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Scattering transform and LSPTSVM based fault diagnosis of rotating machinery

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ABSTRACT

This paper proposes an algorithm for fault diagnosis of rotating machinery to overcome the shortcomings of classical techniques which are noise sensitive in feature extraction and time consuming for training. Based on the scattering transform and the least squares recursive projection twin support vector machine (LSPTSVM), the method has the advantages of high efficiency and insensitivity for noise signal. Using the energy of the scattering coefficients in each sub-band, the features of the vibration signals are obtained. Then, an LSPTSVM classifier is used for fault diagnosis. The new method is compared with other common methods including the proximal support vector machine, the standard support vector machine and multi-scale theory by using fault data for two systems, a motor bearing and a gear box. The results show that the new method proposed in this study is more effective for fault diagnosis of rotating machinery.

1. Introduction

Rotating machinery is widely used in aircrafts, maritime vessels, and ground vehicles, which are increasingly important for movement or power converting. Damage and failure in rotating machinery not only seriously affects the reliability and the safety of the entire engineering system but can also cause severe economic losses. As a result, damage and failure in rotating machines have received increasing attention in the research community. Currently, research is focused on fault feature extraction and classification, mainly through the analysis of signals indicating weak faults, to improve the accuracy and the capabilities of fault diagnosis systems so that real-time monitoring and diagnosis can be performed.

Due to the influence of environment vibration and noise, a large number of noise signals are mixed in real signal, which directly affects the quality of data. In the fault diagnosis of rotating machinery, time frequency analysis is usually used to extract fault features such as fast Fourier transform (FFT), wavelet transform (WT) and empirical mode decomposition (EMD), etc. However, these methods only obtain high-frequency information containing noise, which will lead to the useful information in fault signal being filtered out and the prediction accuracy being difficult to guarantee. Therefore, it is one of the focuses to extract fault features directly from the original acquisition signal as much as possible to retain the fault features and reduce the impact of noise.

Compared with FFT algorithm, WT is the most common signal processing method used for fault detection in rotating machinery [1]. However, the discrete wavelet transform (DWT) and the second-generation wavelet transform (SGWT) adopt

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down-sampling or splitting operation to cause time shift. Furthermore, the decomposition operation in the SGWT can produce erroneous results [2]. As a result of this aliasing, the wavelet coefficients may not reflect the true state information of the system. The dual-tree complex wavelet transform (DT-CWT) [3] is nearly time shift invariant and parity sampling effectively reduces the frequency of the aliasing, which is superior to the SGWT and other methods [2]. The EMD is a self-adaptive signal processing technique that is suitable for nonlinear and non-stationary processes [4]. Importantly, Bruna and Mallat [5–7] developed the scattering transform of convolution networks by using complex wavelets to balance the discrimination capabilities and stability in the wavelet time frequency equation. Scattering transform filters the signal data by using a cascade of wavelet decompositions, complex modulus and local weighted averaging. Compared to other feature extraction methods, the scattering transform includes two advantages fitting for fault diagnosis. (1) Cascade of wavelet decompositions. The co-occurrence coefficients yielded by the cascade of complex wavelet decompositions at multiple scales can provide rich descriptors of complex structures for fault diagnosis. (2) Local weighted averaging. It can reduce the feature variability and try to keep the local consistency of the class labels, and suppress the influence of the noise contained in the acquisition signal. Besides, the scattering transform has been used with great success in handwritten character recognition [8], texture classification [9], and audio signal classification [10].

The machine learning algorithms are commonly used for failure diagnosis including Gaussian mixture model (GMM), artificial neural networks (ANNs), support vector machines (SVMs), logistic regression, and hidden Markov models (HMMs) are used to assist in identifying faults [5,6], but they contain certain problems. For example, in the GMM, the optimal values of the parameters are sensitive to the training method, so it is difficult to determine the optimal number of compositions. In ANNs, there is no standard method to determine the structure of the network. The rough set method requires discretization, which is unsuitable for continuous variables and results in uncertainty in the decision threshold. HMMs require a sufficient number of training samples to satisfactorily train the model, resulting in greater computational complexity and requiring more time [11]. The SVM and its variants (such as proximal support vector machines (PSVM) and twin support vector machine (TSVM)) are more suitable for handling small data so that they spend more time in processing large data [6]. To address the shortcomings of traditional SVM theory, Jayadeva et al. [12] introduced the twin support vector machine (TSVM) for binary data classification, which reduces the computational complexity by solving two smaller Quadratic Programming Problems (QPPs). Similarly, the projection twin support vector machine (PTSVM) is a different way to seek nonparallel hyperplanes by solves two smaller QPPs [13]. Shao et al. [14] proposed a novel nonparallel hyperplane support vector machine (NHSVM) model which constructs the two nonparallel hyperplanes simultaneously to improve the classification accuracy and shorten the training time. Furthermore, in order avoid the singularity and consider the nonlinear classification, a complete projection twin support vector machine with regularization terms, called RPTSVM for short, is proposed [15]. In order to increase the performance of PTSVM, Shao et al. [16] proposed the least squares recursive projection twin support vector machine (LSPTSVM) for binary classification problems which adds an extra regularization term, not only ensuring the positive definite of the QPPs but also resulting in better generalization ability. Besides, the LSPTSVM only needs to solve two systems of linear equations that further reduces the computational complexity. To relieve the training burden, Shao et al. [17] developed a novel multiple least squares recursive projection twin support vector machine (MLSPTSVM) based on least squares recursive projection twin support vector machine (LSPTSVM) for multi-class classification problem.

In the method developed in this study, in order to reduce the sensitivity to noise in feature extraction of rotating machinery signals, the energy of each sub-band of the vibration signal generated by the rotating mechanical system is extracted with the application of the scattering transform. Meanwhile, in order to compensate for the shortcoming of time consuming of fault prediction in learning, the LSPTSVM is used to classify the fault characteristics of the signal. The process is shown in Fig. 1.

The remainder of the paper is organized as follows: in Section 2, an introduction to the theory of the scattering transform and the LSPTSVM is given. The method developed in this study is described in Section 3. Two examples and the results of tests of the performance of the new method are given in Section 4. Conclusions are presented in Section 5.

2. Theoretical background

2.1. Scattering transform

The scattering transform of convolutional networks, which is based on complex wavelets, was introduced by Bruna. The characteristics of signals are obtained through an iterative complex wavelet decomposition, modular arithmetic and local averaging. Multi-scale complex wavelets are used to obtain the low-level features of signals, the moduli of the high-frequency coefficients are computed, and relatively stable frequency characteristics are obtained from "local averages". A second high-frequency complex wavelet is employed to recover the high-frequency information that is lost because of

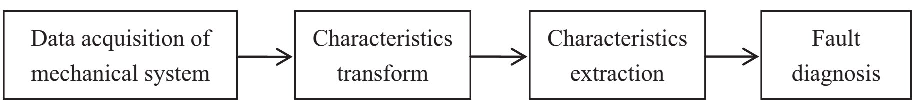

Fig. 1. Fault diagnosis process.