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The P300 Event-related Potential Detection – a Morphological Approach

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***Abstract*— The aim is to investigate the possibility of detecting the P300 event-related potential derived from its shape. We intend to show the way in which the well known variability of the P300 may be surpassed by adequate morphological operations, centred on suited structuring elements and on a new parameter, named emphasising parameter. This method can lead to better P300-based brain computer interfaces (BCIs) by enhancing this attribute of the electroencephalographic (EEG) signal.**

Keywords—brain-computer interface; P300 event-related potential; mathematical morphology, emphasising parameter.

I. INTRODUCTION

The development of a robust and reliable brain computer interface (BCI) is closely linked with the possibility of detecting the changes taking place in the electroencephalographic (EEG) signals and with the ability to extract the features of interest in an efficient and reliable manner. There are several components that can be taken into account and among them it is the P300 event-related potential, in fact a positive deflection of the EEG signal elicited as a response with a latency of about 300 ms from the onset of infrequent visual, auditory or somatosensory stimuli.

There are several methods to implement a BCI by means of the P300 potential detection; the most common one is the so called Farwell-Donchin paradigm [1]. The paradigm is a visual one and its fundamental nature is a Bernoulli-type event presented to a subject that is asked – in one of the many possible implementations - to mentally write a word according to the spelled letters, visualised on a matrix, randomly illuminated on a computer screen. Each time a letter lightened is part of the word, if the subject elicits a P300 event-related potential a successful trial is achieved.

The detection of this potential is not a straightforward task since its variability is significant [2]. Nevertheless, there are attempts to develop new algorithms or to adapt the existing ones to achieve a fast detection and a good rate of success. They are based on the analysis of the frequency content of the signal or the detection of the "peaks" that are afterwards validated by means of statistical methods. In a chronological order, first attempts were focused on using filters and frequency components that described the presence of the P300 [3] followed by dedicated statistical methods [4] that extended the initial work. An actual review [5] presents the most important methods used in the P300 detection step. Among them we remember independent component analysis (ICA), parametric modelling, wavelet transform and genetic algorithms.

Our intention is to present a method of the P300 event-related-potential detection that is based on the emphasis of the shape of the defection.

The next parts of the paper are devoted to the mathematical background needed to achieve this and the description of the data set used. At last, some actual results and a comparison with the known techniques are shown. It is worth pointing out that our method deals only with one aspect of the problem of a BCI i.e. the feature extraction. The classification part is not our concern in this work, but, for the sake of comparison making, a well known result, [6], is used for validation.

II. METHODS

A. new morphological operator

We intend to use the shape of P300 in order to decide if it has been elicited or not. To do so, a few preliminaries concerning the tools of mathematical morphology, as stated in [7,8] will be briefly reminded.

Mathematical morphology deals with the algebraic operations that involve shapes as operators [9]. There are different types of operands, depending on the representation of the shapes involved, but we focus on the mono dimensional case since the EEG signal falls in this category. There are two basic morphological operations that may be defined: erosion and dilation. Both of them are closely linked by two functions: one of them is in our case the time series represented by the EEG signal itself and the other a function called the structuring element. A structuring element may be – as far as its shape is concerned – a line, a circle, an ellipse, a square and, in general, any possible polygon or curve. The main restriction is its size, which must be adjusted to the one of the signal otherwise the whole operation leads to a complete hiding of the details, some of which might be important ones.

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Let us denote by E⊆ℝ and S⊆ℝ two sets of real numbers. The elements of the first one are the N samples of the EEG signal. The second, with M elements, M<N, named the structuring element, contains the sampled values of a function that describes, in the same coordinates as the first one, a certain geometrical shape. To introduce the basic morphological operations let us define two functions *f* and *s* as follows:

$$f:\{1,2...N\}\rightarrow E, f(k)=eeg_k, \tag{1}$$

where eeg_k denotes the k-th sample of an EEG sampled signal, while

$$s:\{1,2...M\}\rightarrow S, s(p)=R\cdot sin(2\cdot\pi\cdot p/M), \tag{2}$$

represents the M sampled values of the representation of a circle with radius R and centre C(0,0).

