Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

ThEP3.13

Wavelet Filtering of the P300 Component in Event-Related Potentials

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***Abstract*— This paper presents an application of wavelet filtering to single-trial P300 component analysis. The objective of this study is to introduce a new method for analyzing the P300 component, when performing a given cognitive task, in this case, a two-choice reaction time task. The discrete wavelet transform with Daubechies wavelet is employed to detect the presence of P300 in individual trials.**

Wavelet filtering is applied to remove noise and unwanted frequency components from discrete wavelet transform (DWT) coefficients based on prior knowledge of event-related potentials (ERPs). The filtering mask is computed from the grand-average of wavelet coefficients over all participants. With this filtering, the P300 component is accurately localized in both time and scale. The findings suggest the procedure to have considerable potential for the analysis of time-series data in the behavioral neurosciences.

***Keywords*—Age, Electroencephalography, EEG, ERP, P300, Wavelet transform, Wavelet filtering.**

I. Introduction

Electroencephalography is the neurophysiologic measurement of the electrical activity of the cerebral cortex of the brain. The recorded brain activity is known as an electroencephalogram (EEG) or brain dynamics. EEG activity occurs continuously in both humans and animals; however, if EEG activity is recorded in relation to a specific stimulus, it is then referred to as an evoked related potential (ERP).

Recently there has been a growing interest in brain dynamics, which provides valuable insights into a wide variety of neurological activities and disorders.

One of the ERP components that is commonly investigated in behavioural neuroscience research is the P300. In cognition terms, P300 is considered to represent stimulus evaluation time (latency) and attention engagement (amplitude). It's worth noting that as the P300 is a particularly large component, it lends itself to single–trial analysis. Since the discovery of P300 in 1965, a large body of research has been carried out to understand the related cognitive mechanisms and their underlying activities of the brain (Bashore & van der Molen, 1991). A whole range of techniques is available for the study of brain responses, which have found important users in several research fields such as evolutionary developments of the brain, aging, pathology and pharmacology. One of the applied research domains is the analysis of P300 ERP in the aging process (Basar, 2004).

EEG and ERP data are good examples of non-stationary signals, with varying frequency content. The time evolution of the amplitudes in single-trial ERPs does not allow the accurate retrieval of the frequency information of the signal. Spectral analysis can offer a more informative way to analyse ERPs. The Fourier transform, which is the most common spectral analysis tool and is almost universally used for stationary signal analysis, fails to provide any information about the time domain. Since the frequency content of ERPs is time dependent, time-frequency analysis is best suited for analysis of this type of signals.

The Short-Time-Fourier Transform (STFT) maps a signal into a two-dimensional function of time and frequency. The STFT represents a compromise between the time and frequency content of a signal. However, the information it provides in either domain is limited, and this limitation is determined by the size of the window function which is zero-valued outside of some chosen interval.

In this paper, the Wavelet transform (WT), a well-known time-scale analysis method, is employed. The major advantage of the WT is the use of variably-sized regions for the windowing operation. Wavelet analysis uses both long time windows enabling more precise estimation of low-frequency information, and shorter time windows for high-frequency information. As it provides time, scale (frequency) and amplitude information, with an all-round satisfactory resolution, it enables efficient multiresolution analysis (MRA).

Thus, the variable time resolution of WT matches the structure of single-trial ERP signals and provides an efficient analysis of the non-stationary nature of transient signals such as ERPs.

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The present study is designed to improve single-trial P300 assessments of human cognition in older and younger healthy adults. The proposed method is based on wavelet filtering techniques and produces “cleaner” P300 components.

The paper is divided into the following sections. In Section II, the data collection procedure and the EEG experiment are described. Section IIIA, provides the background theory of discrete wavelet transform and multiresolution analysis. Section IIIB presents the application wavelet filtering techniques on single-trial ERPs. A discussion of the results is given in Section IV and finally conclusions are given in Section V.

II. Data Collection

EEG data were recorded on a 32 channel Neuroscan system from 16 young and 14 older adults (Anusha to provide M and SDs) at a sampling frequency of 500 Hz. A two-choice reaction time task is administered via a PC time-locked to the EEG recording equipment. A white fixation-cross appeared in the center of the screen for 1000 ms followed by a blank 1000 ms pre-stimulus interval. Stimuli (white 3.5 m diameter circles) were then randomly presented 75 mm either left or right of the fixation-cross for 200ms. Participants responded via the appropriate response key. Responding initiated the next trial. Instructions emphasized speed and accuracy, and that participants should attempt to keep their eyes fixated on the central cross to minimize eye movement.

