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Mean frequency derived via Hilbert-Huang transform with application to fatigue EMG signal analysis

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ABSTRACT

The mean frequency (MNF) of surface electromyography (EMG) signal is an important index of local muscle fatigue. The purpose of this study is to improve the mean frequency (MNF) estimation. Three methods to estimate the MNF of non-stationary EMG are compared. A novel approach based on Hilbert-Huang transform (HHT), which comprises the empirical mode decomposition (EMD) and Hilbert transform, is proposed to estimate the mean frequency of non-stationary signal. The performance of this method is compared with the two existing methods, i.e. autoregressive (AR) spectrum estimation and wavelet transform method. It is observed that our method shows low variability in terms of robustness to the length of the analysis window. The time-varying characteristic of the proposed approach also enables us to accommodate other non-stationary biomedical data analysis.

1. Introduction

The surface electromyography (EMG) signal is the manifestation of the electrical activity produced by actively contracting motor units [1]. EMG analysis is widely used in biomechanics and movement control research to determine how the central nervous system controls muscular contraction to produce motion, and in clinical practice to diagnose the state of neural or muscle malfunction [2–5]. Localized muscle fatigue is a complex process due to various physiological and psychological phenomena. Typically, during a sustained isometric contraction, there is an increase in the amplitude of the low frequency band and a relative decrease in the higher frequencies, which is called EMG spectrum compression. So, spectral parameter derived from the EMG signal, such as mean frequency (MNF), is frequently used to track muscular changes, which occur in fatigue during ischemia [6,7]. Derivation of meaningful, statistically-significant spectral parameters requires some assumptions regarding the characteristics of the signal [8]. In particular, the signal must be of time-invariant (stationary) or periodic frequency content within the analysis window, otherwise, the resulting spectrum will make little physical sense. Unfortunately, the EMG is a non-stationary signal, especially for contraction levels higher than 50% of maximum voluntary contraction (MVC) [9]. So, the conventional methods of determination of the power spectral density (PSD) of a signal via Fourier transform, such as periodogram, may not provide accurate frequency resolution. Furthermore, the shape and size of the analysis window also directly affect the estimation of the MNF. A different approach for PSD estimation is based on the methods referred to as modern parametric or model-based (autoregressive (AR), moving average (MA), autoregressive moving average (ARMA)) [10]. In these model approaches, each sample of the signal is described as a linear combination of present and some past outputs. An additional problem of the methods is the

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choice of the order of the model (number of parameters). If the estimated model order is too small, the spectrum appears excessively smooth due to incorrect assumptions on the generator model, while if it is too large the variance increases and peaks that are not present in the real spectrum are generated as artifacts [11]. This directly affects the estimates of the spectral variables. Wavelet transform is also presented to determine the mean power frequency of EMG signal with a rapid varying frequency content [12]. Essentially, wavelet analysis is still convolutional, and the "mother" wavelet is phenomenon dependent. Also the lack of orthogonality and the limitation of definite length for some of the most commonly used "mother" wavelet can cause unwanted leakage among the different frequency modes [13]. So, the results indicated that the performance of wavelet analysis method is similar to Fourier transform in determination of EMG mean frequency [12].

Recently, Georgakis et al. [14] proposed to analyse 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. However, contrary to the suggestion given by [14], several authors [13,15–19] 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 [19,20]. 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 ranges from 30 to 300 Hz [21].

Hilbert-Huang transform (HHT) is a new time–frequency representation method of signal analysis, which was initially proposed in the study of fluid mechanics [8] and found immediate applications in biomedical engineering [22,23]. 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. 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 non-stationary signal analysis. In this paper, we propose a new method via EMD and Hilbert transform 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 Fourier and wavelet spectral variables deriving method by avoiding the spectral estimation. It does not require any quasi-stationarity and linear assumptions, for the EMD 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 [14], which is directly derived from Hilbert transform. To illustrate the performance of the new method applied in fatigue EMG analysis, it is compared with the AR model and wavelet transform (WT) method.

