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An intelligent fault diagnosis method based on wavelet packer analysis and hybrid support vector machines

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ABSTRACT

In this paper, a new intelligent method for the fault diagnosis of the rotating machinery is proposed based on wavelet packet analysis (WPA) and hybrid support machine (hybrid SVM). In fault diagnosis for mechanical systems, information about stability and mutability can be further acquired through WPA from original signal. The faulty vibration signals obtained from a rotating machinery are decomposed by WPA via Dmeyer wavelet. A new multi-class fault diagnosis algorithm based on 1-v-r SVM approach is proposed and applied to rotating machinery. The extracted features are applied to hybrid SVM for estimating fault type. Compared to conventional back-propagation network (BPN), the superiority of the hybrid SVM method is shown in the success of fault diagnosis. The test results of hybrid SVM demonstrate that the applying of energy criterion to vibration signals after WPA is a very powerful and reliable method and hence estimating fault type on rotating machinery accurately and quickly.

1. Introduction

The efficient and accurate fault diagnosis is important for improving reliability and performance in a mechanical system (Chen, Chua, & Lim, 2008). Most of the rotating machinery such as internal combustion engines, fans and motors may develop faults. These faults may cause the machine to break down and decrease its level of performance (Lei, He, Zi, & Hua, 2007).

Traditionally, the condition of rotating machinery can be monitored by measuring he respective vibration signal or sound emission signal (Wu et al., in press). Many methods such as Time Synchronous Average (TSA), Fast Fourier Transform (FFT)-based spectrum analysis and short-time Fourier Transform (STFT) have been applied in fault diagnosis and condition monitoring of mechanical system. The above methods analyze the signal in frequency domain with low resolution, which is not suitable for non-stationary vibration signal (Chen et al., 2008).

Wavelet packet analysis (WPA) is the typical signal processing method for mechanical fault diagnosis. WPA can multi-decompose the signal into the different frequencies to obtain the localized impulse signals. The energy of the WPA coefficients is used for fault detection. Hasan Ocaka developed a new scheme based on wavelet packet decomposition and hidden Markov modeling (HMM) for tracking the severity of bearing faults (Ocaka, Loparob, & Discenzoc, 2007). A fault diagnosis system (Wu & Liu, 2009) is proposed for internal combustion engines using WPA and artificial neural network (ANN) techniques. The experimental results showed the proposed system achieved an average classification accuracy of over 95% for various engine working conditions. In Zarei and Poshtan (2007), bearing defect is detected using the stator current analysis via Meyer wavelet in the wavelet packet structure, with energy comparison as the fault index. The advantage of this method is in the detection of incipient faults. Compared to conventional methods, the superiority of the proposed method is shown in the success of fault detection.

Among the various methods for condition monitoring of machinery, ANN have become in the recent decades the outstanding method exploiting their non-linear pattern classification properties, offering advantages for automatic detection and identification of gearbox failure conditions, whereas they do not require an in-depth knowledge of the behaviour of the system (Rafiee, Arvani, Harifi, & Sadeghi, 2007). These methods are based on an empirical risk minimization principle and have some disadvantages such as local optimal solution, low convergence rate, obvious "over- fitting" and especially poor generalization when the number of fault samples is limited (Yuan & Chu, 2006).

Support vector machines (SVM) is a very effective method for general purpose pattern recognition based on structural risk minimization principles. This characteristic is very important in fault diagnostics under the condition that the fault samples are few (Guo-hua, Yong-zhong, Yu, & Guang-huang, 2007). The main difference between ANNs and SVMs is in their risk minimisation (Gunn, 1998). In the case of SVMs, structural risk minimisation principle is used to minimise an upper bound based on an expected risk. Whereas in ANNs, traditional empirical risk minimisation is used

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to minimise the error in training of data. The difference in risk minimisation leads to a better generalization performance for SVMs than ANNs (Kim, Pang, Je, Kim, & Bang, 2003). Samantaray, Dash, and Panda (2007) focus on the development of an advanced signal classifier for small reciprocating refrigerator compressors using noise and vibration signals. Three classifiers, self-organising feature map, learning vector quantisation and SVM are applied in training and testing for feature extraction and the classification accuracies of the techniques are compared to determine the optimum fault classifier. The classification technique selected for detecting faulty reciprocating refrigerator compressors involves artificial neural networks and SVMs. The results confirm that the classification technique can differentiate faulty compressors from healthy ones and with high flexibility and reliability. Abbasiona, Rafsanjani, Farshidianfar, and Irani (2007) provides a procedure for fault classification of rolling bearings, using SVM classifier. Vibration data from bearings were denoised using discrete Meyer wavelet. The results that they achieved from wavelet analysis and SVM are fully in agreement with empirical result.

SVM theory is proposed for binary classification. Many approaches have been proposed to extend the binary SVM to multi-class problems. The common scheme is that a multi-class SVM is designed to deal with the problem as a collection of two-classifications that can be solved by binary SVM. In Guo-hua et al. (2007), a hybrid SVM scheme is proposed for multi-fault classification. This hybrid scheme integrates two SVM strategies, 1-v-1 (one versus one) and 1-v-r (one versus rest), respectively adopted at different classification levels, parallel classification and serial classification levels.

