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Wavelet transform for the identification of P300

V A Bulanov[1], A V Zakharov[2] and E V Khivintseva[2]

[1] IT Universe LLC, 3, Eroshevskogo str., Samara, 443086, Russia
[2] Samara State Medical University, 89, Chapaevskaya str., Samara, 443099, Russia

E-mail: zakharov1977@mail.ru

Abstract. The reliability of a newly developed algorithm for the identification of the P300 component of event-related potentials based on a continuous wavelet transform was investigated. The electroencephalogram records of one participant made by using a three-stimulus paradigm (a kind of the odd-ball paradigm) were analyzed. The accuracy of identification of certain wavelet types for the detection of P300 was from 76.32 to 86.84%. Thus, relatively simple algorithms for processing and classifying the electroencephalogram record signal show acceptable results in terms of the accuracy of identification of the P300 component of event-related potentials based on randomly selected data.

1. Introduction

Neurotechnologies, such as neurocomputer interfaces (NCI), are an important branch of modern science. One of the main concepts for the development of neurocomputer interfaces (NCI) using electroencephalogram (EEG) is the use of the P300 component of event-related potentials (ERP) that occurs as a human brain response to the presence of the external visual stimuli [1]. A number of ongoing studies are dedicated to the improvement of algorithms for classifying the components of the ERP-wave [2-4].

For researchers, it is becoming a common practice to share in the public domain the datasets received using expensive lab equipment or in complex experiment conditions. This might be the next step in science development. In our research, we used the data published in the public domain by the following group of scientists: L. Vareka, P. Bruha, R. Moucek [5]. The datasets are available at: ftp://climb.genomics.cn/pub/10.5524/100001_101000/100111/

2. The objective of the research

The objective of this research is to determine the reliability of the algorithm developed by us for the identification of the P300 component of ERP which is based on the continuous wavelet transform by using publicly accessible EEG recording datasets. Another objective is to estimate the effect of the number of target stimulus presentations on the identification accuracy.

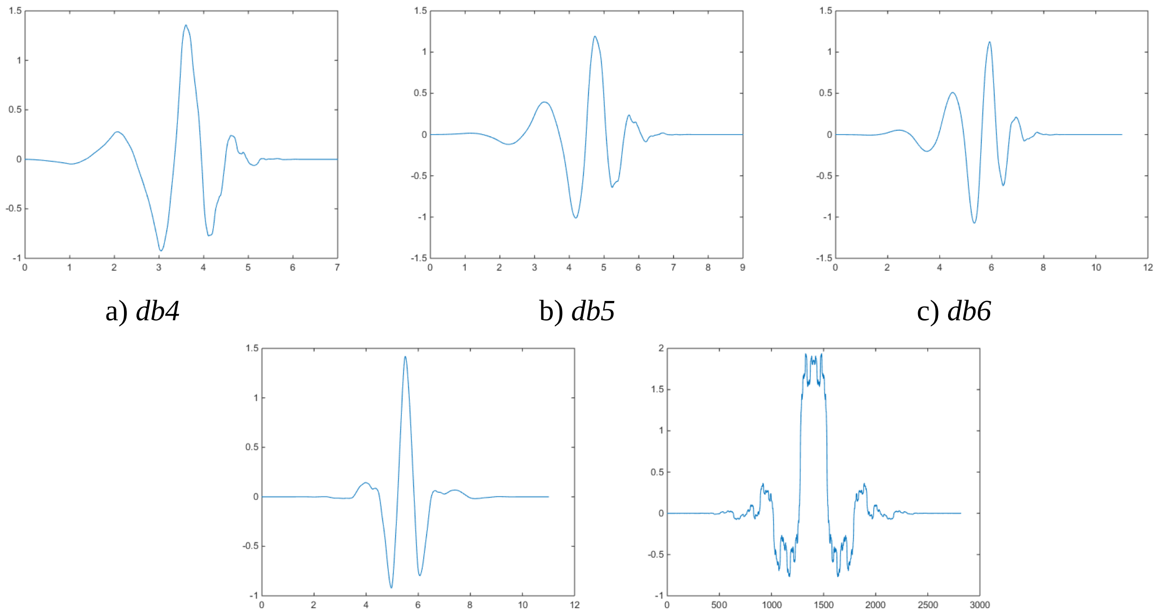
3. Materials and methods

A wavelet is a function $\psi(t)$ which satisfies the following conditions:

$$\int_{-\infty}^{\infty} \psi(u)du = 0, \quad \int_{-\infty}^{\infty} \psi^2(u)du = 1.$$

When these conditions are met, there should be an interval $[-T, T]$ outside of which the function $\psi(t)$ is close to zero. As a result, we obtain a wavelet, i.e. a time-limited wave.

