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BoostEMD: An Extension of EMD Method and Its Application for Denoising of EMG Signals

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***Abstract*—The paper presents a novel extension of the Huang's Empirical Mode Decomposition (EMD) method, called BoostEMD, that allows calculating higher order Intrinsic Mode Functions (IMFs) that capture higher frequency empirical mode oscillations (empiquencies) in the EMG (electromyography) data. We describe the use of the second order IMFs for denoising physical action EMG signals. We demonstrate the efficiency of denoising by performing classification of EMG data before and after application of the denoising procedure as well as by evaluating properties of the extracted noise signal.**

***Index Terms*—Empirical mode decomposition, signal denoising, filtering, electromyography.**

I. Introduction

Neural-computer interface (NCI) is a communication system that translates activity of human nerve system into commands for a computer or other digital device. Most NCI systems work by reading and processing electromyogram (EMG) signals: electro-potentials generated by neuromuscular activation during muscle contraction.

EMG signals are used in many biomedical applications, e.g., for diagnostics of neuromuscular diseases [1], or assessing driver fatigue [2]. EMG signals are also used in physiological computing as a control signal for prosthetic devices (libs, arms) [3], as well as for interaction with computer software, e.g., in EMG-based speller [4], [5]. By monitoring, analysing and responding to EMG signals, physiological computing systems are able to react to the physical emotional and cognitive state of users in real time.

Signal denoising (filtering) plays a critical role in practical applications of EMG. The frequency of the EMG signals vary from 0 to 500 Hz, while most power of a signal is located in the 28 Hz–150 Hz range, with dynamically changing characteristics [6]. Five types of noise sources contribute to the acquired EMG signal: thermal noise of electronics in the recording equipment, power line noise, ambient noise of electromagnetic radiation, motion artefacts from electrode-skin interface or the cable connecting the electrode to the recording equipment, the electro-chemical (baseline) noise originating at skin-electrode interface [7], and inherent instability of the EMG signal due to the quasi-random nature of the firing rate of the muscular motor units [8]. Other variables such as electrode size and placement, muscle size, and distance between electrodes, as well as cross-talk from other muscles affect the spectrum of the signal as well. These noise components contaminate the EMG signal and may lead to an erroneous interpretation.

The characteristics of the filters used to reduce the noise determine the quality of EMG signals. However, there are no empirically based specifications for filtering EMG data from limb muscles. The search for better amplification and filtering circuit design that is able to accurately capture the features of surface EMG signals for the intended applications is still a challenge [8]. The determination of filter parameters is always a compromise between reducing maximum amount of noise and preserving as much as possible information from the EMG signal.

Typical approach to analysis of EMG signals involves using *Discrete Wavelet Transform (DWT)* for wavelet decomposition, denoising and extraction of feature vectors for further analysis and classification (see, *e.g.*, [9], [10]).

Huang *et al.* [11] proposed an alternative approach, called *Empirical Mode Decomposition* (EMD) to decompose a signal into components of different frequencies, called *Intrinsic Mode Functions* (IMFs).

This paper proposes an extension of the EMD method for calculating higher order IMFs. The novelty of the method is a proposed transformation of IMFs that allows EMD to be applied recursively to obtain further decomposition of the IMFs into a sum of empirical mode functions. The paper also proposes using second order IMFs for signal denoising.

II. Method

A. Preliminaries: Classical EMD Method

EMD [11] is a signal processing method based on local characteristics of data in the time domain. The EMD method is based on the concept of instantaneous frequency defined as the derivative of the phase of an analytic signal [12]. A mono-component signal will have positive and well-defined

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instantaneous frequency. A signal with multiple modes of oscillation (such as biophysical signals) must be decomposed into its constituent mono-component signals, called Intrinsic Mode Functions (IMFs). The essence of EMD is to recognize these oscillatory modes of the signal.

