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Frequency analysis of eyes open and eyes closed EEG signals using the Hilbert-Huang Transform

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Abstract— **Frequency analysis based on the Hilbert-Huang transform (HHT) is examined as an alternative to Fourier spectral analysis in the study of EEG signals. This method overcomes the need for the EEG signal to be linear and stationary, assumptions necessary for the application of Fourier spectral analysis. The HHT method comprises two components: empirical mode decomposition (EMD) of the signal into intrinsic mode functions (IMF's); and the Hilbert transform of the IMF's. This technique is applied here in the study of consecutive eyes open (EO), eyes closed (EC) EEG signals of able bodied and spinal cord injured participants. The study found that in this EO, EC pair the instantaneous frequencies in the EO state were higher compared to the EC state. The Hilbert weighted frequency, a measure of the mean of the instantaneous frequencies present in an IMF, is used here to detect these changes from EO to the EC state in an EEG signal. Although there was a good detection of this change with information obtained from just one IMF (94% in able-bodied persons and 84% in SCI persons), almost 100% success in detecting between group differences was achieved using all the IMF's. This result has implications for assistive technology that rely on EEG changes in EO and EC states.**

I. Introduction

Experimental data is often non stationary and non-linear, however, many data analyses have been carried out treating the data as if it is linear and stationary, when in reality it may not be. For example, in spite of the many publications on non-linear dynamical measures and dynamical system analysis of electroencephalogram (EEG) time series [1-8]; and the use of long time series that allow for non-stationary behavior, Fourier spectral analysis is still widely used in the frequency analysis of EEG data. Fourier spectral analysis is based on the assumption that the signal is stationary and linear. These assumptions are overcome in a technique based on the Hilbert-Huang Transform (HHT) [9,10,11,12]. In contrast to transforms like the Fourier transform, HHT is more like an algorithm, an empirical approach that can be applied to a data set rather than a theoretical tool.

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The HHT procedure is comprised of two distinct components: Empirical Mode Decomposition (EMD); and the Hilbert Transform of each of the modes obtained from the EMD to produce a Hilbert Spectrum. EMD is an adaptive decomposition of data which results in the extraction of Intrinsic Mode Functions (IMF's). These IMF's have well prescribed instantaneous frequencies, defined as the first derivative of the analytic signal. These instantaneous frequencies and amplitudes of these IMF's are obtained using the Hilbert transform. Using the EMD method, any complicated data set can be decomposed into a finite and often small number of components referred to as IMF's. By definition, an IMF is any function with the same number of extrema and zero crossings, with its envelopes being symmetric with respect to zero. The definition of an IMF guarantees a well-behaved Hilbert transform of the IMF. This decomposition method operating in the time domain is adaptive and highly efficient. Since the decomposition is based on the local characteristic time scale of the data, it can be applied to nonlinear and non-stationary processes.

Recent EEG studies have proposed using empirical mode decomposition (EMD) and the Hilbert transform in seizure classification [13], classification of motor imagery [14] and detection of synchronization [15]. In this paper, frequency analysis procedure based on HHT is applied in the analysis of eyes open (EO) and eyes closed (EC) EEG data of able bodied and spinal cord injured (SCI) persons. The study focuses on distinguishing consecutive EO, EC states in an EEG signal when eye closure occurs. This study on the EO, EC states of able and SCI persons is of interest since the Mind Switch Control System (MSCS), developed to help disabled people control electrical devices, is based upon changes in EEG signals between the two states [16, 17]. Electrical devices such as a television can be switched on and off and volume and channels can be selected using the MSCS signaled by changes in EO and EC states.

II. Methods

A. Empirical Mode Decomposition and the HHT

Central to the HHT is the idea of instantaneous frequency. The instantaneous frequency is simply the frequency of the signal at a single time point. Since this is described using the signal's Hilbert transform, this is described first before introducing the empirical mode decomposition. For an arbitrary time series, $x(t)$, its Hilbert Transform $y(t)$ is defined as [18].

$$y(t) = \frac{1}{\pi} P \int_{-\infty}^{+\infty} \frac{x(t')}{t-t'} dt' \qquad (1)$$

where P indicates the Cauchy principal value. With this definition, an analytic signal $z(t)$ is defined as:

$$z(t) = x(t) + iy(t) = a(t)\exp(\theta(t)) \qquad (2)$$

Where $a(t) = [x^2(t) + y^2(t)]^{(1/2)}$,

$$\theta(t) = \arctan(\frac{y(t)}{x(t)}) \qquad (3)$$

The instantaneous frequency is then defined as

$$\omega = \frac{d(\theta(t))}{dt} \qquad (4)$$

However it is necessary for the data for the instantaneous frequency defined by equation (4) to be a single valued function of time, that is, at any given time, there is only one frequency value. Based on the discussion in [11], Huang et al., proposed a class of functions referred to as IMF's derived from the original time series that will provide an instantaneous frequency as defined by equation (4).