Wavelets can be applied as a simple and fast classifier of waveforms in a signal [6]. The continuous wavelet transform allows identifying sequences of different waveforms in the signal in question. Many different wavelets with a wide area of applications have been created. They include Morlet wavelets, Daubechies wavelets, "mexican hat" wavelets, etc. The *Matlab wavelet toolbox* presents 16 different wavelet families. Figure 1 shows the wavelets that we used in our research.



a) *db4* b) *db5* c) *db6*

d) *sym6* e) *rbio3.5*

Figure 1. Wavelets used in the research.

The continuous wavelet transform (*CWT*) of a signal $x(t) \in L^2R$ is defined as a dot product between the signal and the wavelet functions $\psi_{a,b}(t)$:

$$C_{a,b} = < x(t), \psi_{a,b}(t) >$$

where $C_{a,b}$ - coefficients of the wavelet transform; $\psi_{a,b}(t)$ - scaled and translated wavelet function $\psi(t)$:

$$\psi_{a,b}(t) = \sqrt{|a|}\,\psi\left(\frac{t-b}{a}\right)$$

where a – scale; b – translation.

The *CWT* gives a decomposition of $x(t)$ in different *scales* which have maximum values at those scales and times where the form of the signal $x(t)$ is similar to that of the wavelet function$\psi(t)$. The continuous wavelet transform was performed with the *Matlab cwt()* function.

We used the *One Rule* classification algorithm which is an algorithm of the decision tree category. *One Rule* is a simple classifier that makes a decision based on one parameter which shows the least number of errors when training the classifier. This algorithm is widely known and used for obtaining well-interpreted results [7].

The EEG signal database used in our research contains 19 datasets. Each dataset is an EEG record of one participant made by using a three-stimulus paradigm which is a variation of the *odd-ball paradigm* [8]. All data were recorded by electroencephalograph (make of device is not specified) with

19 channels and presented in *BrainVision* format. Flashes of three (red, green and yellow) LED indicators were used as visual stimuli. Stimuli were presented in a random order with a predefined frequency distribution: 83% of non-target stimulus presentations (red LED flash), 13.5% of target stimulus presentations (green LED), 3.5% of distracting stimulus presentations (yellow LED). The stimulus duration was 500 ms, the inter-stimulus interval (*ISI*) was 1000 ms. The experiment was conducted in three phases with a short break, and each test subject was presented with 30 target stimuli.

A detailed description of the experimental design is given in the paper [5].

In our research, we used datasets with numbers 76, 85, 86, 87, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 104, 105, 106 and the EEG derivation *Pz* the form of the signal from which has usually the greatest characteristic intensity of the *P300* component. We selected epochs with numbers 2 and 4 in these datasets which correspond to the presentation of a target and non-target stimulus respectively. To classify stimuli, we chose the *db4, db5, db6, sym6 and rbio3.5* wavelets (figure 1) due to the visual similarity of these wavelets to the *ERP*-wave form (figure 2).

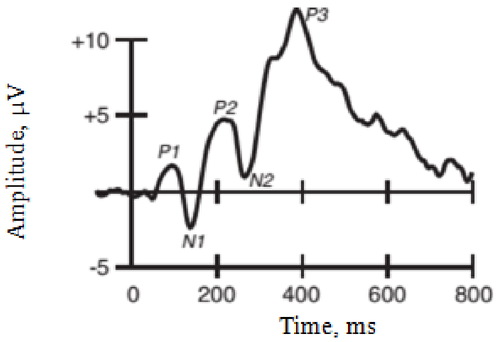


Figure 2. *ERP*-wave generated as a human brain response to the presence of a target visual stimulus.

When preparing the EEG signal for classification, we selected four samples of data from each dataset containing 5, 10, 15 and 20 target and non-target epochs from the beginning of the EEG signal. The epoch duration was from 230 to 700 ms from the start of the stimulus presentation. Then we averaged the selected target and non-target epochs in each dataset. Next we processed the averaged epochs by using the continuous wavelet transform with scale coefficients of 1:2:128. We assumed the total of the maximum values of the coefficients of the wavelet decomposition at each time point as a summarized indicator for further classification:

$$S = \sum_{b=1}^{w} \max\left(C_{a,b}\right)$$

where $C_{a,b}$ - *CWT* coefficients; *w* - time window width.

