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A time-frequency approach for EEG signal segmentation

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Abstract
The record of human brain neural activities, namely electroencephalogram (EEG), is known to be non-stationary in general. In addition, the human head is a non-linear medium for such signals. In many applications, it is useful to divide the EEGs into segments in which the signals can be considered stationary. Here, Hilbert-Huang Transform (HHT), as an effective tool in signal processing is applied since unlike the traditional time-frequency approaches, it exploits the non-linearity of the medium and nonstationarity of the EEG signals. In addition, we use Singular Spectrum Analysis (SSA) in the pre-processing step as an effective noise removal approach. By using synthetic and real EEG signals, the proposed method is compared with Wavelet Generalized Likelihood Ratio (WGLR) algorithm as a well-known signal segmentation method. The simulation results indicate the performance superiority of the proposed method.

Keywords: *EEG Signal Segmentation, Time-Frequency Approach, Empirical Mode Decomposition (EMD), Singular Spectrum Analysis (SSA), and Hilbert-Huang Transform (HHT).*

1. Introduction

Nonstationarity of the signals can be quantified by measuring some statistics of the signals, such as mean and variance, at different time lags. The signals can be deemed stationary if there is no considerable variation in such statistics. In general, the signals are stationary if their distributions do not vary with time. Often it is necessary to label the electroencephalogram (EEG) signals by segments of similar characteristics that are particularly meaningful to clinicians and for evaluation by neurophysiologists. Within each segment, the signals are considered statistically stationary, usually with similar time or frequency distributions. For example, an EEG recorded from an epileptic patient may be divided into three segments of preictal, ictal, and postictal with variable durations [1].

The segmentation may be fixed or adaptive. Dividing the signals into fixed (rather small) size segments is easy and fast. However, it cannot precisely follow the epoch boundaries [2,3]. On the other hand, in adaptive segmentation the boundaries are accurately and automatically followed [2]. Many adaptive segmentation methods have been suggested by researchers in the field such as those in [4-10].

In order to increase the accuracy of the classification in EEG signals, Kosar et al. [6] have proposed to use the segmentation method as a pre-processing step. It was done by a dividing signal to segments of different lengths that are stationary. In this method two characteristics were used that are based on estimation of average frequency in the segment and the value of mean amplitude in the window.

Azami et al. have proposed a method to segment a signal in general and real EEG signal in particular using the standard deviation, integral operation, Discrete Wavelet Transform (DWT), and variable threshold [2]. In this paper we have illustrated that the standard deviation can indicate the changes in amplitude and/or frequency [2]. To remove the effect of shifting and smooth the signal, the integral operation has been used as a pre-processing step.

However, the performance of the method is entirely dependent on the level of noise components.

In Generalized Likelihood Ratio (GLR) method to obtain the boundaries of signal segments, it has been suggested to use two windows that slide along the signal. The signal within each window of this method is modelled by an autoregressive (AR) process. For the signals within such windows the statistical properties don't change; in other words AR coefficients remain approximately constant and equal. However, when the sliding windows fall in the different segments, the AR coefficients change and the boundaries are detected [11]. In [12] Lv et al. have suggested using wavelet transform for decreasing the number of false segments and reducing the computation load. This method has been named Wavelet GLR (WGLR) [12].

Azami et al. for the first time have proposed an adaptive signal segmentation approach using DWT and Higuchi's Fractal Dimension (FD) [5]. In order to obtain a better multi-resolution representation of a signal which is very valuable in detection of abrupt changes within that signal, the DWT has been used. The changes in the Higuchi's FD refer to the underlying statistical variations of the signals and time series including the transients and sharp changes in both amplitude and frequency. The performance of the method is still dependent on the noise components.

Since Time-Frequency Signal Analysis and Processing (TFSAP) exploits variations in both time and frequency, most of the brain signals are decomposed in the time-frequency domain. Because the instantaneous energy depends on the frequency of the signal, in this article, using Time-Frequency Distribution (TFD) for signal segmentation has been proposed [13].

A recent contribution to signal processing is named Hilbert-Huang Transform (HHT) that is combination of the Empirical Mode Decomposition (EMD) and the Hilbert Transform (HT) [14,15]. Fourier transform, wavelet transform, and HHT can be used to discuss the frequency characteristics of stationary signals and system linearity, the time-frequency features of non-stationary signals and outputs of non-linear systems, respectively. Since EEG signals are non-stationary, HHT is most suitable process for analyzing them [14].