In what follows, we shall briefly review the standard morphological operators defined as functions as highlighted in [7], but with specific focus on EEG signals.

The erosion of function *f* by the structuring element *s* is defined as

$$(f\prec s)(k)=min_{p\in\{1,2...M\}}[f(k+p)-s(p)], \tag{3}$$

with k∈{1,2,…,N-M+1}. It is worth noticing that the above definition assures that the inequality

$$(f\prec s)(k)\le f(k) \tag{4}$$

always holds true.

The dilation with the same structure element is defined as

$$(f\propto s)(k)=max_{p\in\{k-M+1,...k\}}[f(p)+s(k-p)], \tag{5}$$

with k∈{M,M+1,…N}. As above, the following inequality takes place:

$$(f\propto s)(k)\ge f(k) \tag{6}$$

Let us emphasise that for both operations defined above, M values are not processed and appear unchanged in the result: at the beginning in the case of dilation and at the end for erosion.

The erosion and the dilation are applied usually in tandem, leading to the operations named opening

$$(f\circ s)(k)=((f\prec s)\propto s)(k), \tag{7}$$

and closing

$$(f*s)(k)=((f\propto s)\prec s)(k). \tag{8}$$

There are cases when operators like these are averaged to suppress the impulsive noise or to normalize the background of the signal [7,10].

We now define a new operator, named *weighted open-closing*, that is more versatile due to an additional factor, λ∈[0,1], named *emphasising parameter*:

$$(f\bullet s)(k)=\lambda\cdot(f\circ s)(k)+(1-\lambda)\cdot(f*s)(k). \tag{9}$$

The signs "·","+","-" denote the usual multiplication, addition, and subtraction between real numbers. The definition in (9) clearly shows that for the extreme values of λ, (zero and one) just the initial morphological operations are selected, closing for zero and opening for one. As a particular case, for λ = 0.5, the average of the initial operators is obtained. Due to the presence of the emphasising parameter λ, one is able to fine tune the operator to suit one's needs according to the task performed.

An important issue is the way in which the structuring element is adapted to the signal. A small structuring element leaves the signal with unwanted features that cover the real one, the P300 deflection; on the contrary, a greater one hides the features and a subsequent classification is practically impossible. To link the structuring element to the signal is not an easy task because there are several choices that may be taken into account, most of them belonging to the statistical characterization frame of the signal.

B. The data set

The EEG signals elicited during a Farwell-Donchin paradigm are usually recorded by means of electrodes placed on the scalp according to predefined positions in a so called 10-20 international system. It is well known that for a certain purpose not all the electrodes are of interest; therefore our study was focused only on Pz, Cz, Fz, Oz, POz, P3, P4, C3, C4, PO7 and PO8 electrodes [11]. This is in accordance with the already known zones of interest where P300 is elicited in a form that is suitable for further processing.

To illustrate the method, the second data set of EEG signals from the third BCI competition, as described in [12], was used. The reason of doing so is that they are publicly available, widely known and already used extensively; in this way, the results may be compared with other implementations based on the same data set.

There were two subjects that performed the experiment, named subject A and subject B. For each subject there are two sets of data: one is the train set and the other is the test one. The train set of data contains 85 epochs and the test one 100 epochs. An epoch corresponds to a target letter and to 12 random lightings – 6 for the rows and 6 for the columns – repeated 15 times. For the train data set, the letters the subject was asked to focus on are known and also his choice. For the test set, only the letters the subject was asked to elicit are provided by the organizers of the competition.

From the train set for subject B, the signals of each type, with and without the P300 event-related potential, averaged for the sake of clarity over 85 epochs, are presented as functions of time, for the Pz electrode, in Fig. 1 and Fig. 2.