An IMF satisfies two conditions. The first condition is that the number of extrema and the number of zero crossings must either equal or differ by one in the whole data set. The other is that the local average defined by the average of the maximum and minimum envelopes is zero. These properties of IMF's allow for defining the instantaneous frequency and amplitude in an unambiguous way. Based on the defining requirements of an IMF, the process of extracting the IMF's from a given signal $x(t)$, t=1,..T is as follows:

1. Identify the extrema of the data set $x(t)$, and form the envelopes defined by the local maxima and minima respectively by the cubic spline interpolation method.
2. Form the mean values $m_1(t)$ by averaging the upper envelope and lower envelope, and subtract the mean values from the data to get the first component:

$$h_1(t) = x(t) - m_1(t)$$

3. Check whether the conditions for an IMF are satisfied. If the first component is not an IMF, let $h_1(t)$ be the new data set. Continue with steps 1 and 2 until the first component is an IMF.
4. Let the first IMF component be $c_1(t)$. Let $r_1(t) = x(t) - c_1(t)$. Continue with steps 1-3 until $r_1(t)$ is smaller than a predetermined value or becomes a monotonic function where no more IMF's can be extracted.

The first component $c_1(t)$ contains the finest scale or the shortest period component of the signal. The higher components $c_2(t),...c_N(t)$ contain progressively the longer period components. Even for data with zero mean, the final residue $r_N(t)$ can be different from zero. For data with a trend, $r_N(t)$ is a trend. At the end of this process, the signal $x(t)$ can be expressed as follows:

$$x(t) = \sum_{i=1}^{N} c_i(t) + r_N(t) \qquad (5)$$

where N is the number of intrinsic mode functions. By virtue of the decomposition, completeness is given by equation (5). Orthogonality of the IMF's is satisfied for all practical purposes although it is not guaranteed theoretically [19].

The IMF's are physical, since the characteristic scales are physical. However in cases where a certain scale of a phenomenon is intermittent, then the component contains two scales in one component [10]. On the other hand, for other decompositions such as the Fourier expansion, even with the entire set of decomposed components, sound physical interpretation is not guaranteed.

B. Hilbert Spectrum

After obtaining the intrinsic mode function components the Hilbert transform is then applied to each IMF. In some cases the residue is not included, not because of the inability of the Hilbert transform to treat a trend but due to the high energy involved in this residue that can be overpowering. However in this paper the residue is included and is treated as the last IMF. The original data $x(t)$ can then be expressed as:

$$x(t) = R(\sum_{j=1}^{N+1} A_j(t)\exp(i\int \omega_j(t)dt)) \qquad (6)$$

where $(N+1)$ corresponds to the inclusion of the residue $r_N(t)$ to the N IMF's. R corresponds to the real part of the expression in the parenthesis. Equation (6) gives the amplitude and frequency of each component as a function of time. The set $\{|A_j(t)|, j = 1,...(N+1); t = 1,...T\}$, $\{f_j(t) = (\frac{\omega_j}{2\pi}), j = 1,...(N+1); t = 1,..T\}$ constitute the amplitude Hilbert spectrum in EMD. Here T is the number time samples in the data set $x(t)$.

C. Hilbert weighted frequency (hwf)

For each IMF we evaluate the Hilbert weighted frequency (*hwf*). The Hilbert weighted frequency is defined as [14,21]:

$$\overline{f_j}(hwf) = \frac{\sum_{t=1}^{T} A_j(t) f_j^2(t)}{\sum_{t=1}^{T} A_j(t) f_j(t)} \qquad j=1,..(N+1) \qquad (7)$$

This Hilbert weighted frequency provides an idea of the mean frequency using instantaneous information.