The steps comprising the EMD method are as follows:

1. Identify local maxima and minima of signal $S(t)$, where t is time.
2. Perform cubic spline interpolation between the maxima and minima to obtain envelopes $E_{max}(t)$ and $E_{min}(t)$.
3. Calculate the mean of the envelopes as $M(t) = (E_{max}(t) + E_{min}(t))/2$.
4. Calculate the difference between a signal and the mean of its envelopes as $C_1(t) = S(t) - M(t)$.
5. IF the number of local extrema of $C_1(t)$, is equal to or differs from the number of zero crossings by one, and the average of $C_1(t)$ is close to zero,

THEN $IMF_1 = C_1(t)$;

ELSE repeat steps 1-4 on $C_1(t)$ instead of $S(t)$, until new $C_1(t)$ satisfies the conditions of an IMF in Step 5.

6. Calculate residue $R_1(t) = S(t) - C_1(t)$.
7. If residue $R_1(t)$ is above a threshold value, then repeat steps 1-6 on $R_1(t)$ to obtain next IMF and a new residue.

As a result, *n* orthogonal IMFs are obtained from which the original signal may be reconstructed as follows

$$S(t) = \sum_i IMF_i(t) + R(t). \tag{1}$$

Henceforth we call the IMFs derived using the standard EMD procedure as the first-order IMFs, denoted further in the paper as $IMF^{(1)}$. The first IMF represents highest frequency oscillations present in the original signal. The subsequent IMFs contain lower frequency oscillations of the signal. Final residue shows only general trends of the signal.

B. BoostEMD: Proposed Extension of EMD Method

The idea behind the proposed method is to continue analysing the derived IMFs using the principles of the EMD method. However, we cannot submit the derived IMF to EMD as it is, as the result of the procedure would be the same IMF. Therefore, the IMFs must be transformed before processing further. A transformation must satisfy a set of requirements as follows:

1. It should not increase signal amplitude;
2. It should be reversible, i.e. an inverse of the transformation should be unambiguously computable;
3. It should have a different number of extrema than the original IMF.

Here we propose decomposing each IMF into a pair of positive and negative semi-definite functions denoted as IMF^{+} and IMF^{-} as follows:

$$IMF^{+(k)}(t) = \begin{cases} IMF^{(k)}(t), \; IMF^{(k)}(t) > 0, \\ 0, \; otherwise, \end{cases} \tag{2}$$

$$IMF^{-(k)}(t) = \begin{cases} IMF^{(k)}(t), \; IMF^{(k)}(t) < 0, \\ 0, \; otherwise. \end{cases} \tag{3}$$

It is obvious that each original IMF can be reconstructed from its decomposition unambiguously as follows

$$IMF^{(k)}(t) = IMF^{+(k)}(t) + IMF^{-(k)}(t). \tag{4}$$

Then, to allow extracting higher frequency components of a signal by EMD, each pair of functions IMF^{+} and IMF^{-} is up-sampled by a factor of 2 using a standard low-pass interpolation filter.

Next, the standard EMD procedure is applied and two sets of higher-order IMFs are obtained:

$$IMF^{+(k)} \leftarrow EMD\left(\uparrow\left(IMF^{+(k-1)}\right)\right), \tag{5}$$

$$IMF^{-(k)} \leftarrow EMD\left(\uparrow\left(IMF^{-(k-1)}\right)\right), \tag{6}$$

where $\uparrow(.)$ is the up-sampling operator, and $EMD(.)$ is the EMD procedure.

Such operation henceforth is called *boosting*, and the proposed extension of EMD method is called *BoostEMD.*

The original lower-order IMFs can be reconstructed from higher order IMFs easily using down-sampling by a factor of 2 as follows

$$IMF^{(k)} = \downarrow\left(\sum_i IMF_i^{+(k+1)}\right) + \downarrow\left(\sum_i IMF_i^{-(k+1)}\right), \tag{7}$$

where $\downarrow(.)$ is the down-sampling operator.

C. Using Higher Order IMFs for Denoising

Signal denoising using IMFs can be described as follows. Having a sampled noisy signal $S(t)$ given by

$$S(t) = \bar{S}(t) + \pm n(t), \tag{8}$$

where $\bar{S}(t)$ is a noiseless signal, $n(t)$ are Gaussian distributed random variables, $\pm$ is noise variance.