Moreover, since noise can significantly decrease the performance of the segmentation methods, first we use Singular Spectrum Analysis (SSA) as a filter. SSA is becoming an effective and powerful tool for time series analysis in meteorology, hydrology, geophysics, climatology, economics, biology, physics, medicine, and other sciences where short and long, one-dimensional and multi-dimensional, stationary and non-stationary, almost deterministic and noisy time series are to be analyzed [16].

The rest of the paper is organized as follows: The proposed adaptive method as well as brief explanations of SSA and HHT is explained in Section 2. The performance of the proposed method is evaluated in Section 3. The last section concludes the paper.

2. Proposed Adaptive Segmentation

First, we use a powerful tool, SSA, to reduce the noise sources. The SSA is much faster than previous widely used filters or smoothers like the DWT. A brief description of the two SSA stages together with the corresponding mathematics is given. At the first stage, the series is decomposed and at the second stage we reconstruct the original series and use the reconstructed series (which is without noise) to predict new data points [17,18].

1) Decomposition: This stage is composed of two sequential steps including embedding and SVD. In the embedding step, the time series **s** is mapped to k multidimensional lagged vectors of length l as follows:

$$\mathrm{x_i} = [s_{i-1}, s_i, ..., s_{i+l-2}]^T, \quad 1 \le i \le k \tag{1}$$

where $k = r - l + 1$, l is the window length ($1 \le l \le r$), and $[]^T$ denotes the transpose of a matrix. An appropriate window length totally depends on the application and the prior information about the signals of interest. The trajectory matrix of the series **s** is constructed by inserting each $\mathbf{x}_i$ as the ith column of an $l \times k$ matrix, i.e.

$$\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_k] = \begin{bmatrix} s_0 & s_1 & s_2 & \cdots & s_{k-1} \\ s_1 & s_2 & s_3 & \cdots & s_k \\ s_2 & s_3 & s_4 & \cdots & s_{k+1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ s_{l-1} & s_l & s_{l+1} & \cdots & s_{r-1} \end{bmatrix} \tag{2}$$

Note that the trajectory matrix **X** is a Hankel matrix, i.e. for all the elements along its diagonals $i+j$=constant.

In the SVD sub-stage, the SVD of the trajectory matrix is computed and represented as the sum of rank-one biorthogonal elementary matrices. Consider the eigenvalues and corresponding eigenvectors of $\mathbf{S}=\mathbf{XX}^{\mathrm{T}}$ are $\lambda_1, \lambda_2, ..., \lambda_l$ and

$\mathbf{e}_1, \mathbf{e}_2, ..., \mathbf{e}_l$, respectively. If $\mathbf{v}_i = \mathbf{X}^T \mathbf{e}_i / \sqrt{\lambda_i}$, then the SVD of the trajectory matrix can be written as

$$\mathbf{X} = \mathbf{X}_1 + \mathbf{X}_2 + ... + \mathbf{X}_d \qquad (3)$$

where $d = \arg\max_i \{\lambda_i > 0\}$ and $\mathbf{X}_i = \sqrt{\lambda_i}\, \mathbf{e}_i \mathbf{v}_i^T$. The *i*th eigentriple of the SVD decomposition comprises of $\mathbf{v}_i$, $\mathbf{e}_i$, and λ_i. Projecting the time series onto the direction of each eigenvector yields the corresponding temporal principal component [17,18].

2) Reconstruction: This stage has two steps: grouping and diagonal averaging. The grouping step divides the set of indices {1, 2, ..., *d*} to *m* disjoint subsets I_1, I_2, ..., I_m. For every group $I_j = \{i_{j1}, i_{j2}, ..., i_{jp}\}$, we have $\mathbf{X}_{I_j} = \{X_{i_{j1}}, X_{i_{j2}}, ..., X_{i_{jp}}\}$. Grouping the eigentriples and expanding all matrices $\mathbf{X}_{I_j}$, (3) can be written as

$$\mathbf{X} = \{\mathbf{X}_{I_1}, \mathbf{X}_{I_2}, ..., \mathbf{X}_{I_m}\} \qquad (4)$$

There is no general rule for grouping. For each application, the grouping rule depends on the special requirements of the problem and the type of the contributing signals and noise.

b) Diagonal averaging: In the final stage of analysis, each group is transformed into a series of length r. For a typical $l \times k$ matrix **Y**, the *q*th element of the resulted time series, g_q is calculated by averaging the matrix elements over the diagonal $i + j = q + 2$, where *i* and *j* are the row and column indices of **Y**, respectively [17,18].