2. Mean frequency estimation methods

2.1. *AR model method*

The method of AR model for spectral estimation has been widely applied in different fields of signal processing [24–26]. The algorithms to determine the AR parameter, such as Burg algorithm, Marple algorithm, could be found in many references [24–27]. The optimal AR model order could be determined using Akaike Information Criterion (AIC) [28]. After estimating the AR parameters, the power spectrum of the data sequence can now be estimated. It is given by:

$$P(f) = \frac{\sigma_p^2 \Delta t}{\left|1 + \sum_{k=0}^{p} a_p(k) \exp(-j2\pi f k \Delta t)\right|^2} \quad (1)$$

where σ_p^2 is the forward prediction error energy, p is the AR model order, Δt is the sampling period of the data sequence and f is the frequency. The details of the algorithm may refer to [24]. Then, the MNF is the average frequency of the power spectrum and is defined as its first-order moment:

$$\mathrm{MNF} = \frac{\int_0^\infty f P(f)\,\mathrm{d}f}{\int_0^\infty (f)\,\mathrm{d}f} \quad (2)$$

2.2. *Wavelet transform method*

Multiresolution wavelet analysis provides a convenient method with which to divide signals into component wavelet levels. In this method, EMG signal is first decomposed into different bands by wavelet transform. The mean power frequency of each wavelet band is then calculated by applying Fourier analysis to the wavelet itself. Each wavelet band's mean power frequency is weighted by the amplitude norm of that band, and the result summed to provide a wavelet-based estimate of the EMG signal's mean power frequency [12].

2.3. *Empirical mode decomposition (EMD)*

As mentioned before, the first step of Hilbert-Huang transform is empirical mode decomposition. The empirical mode decomposition separates a time series into a finite number of its individual characteristic oscillations. In order to define a meaningful instantaneous frequency these intrinsic mode functions (IMF) have to satisfy two conditions [8]: (1) in the whole data set, the number of extrema and the number of zero crossings must either equal or differ at most by one; and

(2) at any point, the mean value of the envelope defined by the local maxima and the envelope by the local minima is zero. The definition of an intrinsic mode function is adopted because it represents the oscillation mode imbedded in the data. Remarkably, each IMF is capable of containing a modulated frequency and amplitude and therefore might be of non-stationary character. Based on the discussion in [8], the numerical procedure to obtain those IMFs can be concluded with the following steps:

(a) Identify the extrema of the data $x(t)$, and form the envelopes defined by the local maxima and minima, respectively, by the cubic spline method.
(b) Form the mean values $m_1(t)$ by averaging the upper envelope and lower envelope, and make the differences between the data and the mean values to get the first component $h_1(t) = x(t) - m_1(t)$.
(c) If the first component is not an IMF, let $h_1(t)$ be the new data set. Continue the steps (a) and (b) until the first component is an IMF.
(d) The first IMF component is called as $c_1(t)$. Let $r_1(t) = x(t) - c_1(t)$. Continue the steps (a)–(c) until $r_n(t)$ is smaller than a predetermined value or becomes a monotonic function that no more IMF can be extracted.

Based on the above algorithm, the original signal $x(t)$ can thus be expressed as follows:

$$x(t) = \sum_{j=1}^{n} c_j(t) + r_n(t) \tag{3}$$

where n is the number of IMFs, $r_n(t)$ is the final residue which can be either the mean trend or a constant, and functions $c_j(t)$ are nearly orthogonal to each other, and all have zero means. By the nature of the decomposition procedure, the technique decomposes data into N fundamental components, each with distinct time scale. More specifically, the first component has the smallest time scale, which corresponds to the fastest time variation of data. Since the decomposition is based on the local characteristic time scale of the data to yield adaptive basis, it is applicable to non-linear and non-stationary data in general and in particular, fatigue EMG data considered in the following section.

