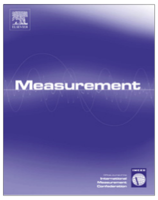
Measurement 82 (2016) 221–239

Contents lists available at ScienceDirect

Measurement

journal homepage: www.elsevier.com/locate/measurement



Time–frequency interpretation of multi-frequency signal from rotating machinery using an improved Hilbert–Huang transform

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A R T I C L E   I N F O

Article history:
Received 7 May 2015
Received in revised form 10 September 2015
Accepted 4 January 2016
Available online 6 January 2016

Keywords:
Time–frequency analysis
Hilbert–Huang transform
Empirical mode decomposition
Rotating machinery

A B S T R A C T

The Hilbert–Huang transform (HHT) has proven to be a promising tool for the analysis of non-stationary signals commonly occurred in industrial machines. However, in practice, multi-frequency intrinsic mode functions (IMFs) and pseudo IMFs are likely generated and lead to grossly erroneous or even completely meaningless instantaneous frequencies, which raise difficulties in interpreting signal features by the HHT spectrum. To enhance the time–frequency resolution of the traditional HHT, an improved HHT is proposed in this study. By constructing a bank of partially overlapping bandpass filters, a series of filtered signals are obtained at first. Then a subset of filtered signals, each associated with certain energy-dominated components, are selected based on the maximal-spectral kurtosis–minimal-redundancy criterion and the information-related coefficient, and further decomposed by empirical mode decomposition to extract sets of IMFs. Furthermore, IMF selection scheme is applied to select the relevant IMFs on which the HHT spectrum is constructed. The novelty of this method is that the HHT spectrum is just constructed with the relevant, almost monochromatic IMFs rather than with the IMFs possibly with multiple frequency components or with pseudo components. The results on the simulated data, test rig data, and industrial gearbox data show that the proposed method is superior to the traditional HHT in feature extraction and can produce a more accurate time–frequency distribution for the inspected signal.

1. Introduction

Rotating machinery plays a significant role in modern industries [1–3]. The vibration generated by industrial machines contains a wealth of complex information that reveals the machine state, and are often used as reference signal in diagnostics and prognostics of mechanical systems [4,5]. Thus, adopting effective signal processing techniques to analyze the vibration signal and to extract signal features will have great significance.

The Hilbert–Huang transform (HHT) [6–8], a relatively new time–frequency analysis technique combining the empirical mode decomposition (EMD) with the Hilbert transform (HT), has proven to be a promising tool for the analysis of non-stationary signals. Biswal et al. [9] as well as Jagadeesh and Biswal [10] have proposed approaches based on HHT for the classification of power quality events. Several authors have proposed methods based on HHT for diagnosing faults in rotating machinery [11–13]. In practice, however, HHT also suffers from some deficiencies [14]. Many studies suggested that IMFs with multiple

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http://dx.doi.org/10.1016/j.measurement.2016.01.001
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Nomenclature

$a(t)$	instantaneous amplitude
$a_{k,i}$	ith filter at the kth decomposition level
c_i	ith intrinsic mode function
C	data set with candidate filtered signals
D_j	information-related coefficient for filtered signal x_j
d_j	difference of information-related coefficients
$f_{k,i}$	central frequency of wavelet filter $a_{k,i}$ (Hz)
f_s	sampling frequency (Hz)
$I_{x,y}$	mutual information between variables x and y
K	number of optimal filtered signals
L	maximum decomposition level
P	spectral kurtosis
$P_{k,i}$	spectral kurtosis of filtered signal $x_{k,i}$
R_j	mutual information between filtered signal x_j and previously selected signals $x_1, x_2, \ldots, x_{j-1}$
$R_{k,i}$	mutual information between filtered signal $x_{k,i}$ and previously selected signals $x_1, x_2, \ldots, x_{j-1}$
S	data set with selected filtered signals
t	time (s)
$u_{x_{ji}x_j}$	correlation coefficient between filtered signal x_j and its ith intrinsic mode function x_{ji}
u_{x_jx}	correlation coefficient between filtered signal x_j and original signal x
U_j	mutual information between filtered signal x_j and original signal x
x	original signal to be analyzed
x_j	jth selected filtered signal
$x_{k,i}$	filtered signal derived using wavelet filter $a_{k,i}$
x_{ji}	ith intrinsic mode function of the optimal filtered signal x_j
$z(t)$	analytic version of signal x
(f, σ)	wavelet frequency combination (Hz, Hz)
M	number of selected filtered signals
α	regulation parameter
Υ	maximal-spectral kurtosis–minimal-redundancy operator
$\omega(t)$	instantaneous frequency (Hz)
$\sigma_{k,i}$	bandwidth of wavelet filter $a_{k,i}$ (Hz)
$\eta_{x_{ji}x}$	similarity score between intrinsic mode function x_{ji} and original signal x
λ	threshold for IMF selection
ς	ratio factor