In the first IMF discarding based method [13], the reconstruction of a signal is made by discarding IMFs that contain primarily noise. The IMFs generated by EMD are ordered by frequency. Noise signals are mainly concentrated in the first few IMFs. So the solution would be to discard the first (or the first ones) IMFs as noise and reconstruct the signal. The method has been criticized for an assumption that first IMFs contain only noise. In fact they contain a mixture of noise and meaningful signal components.

In thresholding based denoising [14], thresholding is applied to each IMF in order to locally exclude low energy parts of IMFs which are expected to be significantly corrupted by noise as follows

$$\hat{S}(t) = \sum h_i(t), \tag{9}$$

where $\hat{S}(t)$ is a reconstructed signal, and $h_i(t)$ is the thresholding function given, *e.g.*, for hard thresholding as

$$h_i(t)=\begin{cases} h_i(t), |h_i(t)|>T_i, \\ 0, |h_i(t)|\le T_i, \end{cases} \tag{10}$$

where T_i is a threshold value, which can be set to a universal threshold [15].

The disadvantage of the EMD thresholding methods is that even for a noiseless signal, the absolute amplitude of the IMF drops below any non-zero threshold in the proximity of the zero crossings of the function values. Therefore, it is impossible to infer if a value of IMF corresponds to noise or to a useful signal based only on the absolute amplitude [14].

D. Proposed Denoising Method

We propose to perform EMD of a noisy signal in two stages. First, classic EMD is applied on a noisy signal $S(t)$ and $IMF_1^{(1)}$ is computed. Next, $IMF_1^{(1)}$ is further decomposed into $IMF_1^{+(2)}$ and $IMF_1^{-(2)}$. These two modes contain all higher frequencies (empiquencies) from $IMF_1^{(1)}$ and can be considered as noise. Finally, based on (1) and (7), the denoised signal $\hat{S}(t)$ is reconstructed as

$$\hat{S}(t)=S(t)-\left(\downarrow\left(IMF^{+(2)}_{1}\right)+\downarrow\left(IMF^{-(2)}_{1}\right)\right). \tag{11}$$

E. Motivating Example

We use a well-studied Lorenz model (parameter values a = 10, b = 3, c = 28, and time step value 0.01) as an example. Using the x component signal with data length of 1000 and adding Gaussian white noise, we generate a noisy Lorenz signal with SNR equal to 5 dB. The first order IMFs derived from the noisy Lorenz signal are shown in Fig. 1.

The transformation of the first-order IMFs and the application of EMD are depicted graphically in Fig. 2.

The second order IMFs derived from the first-order IMF_1 by the BoostEMD method are shown in Fig. 3 and Fig. 4.

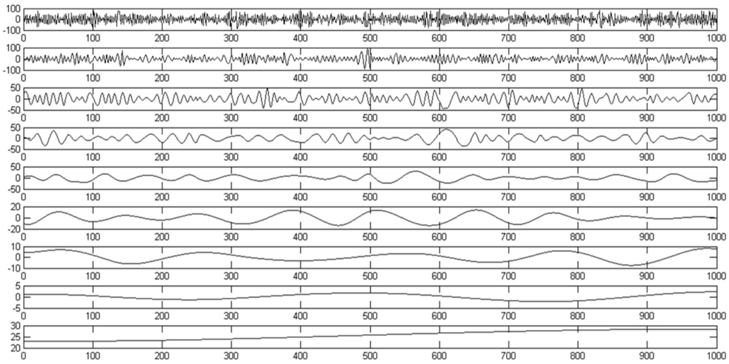

Fig. 1. First-order IMFs of noisy Lorenz data.

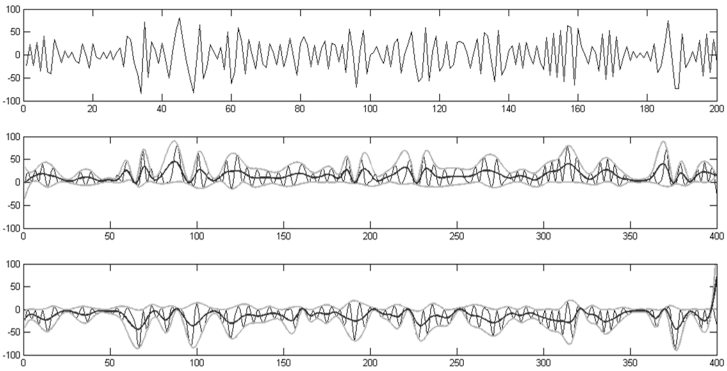

Fig. 2. Decomposition of IMF (top) into IMF+ (center) and IMF- (bottom) with their corresponding minima and maxima envolopes and means.

