A WAVELET-BASED APPROACH FOR THE EXTRACTION OF EVENT RELATED POTENTIALS FROM EEG

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ABSTRACT

Event Related Potentials (ERPs) are of interest to many researchers seeking knowledge about the functions of the brain. ERPs are low-frequency events that are usually obscured in single trial analysis. To visualize these signals; most of the reliable solutions at the present time use the ensemble averages of many single trials. In this paper, a wavelet-based method called Statistical Coefficient Selection (SCS) is used for the extraction of ERPs from EEG signals. Unlike other wavelet-based denoising methods, the current method does not focus on the wavelet coefficients of the signal itself. Instead, it selects the coefficients based on the statistical study of trials from training data set. Simulation results show the superiority of the proposed SCS method in extracting ERPs in comparison with other filtering approaches.

1. INTRODUCTION

Event Related Potentials (ERPs) are parts of the EEG signal that are time-locked to a sensory, motor, or cognitive process and therefore provide an electrophysiological window onto brain function during cognition. They have a characteristic pattern that is more or less reproducible under similar experimental conditions [1]. The origin of an ERP might be an external stimulator (for example a flash light) or it can be initiated internally such as a result of making a movement. In the literature, two significant applications make use of ERPs: diagnosing neurological disorders [2] and development of brain-computer-interface (BCI) systems [3]. For both applications, many methods that extract ERPs from the background EEG have been explored. The main problem of ERP extraction is that the amplitude of an ERP is much smaller than that of the background EEG. This makes its detection very hard in single trial analysis. Instead of extraction of ERPs from single trials many methods have focused on the extraction of ERPs from ensemble averages of several single trials (i.e. data segments including the pre- and post-stimulus activity are averaged). Since ERPs are time locked to the stimulus, it is assumed that their contribution during the averaging process will add up while the ongoing EEG and unrelated components are attenuated. This will result in higher Signal to Noise Ratio (SNR).

Since ERPs are non-stationary, time-invariant approaches such as Fourier Transform are not likely to give acceptable results. On the other hand, the joint time–frequency resolution obtained by the wavelet transform makes it a good candidate for the extraction of the *details* as well as the *approximations* of time-varying, non-stationary signals [4]. For the effective extraction of ERPs from the background EEG using wavelet transform, we need a strategy which 1) chooses the coefficients associated with the ERP and, 2) considers the fact that ERPs vary significantly from time to time [5].

Several methods have been proposed for extracting ERPs from the background EEG with various success. Many researchers use level-dependant thresholding schemes by defining a criterion for the selection of the threshold of each level [6-7]. For example, in [6], the authors apply a level dependant threshold based on the median absolute deviation of wavelet coefficients in each level. In [7], the authors report good noise reduction in ERPs simply by discarding three upper level bands.

Many researchers manually select the wavelet coefficients assumed to be associated with an ERP [8-9]. For example in [8], the authors select Visual Evoked Potentials (VEPs) based on a single wavelet coefficient in the delta band of the EEG. Also in some approaches the wavelet coefficients are selected based on a similarity criterion between the coefficients associated with the waveform and the coefficients associated with the grand ensemble average of all the test waveforms [10].

The main problem with the methods that select coefficients manually is their vulnerability to the human error. These methods also do not take the time varying property of ERPs into consideration. On the other hand, methods based on the threshold selection or a measure of similarity with the grand ensemble averages cannot filter the coefficients associated with the background EEG effectively, because many of these coefficients lie in the same frequency spectrum of ERPs. Therefore, the proposed selection method should not only consider the energies of the coefficients which are attributed to ERPs, but it should also consider their variations throughout the time.

This paper proposes a new scheme, which selects the individual coefficients associated with an ERP automatically. The proposed method attempts to overcome the vulnerabilities of the previously mentioned methods. To be more specific, in this method, the wavelet coefficients that are sought have high amplitude values (the ones with high *energy* in the case of orthogonal wavelets) and low amplitude variance over many trials. In other words, the current method does not focus on the wavelet coefficients of the signal themselves. Instead, it selects the coefficients based on the statistical study of training data set.

The organization of the paper is as follows: the focus of Section 2 is on the wavelet analysis. In Section 3, the proposed method based on the statistical analysis of the wavelet coefficients is developed. The results for the extraction of Voluntary Movement Related Potentials (VMRPs) using this method are discussed in Section 4. Finally the discussions and conclusions of the paper are brought in Section 5.

