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A dependence-based feature vector and its application on planetary gearbox fault classification

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ABSTRACT

To achieve planetary gearbox fault classification, vibration signal analysis has been widely employed with rich information about the health status and easy measurement. It is critical to extract features with enough health status information for fault classification. The self-adaptation of ensemble empirical mode decomposition (EEMD) indicates the dependence between the raw vibration signal and EEMD-decomposed intrinsic mode functions (IMFs). In this study, we develop a novel fault feature vector based on the dependence. To develop the dependence-based feature vector, simulated vibration signals with different sun gear tooth crack levels are analyzed. The dependence between the raw signal and each IMF is investigated by Archimedean copulas. With the goodness-of-fit test, the copula estimation closest to the perfect fit is selected for dependence representation. The parameter of the selected copula is applied to develop the dependence-based feature vector. To test the ability of the dependence-based feature vector in fault classification for a real planetary gearbox, experimental vibration signals with different gear fault levels at different gears are classified by a multi-class support vector machine. The classification accuracy of the developed feature vector is compared with that of a reported indicator. Results show the dependence-based feature vector provides higher classification accuracy than the reported, indicating the developed feature vector contains more health status information. The developed feature vector can serve better for planetary gearbox fault classification.

1. Introduction

As a planetary gearbox can provide a high transmission ratio and a high power density within a compact structure, planetary gearboxes are widely used in heavy industrial applications such as helicopters, wind turbines and construction machinery [1]. However, despite the advantages, a planetary gearbox is vulnerable to gear tooth damages such as tooth crack, tooth pitting and tooth breakage due to the tough working environment and the heavy load [2]. Such gear tooth malfunctions would lead to reduction of transmission efficiency and breakdown of the system, resulting in immense economic losses and even human casualties. Consequently, planetary gearbox fault detection and fault diagnosis have been attracting increasing interest from researchers as an important research topic to guarantee the reliability of the system.

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For machinery fault detection and fault diagnosis, vibration signal analysis has been widely used [3–6] thanks to the easy acquisition of the vibration signal and rich information in the vibration signal about the machinery health status. Gilles [7] reported the empirical Wavelet transform (EWT) to analyze a signal with a wavelet filter bank which is built based on the information in the signal. Chen et al. [8] applied EWT to bearing fault diagnosis for wind turbine generator. With gear faults, relevant fault signatures are introduced into vibration signals [9]. By effective signal processing methods, the features can be extracted to indicate the possible faults [10–12], serving as the condition indicators (CIs) for machinery fault detection and fault diagnosis.