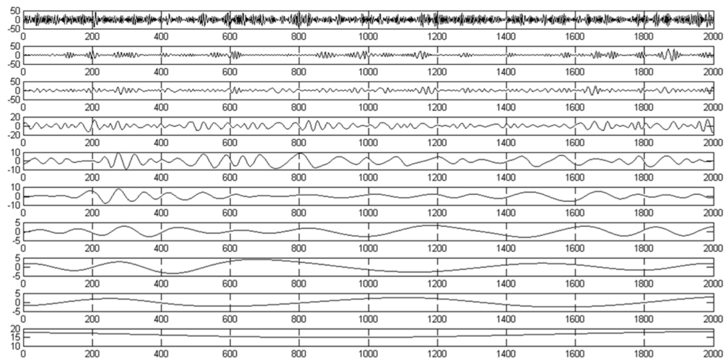

Fig. 3. Second order $IMF_1^{+(2)}$ constructed from $IMF_1^{(1)}$.

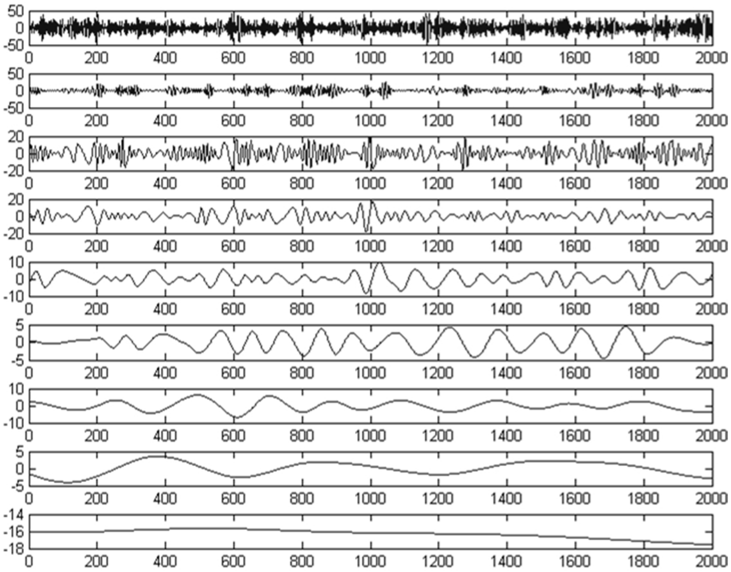

Fig. 4. Second order $IMF_1^{-(2)}$ constructed from $IMF_1^{(1)}$.

III. Evaluation of Denoising Efficiency

Noise signals can be characterized by their statistics, entropy, empirical and practical properties.

By statistical properties, we mean cross-correlation. We assume that noise is constructed from random variable. Since random variables are statistically uncorrelated, the Pearson correlation between extracted noise and denoised signal should be close to zero.

By information theoretic properties, we mean entropy and mutual information (MI). Entropy measures uncertainty of a signal. It should be lower for a denoised signal as compared to a noisy signal, and high for a noise signal. MI between noise and denoised signal should be low.

By empirical properties, we mean predictability of the signal using a selected prediction model. Here we use the auto-regressive AR(4) model. Predictability (measured by goodness-of-fit) of noise signal should be low, as noise is usually introduced by random processes (except cross-contamination), while RMSE (Root Mean Square Error) should be high. On the contrary, predictability of a denoised signal should increase when compared with a noisy signal.

By practical properties we mean suitability of the denoised signal for performing tasks which are important for the domain of interest. In the EMG domain, it is important to classify EMG signals representing different kinds of physical muscular activities correctly. Therefore, we use accuracy of classification as a practical measure to evaluate the efficiency of denoising. If quality of denoising is good, we can obtain higher classification accuracy, because good denoising filter will remove all unnecessary noise but preserve information necessary to perform good classification. Poor denoising does not remove all noise, which will affect the classification results negatively.

