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A new method to classify railway vehicle axle fatigue crack AE signal

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ABSTRACT

This paper presents a new method for classifying railway vehicle axle fatigue crack acoustic emission (AE) signal. The method is developed by integrating self-adaptive empirical mode decomposition (EMD) with Elman neural network (ENN). The method first uses EMD to decompose the signals into six intrinsic mode functions (IMFs) and one residual. From the IMFs and the residual obtained by EMD, a three-dimensional energy (TDE) feature vector consisting of energy entropy, energy distribution ratio, and interval average energy are computed by Hilbert-Huang transform. An ENN will be trained using the TDE feature vector to classify the AE signal caused by railway vehicle axle fatigue crack. The result shows that this method is better than other EMD energy domain classification method on identifying railway vehicle axle fatigue crack AE signal.

1. Introduction

The acoustic emission (AE) signal analysis plays an important role in the field of digital signal processing and fault diagnosis. In recent years, AE signals have been studied on various fields related with fault detection and damage mechanism [1–5]. In general, the AE signals of mechanical systems are greatly affected by the failure occurrence. In the process of non-destructive test using AE signals, the AE signals are sensitive to the material and are easily interfered by mechanical and electrical noise. In the practical applications, it requires expertise in AE signal processing techniques to identify the collected AE signals. Multiple studies have been conducted on investigating and evaluating of AE signals with different signal processing techniques. Elasha et al. [4] applied a series of signal processing techniques on both AE and vibration signals to extract the features and concluded that AE signals provide earlier indication of faults than vibration signals. Van Hecke et al. [5] evaluated numerous features from time synchronously resampled AE signals for bearing fault diagnosis. Their validation results have shown the satisfactory diagnosis performance on various bearing faults at low shaft speeds. Besides, the impacts of working conditions on AE signals generation have also been characterized on healthy machine [6]. Due to the high generation frequency of the AE signals, the sampling rate could reach to about 1000 kHz. During the fracture test, the AE phenomena only happen a few times. It is critical to identify the effective AE signals from the signals heavily involved with ineffectiveness and interference. By identifying the effective AE signals, the fault features can then be extracted from the AE signals for fault diagnosis and prognosis application. In general, fatigue crack classification reported in the literatures mainly identifies the fatigue crack in different phase of crack propagation. Vasudevan and Sadananda [7] classified the entire fatigue crack growth into five different phases using the proposed self-consistent theory to account for the variation in fatigue crack growth with load ratio. Furthermore, Vasudevan and Sadananda [8] classified the environmental effects on fatigue crack growth behavior into five categories with the proposed concept of pure fatigue. Nor et al. [9] successfully identified the classes of reinforced concrete beam by analyzing the monitoring AE signals. Although various studies have been reported on classification of concrete structure cracks, little study has been reported on identification of effective AE signals with metal fatigue crack [10–12]. Essentially, the identification of AE signals is a pattern recognition problem. The effective feature extraction and accurate classifier applications are vital to the AE signals identification accuracy.

Feature extraction is one of the most critical obstacles in the acoustic emission diagnostic procedure. One widely used method is to transform the raw data in the time domain into the frequency domain by using signal processing techniques. Among different applied signal processing techniques, the Fast Fourier transform (FFT) is one of the most useful and convenient method to extract frequency domain features for mechanical system diagnosis [13,14]. For example, FFT was used to detect the rotor broken-bar faults [13] as well as open-circuit faults accurately with a single current sensor [14]. The FFT extracts the

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Table 1
Advantages and disadvantages of common signal processing techniques for AE signal identification.

Signal processing method	Advantages	Disadvantages
FFT [7,8]	Convenient to extract frequency features	Missing time domain information
STFT [9]	Extracting features in time and frequency domain	Best resolution in time and frequency domains cannot be achieved at the same time
WT [10–14]	Better resolution in time and frequency domain can be achieved	Heavy dependence on suitable wavelet function selection
EMD [15–22]	Avoid selection of suitable wavelet function	Characteristics of energy distribution over multiple IMFs have not been studied

trends of frequencies as a feature of signals. This method relies greatly on the extracted features in the frequency domain to identify varies machine health conditions. However, the information in the time domain was missed after the signals transformed into the frequency domain. To avoid such disadvantage, transformation of the raw data from the time domain into the time-frequency domain is more effective. The Short Time Fourier Transform (STFT) is another popular applied Fourier-related signal transform method. By using a window function, STFT transforms the signal into the frequency domain window by window. However, the width of window function used in the STFT is fixed on one resolution. According to the uncertainty principle by Heisenberg [15], the resolutions in the time domain and in the frequency domain are mutually restricted. The best resolutions in time and frequency domains cannot be achieved at the same time. When identifying the collected signals, the AE signals need to be positioned in time domain and analyzed in frequency domain. Thus, both FFT and STFT are not suitable for AE signals identification.