Up to date, various features have been reported as CIs by different statistical extraction approaches in the literature. The conventional features can be calculated from the waveform in the time domain and the spectrum in the frequency domain, such as skewness, shape factor, kurtosis, crest factor, frequency center, standard deviation frequency, and so on [13]. As these conventional features are well established, their descriptions are omitted here. One who are interested can refer to [13] for detailed information. However, due to the complexity of a planetary gearbox vibration signal [14], it is difficult to classify the location or the severity of a fault in the planetary gearbox through the conventional features as CIs [15]. Subsequently, more sophisticated algorithms for advanced CIs have received intensive investigation in recent years, such as algorithm combining fast dynamic time warping (fast DTW) and correlated kurtosis (CK) techniques reported in Ref. [11], the windowing and mapping strategy for gear tooth fault detection reported in Ref. [16], and the accumulative amplitudes of carrier orders (AACOs) reported in Ref. [17] designed specifically for planetary gearboxes. However, for the algorithm reported in Ref. [11], the gear fault location identification is based on the analysis of the residual signal, the absolute difference between the warped signals of the measured signal and the estimated reference signal. The performance of the algorithm highly depends on the estimated reference signal. Only when the accuracy and appropriate usage of the estimated reference signal are guaranteed, can the superiority of the method be highlighted [18]. As for the windowing and mapping strategy reported in Ref. [16], besides the complicated algorithm for the windowing and the mapping, its accuracy depends on the window function selection with a trade-off at the computational cost [19]. The AACO in Ref. [17] is based on the fault mechanism investigation and the observation that the characteristic frequencies of gears in a planetary gearbox are integer multiples of the carrier rotating frequency. For a planetary gearbox with the ring gear fixed, the characteristic frequencies of the planetary gearbox are given as follows in terms of the carrier rotating frequency [1]: $f_p = (N_p - N_r)f_c/N_p, f_s = (N_r + N_s)f_c/N_s, f_r = 0, f_m = N_r f_c$, and $f_{p-p} = M_p f_c$, where N_p, N_r, and N_s are the numbers of teeth of the planet gear, the ring gear, and the sun gear, respectively; M_p is the number of planet gears; f_p, f_s, f_r, and f_c are the rotating frequencies of the planet gear, the sun gear, the ring gear, and the carrier, respectively; f_m is the meshing frequency of the planetary gearbox; f_{p-p} is the passing frequency of the planet gears. By the above equations, it can be noticed that f_r, f_m, and f_{p-p} are integer multiples of f_c while f_p and f_s are not integer multiples of f_c if N_r/N_p and N_r/N_s are not integers. Thus, the AACO may not work as well as presented in Ref. [17] for the fault detection and the fault diagnosis of a planetary gearbox whose N_r/N_p and N_r/N_s are not integers. Therefore, it is desirable to develop new features that are able to better extract the health status information from a vibration signal. In this paper, this concern will be explored and investigated with a novel signal processing method, aiming at developing a feature vector with more health status information to better serve the planetary gearbox fault detection and fault diagnosis. The developed feature vector is expected to detect the existence of a fault and diagnose the fault position and the level.

Specifically, the targeted feature vector is on the strength of the ensemble empirical mode decomposition (EEMD) and the tail dependence between the raw signal and EEMD-decomposed intrinsic mode functions (IMFs). Different from the orthogonal decomposition methods like Fourier transform and Wavelet transform, the EEMD method is an iterative data driven method that does not imply orthogonality amongst the decomposed IMFs and the raw signal [20], which results in the possible dependence between the raw signal and the IMFs [21]. In probability theory, the tail dependence describes the co-movement of variables in the distribution tails [22]. For example, if we have two variables U and V, the upper (lower) tail dependence means that with large (small) values of U, large (small) values of V are expected. By intuitive understanding, when a fault-induced transient impulse is introduced in a vibration signal, the transient impulse will distribute in IMFs decomposed by EEMD, i.e. more extreme values in the raw signal means more chance to observe extreme values in IMFs. Thus, there is possible tail dependence between the raw signal and the IMFs. Besides, different faults introduce different transient impulses which distribute differently in IMFs, meaning that different faults correspond to different tail dependence levels. Consequently, if we could capture and describe the different tail dependences properly, novel features can be developed with potential to achieve machinery fault detection and fault diagnosis.

To describe the tail dependence, copulas are used. A copula is an alternative to correlation for dependence description [23]. More powerful, copulas contain information about the joint behavior of the variables in the distribution tails, i.e. tail dependence, which correlation cannot describe [24]. For a parametric copula, the copula parameter works as the coefficient to describe the tail dependence level [22]. As different faults correspond to different tail dependence levels, copula parameters are different accordingly. Following the above logic and hypothesis, a novel feature vector is developed with the parameter of a parametric copula.

Once the dependence-based feature vector is developed, the next concern is the objective measure to its performance on machinery fault detection and fault diagnosis. To address this concern, its application on the planetary gearbox fault classification as a pattern recognition problem is employed. For a pattern recognition problem, various classification methods have been reported, such as artificial neural network (ANN) [25], decision tree [26], and support vector machine (SVM) [27]. Given a specific classification method, the classification accuracy is affected by the inputs which are the employed features