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A fault diagnosis method based on local mean decomposition and multi-scale entropy for roller bearings

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ABSTRACT

A novel fault feature extraction method based on the local mean decomposition technology and multi-scale entropy is proposed in this paper. When fault occurs in roller bearings, the vibration signals picked up would exactly display non-stationary characteristics. It is not easy to make an accurate evaluation on the working condition of the roller bearings only through traditional time-domain methods or frequency-domain methods. Therefore, local mean decomposition method, a new self-adaptive time-frequency method, is used as a pretreatment to decompose the non-stationary vibration signal of a roller bearing into a number of product functions. Furthermore, the multi-scale entropy, referring to the calculation of sample entropy across a sequence of scales, is introduced here. The multi-scale entropy of each product function can be calculated as the feature vectors. The analysis results from practical bearing vibration signals demonstrate that the proposed method is effective.

1. Introduction

The roller bearings are the most common components in rotating machines. Kinds of factors such as wear, fatigue, corrosion, overloading and so on can cause the local defects of bearings while the machines are running. Even a minor fault may have distinct and pernicious influence on the whole system, so it is important to monitor the bearing condition and diagnose the fault of bearings.

It has always been being a crux in the fault diagnosis how to obtain fault feature information from the vibration signals. Traditional fault diagnosis methods are performed by analyzing the vibration signals only in the time or frequency domain and then recognizing the working condition of bearings [1–3]. However, because of the influence of the non-linear factors including loads, clearance, friction, stiffness and so on, the fault signals usually display strong nonlinear, non-Gaussian and non-stationary features, so it is difficult to accurately recognize the working condition of bearings only in the time or frequency domain [4,5].

Common time frequency analysis methods include the Wigner Ville distribution (WVD), the short time Fourier transformation (STFT), the wavelet transform (WT), etc., but each of these methods has its limitations. For example, the Wigner Ville distribution would cause cross-term interference when dealing with the multi component signals [6,7]; the analysis window of STFT is fixed [8]; the WT has been well applied in fault diagnosis [9–11] but different mother wavelets should be predefined for each component. So they are still not self-adaptive in nature. Empirical mode decomposition (EMD) and local mean decomposition (LMD), different from the above methods, are self-adaptive time-frequency decomposition techniques. EMD is usually combined with the Hilbert transform, turning into the HHT method. However, there still exist some deficiencies in EMD such as the modes

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mixing problem and end effects that are still underway [12,13]. In addition, sometimes the unexplainable negative instantaneous frequency would appear when computing instantaneous frequency by performing Hilbert transform to the decomposition results of EMD and meanwhile the end effects would be more serious [14].

Local mean decomposition algorithm was developed by Smith in 2005 and originally used as a time-frequency analysis tool of the electroencephalogram signals [14]. LMD method is similar to EMD method but it turns out that the former is better than the latter in some aspects [15]. LMD method can be used to adaptively decompose any complicated multi-component signal into a series of product functions (PFs), each of which is the product of an amplitude envelope signal and a purely frequency modulated signal. Specially, each PF, whose instantaneous amplitude (IA) is the amplitude envelope and instantaneous frequency (IF) can be derived from the frequency modulated signal, has physical meaning. LMD method is suitable for analyzing non-stationary signals, so it is introduced to perform fault feature extraction of roller bearings in this paper.

After the original signal is decomposed, it is very likely that different fault conditions can be recognized by dealing with the decomposition results such as the PFs, IFs or IAs which may contain useful fault information. In the past, FFT and other spectrum analysis methods such as the power spectrum analysis have been used to transform the decomposition results to extract fault features [16,17]. However, traditional spectrum analysis methods are suitable for stationary signals rather than non-stationary ones, so the analysis results may not be so satisfactory. Kinds of fault extraction methods, in which LMD is combined with the order tracking method, PCA or AR model, have been put forward and applied to the diagnosis of rotary machines [18–20]. But establishing a new model after performing LMD analysis to the original signal would make the process of fault diagnosis longer or more complex.

Obviously, for the roller bearings, vibration signals of different fault patterns will show varying complexity and therefore the entropy of vibration signals varies. Costa proposed the multi-scale entropy (MSE) on the basis of sample entropy, which was originally used for heart rhythm variability research [21]. Later the multi-scale entropy was applied in the field of fault diagnosis. Zhang has proposed a bearing fault diagnosis method based on MSE and adaptive neuro-fuzzy inference system [22]. MSE is also chosen as the feature extractor in the fault diagnosis of shafts [23]. Compared with the approximate entropy and sample entropy, MSE can analyze the series complexity under different scales. Furthermore, the computation of MSE is simple. Therefore, in this paper MSE is used as the feature extractor. And based upon the above analysis, the recent development of demodulation technique LMD and multi-scale entropy are combined and applied to the roller bearing fault feature extraction.

This paper is organized as follows. The theory of the LMD method is given briefly in Section 2. In Section 3 a fault diagnosis approach in which LMD and multi-scale entropy are combined is put forward. In Section 4, the proposed approach is applied in the fault diagnosis of the roller bearings, which demonstrates that the method is effective and feasible. Conclusions are given in Section 5.

2. LMD analysis method

The purpose of LMD is to obtain a series of frequency modulated signals and envelope signals by decomposing the original multi-component signal. The product of each frequency modulated signal and the corresponding envelope signal is called a product function (PF) which has physical meaning. After all needed product functions are obtained, the completed time-frequency distribution of the original signal can be derived. Given any signal $x(t)$, it can be decomposed as follows [14,18]:

(1) The first step of the decomposition involves finding out all the local extrema n_i and calculating the mean of two successive extrema n_i and n_{i+1}. So the ith mean value m_i is given by

$$m_i = \frac{n_i + n_{i+1}}{2} \tag{1}$$

All mean values m_i of two successive extrema are connected by straight lines. The local means are then smoothed using moving averaging to form a smoothly varying continuous local mean function $m_{11}(t)$.

(2) The ith envelope estimate a_i is given by

$$a_i = \frac{|n_i - n_{i+1}|}{2}. \tag{2}$$

The local envelope estimates are smoothed in the same way as the local means to derive the envelope function $a_{11}(t)$.

(3) Subtract the local mean function $m_{11}(t)$ from the original signal $x(t)$ and the resulting signal, denoted by $h_{11}(t)$, is given by

$$h_{11}(t) = x(t) - m_{11}(t) \tag{3}$$

$h_{11}(t)$ is then divided by the envelope function $a_{11}(t)$, resulting in $s_{11}(t)$.

$$s_{11}(t) = h_{11}(t)/a_{11}(t). \tag{4}$$