The second step of the HHT is Hilbert transform. After the decomposition step, the IMFs are submitted to this process, which is defined as:

$$y(t) = \frac{1}{\pi} P \int \frac{x(t')}{t - t'}\, dt \tag{4}$$

where P indicates the Caushy principle value. With this definition, $x(t)$ and $y(t)$ form the complex conjugate pair, so we can have an analytic signal $z(t)$ as:

$$z(t) = x(t) + iy(t) = a(t)\, e^{i\theta(t)} \tag{5}$$

where

$$a(t) = \sqrt{x^2(t) + y^2(t)} \tag{6}$$

and

$$\theta(t) = \arctan\left(\frac{y(t)}{x(t)}\right) \tag{7}$$

Polar expression of $z(t)$ in Eq. (5) represents the physical meaning of the Hilbert transform: it is the best local fit to time series $x(t)$ in form of a trigonometric function which is amplitude and phase modulated. The instantaneous frequency of the Hilbert spectrum is defined as:

$$\omega(t) = \frac{d\theta(t)}{dt} \tag{8}$$

conveying one instantaneous frequency for one instant in time of the time series. Finally, by means of the combination of the amplitude and the derivative of the phase (i.e. the instantaneous frequency) of each component, it is possible to obtain the resulting amplitude, time, and frequency representation of the original series:

$$x(t) = \mathrm{Real} \sum_{j=1}^{n} a_j(t) \exp\left(i \int \omega_j(t)\, dt\right) \tag{9}$$

Here the residue, $r_n(t)$, is omitted because it is either a monotonic function or it might be smaller than the pre-determined threshold.

2.4. *The Hilbert-Huang transform based MNF estimation*

Then we define the mean instantaneous frequency MIF(j) of $c_j(t)$ with m data points as the weighed mean $\omega_j(t)$ using the square $a_j(t)$ as weight. It is computed with:

$$\mathrm{MIF}(j) = \frac{\sum_{i=1}^{m} \omega_j(i) a_j^2(i)}{\sum_{i=1}^{m} a_j^2(i)} \tag{10}$$

Now, we prove that the mean instantaneous frequency as defined above can be used as a measure of the mean frequency of the signal in the frequency band: the Fourier transform of the narrow band analytical signal $z(t) = a(t)e^{j\theta(t)}$ is denoted by $z(f) = F_{t\to f} z(t)$. The total power of the signal is given by $E_Z = \int_{-\infty}^{+\infty} |Z(f)|^2\, df$; i.e. this is the power of the signal $z(t)$ in the frequency band. Furthermore, the mean frequency of the signal in the frequency band is given by $\langle f \rangle = \int_{-\infty}^{+\infty} f |Z(f)|^2\, df / E_Z$. It can be shown that the mean frequency $\langle f \rangle$ is equal to the average over time of the instantaneous frequency $\omega(t)$ weighted with the square instantaneous amplitude $a(t)^2$: $\langle f \rangle = \int_{-\infty}^{+\infty} \omega(t) a(t)^2\, dt / E_Z$. Therefore, the mean instantaneous frequency as defined above is a proper measure of the mean frequency of the signal in the narrow frequency band.

After the mean frequency of each IMF is obtained, the two norms of each IMF amplitude values are calculated over the epoch 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 EMD-based estimate of the mean

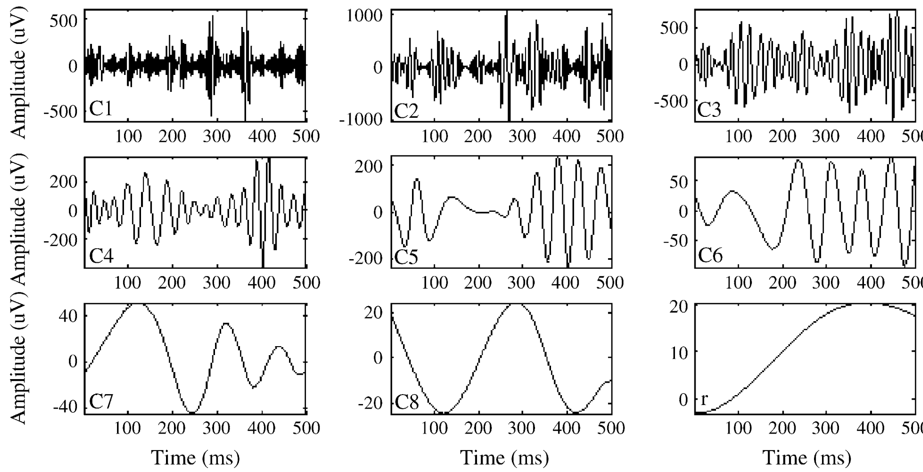

Fig. 1 – The whole set of IMFs of the first segment of EMG with 500 ms analysis window of subject 3. The 9th mode is residue.

