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WAVELET DENOISING FOR P300 SINGLE-TRIAL DETECTION

Carolina Saavedra and Laurent Bougrain
Cortex team-project, Nancy University/LORIA/INRIA Nancy Grand Est
Campus Scientifique - BP 239 - 54506 Vandoeuvre-lès-Nancy Cedex
France
{saavedra, bougrain}@loria.fr

ABSTRACT

Template-based analysis techniques are good candidates to robustly detect transient temporal graphic elements (e.g. event-related potential, k-complex, sleep spindles, vertex waves, spikes) in noisy and multi-sources electro-encephalographic signals. More specifically, we present the impact on a large dataset of a wavelet denoising to detect evoked potentials in a single-trial P300 speller. Using coiflets as a denoising process allows to obtain more stable accuracies for all subjects.

KEY WORDS

Event-related potential, wavelet denoising, support vector machines, brain-computer interface

1. Introduction

The observation of brain activity and its analysis with appropriate data analysis techniques allow to extract properties of underlying neural activity and to better understand high level functions. Several recording techniques exist providing different kinds of information at various scales. Some of them provide very local information such as multiunit activities (MUA) and local field potential (LFP) in one or several well-chosen cortical areas. Other ones provide global information about close regions such as electrocorticography (ECoG) or the whole scalp such as electroencephalography (EEG). If surface electrodes allow to easily obtain brain imaging, it is more and more necessary to better investigate the neural code. Brain study needs to investigate and integrate, (i) in a single-trial, information (ii) spread in several cortical areas and (iii) available at different scales (MUA, LFP, ECoG, EEG).

2. Modeling and detection of transient events in cortical signals

2.1 Transient events in cortical signals

In cognitive experiments, typically the experimental task (one trial) is repeated many times and the resulting brain activity is averaged over trials. The main reason for this averaging is the low signal-to-noise ratio (SNR) in the single-trials and average increases the SNR dramatically. The average activity allows to extract easily event-related components, which are strongly related to cognitive processes in the brain. However,

this averaging assumes that the brain responds to the external stimuli identically in all trials. However it has been shown in several previous studies that this assumption is not valid. Consequently, to improve the analysis we develop an algorithm to extract event-related components from single-trials.

Event-related potentials (ERP e.g. N200, P300, N400, P600...) and error-related potentials are not the only ones transient temporal graphic-elements used in brain analysis. Non-cognitive events such as spikes, sleep K-complex, epileptic spike-wave are other transient events. The information carried by all of them are highly useful to better understand mental state and brain activity.

2.2 Specific data analysis techniques

One major problem with transient events is how to be able to deal with the variability between trials. Thus, it is necessary to develop robust techniques based on stable features. Specific modeling techniques should be able to extract features investigating the time domain and the frequency domain. ERPs are short-time events with characteristic peaks at specific times. So it is useful to be able to extract features in time domain. In the time domain, template-based unsupervised models allows to extract graphic-elements. Both the average technique to obtain the templates and the distance, such as the point-to-point averaging, the cross-correlation distance and the dynamic time warping, used to match the signal with the templates are important, even when the signal has a strong distorted shape. Thus, template-based classifiers first estimate ERP templates by averaging in the time domain ERP responses, and then use the shorter distance between the current response and the ERP templates as a discriminate criterion.

This embedded approach is not the only one. Usually, it is useful to apply a denoising stage before the classification stage to detect the graphic-element.

3 Illustration: P300 single-trial detection for brain-computer interface

Brain-computer interface (BCI) system is a potentially powerful new communication and control option for those with severe motor disabilities [1]. A BCI system translates brain activity into commands for a computer or other devices (e.g. wheelchair, robotic arm). In other words, a BCI allows users to act on their real or virtual environment by using only brain activity.

