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Abstract. Wavelet denoising has been successfully applied to Event-Related Potential (ERP) detection, but it usually works using channels information independently. This paper presents an adaptive approach to denoise signals taking into account the channels correlation in the wavelet domain. Moreover, we combine phase and amplitude information to automatically select a time window which increases ERP detection. Results on the P300 speller show that our algorithm has a better accuracy with respect to the VisuShrink wavelet technique and the XDAWN algorithm among 22 healthy subjects, and a better regularity than XDAWN.

Keywords: Event-Related Potential, Denoising, Wavelets, Signals correlation, Single-trial detection, Brain-Computer Interfaces.

1 Introduction

The P300 oddball paradigm such as used in the speller by Farwell and Donchin is the most frequent paradigm used in Brain-Computer Interfaces (BCI) especially for people with severe disabilities. But the signal-to-noise ratio is so low that it is necessary to apply preprocessing techniques to improve the P300 detection. This paper presents a new method to denoise EEG signals, which considers the shared information in the wavelet domain of all channels, based on their phase angles correlation. Also, our algorithm selects an appropriate time window for each subject, extracting the interval of interest to effectively discriminate between classes.

2 Material and Methods

2.1 Wavelet-based Semblance

The Wavelets Transform represents a signal $x(t)$ in terms of scaled and shifted versions of a mother wavelet, $\psi(t)$. The wavelets coefficients are obtained through equation $W^x_\psi(a,b) = \langle x(t)|\psi_{a,b}(t)\rangle$, where a and b are the scale and translation parameters respectively. Semblance analysis [Cooper, 2009] compare two signals $x(t)$ and $y(t)$, using Continuous Wavelet Transform (CWT) or the Discrete Wavelet Transform (DWT), based on phase correlations between its wavelet decompositions W^x_ψ and W^y_ψ. The first step is to compute the cross-wavelet transform, $W^{x,y}_\psi = W^x_\psi W^{y*}_\psi$, where $*$ denotes the complex conjugate. The cross-wavelet amplitude is given by $A = |W^{x,y}_\psi|$ and its local phase is defined as $\theta = tan^{-1}(\Im(W^{x,y}_\psi)/\Re(W^{x,y}_\psi))$, where $\Re$ and $\Im$ correspond to the real and imaginary parts respectively. The *semblance measure* S to compare two signals using θ, is defined as $S = cos^n(\theta)$ where n is an odd integer greater than zero. Its values range from -1 to 1, where $S = 1$ indicates that signals are correlated , $S = 0$ uncorrelated and $S = -1$ inversely correlated. It is possible to combine the phase information S and the amplitude A as follows $D = cos^n(\theta)|W^x_\psi W^{y*}_\psi|$.

As an extension of the *semblance*, the Mean Resultant Length (MRL) [Cooper, 2009] compares N different signals (ranging from 0 for uncorrelated signals to 1 for fully correlated signals) and it is compute for each time t and scale a as:

$$MRL(t,a) = \frac{\sqrt{(\sum_{i=1}^N \Re(W^{i,t,a}_\psi))^2 + (\sum_{i=1}^N \Im(W^{i,t,a}_\psi))^2}}{\sum_{i=1}^N |W^{i,t,a}_\psi|} \tag{1}$$

2.2 Signal Denoising

The fundamental hypothesis of wavelet denoising is that wavelets are correlated with the informative signal and not correlated with the noise, which globally means that small coefficients correspond to noise. Let $x_c(t)$ be the signal recorded by the c^{th} channel (or electrode) $c \in \{1,\ldots,C\}$ at time t, $t \in \{1,\ldots,T\}$. The matrix of recorded EEG signals can be defined as $X \in \Re^{TxC}$. The MRL is computed using the DWT wavelet decomposition of all channels $W^{x_c}_\psi$, through Eq. 1. It is possible to establish a correlation threshold τ_d in order to set to zero all coefficients that are below it. After this process we can reconstruct the signal using the filtered wavelet coefficients.