The concept of separability is an important part of the SSA methodology. Assume that **s** is the sum of two series $\mathbf{s}_1$ and $\mathbf{s}_2$, i.e., $\mathbf{s} = \mathbf{s}_1 + \mathbf{s}_2$. Separability means that the matrix terms of the SVD of the trajectory matrix of X can be divided into two disjoint groups, such that the sums of the termswithin the groups result in the trajectory matrices $\mathbf{X}_1$ and $\mathbf{X}_2$ of the time series $\mathbf{s}_1$ and $\mathbf{s}_2$, respectively [17,18]. A necessary condition for separability of the sources is disjointedness of their frequency spectrum. It is also worth mentioning that exact separability cannot be achieved for real-world signals; hence, only approximate separability can be considered.

The eigentriples resulting from the SSA also contain information about the frequency content of the data. If there is a periodic component in the data, it will be reflected in the output of the SSA as a pair of (almost) equal eigenvalues [17,18]. Moreover, the highest peaks in the Fourier transform of the corresponding eigenvectors are related to the frequency of the periodic component. These features of the SSA are used to construct data-driven filters.

After employing the SSA, we use the combination of EMD and Hilbert transform, namely HHT. EMD is a powerful and new method applied to decompose the Intrinsic Mode Functions (IMFs) from a complex time series. This decomposition, sifting process, uses the mean of the upper and lower envelopes [19-22]. The sifting process must be repeated until every component satisfies two conditions:

1. The number of extrema and the number of zero-crossings must either be equal or differ at most by one.
2. At any point, the mean value of the two envelopes defined respectively by local maxima and local minima must be zero.

For an arbitrary time series *x*(*t*), the sifting process can be summarized as follows:

1) Identify all the local extrema (maxima or minima) of signal *x*(*t*), and then connect all the local maxima by a cubic spline line (upper envelope)
2) Repeat similarly all the local minima (lower envelope).
3) The mean of the upper and lower envelopes is designated as *m*(*t*). The difference between the data and *m*(*t*) is the first component as follows:
$$h_1(t) = x(t) - m(t) \qquad (5)$$
4) Suppose $h_1(t)$ as the new original signal and repeat above steps.

Generally, this process must be repeated until the last $h_1(t)$ has at most one extrema or becomes constant. However in many cases, it is not a suitable criterion. In this paper we use the criterion applied in [19].

The second step of HHT, definition of instantaneous frequency, is to compute the instantaneous frequency by using the Hilbert transform [20-22]. Hilbert transform of a given time series *x*(*t*) can be computed as:

$$y(t) = HT[x(t)] = \frac{1}{\pi} PV \int_{-\infty}^{+\infty} \frac{x(\tau)}{t - \tau} d\tau \qquad (6)$$

which PV illustrates the principal value of the singular integral [20-22]. *x*(*t*) and *y*(*t*) can be represented as a complex number *z*(*t*) as follows:

$$z(t) = x(t) + iy(t) = a(t)e^{i\theta(t)} \qquad (7)$$

where i is the imaginary unit, $a(t)=[x(t)^2+y(t)^2]^{0.5}$ and $\theta(t)=arctg\left\{\frac{y(t)}{x(t)}\right\}$.

In other words, $a(t)$ and $\theta(t)$ are the instantaneous amplitude and phase, respectively [20-22]. Moreover, instantaneous frequency can be defined as follows:

$$f(t)=\frac{1}{2\pi}\frac{d\theta}{dt} \qquad (8)$$

3. Simulation Results

In order to assess the performance of the suggested method, two kind signals including the synthetic data and a real EEG signal are utilized. The synthetic signal includes the following seven epochs:

Epoch 1: 3.5cos(2πt) + 4.5cos(6πt),
Epoch 2: 3.5cos(3πt) + 5.5cos(10πt),
Epoch 3: 4.5cos(2πt) + 5.5cos(8πt),
Epoch 4: 3cos(2πt) + 7cos(6πt) + 2cos(7πt),
Epoch 5: 4cos(2πt) + 5cos(10πt),
Epoch 6: 4cos(3πt) + 7.5cos(9πt),
Epoch 7: 2cos(4πt) + 7cos(8πt) + 3cos(3πt).

In Figures 1.a and 1.b the synthetic data described above and the filtered signal by SSA with window length 2 are shown, respectively. As can be seen, the filtered signal is smoother than the original signal. After filtering the signal by SSA to decompose the IMFS of the signal EMD is employed. In Figure 2, the result of decomposition performed by EMD of the filtered synthetic signal is depicted. This figure illustrates that the first mode has a higher frequency than the second mode where modes are ordered from the highest frequency to the lowest.

As mentioned previously, the reason for using EMD is that HT can be better computed. HHT of the synthetic signal is shown in Figure 3. As we can see in this figure, all seven segments boundaries are shown accurately.