IV. Data

We use the “EMG physical action data set” from the machine learning repository (UCI) [16]. 4 subjects (3 male and 1 female) took part in the experiment (aged 25 to 30 years). Each subject performed 10 normal and 10 aggressive activities (~15 actions per session for each subject, ~ 10000 samples for each channel). Normal activities were bowing, clapping, handshaking, hugging, jumping, running, seating, standing, walking, and waving, and aggressive activities were elbowing, front kicking, hammering, headering, kneeing, pulling, punching, pushing, side kicking, slapping.

The denoising method was applied to EMG time series and classification using *Support Vector Machine* (SVM) [17] with RBF kernel was performed. For classification, each time series was split into about 100 samples of 100 features length. A new dataset was formed by composing the physical action series of the same subject using EMG data from the same channel. Data representing each physical action was classified against data representing a different physical action, which resulted in a binary classification problem. The results were validated using 10-by-10 fold cross-validation, where each 10-fold cross-validation was repeated 10 times and the results are averaged.

V. Results

The results of the evaluation of EMG signal denoising obtained using the proposed BoostEMD method are presented in Table I (for extracted noise), Table II (denoised signal is compared with extracted noise), and Table III (results of classification (F-measure) using denoised signal).

TABLE I. CHARACTERISTICS OF EXTRACTED NOISE SIGNALS.

EMD based denoising method	Entropy, bits	Predictability using AR(4)	
		Fit	RMSE
Discarding IMF_1	12.5990	26.6895	43.5824
Thresholding IMFs	**13.2445**	54.6281	139.020
Discarding 2nd order IMF_1s	12.9124	**9.5392**	**426.287**

TABLE II. CHARACTERISTICS OF DENOISED SIGNALS AGAINST EXTRACTED NOISE.

EMD based denoising method	Cross-correlation	Mutual information, bits
Discarding IMF_1	-0.099	12.5660
Thresholding IMFs	**0.001**	**12.5429**
Discarding 2nd order IMF_1s	-0.017	12.8792

TABLE III. RESULTS OF CLASSIFICATION USING EMG CH1 DATA: F-MEASURE.

Physical action (N – normal, A – aggressive)	Original data	Discard IMF_1	Thres hold IMFs	Discard 2^{nd} order IMF_1s
Bowing (N) vs Headering (A)	0.833	0.794	**0.932**	0.831
Bowing (N) vs Clapping (N)	0.864	0.838	**0.957**	0.872
Clapping (N) vs Headering (A)	0.734	0.749	0.903	**0.927**
Walking (N) vs Headering (A)	0.790	0.771	**0.933**	0.730
Bowing (N) vs Walking (N)	0.666	0.663	**0.977**	0.663
Clapping (N) vs Walking (N)	0.815	0.720	**0.955**	0.778

VI. CONCLUSIONS

The paper presents: 1) a novel extension of the Huang’s EMD method, called BoostEMD, which calculates higher order IMFs that capture higher frequency oscillations in the data; 2) its application for filtering EMG signals; and 3) validation using entropy, predictability, cross-correlation, mutual information and classification metrics.

The proposed method can be used for time series filtering, prediction and classification, where the original EMD method is applied. Application on EMG data can lead to better evaluation of patient’s state of muscles during rehabilitation exercises.

The advantages of the proposed method are: 1) the method does not have any parameters or basis functions; 2) it is computationally not very expensive: to improve performance it is sufficient to modify the original EMD method so that only first IMF is extracted; 3) the denoising results are superior as compared to traditional first IMF discarding method both in terms of entropy and predictability (fit and RMSE) of extracted noise signal as well as classification accuracy using denoised data, however, the thresholding based method performs better for classification.

The disadvantage of the method is that even higher order IMFs do not separate noise components from signal components clearly, therefore all noise cannot be extracted while retaining all useful information of the signal.

Further research will focus on analysis of spectral and non-linear properties of higher order IMFs and their practical application for important EMG domain tasks.

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