2.3 Time-Window Selection

The P300 responses have a different latency for each person but are studied during a predefined time window after the stimulus onset. We propose to automatically find an efficient time window by detecting where the discriminative information lies to remove features which do not carry useful information. The denoised signal can be denoted by $\widetilde{x}_c(t)$, where c correspond to the channel and t to the instant when the signal started to be recorded. Each $\widetilde{x}_c(t)$ has a label to indicate to which class belongs. Let $\mathscr{M}$ be the set of all signals, $\mathscr{M}$ is composed by signals belonging to the target class $\mathscr{T}$ (containing a P300 wave) and signals $\mathscr{N}$ which are non-targets, $\mathscr{M} = \{\mathscr{T}, \mathscr{N}\}$. The Grand Averages GA for each class are computed as $GA_{\mathscr{T}} = \frac{1}{C|\mathscr{T}|}\sum_{i=1}^{C}\sum_{\widetilde{x}\in\mathscr{T}}\widetilde{x}_i(t)$ and $GA_{\mathscr{N}} = \frac{1}{C|\mathscr{N}|}\sum_{i=1}^{C}\sum_{\widetilde{x}\in\mathscr{N}}\widetilde{x}_i(t)$ where the operator $|.|$ denotes the cardinal number. After obtaining the Grand Averages, we compute the CWT $W_{\psi}^{GA_{\mathscr{T}}}$ and $W_{\psi}^{GA_{\mathscr{N}}}$ to finally compute D. The original time window of 1s can be reduced to the interval $[t_{lo}, t_{up}]$ applying a threshold τ_w, $0 \le \tau_w \le 1$ to the normalized average of D.

We called the combination of the signal denoising and the window selection using the wavelet-based semblance the Denoise and Window Selection (DWS) algorithm.

3 Results

Firstly, we compared ours methods, DWS_1 (using the same time window for all channels) and DWS_2 (using different time windows per channel) to the wavelet denoising technique called *VisuShrink* (Stein Unbiased Risk Estimator) [Donoho and Johnstone, 1995] and the XDAWN algorithm [Rivet et al., 2009]. 10 channels (Fz, C3, Cz, C4, P3, Pz, P4, PO7, PO8, Oz) for 22 healthy subjects were recorded at 256 sps using the g.tec gUSBamp EEG amplifier. An 8th order Chebyshev bandpass filter, 0.1-60 Hz and a 60 Hz Notch were used (see http://akimpech.izt.uam.mx/p300db). Two different sessions of approximately 16 letters each were used to train and test a Support Vector Machine (SVM), which in single-trial corresponds to 5520 realizations for training and 5895 for testing with a time segment of 1s.

Algorithms DWS_1 and DWS_2 perform significatively better, showing that the conjoint channel information is useful for P300 single-trial detection (see Table 1). Finally, we compare DWS_1 and DWS_2 in Table 2. Our algorithms reduce the window selection roughly to [20,850] ms. DWS_2 used a smaller time window.

Method	mean	std	min	max	paired t-test with DWS1
None	48.23	15.55	18.10	76.19	1%
XDAWN	51.03	15.80	24.44	80.00	1%
Filter [0.1-20]Hz	53.60	14.14	28.25	79.52	1%
VisuShrink	54.80	13.90	33.02	78.57	5%
DWS_1	**55.83**	**13.49**	**34.29**	80.95	-
DWS_2	55.41	13.88	33.97	**81.90**	5%

Table 1: Results using Coiflet at level 3, $\tau_d = 0.999$ and $\tau_w = 0.9$. The average and the standard deviation of the letter percentage accuracy over all subjects and the minimum and maximum accuracy obtained among subjects are reported. The last column reports the significance level of a paired t-test.

		DWS_1	DWS_2
t_{lo} (ms)	min	1	1
	mean	20	23
	max	98	305
t_{up} (ms)	min	488	277
	mean	848	820
	max	1000	1000

Table 2: Results obtained by DWS_1 and DWS_2 on the time-window selection. t_{lo} and t_{up} are respectively the lower and the higher bounds in milliseconds found over all subjects and channels.

4 Discussion

In this paper, we introduce a new method based on the wavelet-based semblance to exploit the correlated information among channels. This technique removes noise and establishes automatically an appropriate time window adapted to each subject. We empirically demonstrate using the P300 speller application that our method is useful to remove undesirable component of the signals, improving the letter accuracy compare to the other methods and showing more stability than XDAWN. Further studies are needed to automatically select the thresholds.

References

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