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Non-Gaussian non-stationary wind pressure forecasting based on the improved empirical wavelet transform

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ABSTRACT

In the field of wind engineering, the field measurement on wind pressure is a vital means of wind resistance researches. However, for the field measurement there are some challenges below. The sensors miss partial data due to their failure or service life. Likewise, some locations are difficult to deploy the required sensors. In this paper, a hybrid prediction model of improved empirical wavelet transform (IEWT), particle swarm optimization (PSO) and least squares support vector machines (LSSVM), is developed for purposes of data recovery and spatial extension of non-Gaussian non-stationary wind pressure (complex signal). In this model, IEWT is first proposed to decompose the signals and get rid of their noise components. Meanwhile, LSSVM is utilized to establish forecasting models of the trend component and main components, where their parameters are optimized by PSO algorithm. Then, the single-point and spatial forecastings are carried out to verify the effectiveness of the proposed model. Furthermore, the empirical mode decomposition (EMD), ensemble EMD (EEMD), and empirical wavelet transform (EWT), are exploited to corroborate the advanced de-noising performance of IEWT. The final results indicate that IEWT can effectively reduce the noise interference and enhance the forecasting precision of complex signal.

1. Introduction

Currently, the obtainment of wind pressure mainly relies on the following three methods: field measurement, wind tunnel test, and numerical simulation (Dai, 2010). Since in the wind tunnel test and numerical simulation, the determination of the geometric scale ratio and the simulation of wind environment around buildings are very difficult, the field measurement study is very important. Levitan and Mehta (Levitana and Mehtab, 1992) conducted Texas Tech field experiments for wind loads. They provided the direct and valuable data and results for the study of wind load characteristics of low-rise buildings. Pitsis and Appedey (Pitsis and Apperley, 1991) carried out wind pressure measurements on the cantilevered roof of Belmore stadium in Sydney. Li et al. (Li et al.,; Hu et al., 2012) measured the surface wind pressure of a movable house in Guangdong and compared the wind tunnel test data with the low house of the same type, then obtaining the distribution of wind pressure in the roof of different wind fields. Due to missing sensor data and the layout of fewer measurement points, the prediction of wind pressure is the important issue in wind engineering. However, the wind pressure typically shows the strong non-Gaussianity (Huang et al., 2017a). The prediction of the wind pressure could be more difficult under the non-stationary winds, such as downbursts (Peng et al., 2018).

Fortunately, with the rapid development of artificial intelligence technologies during the past several years, some forecasting models have been successfully developed for non-stationary time series. Liu et al. (2018a) constructed a reliable hybrid forecasting framework based on deep learning strategy using the empirical wavelet transform (EWT), long short term memory (LSTM) neural network and Elman neural network (ENN), which had a satisfactory performance in the high-precision wind speed prediction. Jiang et al. (2018) illustrated the application of the correlation-aided discrete wavelet transform (DWT), least squares support vector machines (LSSVM), and generalized autoregressive conditionally heteroscedastic (GARCH) to improve the accuracy on the wind speed prediction. Daniel et al. (Ambach and Schmid, 2017) carried out a comprehensive prediction of wind speed, wind direction, and air pressure. The final results validated that the wind direction and the air pressure are important to extend the forecasting accuracy of wind speed forecasting. Huang et al. (2017b) applied the back propagation neural network (BPNN) and proper orthogonal decomposition (POD) to forecast the wind loads on high-rise buildings; Ji et al. (2018) used covariance-based POD to interpolate the roof wind pressure for the points where the pressure tap was not installed. Their results were found to be in

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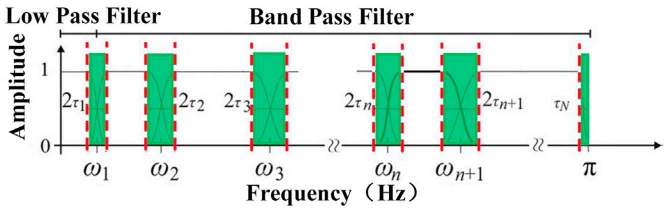

Fig. 1. Segmentation of Fourier spectrum.

good agreement with the wind tunnel test data. Therefore, an advanced signal prediction technology may possess great performance to achieve the recovery of missing sensor data and spatial expansion of obtained sensor data.