D. Participants

EEG data used for this study were taken from thirty able-bodied participants (17males and 16 females) with mean age of 38.4 years (SD=10.3) and 17 SCI participants (16 males and one female) with mean age of 33.7 years (SD= 10.1). The SCI group was a composed of tetraplegic (n=7) and paraplegic (n=10) participants mostly with complete breaks (n=2 incomplete). All participants consisted of volunteers living in the community. All participated in a structured interview immediately prior to the study in order to determine their health status. Participants were included only if they were overtly free of viral or bacterial disease, and reported no prior psychopathology. Participants were also included if they were not taking any medication that could potentially affect the recording of the EEG (eg. anti-depressants). The study was approved by the institutional research ethics committee and participants were only entered into the study after informed consent.

E. EEG Procedure

Able-bodied EEG data was collected using the Neurosearch-24 data acquisition system (Lexicor Medical Technologies, Boulder, CO, USA). All silver/silver chloride electrodes were referenced to linked earlobes and impedances were kept below 8kΩ. EEG data signals were acquired at a sampling rate of 128 Hz and the gain set at 16K to ensure waveform resolution was not lost. Low-pass filter was set at 50Hz to reduce any electrical noise. The SCI EEG data was collected using the Biosemi^{TM} Active-OneSystem. EEG signals were recorded following the International 10-20 Montage system sampled to 256 Hz covering the major areas of the brain [20]. This was down sampled to 128 Hz for this study, so that the number of IMF's will be comparable to the able-bodied sample and thus facilitating interpretation. In both the able-bodied and SCI group only EEG activity from the cortical site O2 was used. All participants were assessed for their EEG activity in sessions of two minutes, which included three consecutive measures of EC and EO. For the able bodied sample, the participant closed his/her eyes at t=22, 62 and 102 s. In the case of SCI participants, eye closure occurs at t=8, 48 and 88 s. In the case of able bodied participants there were 99 consecutive pairs of EO and EC periods, while there were 51 in the case of the SCI sample. In our analysis 10s samples of EEG in each of EC and EO periods were used.

III. RESULTS

Figure 1 shows the time series of a 10s eyes open EEG record of a representative able bodied participants sampled at 128Hz after detrending and removal of mean.

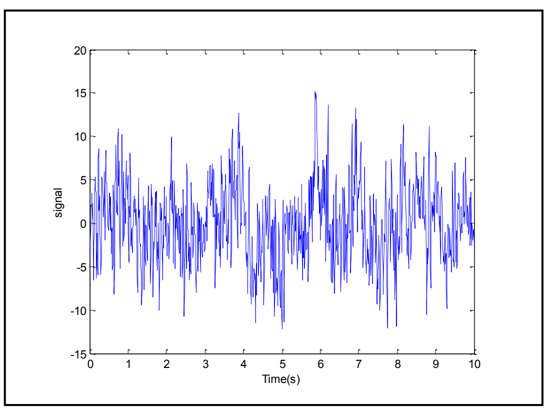

Figure 1. The time series of the 10s eyes open EEG signal collected from the occipital site.

To determine whether the above EEG signal is stationary a weak definition of stationarity is employed. The method used determines whether the mean, and variance changes with time. The presence of such changes is indicative of non-stationary behavior. The mean and variance of overlapping 2s segments separated by 0.0781s (10 samples) was -0.14 ± 0.60 and 20.17 ± 3.88 (± refers to the SD). On the other hand the mean and the variance of the full record was 0 and 19.33. The results thus indicate that the above time series exhibits non-stationary behavior.

Fig 2 shows the intrinsic mode functions and the residue from EMD for the EEG data shown in Fig1. There were 7 IMF's and 1 residue.

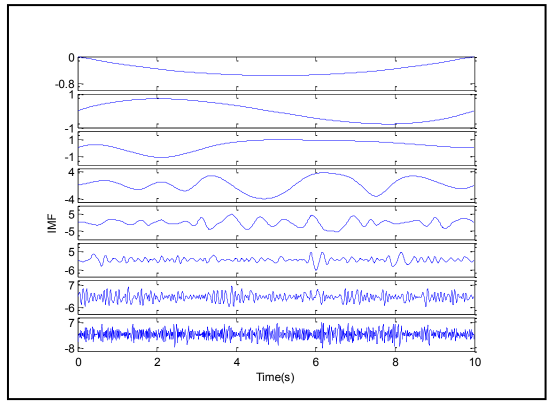

Figure 2. The IMF's and residue of EO. The bottom plot corresponds to IMF (1) with plots arranged from bottom to top in ascending order of mode functions. The top plot corresponds to the residue IMF(8).