frequency components or pseudo components usually exist in the results of EMD, especially for the multi-frequency signals commonly occurred in mechanical systems [8,13,15]. On one hand, the multi-frequency IMFs and pseudo IMFs will produce grossly erroneous or even completely meaningless time–frequency curves, which raise difficulties in characterizing features of the inspected signal by the Hilbert–Huang spectrum; On the other hand, many studies have proposed to utilize IMF statistical features, such as EMD energy entropies [16] and IMF characteristic amplitude ratios [17], to realize fault diagnosis and prognostics, which is an important application of HHT. Obviously, multi-frequency IMFs and pseudo IMFs will result in inaccurate estimates of signal features and limit the use of these kinds of methods. Thus, developing effective techniques to make up for the deficiencies of the HHT will have great significance.

However, till now, limited studies have focused on the problems resulted from the multi-frequency IMFs and pseudo IMFs. Yang [15] attempted to extract monochromatic IMFs with the aid of adaptive bandpass filters. The construction of the filters critically depends on the PSD peak detection, and tends to be influenced by noise. Peng et al. [18,19] utilized the wavelet packet transform as a preprocessor of the HHT. The wavelet packet transform allocates the signal into sub-band signals with same bandwidth, a component that spans the boundary frequencies of two adjacent frequency bands may be split into two parts, and each part retains partial constituent of the component. Several time series were filtered out using a set of bandpass filters that constructed with the frequency combinations inferred from the Kurtogram, Xiong et al. [3] constructed the Hilbert–Huang spectrum based on the first order IMF of each filtered signals. Some IMFs with real constituents may be unintentionally discarded but some irrelevant IMFs are retained, as the Hilbert transform is just performed on a partial set of IMFs. Some attempts have also been made to improve the HHT by exclusion of insignificant and irrelevant IMFs. A merit index for IMF selection is proposed by Ricci and Pennacchi [20] based on the periodicity degree and the absolute skewness value of the IMF. Feng et al. [21] proposed a selection criterion according to the modulation characteristics of the planetary gearbox vibration signals and the wavelet-like filtering nature of ensemble empirical mode decomposition. A number of criteria based on the correlation coefficient between the IMF and the original signal have been developed [13,18,19,22,23]. The mutual information-based [24,12] and energy-based [25,26] IMF selection criteria have also been investigated.

In this study, an improved HHT is proposed to make up for the deficiencies of the traditional HHT using multi-frequency IMFs and pseudo IMFs. Vibration signals collected from rotating machinery usually have a wide frequency spectrum, and are a superposition of sinusoidal components (e.g., the shaft rotating frequency and its harmonics), modulated vibration (e.g., gear meshing frequency and its harmonics), impulse vibration (e.g., the impulses generated by the localized fault in gear or bearing), and the random noise [27]. The dominant components of the signal (sinusoidal components, modulated vibration and impulsive vibration) usually have relatively high energy content and are limited in narrow frequency bands. Therefore, to generate IMFs that are more likely to satisfy the monocomponent condition, an intuitive idea is to firstly separate out these energy-dominated