4. Results and discussion

We processed the obtained set of summarized indicators based on the *One Rule algorithm* using a statistical data processing program *R* (*https://www.r-project.org/*) and the *OneR* package (*https://cran.r-project.org/web/packages/OneR/*).

The accuracy of identification of the target stimulus in each dataset corresponding to the presentation of 5, 10, 15 and 20 target stimuli is shown in tables 1-4 and figure 2. The maximum accuracy values are shown in bold italics.

Table 1. Accuracy of identification of the target stimulus, %.The number of target stimulus presentations: 5.

Wavelet *db4*	Wavelet *db5*	Wavelet *db6*	Wavelet *sym6*	Wavelet *rbio3.5*
76.32	76.32	**78.95**	73.68	65.79

Table 2. Accuracy of identification of the target stimulus, %. The number of target stimulus presentations: 10.

Wavelet *db4*	Wavelet *db5*	Wavelet *db6*	Wavelet *sym6*	Wavelet *rbio3.5*
76.32	**76.32**	**76.32**	**76.32**	**76.32**

Table 3. Accuracy of identification of the target stimulus, %. The number of target stimulus presentations: 15.

Wavelet *db4*	Wavelet *db5*	Wavelet *db6*	Wavelet *sym6*	Wavelet *rbio3.5*
84.21	84.21	**86.84**	84.21	76.32

Table 4. Accuracy of identification of the target stimulus, %. The number of target stimulus presentations: 20.

Wavelet *db4*	Wavelet *db5*	Wavelet *db6*	Wavelet *sym6*	Wavelet *rbio3.5*
78.95	78.95	**81.58**	**81.58**	71.05

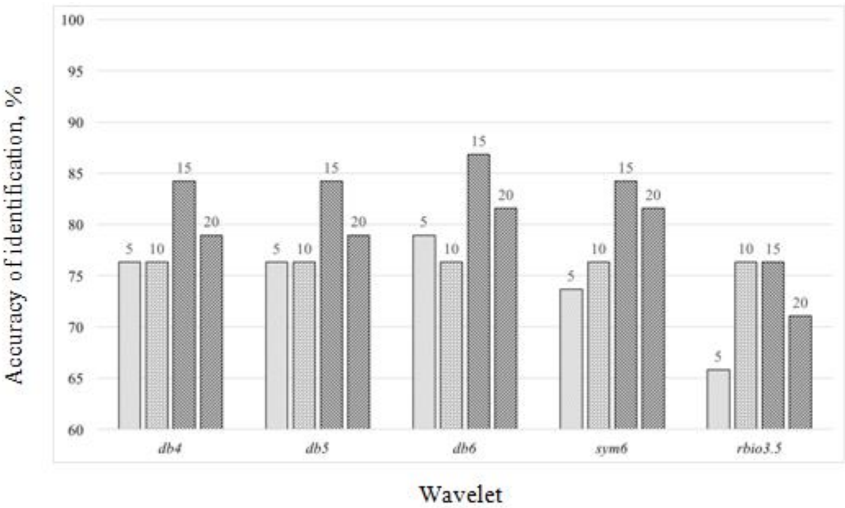


Figure 3. Accuracy of identification for each wavelet. The numbers above the histogram columns indicate the number of the presented target stimuli.

Since we used a small number of datasets (19 datasets with 2 characteristics — target and non-target epoch), when calculating the accuracy, we obtained discrete levels with the increment of $\frac{100\%}{2\times19} \approx 2.63$ %. This can explain the same identification accuracy for all wavelets in table 2 — the identification accuracy values for 10 presented stimuli fell into the same range during classification (75.0-77.6 %) with an average value of 76.32 %.

The identification accuracy is not significantly affected by the selected wavelet. The ***db6*** wavelet showed the highest identification accuracy in all datasets, i.e. for any number of the presented target stimuli. The identification accuracy of the ***db6*** wavelet ranged between 76.32 and 86.84 %.

We can see that when the number of target stimulus presentations increases from 5 to 15, the identification accuracy goes up as well. When the number of target stimulus presentations further increases up to 20, the identification accuracy decreases for all wavelets. We assume that such decrease in the identification accuracy may be caused by increased fatigue of the participants.

5. Conclusion

In this investigation, we have found that relatively simple algorithms for processing and classifying the EEG signal show acceptable results in terms of the accuracy of identification of the *P300* component of *ERP* based on randomly selected data. One of the advantages of the suggested method is a high interpretability of the results. Such algorithms can be used in researches where understanding the obtained results is more important than the identification accuracy.

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