Extraction of Significant Features using Empirical Mode Decomposition and Its Application

Sangjin Cho, and Yejin Seo

Abstract—**Empirical Mode Decomposition (EMD) is recently used in a broad range of applications for extracting signals from data generated in noisy nonlinear and nonstationary processes. However, it has a major drawback, mode mixing, which is defined as a single Intrinsic Mode Function (IMF) consisting of signals of widely disparate scales. This often makes the physical meaning of individual IMF unclear. To solve this problem, a novel algorithm to select significant IMFs is applied to fault signal of the induction motor and musical sound of the percussion instrument.**

Index Terms—**empirical mode decomposition, fault diagnosis, musical signal analysis, significant intrinsic mode function**

I. Introduction

MOST popular signal processing techniques include time domain analysis, frequency domain techniques like a spectral analysis and time-frequency domain methods such as short-time Fourier transform (STFT) or wavelet analysis. The main purpose of signal processing step in a fault diagnosis system, for example, is to reveal fault signatures from the measured quantities obtained from a motor in operation. For this purpose, time–frequency analysis tools are popular as they can provide both time and frequency resolution simultaneously. Most existing time–frequency analysis methods decompose the signal based on a *priori* bases with stationary assumption of the signal. But both of these techniques are not suitable enough for the analysis of fault signals as they can be non-linear and non-stationary at the same time. In contrast, Empirical Mode Decomposition (EMD) is a signal decomposition method which decomposes the signal into some intrinsic mode functions (IMFs) based on the local characteristic time scale of the data [1]. These IMFs represent natural oscillatory modes embedded in the signal and works as the basis functions, which are derived from the signal itself, rather than any pre-determined kernel. Therefore, EMD is a data adaptive decomposition technique which overcomes limitations of other similar tool such as STFT or wavelet. The essence of the EMD method is that, it empirically determines the intrinsic oscillatory modes by the characteristic time scales within a signal and decomposes the signal accordingly. This excellent mode separation capability of EMD makes it an optimum choice for the analysis of natural phenomenon like vibration signal analysis. Every rotating part of a mechanical system contributes to the generation of vibration signal which is acquired through accelerometer. As a result any defect or abnormality in rotating behavior of a rotating part will cause to change contribution of that specific part, which ultimately modifies the normal vibration pattern and indicate the inception of fault of a rotating part. As EMD extract the intrinsic oscillatory modes from a signal, abnormal rotating behavior of a mechanical part can easily be identified by inspecting statistical property of these oscillatory modes. Therefore, EMD is a suitable signal analysis tool and can be exploited for the development of a fault detection and diagnosis system. Y. Yu, Y. Dejie, C. Junsheng proposed the concept of EMD energy entropy and showed that its value for vibration signals differs in case for different bearing fault types [2]. In the proposed fault diagnosis method IMFs with dominant fault information were identified and their energy values constituted feature vector which was later utilized by back propagation artificial neural network to recognize fault pattern. C. Junsheng, Y. Dejie, T. Jiashi, Y. Yu proposed a fault diagnosis method for gear and bearing signals which utilized singular values of the matrices constituted by the IMFs as feature vectors for the support vector machine classifier [3]. Z. K. Peng, P. W. Tse, F. L. Chu proposed an improved Hilbert-Huang transform combining the wavelet packet transform, EMD and IMF selection technique to detect rubbing between stator and rotor of an induction motor [4]. In this case vibration signal is first decomposed into a set of narrowband signals which are further decomposed into IMFs by EMD and useful IMFs are selected by thresholding correlation coefficient between the IMFs and the original signal. Finally, rubbing symptoms are detected through the analysis of Hilbert spectrum of the selected IMFs.

