An improved ensemble empirical mode decomposition and Hilbert transform for fatigue evaluation of dynamic EMG signal

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A B S T R A C T

A hybrid dynamic fatigue diagnosis method based on a variation of ensemble empirical mode decomposition (VEEMD) and mean instantaneous frequency (MIF) is presented. This new approach consists of sifting an ensemble of white noise-added signal (data) and treats the mean as the final true result. In the method here proposed, a particular noise is added at each stage of the decomposition and a unique residue is computed to obtain each mode. Our results showed that MIF estimated from each instantaneous frequency of intrinsic mode functions (IMFs) decomposed by the proposed VEEMD is a relevant feature to muscular fatigue diagnosis. We found that MIF reduces when the force level of the muscle contraction increases.

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1. Introduction

Hilbert–Huang transform (HHT) is a new time–frequency representation method of signal analysis, which was initially proposed in the study of fluid mechanics [9] and found immediate applications in many fields [11–15]. HHT comprises the empirical mode decomposition (EMD) and Hilbert transform. The aim of EMD is to decompose a signal into a set of “intrinsic mode functions” (IMFs), where the characteristics of each IMF are such that they may be Hilbert transformed [16–21]. Then, through the Hilbert transform, the instantaneous frequency with meaningful feature of each IMF at any point in time may be calculated. The decomposition is based on the local time scale of the data and yields adaptive basis functions. Hence it can be used for non-linear and nonstationary signal analysis [11–15]. As useful as EMD proved to be, it still leaves some annoying difficulties unresolved [18,19]. One of the major drawbacks of the original EMD is the frequent appearance of mode mixing, which is defined as a single IMF either consisting of signals of widely disparate scales, or a signal of a similar scale residing in different IMF components. Mode mixing is often a consequence of signal intermittency.

To overcome these problems, a new method was proposed: the ensemble empirical mode decomposition (EEMD) [22–32,34]. It performs the EMD over an ensemble of the signal plus Gaussian white noise. The addition of white Gaussian noise solves the mode mixing problem by populating the whole time–frequency space to take advantage of the dyadic filter bank behavior of the EMD [3]; however it creates some new ones. Indeed, the reconstructed signal includes residual noise and different realizations of signal plus noise may produce different number of modes. In order to overcome these situations, in this paper we propose a variation of the EEMD algorithm that provides an exact reconstruction of the original signal and a better spectral separation of the modes, with a higher computational cost.

In this paper, we propose a new method via the VEEMD and Hilbert transform (HT) to determine the physically meaningful mean frequency of fatigue EMG and validate the effectiveness of the variable to quantify EMG manifestations of muscle fatigue. The new method overcomes the difficulties of the conventional EEMD method. The paper is arranged as follows: Section 2 introduces the methodology that gives the details of the proposed VEEMD and Hilbert transform. Section 3 gives the performance comparison among EMD, EEMD and VEED. The novel index of muscle fatigue based on VEEMD and HT is arranged in Section 4. Section 5 will display the usefulness and capability of the proposed fatigue index based on VEEMD and HT through three dataset. Section 6 draws the conclusions.
2. Methodology

2.1. Standard EEMD

Today, the definition of noise varies in different circumstances. In science and engineering, noise is defined as disturbance, especially a random and persistent kind that obscures or reduces the clarity of a signal. In natural phenomena, noise could be induced by the process itself, such as local and intermittent instabilities, irresolvable sub-grid phenomena, or some concurrent processes in the environment in which the investigations are conducted. It could also be generated by the sensors and recording systems when observations are made. When efforts are made to understand data, important differences must be considered between the clean signals that are the direct results of the underlying fundamental physical processes of our interest (“the truth”) and the noise induced by various other processes that somehow must be removed. In general, all data are amalgamations of signal and noise, i.e.,

\[ x(t) = s(t) + n(t) \quad (1) \]

where \( x(t) \) is the recorded data, \( s(t) \) and \( n(t) \) are the true signal and noise, respectively. Because noise is ubiquitous and represents a highly undesirable and dreaded part of any data, many data analysis methods were designed specifically to remove the noise and extract the true signals in data, although often not successful.

The earliest known utilization of noise in aiding data analysis was due to Press and Tukey [33] known as pre-whitening, where white noise was added to flatten the narrow spectral peaks in order to get a better spectral estimation. Since then, pre-whitening has become a very common technique in data analysis. In the following, the new noise-added EMD approach will be explained, in which the cancelation principle will be fully utilized, even with finite amplitude noise. Also emphasized is the finding that the true solution of the EMD method should be the ensemble mean rather than the clean data. This full presentation of the new method will be the subject of the next section.