To demonstrate the emphasis of this algorithm, in Figure 4, the output of the WGLR method is shown. Figure 4.a and Figure 4.b show respectively the original signal the same as Figure1.a and the decomposed signal using wavelet transform. Here, the DWT with Daubechies wavelet of order 8 is used. Note that the WGLR parameters for this paper are attained by considering many trials. In a general manner, the decomposed signal indicates the slowly and rapidly changing features of the signal in the lower frequency and higher frequency bands, respectively. As can be seen in Figure 4.c, there are some false boundaries selected by the WGLR. Comparing the last two figures, it has been shown that the proposed method has a superior performance compared with WGLR for signal segmentation. Although, as mentioned before, there are several advantages in combining HHT and SSA, the computation time for the proposed method is not as intensive as that of the WGLR method.

As described before, signal segmentation is a pre-processing step for EEG signal analysis. In this part one epoch of a real newborn is shown in Figure 5.a. Firstly, for smoothing the EEG signal, we use SSA as a fast and powerful pre-processing step. The result of using SSA is shown in Figure 5.b. The SSA used for this real signal has window length equal to 20 that is selected with trial and error. After using SSA, the combination of EMD and HT named HHT is applied on the filtered signal in Figure 6 and Figure 7, respectively. We can see the influence of this method on the achieved outputs in the both synthetic signals and real EEG signals.

As can be seen in the result of the proposed method all three segments can be accurately segmented. In order to represent efficiency of the proposed method, in Figure 8, WGLR is used for real newborn EEG signal the same as Figure 5.a. Output of WGLR method is shown in Figure 8.b. It should be mentioned that the DWT with Daubechies wavelet of order 8 is used. As can be seen in this figure, there are some false boundaries and one missed boundary. Therefore, for this application, WGLR is not a reliable method for signal segmentation.

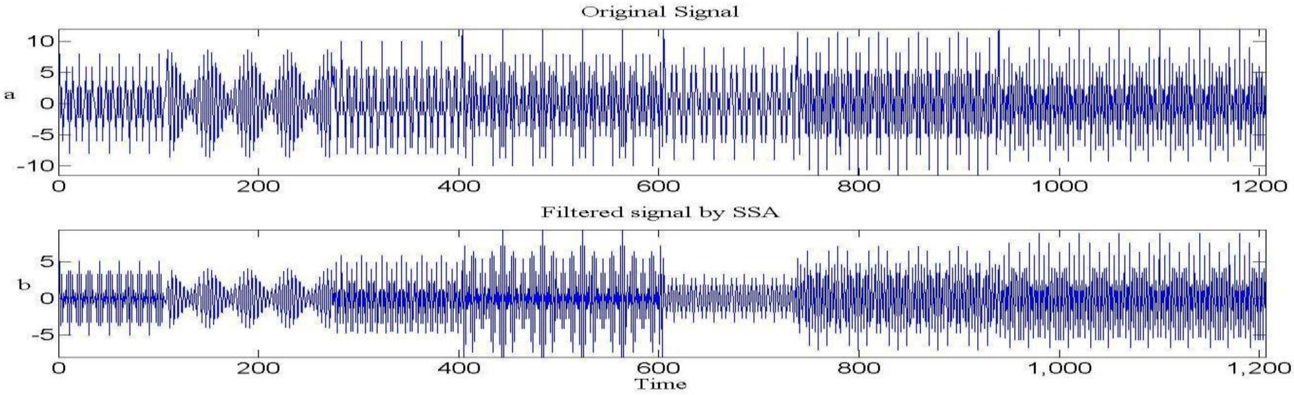

Figure 1. Filtering the synthetic signal; (a) original signal, and (b) filtered signal by SSA.