frequency. So, the mean frequency of the original signal is defined by:

$$\mathrm{MIF} = \frac{\sum_{j=1}^{n} \left\| a_j \right\| \mathrm{MIF}(j)}{\sum_{j=1}^{n} \left\| a_j \right\|} \tag{11}$$

3. Materials

Twenty-four healthy, right-handed volunteers (12 males: mean age 24.5 ± 3.9 [S.D.] years, 12 females: mean age 23.4 ± 4.2 years), participated in the experiment. All subjects gave their informed consent to participate in the study. No subject had known symptoms of neuromuscular disorders. EMG signals were obtained from the right biceps brachii in an isometric constant force experiment. The subject sat in front of a table. The position of the arm was such that the angle of elbow joint was 90°. In this way, isometric elbow flexion force was measured by a wrist belt attached to a strain gauge sensor. The surface electrodes used for the EMG recording were Ag/AgCl 10 mm diameter on self-adhesive supports. The electrode site was initially cleansed with sterile alcohol pads by exerting a sufficient abrasive action to reduce the resistance of the skin 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 50 s. Surface EMG were acquired at a rate of 1000 Hz by ME3000P2 (Mega Electronics, Finland) with passband 5–500 Hz.

All software implementations were done in MATLAB 6.5 with the Signal Processing toolbox 6.0, Statistics toolbox 4.0, and Wavelet toolbox 2.2 (The MathWorks Inc., Natick, MA)

4. Results

The EMG manifestations of muscle fatigue in the sustaining contraction signals were analyzed by tracking the MNF variable character over time. In order to monitor the variability of the variable extraction by three different methods in the course of the experiment, each signal was first segmented into consecutive, non-overlapping epochs. Empirical mode decomposition was applied to each epoch to obtain the IMFs using the shifting method described in the previous section. Fig. 1 shows the results of IMFs for a segment EMG signal with 500 ms length from subject 3. MNF was then calculated by applying Hilbert transform to each IMF and weighted sum. The PSD of the same epoch data was subsequently estimated through the AR model method, and MNF was also estimated from the PSD [24] and the wavelet transform method described in [12]. In this fashion EMD-derived and the other two methods derived MNF variable could be compared. A least-square error linear regression of the MNF values provided the slope and point of intercept with the frequency axis for each method. Fig. 2 shows the time courses of the MNF of three methods of one subject when the epoch length was fixed to 500 ms. The linear regressions of these data are also superimposed on the graphs. The analysis was repeated for eight different epoch lengths ranging equidistantly from 250 to 2000 ms. Fig. 3 compares the values of the slope and intercept obtained by the three different methods for different epoch lengths, for the same subject. This figure is indicative of the stability of the estimates of the slope and intercept over different epoch lengths when using the HHT method. Indeed, similar results were obtained for all subjects.

Similar to the statistical analysis in [14], the coefficient of variation (CoV: standard deviation over absolute mean) of the estimates of the slope and intercept obtained by the three variables for different epoch lengths was used to quantify these results. For the case shown in Fig. 2 the CoVs of the slope for the HHT, AR model and WT method was 0.0061, 0.0407, and 0.1190, respectively. For the intercepts the corresponding CoVs were 0.0031, 0.0089, and 0.0305. The results of average CoVs