As given in Eq. (1), all data are amalgamations of signal and noise. To improve the accuracy of measurements, the ensemble mean is a powerful approach, where data are collected by separate observations, each of which contains different noise. To generalize this ensemble idea, noise is introduced to the single dataset \( x(t) \), as if separate observations were indeed made as an analog to a physical experiment that could be repeated many times. The added white noise is treated as the possible random noise that would be encountered in the measurement process. Under such conditions, the \( i \)th “artificial” observation will be

\[ x_i(t) = x(t) + \omega_i(t) \quad (2) \]

In the case of only one observation, each multiple-observation ensembles is mimicked by adding not arbitrary but different realizations of white noise \( \omega_i(t) \), to that single observation as given in Eq. (2). Although adding noise may result in smaller signal-to-noise ratio, the added white noise will provide a relatively uniform reference scale distribution to facilitate EMD; therefore, the low signal–noise ratio does not affect the decomposition method but actually enhances it to avoid the mode mixing. Based on this argument, an additional step is taken by arguing that adding white noise may help to extract the true signals in the data, a method is termed EEMD, which is shown in Fig. 1.

Therefore, the means of the corresponding IMFs of different white noise series are likely to cancel each other. With these properties of the EMD in mind, the EEMD is developed as follows:

1. Add a white noise series to the targeted data.
2. Decompose the data with added white noise into IMFs.
3. Repeat step 1 and step 2 again and again, but with different white noise series each time.
4. Obtain the (ensemble) means of corresponding IMFs of the decompositions as the final result.

The effects of the decomposition using the EEMD are that the added white noise series cancel each other in the final mean of the corresponding IMFs; the mean IMFs stay within the natural dyadic filter windows and thus significantly reduce the chance of mode mixing and preserve the dyadic propery. To demonstrate the EEMD performance of overcoming the mode mixing problem, the following part provides two datasets to test the EMD and EEMD.

2.2. Our method (VEEMD)

In the method here presented, the decomposition modes will be noted as \( \text{IMF}_k \) and we propose to calculate the first residue as:

\[ r_1(t) = x(t) - \text{IMF}_1 \quad (3) \]

where \( \text{IMF}_1 \) is obtained in the same way as in EEMD, the \( \text{IMF}_2 \) can be obtained by the EEMD over an ensemble of \( r_1(n) \) and different white noise. The next residue is defined as: \( r_2(t) = r_1(t) - \text{IMF}_2 \). The \( k \)th residue is represented as follows:

\[ r_k(t) = r_{k-1}(t) - \text{IMF}_k \quad (4) \]

This procedure continues with the rest of the modes until the stopping criterion is reached.

Let \( w \) be white noise with \( N(0, 1) \). If \( x(t) \) is the targeted data, we can describe our method shown in Fig. 2 by the following algorithm:

1. Obtain the \( \text{IMF}_1 \) by our method and produce the first residue \( r_1(t) \).
2. Add white noise series to the residue and obtain the update targeted data \( r_k(t) + n_i(t) \), \( k = 1 \ldots m \).
3. Decompose the update targeted data with added white noise and obtain \( \text{IMF}_{k+1} \).
4. Repeat step 2 and step 3 with different white noise series each time until the obtained residue is no longer feasible to be decomposed (the residue does not have at least two extrema). The final residue satisfies:
\[ R(t) = x(t) - \sum_{k=1}^{m} IMF_k \] \tag{5}

2.3. Hilbert transform

Having obtained the intrinsic mode function components, we will have no difficulties in applying the Hilbert transform to each component, and computing the instantaneous frequency according to the following steps. For an arbitrary time series \( X(t) \), we can always have its Hilbert transform \( Y(t) \), as

\[ Y(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} X(t') \frac{X(t')}{t - t'} \, dt' \] \tag{6}

where \( P \) indicates the Cauchy principal value. With this definition, \( X(t) \) and \( Y(t) \) form the complex conjugate pair, so we can have an analytic signal \( Z(t) \),

\[ Z(t) = X(t) + iY(t) = a(t)e^{i\theta(t)} \] \tag{7}

in which we can also write as

\[ a(t) = \sqrt{X^2(t) + Y^2(t)} \] \tag{8}

\[ \theta(t) = \arctan \left( \frac{Y(t)}{X(t)} \right) \] \tag{9}

and the instantaneous frequency (IF) was defined as

\[ \omega = \frac{d\theta(t)}{dt} \] \tag{10}

After performing the Hilbert transform on each IMF component, we can express the data in the following form:

\[ X(t) = \sum_{j=1}^{n} a_j(t) \exp \left( i \int \omega_j(t) \, dt \right) \] \tag{11}

The equation also enables us to represent the amplitude and the instantaneous frequency as functions of time in a three-dimensional plot, in which the amplitude can be contoured on the frequency–time plane.