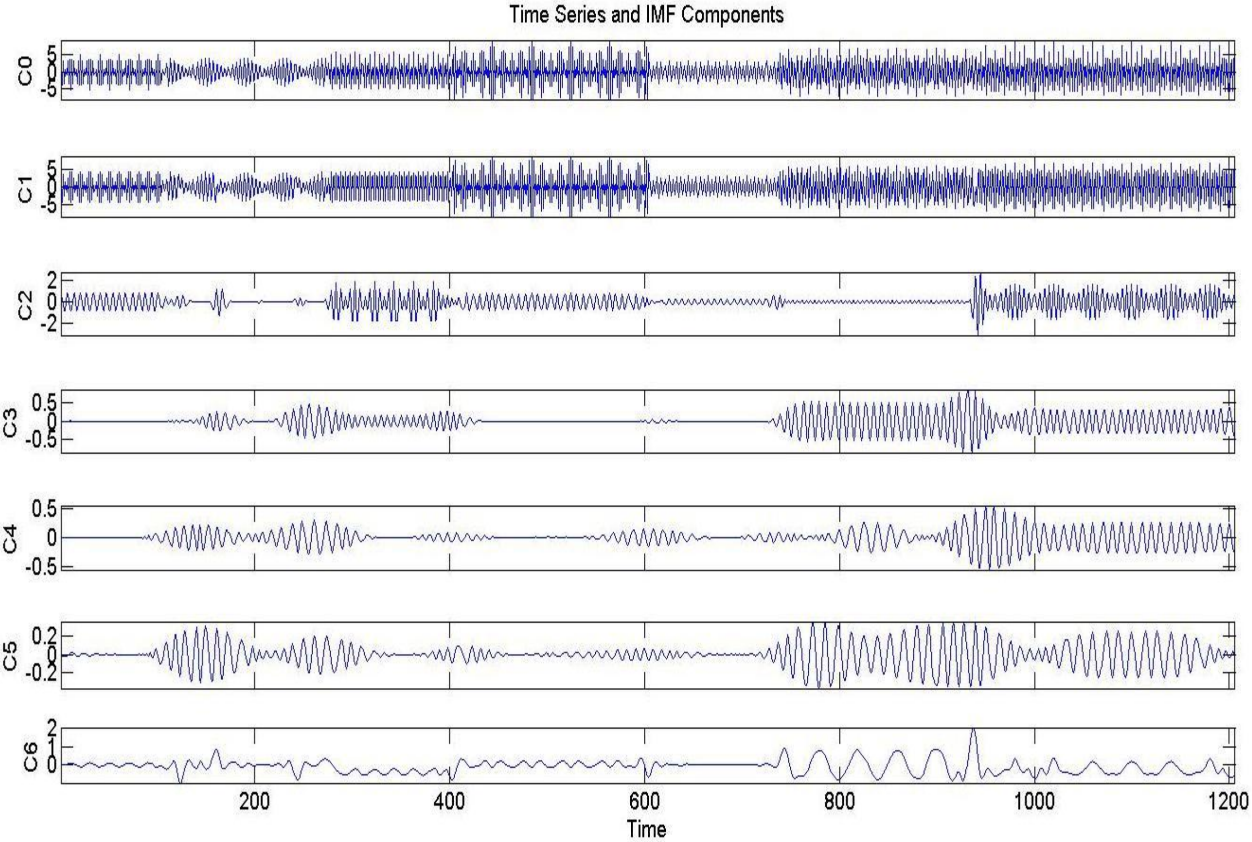

Figure 2. Components of the filtered synthetic signal by EMD. The first time series is the filtered signal by SSA. The decomposition yields 5 IMF and a residual. The IMFs are the time-frequency constituents or components of the synthetic signal.

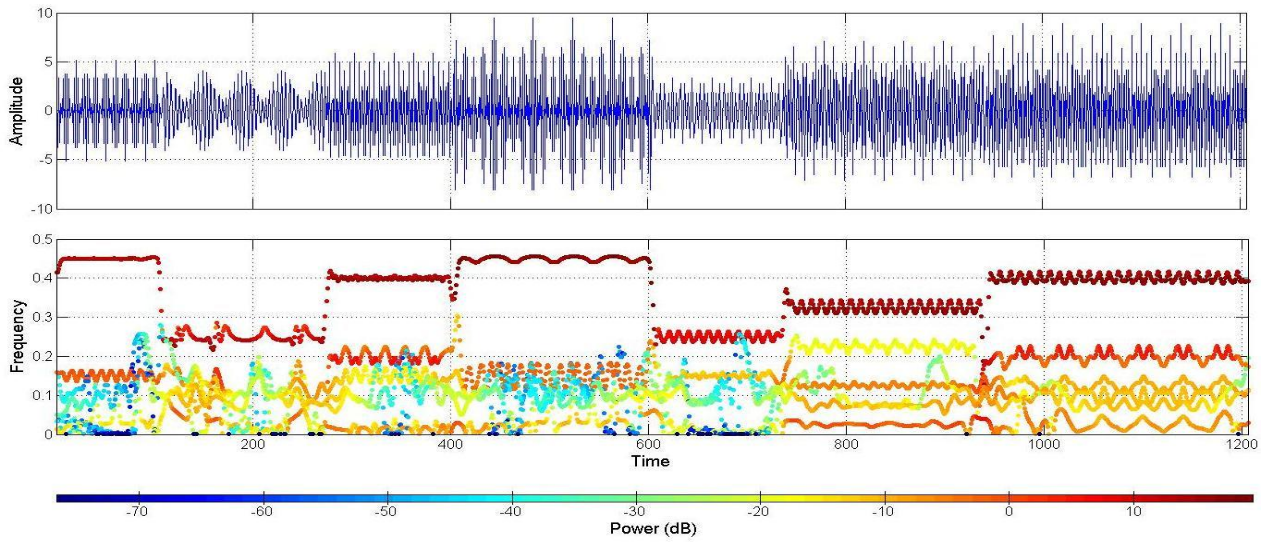

Figure 3. Hilbert transform of the synthetic signal gather prepared using EMD(i.e. HHT of the synthetic signal); (a) the time series analyzed, and b) signal power plotted in time-frequency.