4.1 Denoising by wavelet decomposition

The Wavelets Transform (WT) was developed as an alternative to the Short Fourier Transform to overcome the resolution problem [9]. WT is a windowing technique with variable regions size. The main idea is to represent a signal $x(t)$ in terms of displaced and shifted version of a mother wavelet $\Psi(t)$.

$$\Psi_{a,b}(t) = |a|^{-\frac{1}{2}} \Psi\left(\frac{t-b}{a}\right)$$

where a and b are the scale and translation parameters respectively.

The signal coefficients are obtained by the convolution of the original signal and the different version of the mother wavelet.

$$W_{\Psi}X(a,b) = \langle x(t) | \Psi_{a,b}(t) \rangle$$

The coefficients refer to the similarity in frequency content between the signal and the wavelet at the current scale.

Using the matlab, we extract at level 3 the coefficients of original signals using Coiflets and quadratic B-spline mother wavelets, due to their waveform similarity to the P300 and because they are recommended by the literature. These wavelets families are used to remove noise from the details coefficients belonging to the original signal. To do this we identified the components that contain the noise, and then reconstructing the signal using the approximation coefficients (A3) and the details coefficients without those noisy components. The noise is removed using a threshold, this involves discarding only the portion of the details that exceeds a certain limit (figure 3).

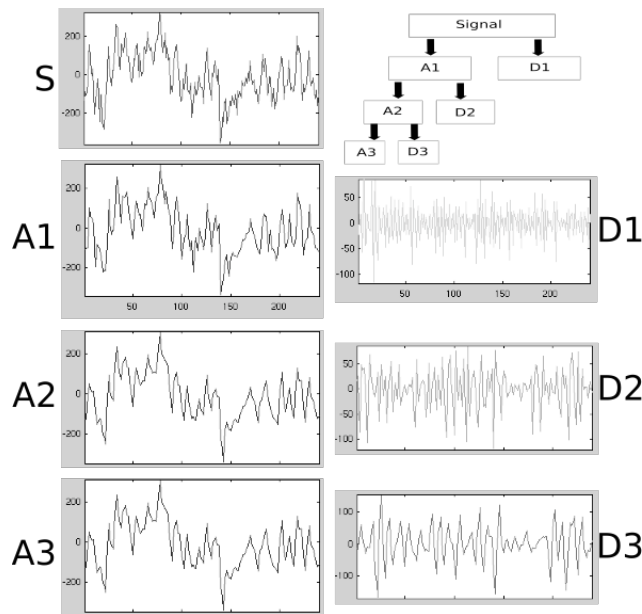


Figure 3: Signal decomposition illustration. The original signal S (top left) is decomposed at 3 levels (top right) obtaining the approximation (A1, A2 and A3) and details (D1,D2,D3) coefficients. The signal is reconstructed using A3 and the denoised versions of D1, D2 and D3.

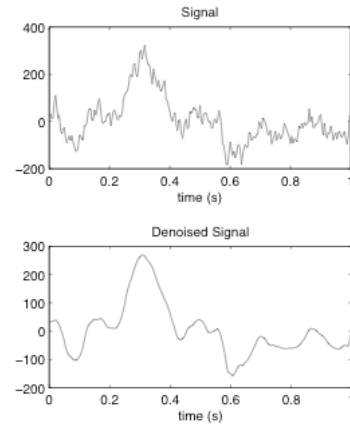


Figure 4: Effect of the denoising process on a P300 response. The original signal (on top) corresponds to the average of all targets signals for letter C in word CAT into the BCI competition IV, subject AA. The P300 is elicited around 0.3 second. The signal obtained after denoising using wavelets is shown at the bottom.

4.2 Classifiers

The Linear Discriminant Analysis (LDA) is the standard method used as a reference method for P300 detection in BCI. We used the stepwise version (SWLDA) implemented in BCI2000 to get results.

Support vector machines (SVM) are one of the most popular data mining techniques [10]. They are especially powerful for two-classes problem with a large number of variables. The complexity cost is dependent on the number of examples. So SVM are good candidates. We classified our binary dataset (target vs non-target) with linear kernel and a cost $C = 1$. A linear kernel is more robust than polynomial one for very noisy data with high variability.

