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Train axle bearing fault detection using a feature selection scheme based multi-scale morphological filter

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ABSTRACT

This paper presents a novel signal processing scheme, feature selection based multi-scale morphological filter (MMF), for train axle bearing fault detection. In this scheme, more than 30 feature indicators of vibration signals are calculated for axle bearings with different conditions and the features which can reflect fault characteristics more effectively and representatively are selected using the max-relevance and min-redundancy principle. Then, a filtering scale selection approach for MMF based on feature selection and grey relational analysis is proposed. The feature selection based MMF method is tested on diagnosis of artificially created damages of rolling bearings of railway trains. Experimental results show that the proposed method has a superior performance in extracting fault features of defective train axle bearings. In addition, comparisons are performed with the kurtosis criterion based MMF and the spectral kurtosis criterion based MMF. The proposed feature selection based MMF method outperforms these two methods in detection of train axle bearing faults.

1. Introduction

A train wheelset consists of three main components: wheels, an axle and axle bearings. Nowadays, running speed increase is a primary trend of railway transportation development all over the world. The increase in train operation speed makes wheelsets commonly operating under harsh conditions, such as random impacts, exposure to rapid humidity and thermal variations, natural wear and rolling contact fatigue. The heavy load and long term alternating stress operation conditions may easily result in axle bearing failure. If an axle bearing defect is not detected promptly, it may lead to damages of other train components even the tracks [1], which endangers railway running safety. Consequently, establishment of methods for early detection of axle bearing defects is of great important to avoid train stoppages or even catastrophic derailments.

Many technologies, such as temperature detection [2], acoustic analysis [3], acoustic emission technology [4] and vibration signal analysis [5–8], have been investigated over the years for detecting axle bearing fault. However, the temperature would not raise much for an early stage bearing fault; noises from wheel/rail contacts, train drive system as well as aerodynamic forces may contaminate the signal acquired by the acoustic arrays; the attenuation of acoustic emission signal is so severe that how to effectively process and interpret the acquired data is difficult and challenging. In this study, we focus on vibration signal analysis based train axle bearing fault detection.

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Time-frequency domain signal processing methods, including empirical mode decomposition (EMD) [5,6], wavelet transform (WT) [6], empirical wavelet transform (EWT) [7] and harmonic product spectrum [8], have been employed for axle bearing fault detection. WT suffers from the selection of a proper mother wavelet function. If the preselected mother wavelet function does not match the frequency characteristic of the data being analyzed, incorrect analysis results may occur. EMD is an adaptive signal analysis method, which does not require predetermined basis function. However, on account of its inherent mode mixing problem, the detection ability decreases sharply when the background noise is strong [5]. EWT is a novel signal processing scheme proposed in 2013, but how to adaptively segment the spectrum is still a challenge [9].

Unlike these time-frequency domain signal processing methods, morphological filter is capable of extracting geometric structure of the impulsive feature directly in the time domain [10,16,18,31]. It has high computation efficiency as the morphological transforms involve only addition, subtraction and Boolean operations [11,12,27]. Considering these unique advantages, this paper aims to develop an improved morphological filter for train axle bearing fault detection.

Classic morphological filter performs a single-scale analysis in which a structure element (SE) with fixed length is utilized. However, the single-scale morphological filter (SMF) may suffer from the lack of completeness in the extracted impulsive features [13]. Later, multi-scale morphological filter (MMF) was proposed [14]. It performs the morphological transforms multiple times. For each time, the analysis scale (length) is different. It was demonstrated in [15] that the MMF analysis of bearing vibration signals is more effective than the SMF analysis in terms of fault diagnosis of rolling bearings. Although MMF is an interesting attempt to examine the signals in different resolutions, a main factor which may greatly influence the filtering accuracy of MMF remains unsolved: there is no effective guideline for determining proper analysis scales (SE lengths) of MMF.

Various attempts have been done over the years aiming at solving this issue [13,16,17,20–22,24]. The proposed approaches so far can be classified into four categories:

(a) Feature indicator based method. Nikolaou et al. [16] defined the reciprocal of the fault characteristic frequency of a rolling bearing as the pulse repetition period T. They recommended that the length of a flat SE should range from $0.6T$ to $0.7T$ to get a satisfactory filtering result. Consequently, the SE scale can be obtained as it is uniquely determined by the SE length ($scale = length - 2$) [17]. Patargias et al. [18] and He et al. [19] set the SE length as $0.6T$ for bearing defective identification according to the analysis of [16]. Following the work of Nikolaou et al. [16], Dong et al. [20] and Raj et al. [21] proposed several new criterions, including the maximum signal-to-noise ratio (SNR) criterion and the maximum kurtosis criterion, for the selection of a SE length from the following 10 lengths: $0.1T$, $0.2T$, $\ldots$, $0.9T$, T. Later, Li and Liang [13] and Li et al. [22] used a maximum spectral kurtosis (SK) principle to select a scale subset of MMF for mechanical fault diagnosis. Overall, a proper feature requires to be selected for this type of methods to have a good performance. The fault diagnosis may fail for using inappropriate features.

(b) Averaging method. Refs. [23–25] employed the flat SE for MMF. The minimal length SE selected is $\{0, 0, 0\}$ (SE length is 3) and the maximal length SE is $\{\underbrace{0, 0, \ldots, 0}_{T}\}$(SE length is T). SEs have a length increment of 1. Therefore, they selected total $T - 2$ SEs and correspondingly performed the morphological transforms $T - 2$ times. Then, they computed the averaging from these $T - 2$ filtering results as the final filtering output. However, if the raw signal is processed by a scale far away from the theoretical central scale, the filtered result is often heavily polluted [13] and hard to reflect the factual features. Therefore, the averaging strategy is actually compromised.

(c) Adaptive method. In order to avoid the uncertainty of scale selection on analysis results, Zhang et al. [15], Jiang et al. [26], Shen et al. [11] and Li et al. [12] respectively utilized an adaptive scale determination method according to the local peaks of a raw signal. However, not all the impulses in the raw signal are related to the mechanical faults. This type of methods is inevitably suffering from noise, thereby decreasing the filtering accuracy.

(d) Other methods. Hu et al. [27] adopted frequency response of a morphological filter as the theoretical basis to determine the length of a SE. Refs. [28–31] determined the analysis scales based on trials or experiences. Ref. [32] did not mention their selection scheme.

From the above analysis, it's hard to find which feature to use in feature indicator based method for determining the analysis scale of MMF. Current studies use a single feature, e.g., SNR in Ref. [20], kurtosis in Ref. [21] and SK in Refs. [13,22], to search for the proper scale for the MMF. Each feature has its strength and weakness. One feature indicator may work well for one working scenario but bad for another one. How to effectively select one or a few representative features to improve the analysis accuracy and reliability of the MMF is still an essential research challenge. We propose a GRA aided feature selection scheme to automatically select a feature subset for the scale determination of the MMF. The selected feature subset can reflect the fault characteristics of the signals more effectively. Using the selected feature subset, a better filtering scale can be determined for the MMF. The fault detection accuracy of the proposed feature selection scheme based MMF outperforms SNR, kurtosis and SK criterion based MMFs, which is demonstrated in Section 6 of this paper. The main novelty of this study is the application of the GRA to identify the most efficient set of diagnostic features and proper scale for the MMF.

The rest of this paper is organized as follows: Section 2 briefly introduces the reported MMF; Section 3 describes the basic theory of GRA; Section 4 proposes the feature selection based MMF; Section 5 describes the experimental setup and feature