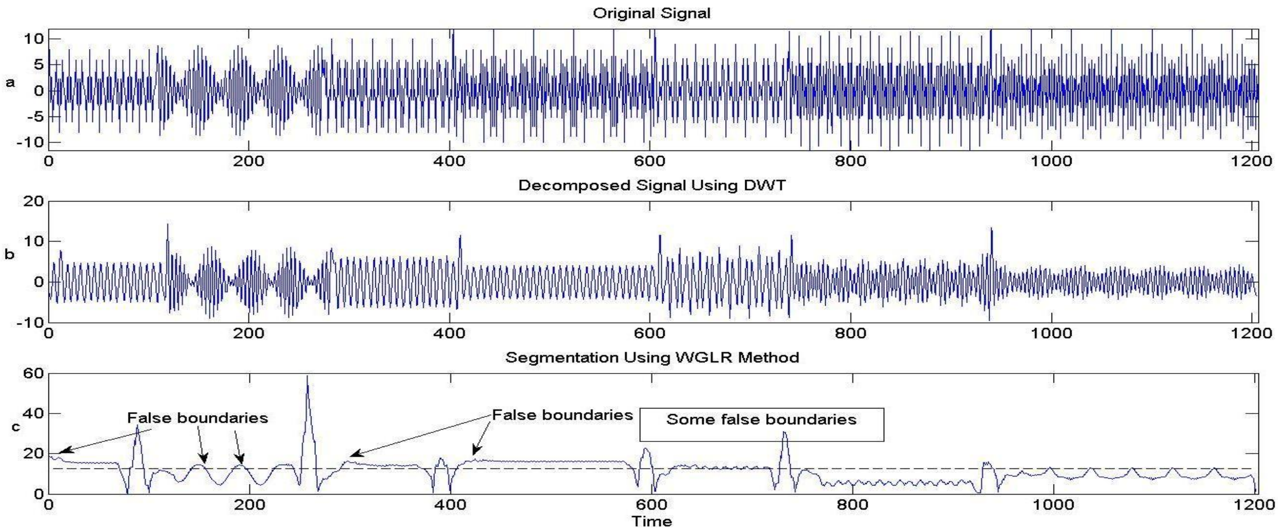

Figure 4. Signal segmentation in synthetic signal, (a) original signal, (b) decomposed signal by DWT, and (c) output of the WGLR method.

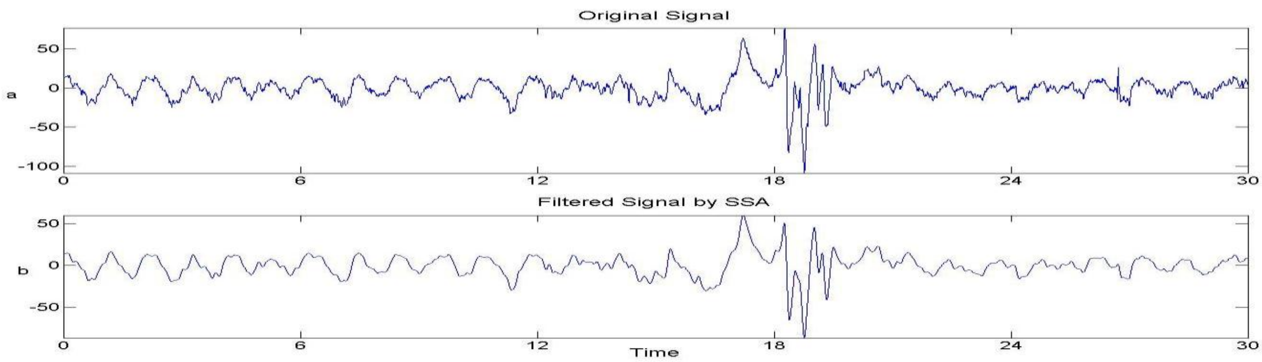

Figure 5. Filtering the real EEG signal; (a) original signal, and (b) filtered signal by SSA.