We used libsvm, a library for Support Vector Machines by Chih-Chung Chang and Chih-Jen Lin and its simple interface for matlab [11].

For each subject, we used the data of session 1 to train the classifier (SWLDA or SVM) and session 3 to test it (free spell of 3 words).

5. Results

The standard SWLDA method obtains good results on averaged responses but it is not very efficient for single-trial detection (Figure 5).

SVM overtakes SWLDA (Figure 6). Using as a preprocessing wavelet denoising has some effects on the robustness of the classifier especially with the coiflets. The mean or median of the accuracies are similar with and without wavelet denoising. But a coiflet denoising more stable.

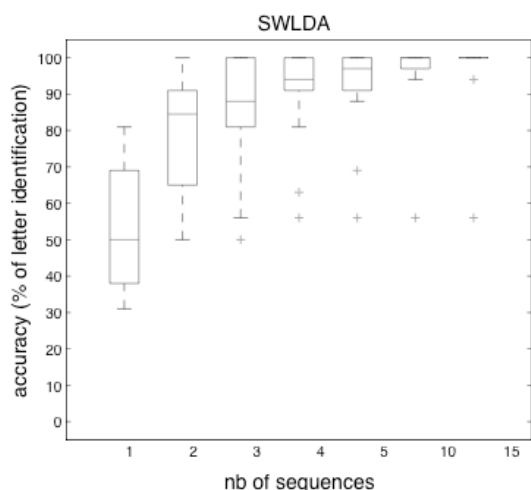


Figure 5: percentage of correct letters using stepwise linear discriminant analysis (SWLDA) via the P300GUI tool contribution for BCI2000. The box and whisker plots present a study of the 16 accuracies obtained using subject dependent classifiers. Each accuracy is based on the full test set i.e. on the three free-spelling runs (user-selected words, around 15 characters per subject).

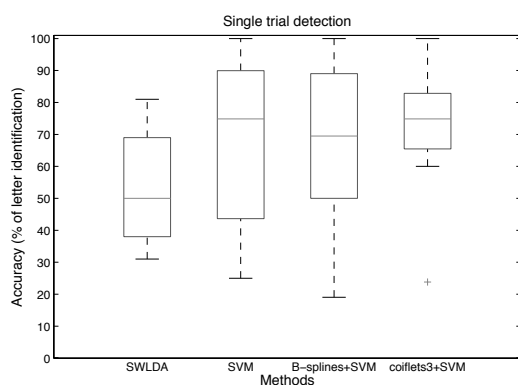


Figure 6: percentage of correct letters for the four competitive approaches on single-trial detection. Stepwise linear discriminant analysis (SWLDA) and support vector machines (SVM) without denoising plus SVM with two wavelet denoisings : B-spline wavelets and coiflets at level 3. The box and whisker plots present a study of the 16 accuracies obtained using subject dependent classifiers. Each accuracy is based on the full test set i.e. on the three free-spelling runs (user-selected words, around 15 characters per subject i.e. around 30 P300 responses and 150 non target responses).

6. Conclusion

In this work, we present the impact on a large database of specific wavelet families for denoising evoked potential from EEG background activities to easily detect them in a single-trial P300 Speller. These wavelet families are adapted to ERP waveform. Two different mother wavelets (B-Spline and Coiflets3) were used in the experiments according to their performance for ERP denoising in literature. Despite the fact that both mother wavelets “look similar” to the P300 wave, in a single-trial detection, the improvement of wavelet denoising is visible in terms of stability especially using Coiflets3.

Due we are working with a large dataset, it is difficult to get an algorithm that improves accuracy for all subjects, because of the differences between subjects

brain activities and the noise effect in dataset. But SVM clearly overtakes SWLDA.

As a future work, we want to investigate a method to adapt the parameters involved in the denoising method to improve the performance according to the grand average P300 response of each subject.

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