Twenty-four practice trials, followed by six blocks of 50 trials, were administered. This procedure allowed participants frequent breaks to minimize fatigue.

III. Methods

A. Wavelet Transform: brief theoretical background

The wavelet transform (WT) is an efficient method for investigating the local characteristics of non-stationary EEG signals. The discrete wavelet transform (DWT) of a signal, *x (t),* is expressed as a scalar product :

$$T_{m,n} = \langle x, \varphi_{m,n} \rangle \tag{1}$$

Where $\varphi_{m,n}$ are dilated and translated versions of a wavelet function, and m and n are the dilation and translation parameters, respectively:

$$\varphi_{m,n} = \frac{1}{\sqrt{a_0^m}} \varphi\left(\frac{t - n b_0 a_0^m}{a_0^m} \right) \tag{2}$$

The parameter a_0 and b_0 defined at discrete scales are often based on powers of two, which forms a so-called dyadic grid:

$$a_0 = 2^{-j} \text{ and } b_0 = 2^j k \text{ for } j,k \in z$$

As a result of this, the DWT algorithm is fast in computation and efficient due to non-redundancies of information.

The dilated and translated version of the wavelet function performs a high-pass and low-pass filtering respectively. Hence the convolution of the original signal with the high-pass filter produces the Detail coefficients. Similarly, approximation coefficients are computed by a convolution of the signal with a low-pass filter. This is also known as multiresolution analysis (MRA) (Addison, 2002).

In this study, Daubechies 4 wavelets were used for all DWT processing. Daubechies wavelets have been recently used for EEG studies in the literature for analysis of auditory-brain stem response (ABR) (Wilson. 2004), auditory oddball paradigms (Gurtubay et al., 2004) and epileptic seizure detection (Adeli et al., 2002; Subasi, 2005). The Daubechies 4 wavelet was chosen for this study primarily because Daubechies 4 wavelet has a shape similar to the P300 waveform. It also possesses an exact reconstruction and a considerable degree of smoothness (Addison, 2002).

B. The Wavelet Filtering Algorithm

The original ERP signal is decomposed into different levels of high frequency components or details (D1-D6) and low frequency components or approximation (A1-A6). The levels of decompositions are chosen in such a way that the resulting frequency ranges correlates with the EEG rhythms: delta, theta, alpha and beta. These frequency bands have been found to provide the sufficient set of wavelet coefficients for detecting P300 components (Subasi, 2005; Adeli, 2002).

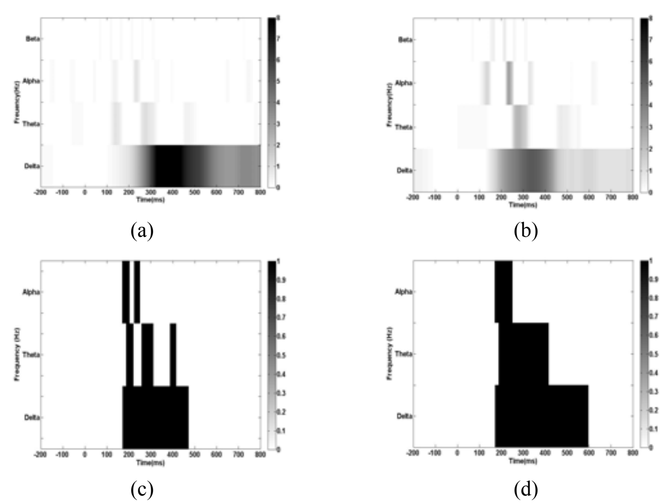


Figure 1: (a) Grand-average of DWT of old subjects. (b) Grand-average of DWT of young subjects. (c) Mask produced by applying hard thresholding on (a) and (b) and combining the resulting maps in a “logical disjunction” sense. (d) Global mask

Table 1 : Frequency ranges corresponding to 6 levels of decomposition using Daubechies 4 wavelet with a sampling rate of 500 Hz.