2. WAVELET ANALYSIS

During the past two decades, Discrete Wavelet Transform (DWT) has been applied extensively by using wave-like signals called the "wavelets" to decompose and extract information from the time-varying, non-stationary signals such as neuro-electric waveforms [4]. The joint time–frequency resolution obtained by wavelet transform makes it a good candidate for the extraction of details as well as approximations of the signal which can not be achieved by other signal processing analysis techniques such as Fourier Transform (FT). The breakthrough in wavelets applications in signal analysis happened after Multi Resolution Analysis (MRA) was proposed by Mallat for the calculation of wavelet coefficients [11]. MRA is based on the consecutive application of high-pass and low-pass filters to the original signal *x*. At stage *n*, the detail signal *Dn* (the output of the high-pass filter where *D* stands for Detail and *n* specifies the level of decomposition) is stored and the output of the low-pass filter (*An* where *A* stand for the Approximation*)* is passed to the next level to be further decomposed into detail and approximation functions. The general shape of the high-pass and low-pass filters is determined by the type of wavelet function. After each filtering stage, down sampling is applied in order to keep the overall amount of samples at a specific number. The outputs of these filter banks are the wavelet coefficients.

DWT, however, suffers from a major drawback: it is shift-variant. This limits its application in pattern detection problems. In order to overcome this shortcoming, Stationary Wavelet Transform (SWT) has been developed which is the shift-invariant version of DWT. In SWT, the down sampling stage is eliminated and instead, up-sampling is applied to the wavelet filters [12]. Keeping the sample number the same as that of the original signal and omitting the down sampling stage, makes the method shift invariant. In this paper, SWT is applied for the analysis of ERPs.

3. STATISTICS BASED COEFFICIENT SELECTION METHOD

In this section, a new method is proposed for the effective extraction of ERPs. This method is based on the statistical analysis of wavelet coefficients. First, signals from training data set are decomposed into different frequency bands using the Mallat approach. It is assumed that N EEG segments of the same size containing an ERP are available for the analysis $(y_1, y_2, \cdots, y_N)$ where y denotes the EEG segment containing the ERP. Furthermore, it is assumed that each window contains exactly one ERP and the latencies of all the ERPs are adjusted. Next, each segment is normalized as follows:

$$y_{inorm} = \left(\frac{y_i - \bar{y}_i}{rms(y_i)}\right) \qquad (i = 1, 2, \cdots, N) \tag{1}$$

where in (1), y_i *denotes* the *i*th EEG segment and $\bar{y}_i$, $rms\ (y_i)$ and y_{inorm} are its corresponding average, root mean square and normalized version respectively. Next, SWT is applied and each segment is decomposed into wavelet coefficients $C(S,T)$ where S and T stand for the Scale and Translation respectively. The next step involves calculation of the average (AV), the standard deviation (SD) and the AV / SD for the energy of all the wavelet coefficients over N trials. The criterion for the selection of wavelet coefficients is as follows:

$$C_{den}(S,T) = \begin{cases} C(S,T) & if\ \dfrac{\overline{\|C(S,T)\|}}{\sigma(S,T)} > THR_S \\ 0 & otherwise \end{cases} \tag{2}$$

where C_{den} , $\overline{\|C\|}$ and σ denote the denoised version , the average of the energy and the standard deviation of the energy of wavelet coefficient $C(S,T)$, respectively and THR_S is the threshold at scale S. In this method (which for the rest of the paper will be referred to as Statistical Coefficient Selection or SCS), wavelet coefficients are simply mapped to a space with similar structure of the wavelet space, but it consists of the AV/SD of the energies of coefficients. In this space, the level-based thresholding is applied and the coefficients which have the higher values of energy and lower energy variations are selected according to the set thresholds. Next the original wavelet coefficients, which are associated with the selected coefficients, are chosen as the features associated with ERP.

In the proposed method, the only parameters that have to be set (besides the wavelet type and the levels of decomposition) are the thresholds. This is rather straightforward: the less the ratio of the AV/SD, the less reliable is the data analysis and consequently the extension of the method to other data sets. Also very strict limits cannot be considered, because it will make the number of coefficients insufficient for the representation of a "clean" signal. Hence, a compromise should be made here. In this paper, the thresholds are set manually based on trial and error but for future research, an automated method would be desired.

It should be noted that the current method has some resemblance with another approach in the literature [13]. Since in [13], the details of the method are unclear and the wavelet transform used is not stated, thus a thorough comparison is not possible. Based on the details described in [13], some significant differences are as follows:

1) the method described in [13] does not take the normalization of data into consideration. This is very important because of possible variations in signal acquisition from trial to trial and as it is pointed out in [14], the normalization of data is necessary for valid results.