Additionally, it should be emphasized that the actual data for wind pressure forecasting inevitably contains the noise components, which will affect the forecasting accuracy of the machine learning methods (Yu et al., 2018; Niu et al., 2018). Some researches show that noise removal can improve prediction accuracy (Jiang et al., 2018; Jiang and Huang, 2017). Therefore, noise-elimination may be a good attempt in prediction. In recent years, many de-noised methods have been developed and showcased a good performance in nonlinear and non-stationary signal de-noising (Abdoos, 2016), which can be divided into two categories. One is the frequency domain signal processing technique, such as fast Fourier transform (FFT), wavelet transform (WT), wavelet packet transform (WPT). The other is the time domain signal analysis means, such as the empirical mode decomposition (EMD), ensemble EMD (EEMD), and multivariate EMD (MEMD) (Huang et al., 2017c). Among them, the frequency domain WT has been used in many fields because of its convenience and generality (Peng et al., 2018; Silsirivanich, 2017; Wang et al., 2018a). However, its performance depends highly on the selection of mother wavelets and optimal numbers of decomposition levels (Zheng et al., 2017). In order to address these problems, some improved WT methods, such as fast WT (FWT) and WPT, have been developed. However, these methods have the problem of over-decomposition (Okumus and Dinler, 2016; Liu et al., 2018b; Cao et al., 2009). On the other hand, the time domain EMD can well process non-linear and non-stationary signal by adaptively decomposing the signal into several intrinsic mode functions (IMFs) (Li et al., 2018). However, the existence of mode mixing and the disturbance of end effect will reduce its performance (Du et al., 2017). On the basis of EMD, Wu et al. (Wu and Huang, 2009) proposed the EEMD method to solve the mode mixing problem in a certain extent through adding white noise to the signal (Jiang and Huang, 2017), which makes the decomposition more robust. However, it is very difficult to determine the number of realizations and noise standard deviation in the

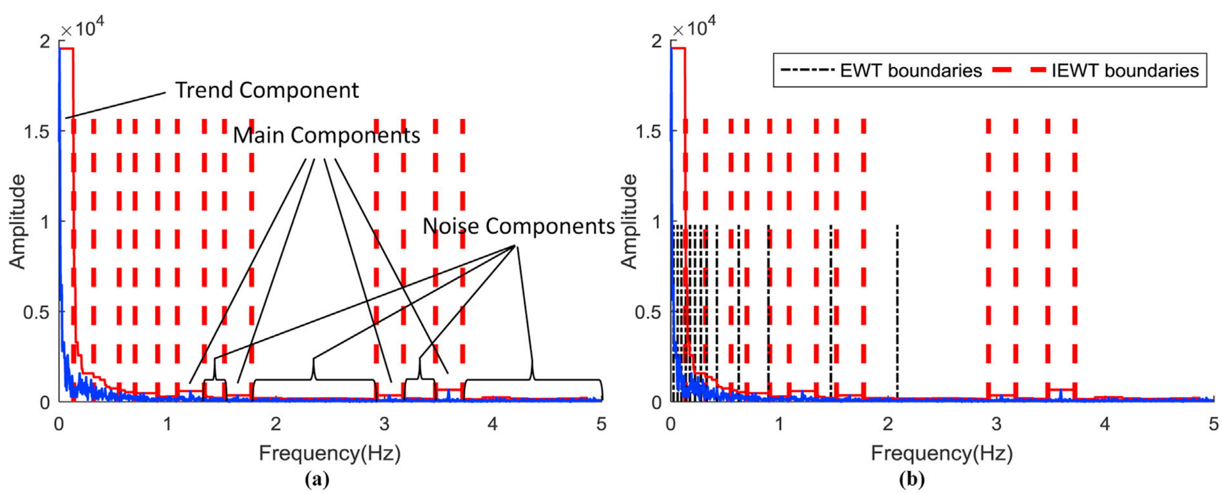

Fig. 2. Illustration of detected boundaries on Fourier spectrum based on EWT and IEWT. ((a) Boundary Division by IEWT and (b) Comparison of boundary division by EWT and IEWT).

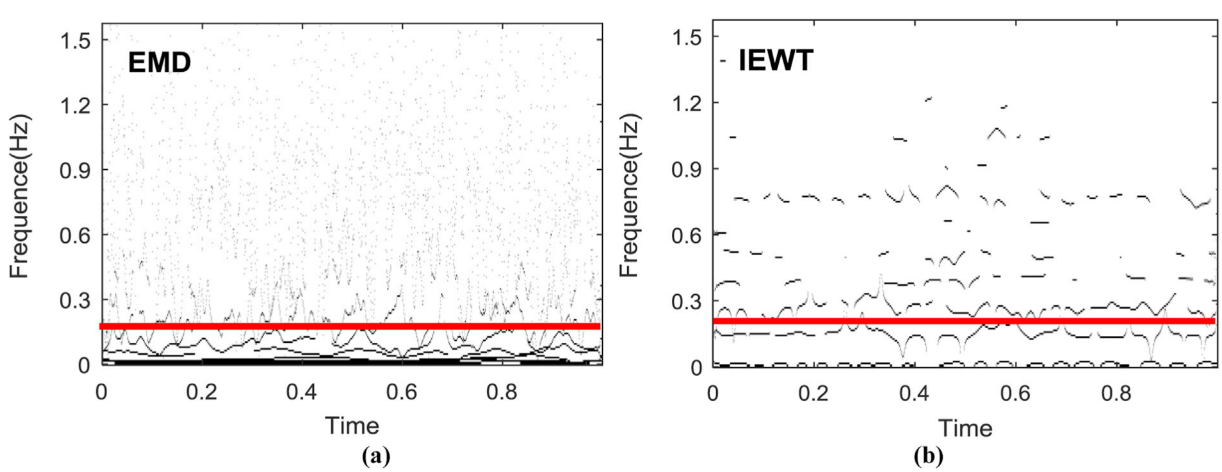

Fig. 3. Comparison of Time-frequency representation. ((a) Time-frequency representation based on EMD and (b) Time-frequency representation based on IEWT).