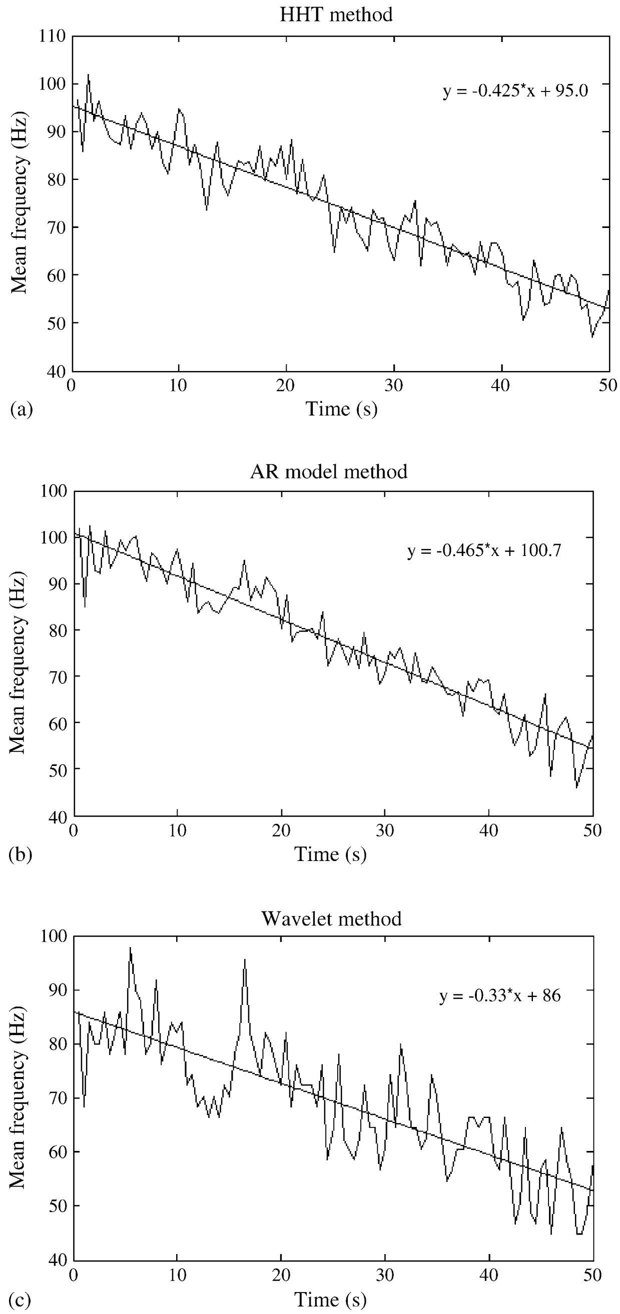

Fig. 2 – Time courses of the mean frequency derived from Hilbert-Huang transform (a), AR model (b), and wavelet transform (c) method of one subject. The analysis window was 500 ms.

show that the time course of the HHT method exhibits the lowest dependence on the size of the analysis window. Then, the means and their confidence intervals (at 5% significance level) for the slope and intercept, as derived from individual t-estimates for all subjects, are given in Fig. 4. The results suggest that any biases in the slope and intercept of the linear regression of the HHT method are not only close to zero but also almost constant with the epoch length. The significantly low values of CoV suggest further that the standard deviation (from the true value) of slope and intercept for the HHT