3. Performance comparison between conventional EMD and our method

The effects of the decomposition using the ensemble empirical mode decomposition are that the added white noise series cancel each other in the final mean of the corresponding IMFs; the mean IMFs stay within the natural dyadic filter windows and thus significantly reduce the chance of mode mixing and preserve the dyadic property. To demonstrate the performance of ensemble empirical mode decomposition, the following part provides two datasets to test the EMD and EEMD.

Example 1. In this experiment, the proposed model was applied to a static sEMG signal dataset.

Dataset information: There are three EMGs from the MIT-BIH Normal Sinus Rhythm Database available at http://physionet.org/physdbase/database/emsdb/. The records are emg Healthy, emg_myopathy, emg_neuropathy. 1280 points which are selected from the 4th second of the first channel of emg Healthy signal have been used in this paper.

Fig. 3(a) and (b) depicted, respectively, the decompositions of “emg Healthy” signal by EEMD and EMD. In the right panel, it can be seen that EEMD produces 10 modes, while in the left panel, only nine modes are obtained by the conventional EMD method. Obviously, compared with EMD, EEMD can provide more details and decomposition parts of the static sEMG signal. Obviously, EEMD can overcome the mode mixing problem compared with EMD. To prove the advantage of VEEMD, we decompose the same EMG signal by VEED and EEMD. In the following example, performance comparison between EEMD and our method (VEEMD) was presented.

Example 2. In this experiment, the proposed model was applied to a dynamic sEMG signal dataset.

We decomposed another sEMG signal from one dynamic experiment by EEMD method and our method, respectively. The result that EEMD produced 8 modes can be shown in Fig. 4(a), while our method produced 11 modes can be shown in Fig. 4(b). We have the same conclusion with the above example. Our method performs better than EEMD in dynamic sEMG signal.

On the basis of the analysis of the above two examples, we can find that our method is able to solve the problem of mode mixing and achieve an improved decomposition with physical meaning.

4. Fatigue evaluation

Recently, Georgakis et al. [4] proposed to analyze the instantaneous frequency (IF) of fatigue EMG directly using Hilbert transform. They reported that the reliability and accuracy of the
IF was better than the conventional spectral variables, i.e. mean frequency and median frequency [1,2]. However, contrary to the suggestion given by [4], several authors [5–9] argued that one should not just take any data to perform a Hilbert transform, find the phase function, and define the instantaneous frequency as the derivative of this phase function. They pointed out, if one follows this path, one would obtain a finite number of points where the frequency becomes very high and even assumes negative values that bear no relationship to the real oscillation of the data. It is to say that the instantaneous frequency derived from this method is typically oscillatory and often extends beyond the spectral range of the signal. The instantaneous frequency concept is only meaningful for monocomponent or narrow band signals. To obtain meaningful and well-behaved instantaneous frequencies, the signal to be analyzed must have no riding waves and be locally symmetrical about its mean point as defined by the envelopes of local maxima and local minima. This limitation of the data for the straight-forward application of Hilbert transform means that the method is of little practical value on analysis of EMG signal whose frequency band range from 30 to 300 Hz.

4.1. Mean instantaneous frequency

To evaluate the fatigue phenomena of EMG signal, the mean instantaneous frequency is used to represent the trend of frequency in continuous time windows. Then, we defined the mean instantaneous frequency of each IMF with m data points in Eq. (12), and the instantaneous frequency \( \omega_j(i) \) used the square \( q_i(t) \) as weight.

\[
mif(j) = \frac{\sum_{i=1}^{n} \omega_j(i)q_i^2(t)}{\sum_{i=1}^{n} q_i^2(t)}
\]  

(12)

where \( \omega_j(i) \) is instantaneous frequency of the i-signal point, \( \omega_j(i) \) is the amplitude of the i-signal point from the j-IMF.