Decomposed Signal	Frequency Range (Hz)
cD1	125-250
cD2	62.5-125
cD3	31.25-62.5
cD4	15.625-31.25
cD5	7.8125-15.625
cD6	3.9063-7.8125
cA6	0-3.9063

Six levels of decomposition of the data generate 7 sets of coefficients each belonging to a different frequency band. Table 1 shows the ranges of the various frequency bands. From the table, it can be seen that cD4 lies within beta band (14-30Hz), cD5 within alpha band (8-14 Hz), cD6 within theta band (4-8Hz) and finally cA6 within delta band (0-4 Hz). Higher frequencies do not contain any significant information with regard to EEG components.

Reconstruction is performed by a convolution of all the details (cD1-cD6) and the last approximation (cA6) with the inverse filter. The signal is reconstructed computationally by adding up all the wavelet coefficients, as represented by the multiresolution components (i.e., S= A6+ D6+ D5+ D4+ D3+ D2+ D1). Since the reconstruction of the original ERP uses the entire set of wavelet coefficients, the DWT is shift invariant, which is an important property in certain applications, such as pattern recognition (Bradley et al., 2004).

Grand averages are computed by averaging the individual wavelet coefficient maps. Consequently two distinct maps of grand averages for old and young groups are produced (Figures 1(a) & 2(b)).

The hard thresholding algorithm is then applied to the grand average of wavelet coefficients in order to filter out the significant amplitudes within the maps in figure 1(a) and 1(b). The use of a hard-threshold will set any coefficients less than or equal to the threshold value to zero, resulting in two comparable masked maps for each group. In order to produce a non-biased mask for classification purposes, the masked maps above are combined by means of a “logical disjunction” operation. This generates a single patchy and inconsistent mask as presented in figure 1(c). To produce a uniform global mask, the smoothed version can be applied for all single trial epochs, which is illustrated in figure 1(d). Ultimately, similarities of ERPs can be observed by masking/filtering out the variability across subjects. The components of the designed filtering mask reside only in the three lower frequency sub-bands: delta, theta and alpha.

IV. RESULTS AND DISCUSSION

The neural activity in the brain is the result of temporal and spatial time-varying oscillations occurring in different frequencies (Samar, 1999). Quantifying the P300 parameters

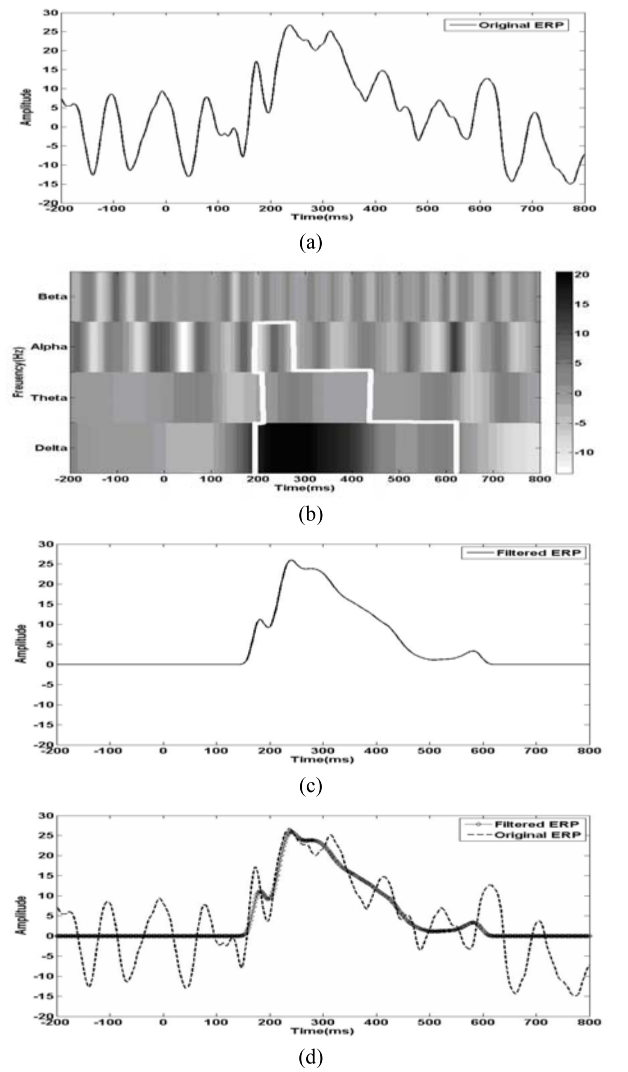


Figure 2: (a) Single trial ERP. (b) DWT of single trial ERP. (c) Masked P300 components of ERP. (d) Comparison before and after masking on a single trial ERP.