This EMD can be also applied to the musical instrument research because it is important to analyze natural mode of vibration in the musical acoustics; it is utilized for the extraction of the resonance or vibrational mode of the percussion instruments. S. Cho applied EMD and Ensemble EMD (EEMD) to the extraction of the vibrational mode of the percussion instrument. In [5], the *Jing,* which is kind of *gong*, was target instrument and an algorithm was proposed

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Sangjin Cho is with School of Electrical Engineering, University of Ulsan, 93 Daehak-ro, Nam-gu, Ulsan 680-749, Republic of Korea (corresponding author to provide phone: +82-52-295-2724; e-mail: sjcho75@ ulsan.ac.kr).

Yejin Seo is with Department of Computer Engineering and Information Technology, University of Ulsan, 93 Daehak-ro, Nam-gu, Ulsan 680-749, Republic of Korea (e-mail: syj1122@mail.ulsan.ac.kr).

to solve endpoint problem of the EMD. In [6], EEMD was used to extract features of non-harmonic characteristics of the Korean percussion instrument called *Kkwaenggwari*.

II. Proposed IMF Selection Algorithm

A. Empirical Mode Decomposition

EMD algorithm employed here incorporates the modifications proposed in [7] to overcome limitations. A summary of the implementation process of this improved EMD process is given below.

1) For any given data, $x(t)$, data validity is checked.
2) Expected number of IMF components are determined as log2N, where N = total number of data points. Also, number of iteration for each sifting process is set at 10.
3) Now, for data $x(t)$ all the local extrema are identified.
4) All the maxima and minima are separately connect with natural cubic spline lines to form the upper, $u(t)$, and lower, $l(t)$, envelopes.
5) The mean of the envelopes are determined as $m(t) = [u(t) + l(t)]/2$.
6) The difference between the data and the mean is taken as the proto-IMF, $h(t) = x(t) - m(t)$.
7) Check number of iteration in the sifting process and repeat the operation step 3 to 6 until its value reaches 10.
8) When the iteration number reaches 10, assign the proto-IMF as an IMF component, $c(t)$.
9) Repeat the operation step 1 to 8 on the residue, $r(t) = x(t)-c(t)$, as the data.
10) The operation ends until (log2N)-1 number of IMFs are obtained and the latest $r(t)$ is taken as the final residue.

B. IMF Selection Method

The significant IMFs usually hold unique characteristics. These characteristics worked as the basis of the proposed IMF selection process. The first characteristic is that, they are usually of higher power which is also supported by the objective of the EMD process. The EMD efficiently extract the natural oscillatory modes from a given signal. For instance, oscillations which occur due to the fault of an induction motor should have higher power in comparison to other oscillations which do not represent a fault situation. This phenomenon is observed in an excited body of the instrument. The body amplifies oscillations when the excitation oscillation matches the resonant mode of the body. As a consequence, these oscillatory modes are characterized by higher power. The second characteristic is about harmonic contents of the IMFs. Usually, most of the fault signatures appear themselves as peak amplitude at several harmonics of some fundamental frequency. Due to the dyadic filter bank nature of EMD process, few of these harmonic peaks will be observed in the Fourier spectrum of lower index IMFs; whereas, fundamental fault frequency peak can be found in the higher index IMFs. Considering above two facts, an index named as Power-Harmonic Ratio (PHR) is calculated for each IMF. This higher value of PHR helps us to identify the IMFs with higher average power containing fault related frequency peaks. A low value of PHR indicates that the IMF may be of low power or contain many low amplitude harmonics. A summary of this IMF selection algorithm is as follows

1) For each of the IMFs c_j, where IMF index j = 1,2,...,n, power P_j is calculated.
2) To select candidate IMFs, threshold power P_{th} = mean{ P_k } is calculated; here $k = 1,2,...,m<n$.
3) Identify IMFs c_j for which $P_j > P_{th}$.
4) Evaluate Fourier spectrum of IMFs C_j = FT{c_j} and given data X = FT{$x(t)$}.
5) Determine frequency peaks f_l, l = 1,2,...,p in the spectrum X which has amplitude higher than average peak frequency amplitude above the mean of spectrum.
6) Calculate power contained in the determined peak frequencies and their harmonics in case of both IMFs and given data which are represented by E_j and E_X, respectively.
7) After calculating $PHR_j = E_j/E_X$, IMFs are rearranged according to descending values of PHR_j and first M IMFs are chosen. M is the number of desired IMFs.