2) the method in [13] uses a fixed threshold for all levels based on the number of signals participated in the analysis while the current method allows different thresholds for different frequency bands thus allowing more freedom in the selection of wavelet coefficients.

In the next section, the SCS will be applied in the extraction of a special class of ERPs from the background EEG.

4. SIMULATION RESULTS

In this section, the SCS is applied offline to data related to Voluntary Movement Related Potentials (VMRPs)collected for the development of a Brain Computer Interface system. A detailed description about the collection of data is brought in [14]. In the experiments, subjects were asked to trigger a finger switch upon the presentation of a stimulus cue. Between the trials, the subjects were in a passive observation state. Thus, the EEG signal, containing both Control and No Control data, and a control signal revealing the finger switch activation time were obtained. EEG signals contaminated by ocular artifacts were discarded. In this study, pre-recorded data from one right-handed able-bodied male was chosen for analysis. Six bipolar electrodes (which were placed on the scalp of the subject) recorded the EEG signals. The subject's EEG was recorded with a sampling frequency of 128 Hz. For each run, approximately 15 VMRP samples free of ocular artifact were collected. The total of single run sessions was eight. Then the data on each two runs were averaged to give the ensemble averages of about 30 trials. The combination of different runs resulted in a total of 28 data sets; 24 of them were used for finding the coefficients by the SCS and the remaining four were used for testing. In this paper, only one selected channel out of the six channels (Channel FC2-C2) is presented in the analysis.

Daubechies5 (db5) wavelet [4] was chosen for this analysis because of its particular shape, which has similarities to the presumed general shape of ERPs. After normalization, EEG signals were decomposed into five levels via db5. Next the AV/SD of the energies of approximation coefficients at level 5 (*A5*) and detail levels *D1* to *D5* were calculated. In order to single out these coefficients for the current approach, all the thresholding levels were chosen to have a value=2 by trial and error and visual inspection.

By applying the proposed method, about 200 wavelet coefficients were selected as the desired features of each channel. The results of the extraction of ERPs from channel FC2-C2 are shown in Fig.1.a and Fig.2.a In Fig.1.a the results are shown for one of the test datasets (dataset#1) . In order to show the effectiveness and the generalization of the current method, the method was applied to a dataset from the same subject but from another session (dataset#2 in Fig.2.a).

In order to compare the results obtained by the SCS and other denoising methods, several wavelet-based and non-wavelet-based methods were also explored. These methods are :

1) FIR filter (a non-wavelet-based FIR filter used in [3]): this is a low-pass FIR filter of order 15 for filtering signals to the range of [0, 4] Hz . The results of applying this filter are shown in Fig1.b and Fig 2.b.

2) SWT denoising based on Donoho's Hard-thresholding Scheme [17]: here the Donoho's original hard-thresholding scheme was applied [15] in order to recover VMRPs from the background EEG. Choosing the Minimax method for the selection of thresholds, and a hard thresholding non-white noise scheme with db5 and five levels of decomposition gave the results in Fig 1.c and Fig 2.c.

3) Wavelet Packet Denoising based on Shannon Entropy: another successful wavelet denoising is based on the selection of a tree of coefficients in wavelet packet(WP) analysis. The best tree in this method is found by Shannon Entropy [16]. The results of applying WP are shown in Fig1.d and Fig 2.d.

5. DISCUSSION AND CONCLUSIONS

Comparison amongst the results obtained in Fig.1 and Fig.2 clearly shows the advantage of the proposed algorithm. Although the low-pass FIR filter is successful in removing the high frequency noise components it does not perform well in removing the background noise from the signals. This is because the noise as well as the VMRP lie in the same frequency band. The two wavelet-based denoising algorithms (especially the one based on the WP) perform a little better in removing the background noise not associated with the VMRP, but lots of chattering can still be seen throughout the extracted ERP, especially in the traditional SWT. On the other hand, our SCS method performs very well in test trials. It effectively removes the noise not associated with the VMRP so an almost zero-value signal is obtained before and after the occurrence of a VMRP. Also the general shapes of VMRPs are successfully recovered. The results were similar for other channels. The main reason for the difference between the results obtained by the SCS and other methods is that the results of the SCS are based on the statistical analysis of the signal throughout the time so noise (whatever the source is) cannot have a significant effect on the general shape of extracted event. Our proposed method also significantly simplifies the study of ERPs; because instead of adding up hundreds of ensemble averages in order to acquire a rather smooth signal with almost-zero background EEG, the denoised shape of the signals is obtained by applying the proposed method to ensemble averages with fewer trials.

The other advantages of using the proposed method are:

1) The selection process is automatic, so there is no need to set the threshold for each data set independently.