As it is seen, in order to evidence the global behavior of the P300 potential, one need to get rid of small but the frequent

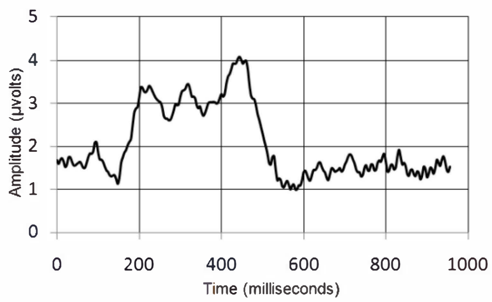

Fig. 1. The EEG signal with the elicited P300 vs. time for the Pz electrode.

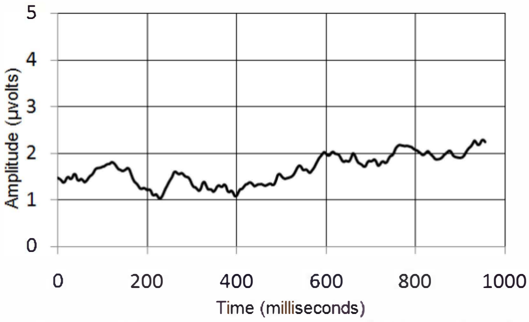

Fig. 2. The EEG signal without the elicited P300 vs. time for the Pz electrode.

variations of the EEG signal. This can be achieved by filtering, but in our case the filter itself is the morphological operator and its subsequent structuring element. There is also an important decision: what is the optimum number of samples that are taken into account? The mean is of the moving average type, since considering the averaging of the signal during a whole experiment is useless; even an interval around one second (i.e. 240 samples in our case) proved to be inadequate and led to poor results.

The mean of the entire signal used in the analysis plays an important role if it is subtracted from the original signal, providing a background normalization-like operation.

There is also another parameter that needs to be selected, the one expressing what *percentage* of the chosen statistical indicator should be used as the radius of the structuring element.

The results presented in the next section are a hint to the way in which the mean should be adopted, the length (i.e. the number of samples) on which it must be computed and what is the best percentage of the moving average used for the radius of the structuring element.

III. Results

A. The validation of the method

It is not our purpose to implement a new BCI system to deal with the classification task; speaking in the terms of [12], our contribution is focused only on "feature extraction" and therefore does not include our own classification method. For the classification step, we have used the method proposed in [6] as it was the best one of the BCI Competition III for the data set II. For short, the main advantage lies in using a set of offline support vector machine classifiers instead of a single one. The train sets was obtained by dividing the 85 runs into 17 partitions, each associated with 5 characters. The outputs of all the 17 classifiers are summed in order to get the result of classification. On the other hand, the test set, after handled in a similar manner as the train set, was fed to the ensemble classifier. The performances of our method are evaluated taking into account the accuracy of the predicted letter from the test set.

The proposed method has five factors that may be modified to maximize the rate of successful P300 detection: the structuring element, the morphology type, the length of the structuring element, the emphasising parameter and the percentage.

The initial tests were carried out using three types of structuring elements: a line (constant), a second degree function and a circle. The parameters that characterize the shape of the structuring element must be linked in a suitable manner to the signal itself. The tests showed that the best success rates in detection were obtained for the circle and only this case is taken into account.

We have studied the cases of opening and closing as morphology type, three values for the length, namely 5, 11 and 15 samples and two values for percentage, 1% and 10%. The results of the classification rates for these cases are illustrated in Table I. The best value for the classification rates is highlighted. So, we get three states in which the classification rates are equal to 83%, all of them using opening as morphology type, but for different combinations between the number of samples and the percentage used. Even the other combinations lead to a good result (only 1% lower). All the results when the closing morphology was applied are worse than the above mentioned ones.

The emphasizing parameter λ was used to influence the rate of success of the classifier. The results in the case when the value of the emphasising parameter was taken into account are reported in Table II. The same values for the other parameters as in the previous approach were handled. We see that some results are very near each other. As in previous table, a grey shadow marks the best result. We notice that 85% is the best classification rate and that there are four cases is which it is achieved, all for the emphasizing parameters equal to 0.6, 0.7 and 0.8. In (9) λ multiplies the opening morphological operator. This fact means that the best results are obtained when the opening is dominant.

