

Rolling Bearing Fault Pattern Recognition of Wind Turbine Based on VMD and PNN

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Abstract. A novel method based on variational modal decomposition (VMD), improved multiscale permutation entropy (IMPE) and probabilistic neural network (PNN) is proposed to solve the problem of the rolling bearing fault pattern recognition for wind turbine. Firstly, the vibration signal is decomposed into several components using VMD. Then, the IMPE of the optimal component which has the maximum kurtosis is computed and constructed to feature vector. Finally, the feature vector is inputted into PNN classifier to train and test the fault pattern respectively. Experimental analysis results show that the proposed method can effectively identify the damage locations and different damage degree for bearing. It has good engineering application value.

Introduction

The drive shaft system of wind turbine is often supported by rolling bearing. The periodic impact signal is produced when the bearing is in fault situation such as pitting etc. It is difficult to diagnose the fault type due to the influence of wind turbine structure, working environment noise etc. It has important significance to explore the intelligent diagnosis method of bearing fault of wind turbine.

A method integrated Least Squares Support Vector Machines and EMD was proposed to diagnose bearing fault by Liu[1]. Dragomiretskiy et al.[2] proposed a new multi-component signal quasi-orthogonal decomposition method named variational mode decomposition (VMD). This method determines the center frequency and bandwidth of each component through iterative search variational model optimal solution mod. VMD has solid theoretical foundation and higher decomposition accuracy than EMD and has been introduced to mechanical fault diagnosis. Improved multiscale permutation entropy (IMPE) can measure the dynamic behavior of the time series at different scales, and it is more robust than the multiscale entropy[3]. Combined with probabilistic neural network (PNN) has short training time and strong classification ability, a rolling bearing pattern recognition method for wind turbine based on VMD, IMPE and PNN is proposed. The experimental analysis results show the effectiveness of this method.

Variational mode decomposition

VMD considers that real valued signal f is composed of a number of sub-signals u_k (modes). Each mode is regard as an AM-FM signal and has mostly compact frequency ω_k around a frequency center. These modes are called Intrinsic Mode Functions (IMFs). The constrained variational problem is the following

$$\min_{\{u_k\}, \{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\sigma(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \quad (1)$$

$$s.t. \sum_k u_k(t) = f$$

The augmented Lagrangian is introduced to solve the constrained variational problem in Eq.1, and the non-constrained variational problem is got by Eq.2.

$$L(\{u_k\}, \{\omega_k\}, \lambda) = \alpha \sum_k \left\| \partial_t \left[\left(\sigma(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| f(t) - \sum_k u_k(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum_k u_k(t) \right\rangle \quad (2)$$

Where, α denotes the balancing parameter of the fidelity constraint. The saddle point of Eq.2 is the optimal solution of original problem, which can be gained using alternate direction method of multipliers (ADMM) [4]. All the modes can be obtained by Eq.3 in the frequency domain through updating each mode and its center frequency ω_k constantly.

$$\hat{u}_k^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i \neq k} \hat{u}_i(\omega) + \hat{\lambda}(\omega) / 2}{1 + 2\alpha(\omega - \omega_k)^2} \quad (3)$$

\hat{u}_k^{n+1} is regarded as the Wiener filtering result of the residue $\hat{f}(\omega) - \sum_{i \neq k} \hat{u}_i(\omega)$, which makes the VMD algorithm much more robust to sampling and noise. The new center frequency ω_k^{n+1} is put at the center of gravity of the corresponding mode's power spectrum, which can be updated by Eq.4.

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega |\hat{u}_k(\omega)|^2 d\omega}{\int_0^\infty |\hat{u}_k(\omega)|^2 d\omega} \quad (4)$$

The detail iterative process can reference literature [2]. The wind turbine vibration signal is multi-carrier and multi-modulation. Among the VMD components, the maximum kurtosis component can better represent the bearing impact fault. So it is chosen to next IMPE analysis and construct feature vector.

Improved Multiscale Permutation Entropy and Probabilistic Neural Network

It is one of the key that how to select and construct fault feature vector for recognizing the status of rolling bearing. Because the IMPE can detect a signal dynamics changes in different scales to realize the refinement analysis, so the IMPE is selected in this paper to construct feature vector. The calculation of IMPE has two steps. First, the time series $\{x(i), i=1,2,\dots,N\}$ is coarse-grained through Eq.5

$$y_j^s = \frac{1}{s} \sum_{i=(j-1)s+1}^{js} x_i \quad j = 1,2,\dots,[N/s] \quad (5)$$

Where, s is the scale factor, and it determines the coarse-grained degree. When $s=1$, it is the original time series; $\{y_j^s\}$ are the coarse-grained series. Then, the phase space reconstruct is done to each $\{y_j^s\}$ by embedding dimension m and time delay τ . And the permutation entropy (PE) is calculated to reconstruct series, so the IMPE is obtained. In this paper, m is set to 6, τ is set to 1 and s is set to 10.