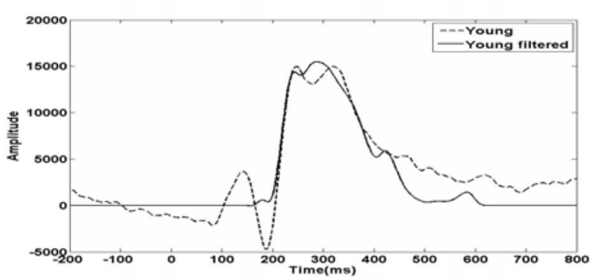
namely; amplitude (attention engagement), latency (stimulus evaluation time) and width in a reliable way is of high importance for neuroscience research. However, the computation of the three parameters is affected by random fluctuations in the signal.

Conventional time domain analysis of ERPs, which is based on computing the amplitude and latencies of prominent peaks, does not always provide a robust measurement of the P300 parameters. Additionally, the noisy nature of ERPs makes accurate selection of peak amplitude a complex process. This is demonstrated here by an example (see figure 2(a)).

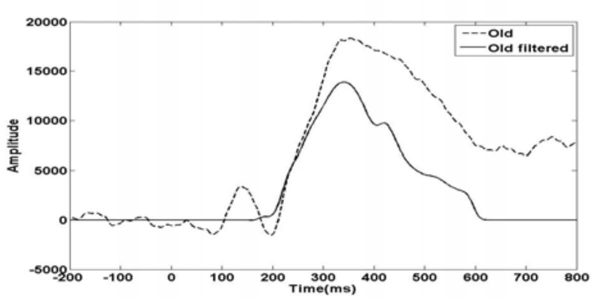
Figure 2 illustrates the P300 wavelet filtering procedure for one epoch. Through wavelet decomposition of single-trial ERP signal, transient features are accurately detected and localized in a joint time-scale (or frequency) representation shown in figure 2(b). Application of the designed global mask (shown in figure 1(d)), which is intended for operation on single-trial epochs, highlights the significant parameters of P300 as well as removes the unwanted frequency components (figure 2(b)). Computing the marginal of the wavelet coefficient map helps to visualize the single-trial ERP signal only in the time domain irrespective of the scale (or frequency). To smooth out the high-frequency artifacts that occur due to the usage of a sharp cut-off in the masking procedure a simple equiripple FIR filter is used (results shown in figure 2(c)). The figure demonstrates that noise is much reduced, and the P300 components are more robust. The filtered signal retains the shape of the expected P300 waveform and is much closer to the real P300. Figure 2(d) compares the wavelet filtered single-trial ERP with time domain non-filtered single-trial ERP. It can be clearly seen that the P300 components after filtering carries much less noise as well as simplifies the calculation of the three parameters mentioned above.

The method has been applied on all eligible epochs of all participants (old and young) and grand-averages of filtered single-trial epochs have been computed only on those epochs whose peak amplitude lie within the range of 200-400ms. Figure 3(a) & (b) demonstrate a significant improvement in detecting P300 parameters for the grand-averages of time domain ERPs in comparison to grand-averages of wavelet filtering procedure.

Due to the fact that old subjects appear to have the peak amplitude at a later point in comparison to young subjects (figure 3) the use of static global mask limits the analysis of P300.The authors are currently seeking to extend this research to design a more advanced, adaptive filtering algorithm that can adjust its performance based on the peak amplitude of the single cycle EEG input. This will be the subject for the future research.



(a)



(b)

Figure 3: Comparison of time domain grand-averages of single-trial ERPs and wavelet filtering grand-averages for (a) Young participants. (b) Old participants.

V. Conclusion

By means of the wavelet transform, oscillatory transient features in the brain are detected and the distinct functional components of P300 are extracted. The discrete wavelet transform in this study employ a Daubechies 4 wavelet to decompose the signal at different frequency bands, with different temporal resolution. Firstly through the calculation of the grand-average of wavelet coefficients, and secondly through the application of a hard threshold, the averaged wavelet coefficients provide a good design for the wavelet filtering mask. The mask has been applied to single-trial ERP epochs and provided well localized ERP components in time and scale, which resulted in cleaner, more informative P300 components. Since the limitation of this study stems from the non-dynamic nature of the designed wavelet filter, future research will be focusing on devising an adaptive filter.

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