B. A comparison with other methods

The described method doesn't fall exactly in a certain category, so a comparison is not an easy task: it is near the methods that filter the signal (because using the morphological operators implies major changes in the frequency content of the signal).

The outcome of the method in terms of success rate is more than satisfactory, according to the other detection methods, [12]. The classification performances when there were used a number of fixed electrodes are presented in Table III. If we compare it with [7], we see that a better value is attained when the morphological operator based method was applied (80% vs. 85%). Much better classification rate (96,5%) was reported in [7] in the case of channels selection from all the 64 electrodes. With this performance, the winner of the third BCI competition was [7], but supplementary steps need to be performed for this.

We shall briefly take into account the main stages found in the above mentioned methods and compare them with our own. The first is the so called signal pre-processing that implies low-pass filtering with a (usually) high order digital filter to eliminate the noise and the artefacts. This stage is not required since our method, by means of the morphological operators, eliminates not only the noise and the artefacts, but

TABLE I
THE CLASSIFICATION RATES FOR DIFFERENT MORPHOLOGY TYPES

Morphological operator	Number of samples	Percentage %	Classification rate %
Opening	5	1	82
	5	10	83
	11	1	83
	11	10	82
	15	1	83
	15	10	82
Closing	5	1	79
	5	10	80
	11	1	79
	11	10	80
	15	1	81
	15	10	80

TABLE II
THE CLASSIFICATION RATES FOR DIFFERENT EMPHASISING PARAMETERS

Emphasizing parameter (λ)	Number of samples (M)	Percentage %	Classification rate %
0.5	5	1	84
	5	10	81
	11	1	81
	11	10	81
	15	1	82
	15	10	83
0.6	5	1	84
	5	10	83
	11	1	84
	11	10	84
	15	1	84
	15	10	85
0.7	5	1	85
	5	10	84
	11	1	85
	11	10	83
	15	1	85
	15	10	84
0.8	5	1	81
	5	10	80
	11	1	84
	11	10	85
	15	1	84
	15	10	84

TABLE III
TABLE OF PERFORMANCES OF OUR METHOD AND OTHER RELATED METHODS

Method	Classification rate %
Other 5 methods	87,5-90.5
Other 4 methods	75.5-83
method in [7]	80
Our method	85

also those parts of the signal that are unnecessary for the P300 detection. Sometimes, a drifting correction or background normalization is performed; this stage is eliminated in our method by an adequate choice of the threshold used for detection: the mean value of the processed signal.

It is also worth remembering that the computing time for the whole algorithm is greatly reduced because of the nature of the computing operations performed: mostly comparisons for the morphological operations and sums for the computation of the mean. These facts show that the method is computationally inexpensive and fast. The decisive role in the speed lays in an adequate choice for the length of the structuring element. An optimum choice for M should take into account two contradictory requests: a greater M to eliminate the unnecessary parts of the signal and a smaller one for greater speed and a more detailed morphological processing.

Let us mention that in our study, the same parameters characterising the method were used for the signals acquired for all the electrodes. A real on-line investigation will certainly use different parameters (λ, the number of samples M used to compute the moving average and, possibly, the shape of the structuring element) for different channels, to maximize the overall success rate.

The final decision will be based on an aggregate of electrodes and an adequate classification method.

IV. CONCLUSION

A new method to detect the P300 related-event potential was developed based on the morphological operators like opening, closing and weighted open-closing. The analysis of the best proportion for the mixed signal used for the detection, by means of an appropriate choice of the emphasising parameter, was performed. The method behaves "naturally" because it acts like any human expert that extracts only the essential morphological features necessary to reveal the P300 event-related potential from a recorded EEG signal.

In conclusion, this research is devoted to advance in detection of the P300 potential with the ultimate goal to achieve better performances in a BCI speller paradigm.

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