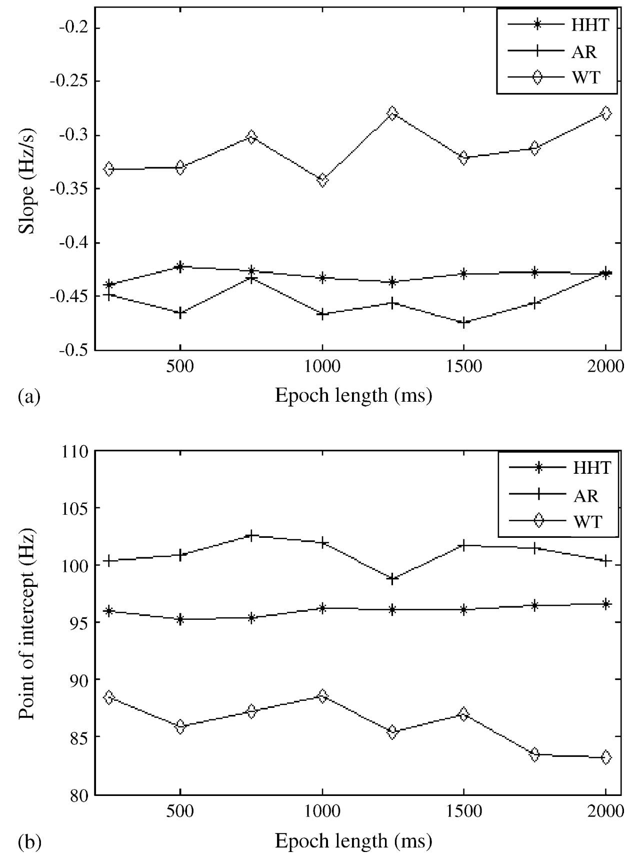

Fig. 3 – Slope (a) and point of intercept (b) parameters of the linear regression of the MNF calculated by Hilbert-Huang transform (diamond), AR model (asterisk), and wavelet transform (pentagram) method for different epoch lengths of subject 3.

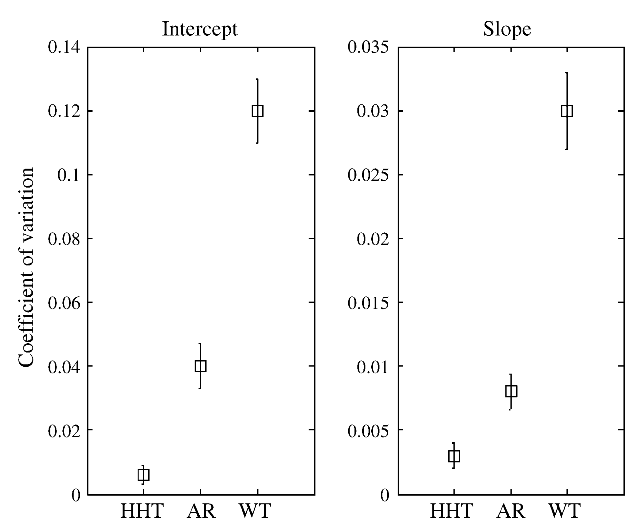

Fig. 4 – Mean values and confidence intervals (at 5% significance level) of the CoV of slope and intercept over the different epoch lengths of all subjects for three methods.

method is very small and nearly constant against the epoch length.

5. Discussion and conclusions

In this paper, we propose the use of the Hilbert-Huang transform as an alternative method for the analysis of the surface electromyography signal for studying local muscle fatigue during sustained isometric constant force muscle contractions. To avoid the directly using the Hilbert transform and differentiating its phase function to obtain the frequency variable, which often ranges beyond the spectral support of many signals, the empirical mode decomposition is first utilized and the time-dependent surface EMG is decomposed into several well-behaved functions that have meaningful instantaneous frequencies. These disintegrated IMFs correspond to physiological process in the signal, which relate to the motor unit firing, recruitment, muscle fiber conduction and other neuromuscular physiological factors. The frequency variable derived from the proposed method is a proper measure of mean frequency of a complicated data set. Contrary to almost all other earlier methods, this new method is intuitive and direct, its basis is a posteriori and also adaptive, which means it is based on and derived from, the data. It elaborately circumvents the deficiency of the conventional mean frequency derived from the Fourier method. The time-varying characteristic of the method enables us to accommodate non-stationary EMG data in higher-level contraction.

The reliability and accuracy of the HHT method is compared with the commonly used AR model and wavelet transform method, in terms of their robustness against the size of the analysis window. The results suggest that the HHT method is a better choice for the estimation of the slope and intercept of the regression line, a process commonly used to quantify surface EMG signal manifestations of muscle fatigue. In the three methods, the wavelet transform gives the worst performance. We deduce this may be due to the following two aspects. First, the Fourier transform is used in calculating the mean frequency of each sub-band after wavelet decomposition. It is well known the Fourier transform has problems with its resolution. Then, there is still spectral leakage between subbands of wavelet transform. The spectrum estimation method based on AR model yields better resolution without the problem of spectral leakage. However, it should be careful to choose the order of AR model in this method. There are no these problems in Hilbert-Huang transform based method. The suggested approach also enables us to accommodate other non-stationary biomedical data analysis.

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