After mif(j) of the j-IMF is obtained by our method and Hilbert transform, the two norms of each IMF amplitude are calculated to provide a measure of relative magnitude of each frequency band at the epoch. Each narrow band mean frequency is weighted by the amplitude norm of that band, and the results sum to provide an our method-HT-based estimate of the mean frequency. So, the mean instantaneous frequency (MIF) of the original signal is defined by:

\[
MIF = \frac{\sum_{j=1}^{n} \| a_j \| \cdot mif(j)}{\sum_{j=1}^{n} \| a_j \|}
\]  

(13)

It does not require any quasi-stationarity and linear assumptions, for our method (EEMD) and Hilbert transform are inherently suitable for non-linear non-stationary signals. The method provides a compact and physically meaningful representation of EMG signal unlike the IF variable, which is directly derived from Hilbert transform.

5. Experiment

5.1. Experiment setup

Ten male healthy, right-handed volunteers (mean age 22 ± 2.8 years) participated in the experiment. All subjects also read and signed an informed consent before this experiment. No subject had a lower extremity injury, physical disability, or discomfort problem. Surface EMG signals were obtained from the left and right biceps brachii in an isometric constant force experiment.

The subject sat with a dumbbell in his right hand. The initial position of the arm was such that the angle of elbow joint was 90°. And the subject bent the left and right hand elbow at the same time once every 1.5 s.

Before placing the measurement electrodes, placement site was identified. The electrode site was initially cleaned with sterile alcohol pads to by exerting a sufficient abrasive action to avoid impedance mismatch and therefore improve the SNR. Motor points were located by means of a stimulator and the electrodes were
positioned on the middle portion of muscle belly (short head) parallel to the longitudinal axis of muscle fibers and away from the main motor point. Prior to the experiment, the maximum voluntary contraction (MVC) force was determined within a few trails. The maximal value of MVC was used as the reference value. The subject was asked to produce contraction at 60% MVC lasted 20 s only by his right hand, while his left elbow bends at the same time without holding anything shown in Fig. 5. We select two subjects to repeat the experiment and then, two dynamic sEMG signals were also represented in Figs. 6 and 8, respectively. These surface EMG signals were acquired at a rate of 4000 Hz by Trigno Hybrid Sensors (fully wireless, Trigno LAB, America) with passband 20–500 Hz. All software implementations were done in MATLAB 7 with the Signal Processing toolbox 6.0 and Statistics toolbox 4.0. The EMG signals from Figs. 4–6 were a 16 s time-series that was divided into 9 time widows, which time widow has 1.6 s sEMG signal.

sEMG amplitude changes during fatiguing contractions, with smaller amplitudes during maximal sustained contractions and higher amplitudes during sub-maximal contractions held to fatigue. In static experiment the mean power spectrum moves the low frequency position when fatigue comes out. Obviously, the movement of mean power spectrum has no enough capability to represent the fatigue phenomena in dynamic muscle contraction.

In the following part, our method presented in this paper is used to decompose the EMG signal and produce some IMFs, then the mean instantaneous frequency can be obtained by Hilbert transform. The EMG signals has 16 s time-series in the above two examples. To get the adaptability of the MIF in longer time-series signal, we...
select more time windows to handle the EMG signals with 250 s shown in Fig. 10 by Hilbert transform. It is also found that instantaneous frequency has no special rule in all time windows, while the mean instantaneous frequency go down during the continuous fatigue process, which can be shown in Fig. 11.

From the above three experiments, it can be conclude that the MIF is move the low position frequency shown in Figs. 7, 9 and 10, means the frequency deceases generally during our dynamic fatigue course. For dynamic sEMG signal, mean instantaneous frequency can reflect the inherent character of fatigue signal. So, our result is consistent with the traditional approaches and more convenient and evident. From them it is possible to conclude that the trend of the MIF reduces when the force level of the muscle contraction increases.

6. Conclusion

Obviously, the indexes of conventional time–frequency domain have the accordant result with local fatigue of the published literature. However, it is difficult for these conventional time–frequency indexes to represent the dynamic EMG signal. In this paper, we adopted the hybrid method based on the improved EEMD method and Hilbert transform to handle the dynamic sEMG signal, and then we obtained the instantaneous frequency. By the computation of mean instantaneous frequency, the continuous decrement trend of MIF was found in three examples. This result was consistent with the published conclusions.

In this work, we also have presented a new algorithm for analyzing and processing non-linear and non-stationary signals. The new method was successfully tested on benchmark dataset and real signals. The method here proposed has the advantages of decomposing more IMFs than EEMD, and that the original signal can be exactly reconstructed by summing the modes. Decomposition completeness was numerically verified in the case of fatigue evaluation of EMG signal. In that sense, the novel method recovers some of the EMD properties lost by EEMD, such as completeness and a fully data-driven number of modes.

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