2) "The correlated coefficients" are the ones with high absolute value of AV/SD, so it is easy to identify them based on the value of the threshold.

3) The method is shift invariant, so it is potentially a good candidate for ERP detection applications.

Future works include testing SCS on single trials and different subjects. Also Genetic Algorithms can be applied for the (sub) optimal selection of the threshold values in order to yield better results.

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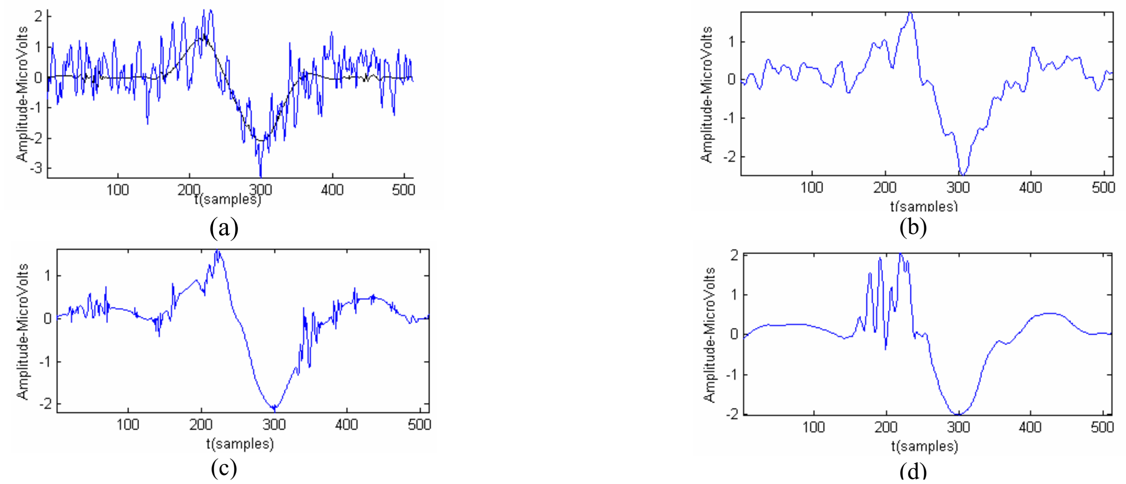

Fig.1 The Results of denoising the test signal #1 (a) SCS + Original (b) FIR (c) SWT (d) WP

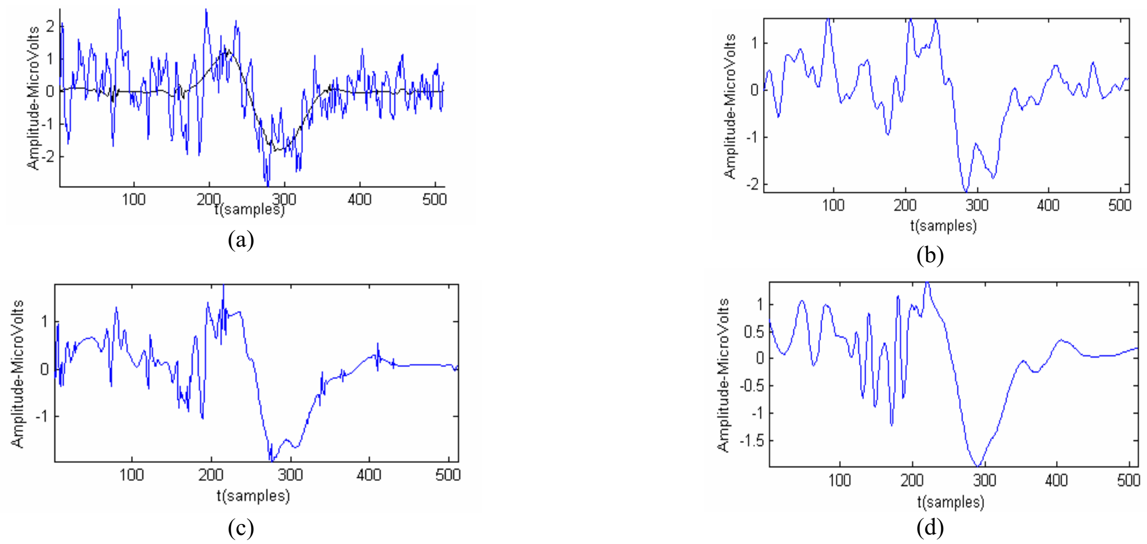

Fig.2 The Results of denoising the test signal #2 (a) SCS + Original (b) FIR (c) SWT (d) WP

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