III. Simulation and Results

For the purpose of evaluating performance of the proposed IMF selection algorithm, a fault signal of the induction motor and a sound signal of the *Jing*, traditional Korean percussion instrument, are utilized.

A. Signature Analysis of Broken Rotor Bar Fault

In the experiment, 0.5 kW, 60 Hz, 2-pole induction motor is used to produce the fault data under full load conditions and three accelerometers are used to measure vibrations in horizontal, vertical and axial directions. The sampling frequency of the data acquisition unit was 7.68 kHz. The maximum frequency of interest of the measured signals was 3 kHz.

Eleven different IMFs are obtained by the EMD of horizontal vibration signal in case of broken rotor bar fault. In Table I, PHR values of different IMFs, calculated from associated parameters, according to the proposed IMF selection technique are shown. According to Table I, IMF 5 has the highest PHR value, meaning that it is one of the most significant IMFs. Physical significance of IMF 5 can be realized from the corresponding power spectrum (Fig. 1(a)) where the rotating frequency (56 Hz) peak is clearly evident with sidebands of one time pole passing frequency (f_P), i.e., peaks at about 64 Hz and 48 Hz are evident. IMF 4 power spectrum (Fig. 1(b)) contains side bands peaks at two, four and sixth times of pole passing frequency around three times

TABLE I.
PHR VALUE CALCULATION FOR IMFS OF FAULT SIGNAL

IMF index	P_j ($\times10^{-5}$)	P_{th} ($\times10^{-5}$)	E_j ($\times10^{-9}$)	PHR_j ($\times10^{-2}$)
1	91.59		18.80	1.56
2	58.64		14.50	1.21
3	431.51		195.00	16.17
4	465.25		204.00	16.95
5	495.66		282.00	23.38
6	80.65	46.13	7.71	0.64
7	20.13		-	-
8	19.46		-	-
9	11.10		-	-
10	3.14		-	-
11	84.35		-	-

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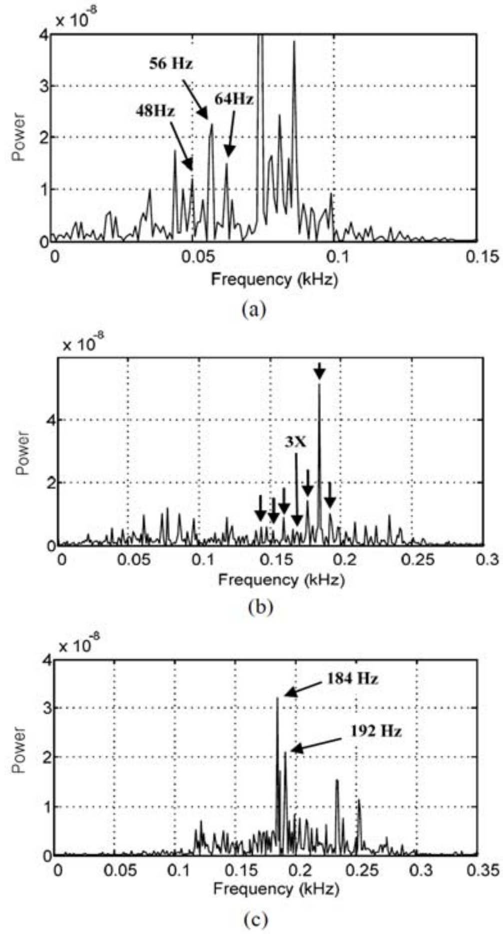

Fig. 1. Spectra of (a) IMF 5, (b) IMF 4, and (c) IMF 3.

rotating frequency shown by the downward arrows. Besides in case of IMF 3 which is another significant IMF, contains peaks at $3X+4f_P$ and $3X+6f_P$ frequencies in the power spectrum (Fig. 1(c)). Therefore, PHR value enables us to perform the reasonable selection of significant IMFs according to the fault symptoms.