This section reports the results of the study on the consecutive EO and EC states of an EEG signal using the HHT method. As previously seen an EEG signal can be written as a sum of IMF's. Each of these IMF's represents an oscillatory mode, but instead of a constant amplitude and frequency, it has variable amplitude and frequency. It is the frequency content of the IMF's that is being utilized in this study. This was performed using the Hilbert weighted frequency (*hwf*)(eqn.7) which gives the mean frequency of an IMF. The analysis is carried for the 99 EO, EC pairs of EEG signals of able bodied participants and the 51 EO, EC pairs of the SCI participants. The Δhwf are given for the 8 IMF's in Table 1 and Table 2 for the able bodied and SCI samples respectively. Dependent t-tests were carried out on the samples of Δhwf . The observed mean was shown to be greater than zero in all the IMF's. The probability values (p-value) in the t-test obtained for the different IMF's are included in each Table.

TABLE I. MEAN OF (Δhwf) FOR THE 99 EO, EC PAIRS OF ABLE-BODIED PARTICIPANTS

IMF	1	2	3	4	5	6	7	8
Δhwf	2.46	1.15	0.27	0.21	0.20	0.10	0.04	0.02
p-value	1.2(-8)	2.5(-7)	0.02	0.0045	7.6(-6)	4.7(-5)	3.4(-4)	0.0075

TABLE II. MEAN OF (Δhwf) FOR THE 51 EO, EC PAIRS OF SCI PARTICIPANTS

IMF	1	2	3	4	5	6	7	8
Δhwf	4.40	1.24	0.48	0.25	0.07	0.03	0.02	0.01
p-value	8(-21)	3(-13)	7(-7)	6(-7)	0.002	0.006	0.006	0.023

IV. DISCUSSION

The results of both Table 1 and Table 2 shows that the frequency content in each IMF is higher in EO when compared with the corresponding IMF in the EC state. This result can be utilized to distinguish consecutive EO, EC states. For example the frequency distribution of an EO signal which contains 8 IMF's (including the residue) can be represented as an 8 component row matrix $[f_1^o, f_2^o, f_3^o, f_4^o, f_5^o, f_6^o, f_7^o, f_8^o]$ where f_i^o, *i=1,..8* are the *hwf* frequencies of the EO state. A similar row matrix can be written for the consecutive EC state as $[f_1^c, f_2^c, f_3^c, f_4^c, f_5^c, f_6^c, f_7^c, f_8^c]$ where f_i^c, *i=1,..8* are the *hwf* frequencies of the EC state. Although the differences in the frequencies $\Delta f_i = (f_i^o - f_i^c)$ are statistically significant for all *i,* the differences decrease with an increase in *i.* For the able bodied data, the percentage of EO-EC pairs where $\Delta f_i > 0$ is found to be 93.9, 81.8, 74.8, 70.7, 59.6, 56.6, 57.6 and 62.6 for i=1, 2, 3, 4, 5, 6, 7 and 8 respectively. For the SCI data this result is 84.3, 76.5, 64.7, 62.8, 76.5, 70.6, 68.6 and 62.8 for i=1, 2, 3, 4, 5, 6, 7 and 8 respectively. Thus using only the first IMF, the percentage of pairs where $\Delta f_1 > 0$ was nearly 94% satisfied for able bodied participants and 84 % for SCI participants. However if all IMF's are used along with the condition that any $\Delta f_i > 0$, *i*=1, 2, 3, 4, 5, 6, 7,8 is sufficient to detect EO-EC changes, then the success rate of meeting the required condition increases to 99% for able bodied participants and 100 % for SCI participants.

The key value of using the HHT technique to study the changes in the consecutive EO, EC states in an EEG signal is that there is no assumption made about the data being linear and stationary. In contrast, this assumption is made in all Fourier spectral analysis. In the study of EO, EC states using Fourier spectral analysis, it is assumed that all frequencies are present in both states. This distinction is made using the amplitudes of certain frequency components such as changes in alpha wave activity at 8-13Hz [17]. The method used here differs from the above in that it does not assume all frequencies are present in both states. In fact, discrimination is achieved here using the different frequencies present in the two states. Therefore, the application of the HHT method to analyzing EO and EC EEG data for driving hands-free control for severely disabled people should potentially improve the reliability of their control of selected devices.

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