The measurement data and sample data are de-noised, restored, standardized and normalized.

Feature extraction and selection. Bispectral analysis was carried out to extract the bispectral feature [12,13]. Bispectral feature is a series of contour maps composed of bispectral estimates, and the amount of data is large. Therefore, the contour contour boundary of bispectral feature map is extracted again, which is used as the eigenvalue of bearing running state, and the sample data of data space is converted to feature space.

Pattern recognition. The projection index is set by kernel based projection pursuit analysis method, the sample data of feature space is trained, the projection function is constructed and optimized, the decision rule with the minimum error rate is worked out, and the projection diagram of eigenvalue is obtained. State classification and fault diagnosis are carried out.

4. Example Analysis and Simulation

In this paper, the rolling bearing fault simulation experimental data of Casey University Electrical Engineering Laboratory are used to analyze and simulate. The experimental platform consists of three parts: motor, torque sensor and power tester. Motor rotating shaft is supported by bearing to be tested, the driving end and fan end bearing models are respectively SKF6205, SKF6203, both are deep groove ball bearings, the number of rolling body is 9,8, contact angle is 90 degrees, other parameters of bearing are shown in table 1.

|                  | Driver port(mm) | Fan terminal(mm) |
|------------------|-----------------|------------------|
| Pitch diameter   | 39.04           | 28.5             |
| Inner ring diameter | 25              | 17               |
| Outer ring diameter   | 52              | 40               |
| Ball diameter     | 7.94            | 6.75             |
| thickness         | 0.59            | 12               |

During the operation of the equipment, the vibration signal of the bearing is measured by multiple acceleration sensors mounted above the bearing seat of the frame, the driving end and the fan end. Experiments have collected the vibration signals of the driving end bearing in four states: normal state, outer ring fault, inner ring fault and rolling body fault at 1797 rpm. The sampling frequency is 12 kHz, 1000 groups of sample data are selected for simulation analysis. The original signal waveform is shown in Figure. 2.
Figure 2. Original waves of vibration signals for all running states

Figure 2 shows that the vibration signal has obvious periodicity except for the outer ring fault, and the other three operating states are difficult to classify and identify. After wavelet denoising of the original vibration signal, bispectral analysis is carried out to obtain the contour map of bispectral feature, as shown in Figure 3.

Figure 3. Dual spectrum feature map for different running states
It can be seen from Figure. 3 that the bispectral features of the four operating states are very different. Taking the bispectral estimation of vibration signals in different operating states as the feature vector, fault diagnosis and pattern recognition is an effective method. Bispectral feature graph is a series of contour maps composed of bispectral estimates. The contour lines are dense, the sample data is numerous, the training sample is heavy, the calculation is large, and the time is long. Therefore, the contour contour contour boundary of bispectral features (Figure .4) is extracted and retained as the eigenvalue of the bearing running state, and the original sample data is converted to the feature space, which preserves the original feature of the signal. However, the computation and calculation time of pattern recognition process are greatly reduced.

![Contour profiles of dual spectrum feature for different running states](image)

**Figure 4.** Contour profiles of dual spectrum feature for different running states

It can be seen from Figure. 4 that the normal operation state is easy to distinguish from various fault states, and only the contour profile is close to that of the outer ring fault and the rolling body fault. From the feature space .50 groups of sample data of four running states are taken out, and the program code is written according to projection pursuit analysis method in the Matlab software platform. The projection of all kinds of sample data in the feature space is obtained, as shown in Figure. 5.
In Figure 5, the a diagram is a projection diagram of all sample data of the four running states, and the b,c,d diagram is a local magnification effect of the three regions of the left, middle and right upper of the a diagram. According to the projection diagram, the projection regions of all kinds of running states are scattered and independent of each other, and the projection points of the same sample data are dense together, and the cohesion is good. Although the projection area of the outer ring fault and the inner ring fault is close to each other, it can be seen from the local magnification effect of the d diagram that the projection areas of the two are also separated and independent of each other and can be classified and recognized. Therefore, the four running states of rolling bearings can be classified and identified, all kinds of self-condensation is high, the dispersion between categories is good, and fault pattern recognition can be completed well.

5. Conclusion
Fault pattern identification is the key technology and difficult problem in the fault diagnosis process of wind turbine rolling bearing. In the non-stationary wind speed environment, the fault characteristics of bearings show non-Gaussian, nonlinear, strong noise and strong coupling. The vibration characteristic statistics of different types of faults are different. If the severity of the same fault is different, the vibration characteristic statistics will also change. The signal monitoring and fault diagnosis are greatly affected. In this paper, the kernel-based projection pursuit analysis method is used to transform the original fault features from nonlinear data space to feature space for linear processing, thus completing the classification and recognition of various running states. It is a fast, efficient and accurate pattern recognition method. The research and application of this method is of great significance to improve the reliability and safety of wind power system.
Acknowledgments

Fund Project: Natural Science Fund Project of Xinjiang Uygur Autonomous Region (2018D01C046)

References

[1] Z.X Bai, B.C Xu, H.L Chen, Control and Instruments in Chemical Industry. J.E 46 6 (2019).
[2] Y. Ding, Scientific and Technological Innovation. 10 (2020)
[3] S.P Hao, H.G Zhang, G.H Yue, F.Yu, Z.Z Shen, Science and Technology & Innovation. 9 (2019)
[4] Z.J Wei, A.W Li, S. Shao, Y. Hu, H.L. Zhu, Advances in New and Renewable Energy. J.E 6,4 (2018)
[5] X. Zhang, Fault Feature Extraction and Diagnosis of Rolling Bearing Based on Spectral Kurtosis Algorithm. (2019).
[6] C. Ju, C. Zhang, H.W Fan, Industry and Mine Automation. J.E 46,8 (2020)
[7] N. Lv, P.X Yao, Coal Mine Machinery. J.E 41,8 (2020)
[8] S.J Dong, X.W Pei, W.L Wu, B.P Tang, X.X Zhao, Journal of Mechanical Engineering. 1 (2021)
[9] G.G Xu, Y Jia, MATLAB Implementation of Pattern Recognition and Intelligent Computing. (2012).
[10] S.Y Yang, H Zhang, Technology realization of pattern recognition and intelligent computing — MATLAB. (2015).
[11] L. Rokach, W.L. Huang, X.D, Wang, Y. Wang, Y. Xiao, Integrated Method of Pattern Classification. (2015).
[12] J. Cheng, W.Q. Wang, S. He, Process Automation Instrumentation. J. E 37,7 (2016).
[13] R.G Zhang, J Li, Journal of Wuhan Polytechnic University. J. E 36,2 (2017).