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Study on planetary gear fault diagnosis based on entropy feature fusion of ensemble empirical mode decomposition

Gang Cheng, Xihui Chen *, Hongyu Li, Peng Li, Houguang Liu

School of Mechatronic Engineering, China University of Mining and Technology, 221116 Xuzhou, China

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ABSTRACT

Because planetary gear is characterized by its small size, light weight and large transmission ratio, it is widely used in large-scale, low-speed and heavy-duty mechanical systems. Therefore, the fault diagnosis of planetary gear is a key to ensure the safe and reliable operation of such mechanical equipment. A fault diagnosis method of planetary gear based on the entropy feature fusion of ensemble empirical mode decomposition (EEMD) is proposed. The intrinsic mode functions (IMFs) with small modal aliasing are obtained by EEMD, and the original feature set is composed of various entropy features of each IMF. To address the insensitive features in the original feature set and the excessive feature dimension, kernel principal component analysis (KPCA) is used to process the original feature set. Kernel principal component extraction and feature dimension reduction are performed. The fault diagnosis of planetary gear is eventually realized by applying the extracted kernel principal components and learning vector quantization (LVQ) neural network. The experiments under different operation conditions are carried out, and the experimental results indicate that the proposed method is capable of extracting the sensitive features and recognizing the fault statuses. The overall recognition rate reaches to 96% when the motor output frequency is 45 Hz and the load is 13.5 N m, and the fault recognition rates of the normal gear, the gear with one missing tooth and the broken gear can reach to 100%. The recognition rates of different fault gears under other operation conditions also can achieve better results. Thus, the proposed method is effective for the diagnosis of planetary gear faults.

1. Introduction

Planetary gear transmission has many advantages, including small size, light weight and large transmission ratio, so it is widely used in the drivetrain of mechanical equipment. However, the planetary gear often subject to heavy duty operation, intense impacts and large amounts of pollution, so it is prone to appear various faults. These faults can result in the catastrophic failure of mechanical equipment, therefore, the fault diagnosis of planetary gear is important. The planetary gear is composed of a sun gear, a ring gear and multiple planet gears. Usually, the sun gear is a fixed axis gear, and the ring gear is stationary. The planet gears meshing with the sun gear and ring gear simultaneously not only rotate around the planet gear shaft but also revolute around sun gear shaft. Due to complex movement of planetary gear, working conditions, manufacturing errors and installation errors, the various complex frequency components are produced. The vibration signal of planetary gear has the frequency modulation (FM) characteristic when various frequency components are coupled. Meanwhile, in general, the acceleration sensors are installed on the fixed position of planetary gearbox to collect vibration signals. The relative distances among the acceleration sensors and the meshing positions of sun gear with planet gears and planet gears with ring gear are time-varying, and the changing of vibration transmission path would produce the amplitude modulation (AM) effect on the vibration signals of planetary gear. So the vibration signals of planetary gear exhibit the AM and FM phenomena, which show the nonlinear and non-stationary characteristics increasing the difficulty of planetary gear fault diagnosis [1]. The fault feature extraction method adopted to process the vibration signal of planetary gear could be studied, and the fault diagnosis of planetary gears should be achieved through the application of the advanced classification methods [2].

The traditional fault diagnosis methods are performed such that the monitored time-domain signal is transformed into the frequency domain by comparing feature frequencies and other frequency indicators. However, those methods are only suitable to distinguish the fault occurring part of planetary gear (sun gear fault, planet gear fault or ring gear fault), that is because the fea-

* Corresponding author.
E-mail address: chenxh@cumt.edu.cn (X. Chen).

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ture frequency components generated by sun gear fault, planet gear fault and ring gear fault are significantly different. But the frequency components generated by different gear fault statuses occurring on the same part of planetary gear are only have a little difference in terms of the amplitudes and the sidebands of feature frequencies, and the difference would be usually very weak [3,4]. So the fault status of planetary gear cannot be diagnosed based on the changes in the feature frequencies and other frequency indicators. Time–frequency analysis methods not only reflect the frequency components but also show their time-varying features, and the time–frequency analysis methods include the short-time Fourier transform, wavelet transform and empirical mode decomposition (EMD). The short-time Fourier transform is a type of linear analysis method, and the wavelet transform requires that the wavelet basis and decomposition layer should be determined in advance. Thus, it is not an adaptive decomposition method, and it suffers from the shortcoming of frequency leakage. EMD is a time–frequency analysis method proposed by Huang in 1998, wherein the vibration signal is decomposed into many IMFs with strict definitions. The definitions of the IMF are as follows: (1) For all of the data, the number of extreme points and the number of zero crossing points must be equal or differ by no more than one. (2) At any point, the average of the upper envelope value formed by the local maximum point and the low envelope value formed by the local minimum point is zero [5,6]. However, EMD suffers from modal aliasing. To solve this problem, EEMD method was proposed by Wu and Huang [7]. The extreme point distribution of the original signal is varied by adding Gaussian white noise, and EMD is used to decompose the corrected vibration signal. Adding multiple Gaussian white noise, multiple IMF sets can be obtained. According to the frequency homogeneity characteristic of Gaussian white noise, pure and effective IMFs can be calculated by computing the average of multiple IMF sets. In addition, EEMD has no basis function, so it is an adaptive decomposition process. The effective IMFs obtained by EEMD, therefore, how to extract the feature information included in IMFs is the important topics of further research.