Another key factor for rolling bearing fault pattern recognition is a pattern recognition method. PNN has the advantages of short training time and high classification ability. The PNN is a forward feed neural network based on Bias classification rules and Parzen window probability density function estimation. PNN has input layer, model layer, summation layer, and output layer[5].

Rolling bearing fault pattern recognition method

Based on the advantages of VMD, IMPE and PNN, the proposed method of fault pattern recognition for rolling bearing of wind turbine is following:

(1) For the 7 types of bearing status (shown in Table 1), we gather 50 samples data for each status by a certain sampling frequency, so the total sample data $N=50 \times 7=350$, we randomly select 20 samples from each fault to train PNN, and the remaining 30 samples are test sample respectively.

(2) Each sample is decomposed using VMD, and the maximum kurtosis component is chosen out.

(3) Calculate the maximum kurtosis component's IMPE which is the i status and the m sample. Structure feature vector $T_{im}=[PE_1; PE_2; \dots; PE_s]$, where PE_s denotes the PE of s scale, $i \in [1,7]$ represents bearing status, $m \in [1,50]$ denotes the number of samples, so the feature vector of the i

bearing status is $T_i = [T_{i1}, T_{i2}, \dots, T_{im}]$, therefore, the structural fault feature vector $T = [T_1, T_2, \dots, T_i, \dots, T_7]$.

(4) The training samples feature vector as input and the corresponding 7 types of bearing fault as the output is set to train the PNN (the diffusion speed parameter spread is set to 1).

(5) The testing samples feature vector is inputted the trained PNN, and the output result shows the bearing work status to realize the pattern recognition.

Table 1. Rolling bearing status and number

Status	Fault type	Status	Fault type
1	Normal	5	Outer race serious fault
2	Inner race flight fault	6	Rolling element flight fault
3	Inner race serious fault	7	Rolling element serious fault
4	Outer race flight fault		

Experimental analysis

The rolling bearing vibration data is obtained from Bearing Data Center of Western Reserve University[6], The bearing type is SKF6205, the shaft speed is 1772r/min, sample frequency is 12kHz, and each sample are 1024 points. Fault feature vectors are constructed for training and testing PNN respectively.