In this paper, the object of the fault diagnosis is the rotating machinery. For designing WPA and hybrid SVM based fault design system, the features of the rotating machinery were used for training and testing of hybrid SVM after preprocessing. A serial classification method based on 1-v-r SVMs strategy is proposed in our research.

2. Principle of wavelet packet analysis and feature extraction

2.1. Wavelet packet analisis

Both of WPA and discrete wavelet transform (DWT) have the framework of multi-resolution analysis (MRA). The main difference in the two techniques is the WPA can simultaneously break up detail and approximation versions, but DWT only breaks up as an approximation version. Hence, the WPA have the same frequency bandwidths in each resolution and DWT does not have this property. The mode of decomposition does not increase or lose the information within the original signals. Therefore, the signal with great quantity of middle and high frequency signals can offer superior time–frequency analysis. The WPA suits signal processing, especially nonstationary signals because the same frequency bandwidths can provide good resolution regardless of high and low frequencies. The theory of WPA can be defined as below (Li, Song, & Li, 2004; Ortiz & Syrmos, 2006; Wu & Liu, 2009; Xu & Li, 2007; Yen & Lin, 2000).

The WPA is a generalization of the wavelet transform and the wavelet packet function is also a time–frequency function, it can be described as

$$w_{j,k}^{n}(t) = 2^{j/2} w(2^{j}t - k), \quad j, k \in Z \tag{1}$$

where the integers j and k are the index scale and translation operations. The index n is an operation modulation parameter or oscillation parameter. The the scaling function $\phi(t)$ and mother wavelet functions $\psi(t)$ can be defined as:

$$\phi(t) = \sqrt{2}\sum_{k} h_{0k}\phi(2t - k), \tag{2}$$

$$\psi(t) = \sqrt{2}\sum_{k} h_{1k}\phi(2t - k). \tag{3}$$

When $n = 2; 3; \ldots$ the function can be defined by the following recursive relationships:

$$w_{2n}(t) = \sqrt{2}\sum_{k\in Z} h_{0k} w_{n}(2t - k), \tag{4}$$

$$w_{2n+1}(t) = \sqrt{2}\sum_{k\in Z} h_{1k} w_{n}(2t - k), \tag{5}$$

where h_{0k} and h_{1k} are the quadrature mirror filter (QMF) associated with the predefined scaling function and mother wavelet function. The wavelet packet coefficients, $w_{j,k}^{n}$ are defined as

$$w_{j,k}^{n} = \int \Phi(t) w_{j,k}^{n}(t)\, dt. \tag{6}$$

The symbol W_{3}^{0} presents the symbol for a subspace that stands for the third resolution and the 0th subspace. In the experimental study, the signals will be broken up to four resolutions. As a result, four resolutions will produce sixteen subspaces and the frequency intervals of each subspace can be computed by Hu, Wang, and Ren (2005):

$$\left(\frac{n-1}{2^{j+1}}S_f, \frac{n}{2^{j+1}}S_f\right], \quad n = 1, 2, \ldots, 16 \tag{7}$$

where S_f is sampling frequency. In this research $S_f = 2000$ Hz, f_0^0 is the original signal with the frequency interval $\left(0, \frac{S_f}{2}\right] = (0, 1000]$, f_1^0 with the frequency interval (0,500], f_2^0 with the frequency interval (0,250], f_3^0 with the frequency interval (0,125], f_3^7 with the frequencies interval (875,1000]. The wavelet packet analysis is used regarding the data preprocessing for fault diagnosis.

2.2. Feature extraction of fault conditions using Shannon entropy and wavelet selection

A high-frequency-resolution wavelet is obtain to study the frequency characteristic of a signal. Shannon wavelet has the most resolution theoretically (Mallat, 1998) among orthogonal wavelets. Sharp edges of these filters make them non-causal, therefore their approximation is utilized in practical application.

In the field of signal processing, entropy is a common idea used (Zhang, Walter, Miao, & Lee, 1995). Wavelet packet decomposition is applied to the fault signal using wavelet packet filters ψ with the "Shannon entropy" and is defined as below

$$E_n = \sum_{n=0}^{15} w_{j,k}^{n2} \log\left(w_{j,k}^{n2}\right), \quad j, k \in Z \tag{8}$$

where $w_{j,k}^{n}$ is the coefficients of the subspace after wavelet packet decomposition and $n = 1, 2, \ldots, 15$ (Avic & Akpolat, 2006). For containing massive noise, the low frequencies in Shannon entropy of E_0 will not used. Hence, after being normalized the feature vector T composed of E_n can be expressed as

$$T = [E_1/E, E_1/E_2, \ldots, E_{15}/E]. \tag{9}$$

For identifing the different faults of rotating machinery by support vector macine, the feature vector T will be used in fault classification.

Meyer wavelet is an approximation of Shannon wavelet. This wavelet is a frequency bandlimited function whose Fourier transform is smooth, unlike that of the Shannon wavelet, and cause a faster decay of wavelet coefficient in the time domain. However, the time decay of this wavelet in time domain is high. It is faster than Shannon wavelet, but the supporting area in time domain is