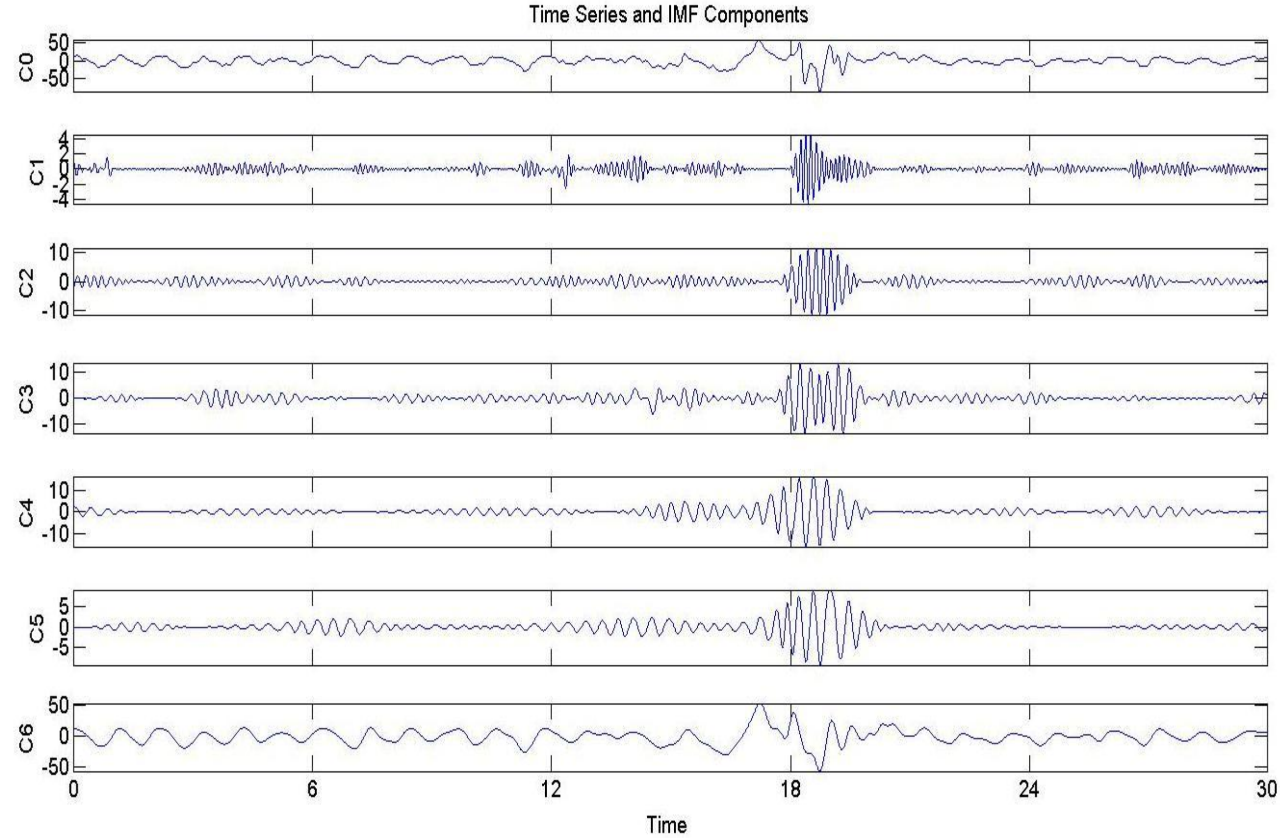

Figure 6. Components of the filtered real EEG signal by EMD. The first time series is the filtered signal. The decomposition yields 5 IMF and a residual. The IMFs are the time-frequency constituents or components of the EEG signal.