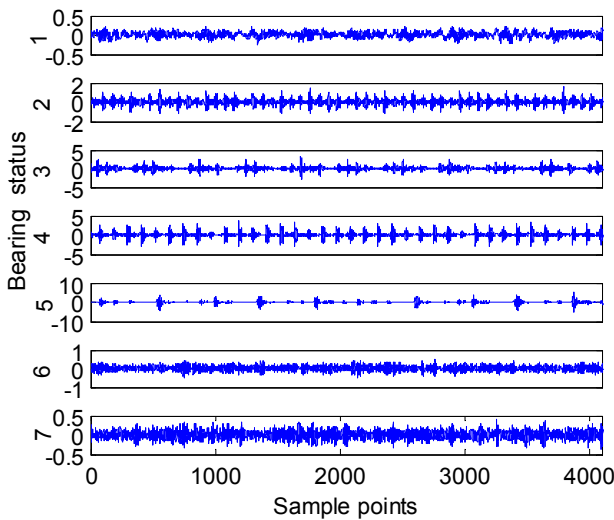


Fig.1 Original signal waveform of 7 bearing status VMD

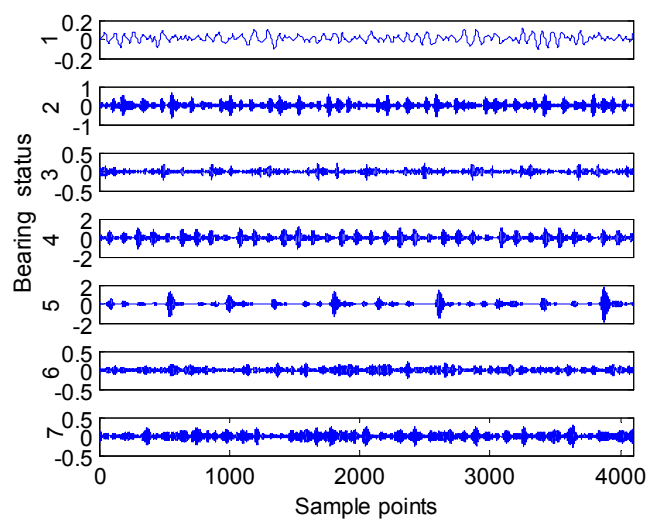


Fig.2 Waveform of optimal components by

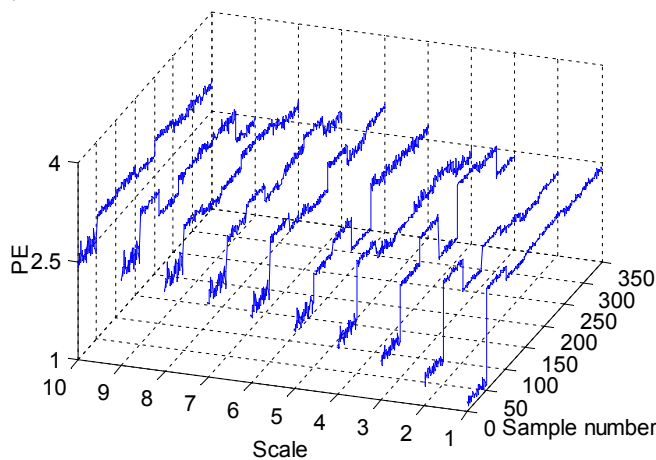


Fig.3 IMPE of the optimal components

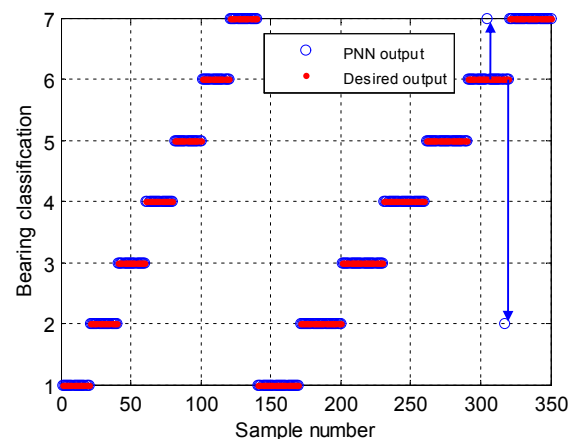


Fig.4 Pattern recognition results by PNN

Waveforms of 4096 points for 7 types of bearing status are shown in Fig.1. It is difficult to distinguish fault type and damage degree of bearing. These signals are decomposed by VMD and the maximal kurtosis components are selected out respectively, the corresponding waveform of the optimal components are shown in Fig.2. It can be seen that the impact characteristic are separated

clearly and interference components are removed. It shows the better decomposition ability of VMD to multi-component signal, and it also illustrates the necessity of VMD decomposition.

To show the validity of the feature vector, we put all of the training samples and the testing samples together. All samples are decomposed by VMD, the corresponding maximum kurtosis components are selected out, calculated IMPE, and constructed IMPE feature vector. The results of the 10 scales to 50 samples of 7 status is shown in Fig.3. The sample number in Fig.3 is the order of 50 samples in 1~7 status successively. Scale 1 is the permutation entropy of the kurtosis maximum component, it is not obvious to distinguish status 4~7, and it also explains the necessity of IMPE analysis.

It can be seen from Fig.3 that the IMPE of different bearing status has two main characteristics:

(1) the same scale's PE is stability for different samples in same bearing status.

For example, the 51st to 100th samples in Fig.3 are status 2 (inner race slight fault) with total 50 samples, the PE value of scale 1~10 basically remain unchanged respectively. This characteristic provides a reliable property for the analysis of the same scale contrast of the different bearing states.

(2) there are good difference among the same scale in difference bearing status.

Take the scale 3 in Fig.3 for example, the PE of bearing status 1~7 are different each other. this difference makes the distinguish for different status possible. In order to obtain higher fault pattern recognition rate and reduce the computation, the PE of the scale 2~7 is used to construct the feature vector in this paper.

20 samples in Fig.3 are randomly selected for each status for training samples and the remaining 30 samples for testing samples. Two types of samples are calculated IMPE and constructed feature vector respectively. For the PNN classifier, the six scale PE feature vector is regarded as input and 7 bearing status is regarded as output. Firstly, the training sample feature vector is inputted into the PNN for training. Then, the testing sample feature vector is inputted into the PNN for testing. The result of pattern recognition is shown in Fig.4. It can be seen from Fig.4 that 1st~140th training samples are all recognized correctly by PNN. 141st~350th test sample are almost classified correctly except two samples, the recognition rate is 99.05%. It can meet the needs of engineering applications. There are two identify errors. The slight rolling element fault is regard as inner race slight fault and serious rolling element fault. The reason is that the sensor is close to the outer race, so the outer slight fault and serious fault can be both measure accurately, and the faults are recognized perfectly. But the position of inner race fault and rolling element fault are far from the sensor, especially the rolling element are both rotation and revolution, so rolling element slight fault is difficult to diagnose and maybe confuses to its serious fault or to inner flight fault. This is the reason that make the wrong recognition occur.

Conclusions

VMD algorithm is a new multi-component signal decomposition method and has high decomposition accuracy. A bearing fault pattern recognition method combined with VMD, IMPE, and PNN is proposed in the paper. The signal is decomposed into several components firstly, and the IMPE is calculated to the maximum kurtosis component which contain more mechanical fault impact information, and IMPE is used to construct the feature vector. The PNN fault classifier is used for training and testing the fault status by analyzing the feature vector. This method can accurately recognize the different fault types of rolling bearings. It has the advantages of easy implementation and high recognition rate.

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