Because the decomposed IMFs have nonlinear and non-stationary characteristics, the traditional statistical properties and frequency-domain features cannot meet the requirements. Some non-linear parameter estimation methods have proved to be excellent methods to obtain the feature information contained in IMFs, and the entropy theory used to estimate the complexity and stationarity of signal is introduced in the signal processing field. Zhang et al. [8] presented a hybrid model that combines EEMD and integrated permutation entropy and used this model for the fault detection and classification of motor bearings. Zeng et al. [9] proposed the wavelet correlation feature scale entropy that combined entropy theory and a wavelet correlation filter achieving the fault feature information extraction of rolling bearings under various degraded conditions. However, when the entropy features are used to indicate the complexity and stationarity of signal, the signal can be expressed from multiple angles, such as signal energy and signal similarity. Regarding the feature extraction procedure of fault diagnosis, the essence of feature extraction is that the most distinguishing features should be extracted as much as possible. When different faults occur, a more comprehensive expression for the vibration signal can be obtained by extracting the entropy features from multiple angles. However, for multiple decomposed IMFs, the dimension of entropy features is excessive. In addition, not all entropy features are beneficial to distinguish planetary gear faults; for example. For multiple planetary gear faults, the differences between some entropy features of some IMFs are small, and the insensitive features would affect the accuracy of the fault diagnosis. The fusion of the original feature set composing of entropy features, data dimension reduction and insensitive feature elimination must be applied. In terms of data dimension reduction and sensitive feature extraction, the more common used method is principal component analysis (PCA). However, PCA is based on a linear space transformation, so it cannot obtain the required results for addressing nonlinear problems. KPCA is a nonlinear feature extraction method based on a kernel function that is used to map the original data to a high-dimensional feature space. Then, the linear principal components of the mapped data are extracted in the high-dimensional feature space, and the dimension reduction and nonlinear fault feature extraction are obtained [10].

The recognition precision is important after the effective extraction of fault feature information, and there are many research works studied for fault recognition, for example support vector machine (SVM), extreme learning machine (ELM), nearest neighborhood model and neural network, etc. [11–13]. SVM is a fault recognition model that is suitable for processing the problem with small samples. It takes the inner product kernel function to replace the nonlinear mapping of the high-dimensional space, and the nonlinear problem can be solved. But the recognition effect of SVM is greatly affected by the selection of kernel function and its parameters. The optimal parameters are difficult to find, and the inappropriate parameters will cause the model perform badly in generalization ability. To solve this problem, some parameter optimization methods such as artificial colony bee algorithm and genetic algorithm are used to improve the performance of SVM [14]. But that will increase the complexity of the model, and cause a reduction in computational speed. ELM is a new leaning algorithm for feed forward neural network with single-hidden layer. The weights between the input layer and the hidden layer are randomly generated, and there is no need to adjust in the training process. It has the advantages of easy parameter selection, fast learning speed and good generalization performance [15]. However, ELM still has some disadvantages. The parameters of hidden layer are randomly generated, that may cause the over fitting phenomenon of hidden layer in the training process, and the accuracy of training process is not consistent with that of testing process. Meanwhile, the classification effect of ELM also depends on the activation function of hidden layer, and it has a weak robustness for the blended data. On the other hand, the output weights of ELM are directly calculated by the least square method, which cannot be adjusted according to the specific circumstances of the data set [16,17]. LVQ neural network is an input-forward neural network with supervised learning [18], and it is widely used in the field of pattern recognition and optimization. The competition layer of LVQ neural network can automatically complete the learning process based on the training data, and the complex classification can be achieved by the interaction of the competition layer neurons and the distance between the competitive layer and the input layer. In addition, LVQ neural network does not require the normalization and orthogonalization for the input vectors. So LVQ neural network has the advantages such as simple structure, fast learning speed, strong self-learning ability and easy to realize in the practical application, the disadvantages of other neural networks can be overcome [19]. Through the above analysis, ELM and LVQ neural network are superior to SVM in the aspects of parameter selection and learning speed. At present, SVM is often used in the combination with some parameter optimization algorithms. Even though LVQ neural network needs to set more parameters than ELM, but LVQ neural network has a better self-learning ability and does not require the preprocess for input vectors. It is easy to realize in the practical application. So LVQ neural network can be used to recognize the planetary gear status based on the fault feature information.

The remainder of this paper is as follows: In Section 2, the mathematical fault diagnosis model of planetary gear based on