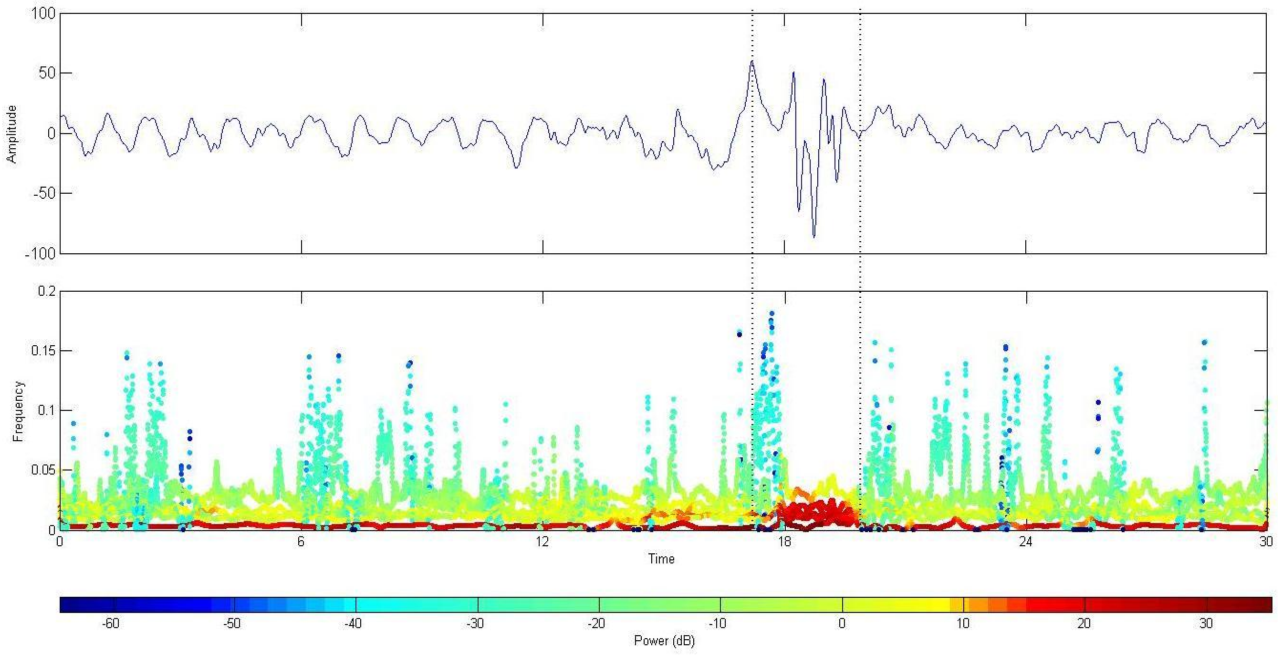

Figure 7. Hilbert transform of the real filtered EEG signal gather prepared using EMD(i.e. HHT of the filtered EEG signal); (a) the time series analyzed, and b) signal power plotted in time-frequency domain.

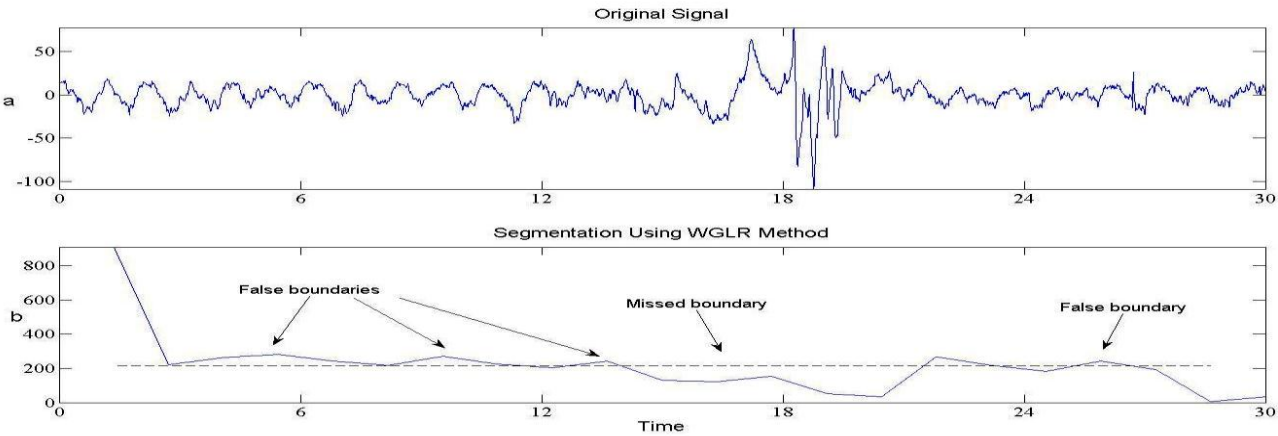

Figure 8. Signal segmentation in real EEG signal, (a) original signal, and (b) output of the WGLR method.

4. Conclusion

The objective of this work has been to investigate and demonstrate the ability of combination of the SSA, EMD and HT in segmenting the non-stationary signals such as EEG. Unlike commonly used segmentation methods, the proposed time-frequency approach has effectively exploited the nonstationarity of the signals and non-linearity of the medium. Since noise can significantly affect the performance of the segmentation methods, the SSA as a fast and powerful tool for mitigation of noise has been employed. After filtering the signal by SSA, HHT has been used for segmenting the signals. The integrity of the EMD is crucial to the ability of the HHT to outperform traditional Fourier-based techniques. The results have indicated superiority of the proposed method comparing with a well-known method, WGLR, for EEG signal segmentation.

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