B. *Signature Analysis of Jing Sound*

The sound used in this analysis is performed by the professional player and is recorded by digital recorder in the anechoic room. The recorder was set for 48kHz sampling frequency and 16 bits quantization.

As shown in Table II, five IMFs are automatically selected by proposed algorithm, whereas, in [6], six IMFs are selected empirically by the author. According to Fig. 2, IMF 3, 4, and 5 contain high peak respectively and they show harmonicity as described in Table III. This characteristic is identical to

TABLE II.
PHR VALUE CALCULATION FOR IMFS OF JING SOUND

IMF index	P_j ($\times10^{-2}$)	P_{th}	E_j ($\times10^{-2}$)	PHR_j ($\times10^{-2}$)
1	1466.71		13.25	0.82
2	4615.38		29.12	5.70
3	19510.98		51.45	42.57
4	3017.17		24.08	3.08
5	599.47	1.63	26.58	0.68
6	78.50		-	-
7	40.32		-	-
8	34.57		-	-
9	22.09		-	-
10	22.04		-	-

TABLE III.
COMPARISON OF EIGEN FREQUENCY AND PARTIAL TONE'S FREQUENCY RATIO OF THE JING

Eigen frequency (Hz)	118	234	351	468
Partial tone's frequency ratio	1	1.98	2.97	3.97

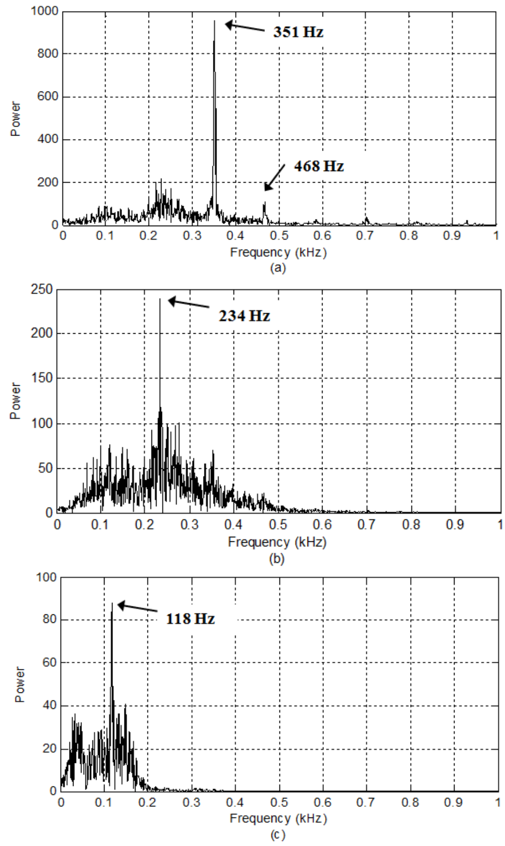

Fig. 2. Spectra of (a) IMF 3, (b) IMF 4, and (c) IMF 5

that of [8]. In other words, selected IMFs are physically meaningful.

IV. CONCLUSION

An automatic significant IMFs selection algorithm was described and its applications to fault signal and musical signal was shown. The algorithm based on the signal power and harmonicity was reasonable and efficient to extract features from those signals. Extracted IMFs contained physical significance such as rotating frequency, passing frequency and partial of the musical instrumental sound. However, we assumed the specific signal containing significant feature had high power and harmonicity. In other words, we may not assure the effectiveness and validity of the propose algorithm when it is applied to the noise-like signal in which harmonicity does not exist. We need to provide additional analysis about non-harmonic signal and future work in making the algorithm more stable is required.

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