As another widely studied signal processing method wavelet transform (WT) can provide an adjustable window function resulted in a good resolution in both the time and frequency domains. The higher frequency is, the shorter size of window size becomes. Therefore, WT has been applied in various applications for signal feature extraction and fault diagnosis. For example, the continuous wavelet transform (CWT) with both time-based and frequency-based information has made muscle diagnosis easier [16]. The discrete wavelet transform (DWT) [17] was used for detection and classification of internal faults in a two winding three-phase transformer. The wavelet packet decomposition (WPD) was used to resolve the problem of extracting fault characteristics in electromotor [18]. Several WT related methods mentioned above have been widely used in various fields of signal analysis with good results especially in fault diagnosis of rolling bearing [16] and power systems [20].

Although WT shows a good result on the signal processing, the application of WT requires selection of a suitable wavelet function before analysis. The different wavelet functions result in different outputs from WT. To reduce the impact of pre-defined wavelet function, empirical mode decomposition (EMD) was introduced in 1998 [21]. It is self-adaptive and good at analyzing the non-linear and non-stationary signals. This method mainly includes two steps. The EMD decomposes signals into intrinsic mode functions (IMF) based on the local time domain signals themselves. Then, the IMFs are transformed by Hilbert-Huang Transform (HHT) to get the frequency [22] and energy domain [23] information of the signal.

The EMD is widely used in the feature extraction. By decomposing the signal into multiple IMFs, the energy distribution ratio of the IMFs can be computed [24]. However, such feature of the signal is insufficient to identify the signals since the most identical characteristics of signals as released energy is missing. The interval average energy computed as the average energy released by the signal in a certain interval of time is a good feature to identify different signals. Meanwhile, the energy of each IMF component is also used as a feature to identify different signals [25]. The methods reported in Refs. [24,25] focus on the energy distribution. However, the characteristic of energy distribution over the considered multiple IMFs is not included for study. The entropy of the feature energy can describe the energy distribution over the multiple IMFs. Thus, interval average energy, energy entropy and energy distribution ratio are important in the feature extraction for signal identification.

Energy domain features computed by the EMD method are widely used in the signal identification. This paper systematically sums up these energy domain features. The energy distribution ratio (EDA) can be used as the feature to identify AE signals of offshore structures. Such identification method is regarded as EDA method [24]. In Ref. [25], the energy value (EV) of each IMF was used as features to diagnose faults of an automotive air-conditioner blower. AE signal is non-linear and non-stationary, which is beyond the capacity of traditional signals to analyze and identify. Some successful applications of AE signals have been reported in plywood damage signals [26], partial discharge (PD) and several defect types of PD [27]. As pointed out in [28], though EMD method is an effective approach to analyze the AE signals, there are still many problems to solve. In this paper, a new three-dimensional energy (TDE) analysis method is proposed to extract effective features for AE signals identification, including energy entropy, energy distribution ratio, and interval average energy. Table 1 summarizes the advantages and disadvantages of different common signal processing techniques used for AE signal identification.

In recent years, the neural network (NN) has become a popular method in pattern recognition. The combination of EMD and NN has been applied to data trend forecast and faults diagnosis, for example, wind speed forecast [29]. It is common that overlapped damage features exist in one signal. The EMD method can decompose the signal into multiple IMFs and each IMF contains portion of complete damage features. Then a 3D Hilbert spectrum can be computed by HHT and used to extract valuable features. In the end, the NN is applied to learn and recognize types of signals. A modified EMD-fuzzy neural network (EMD-FNN) model was proposed to predict the daily and mean monthly wind speed at Zhangye of China [30]. An EMD-radical basis function (EMD-RBF) model was used to forecast precipitation with good performance [31]. In the field of fault diagnosis, the method combining AE parameters, EMD and backpropagation (BP) NN was introduced to recognize the AE signals of rock fracture [32]. A flow regime identification method using the EMD combined with Elman NN was successfully applied to predict gas-liquid two-phase flow [33]. Thus, an advanced machine learning method can be combined with the EMD analysis method for AE signals identification.

In this paper, an EMD-TDE-ENN model that combines EMD and ENN is proposed to identify AE signals. First, the AE signals are decomposed into a collection of IMFs and a residue by EMD. Second, both the IMF components and the residue are transformed by HHT to get the energy domain features. Then, these features are used to train the ENN model. Finally, this trained ENN model is used to identify the AE signals railway vehicle axle fatigue crack.

The remainder of the paper is organized as follows: Section 2 presents in detail the proposed approach. The different steps of the EMD method are also given in this section. Section 3 presents the experimental setup and analysis results. Finally, the conclusions are provided in Section 4.