Increased Signal to Noise Ratio in P300 Potentials by the Method of Coherent Self-Averaging in BCI Systems

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***Abstract*—**The coherent Self-Averaging (CSA), is a new method proposed in this work; applied to simulated signals evoked potentials related to events (ERP) to find the wave P300, useful systems in the brain computer interface (BCI). The CSA method cleans signal in the time domain of white noise through of successive averaging of a single signal. The method is compared with the traditional method, coherent averaging or synchronized (CA), showing optimal results in the improvement of the signal to noise ratio (SNR). The method of CSA is easy to implement, robust and applicable to any physiological time series contaminated with white noise.

***Keywords*—**Evoked potentials, wave P300, Coherent Self-averaging, brain - computer interface (BCI).

I. Introduction

BRAIN COMPUTER INTERFACE (BCI), is a communication system that allows by means of brain activity, control devices with no peripheral muscle activity [1]. Its main objective is to provide a person with severe motor disabilities, the ability to control mechanisms that enable greater independence, improving the quality of life and reducing the social costs [2]. The BCI system recognizes patterns in the brain activity of the user, registered by electroencephalography generally superficial (EEG) and translates them into commands [2], [3]. This identification is performed using various algorithms that process the signal and classified by the characteristics of the vector [4], [5]. BCI system consists of: 1) a block of instrumentation, which is acquired and EEG signal conditioner and/or evoked potentials (EP); 2) feature extraction, which generates a signal representing the pattern, which improves the performance of the classifier, and 3) a classifier that determines what class the new sample, taking into account the information that is extracted from the training set [6]. To measure the BCI system performance is evaluated classification accuracy, sensitivity and specificity [7].

One of the patterns of brain activity commonly used in BCI are event-related potentials (ERP). One of these potentials is the P300 wave [1], [8], [9], which is a variable amplitude positive peak occurring approximately 300ms after a stimulus that can be visual, auditory or somatosensory, described by Sutton in 1965 [10]. This wave is composed of two sub-waves known as: P3a originates from mechanisms of attention front led by stimuli during processing tasks, and P3b activity originates in the parietal-temporal associated with attention and seems to be related to the memory of post-processing [11].

There are many techniques at present to obtain the ERP, but the paradigm "Odd Ball" is the more usual [10], [12]. In this technique the patient is instructed the stimuli which are frequent and which the rare. The events of one of the categories are listed randomly so that the patient will not be able prediction once the stimulus is identified objective subject should perform a specific task [12]. The ERP obtained by the acquisition system is contaminated samples with potential of the activity of the eyes (EOG), muscles (EMG) [13] and different rhythms of the EEG, additionally there is pollution as technical motion artifacts, the voltage to 60Hz, thermal noise and noise of the instrumentation itself [14]. In such a way that the amplitude of the signal of ERP is much lower than the amplitude of the noise, this causes a significant decrease in signal-to-noise ratio (SNR) [15], for this reason, it is desirable to obtain more than one record or time, to discover the target signal.

The records obtained from the EEG can be represented by the model $x_k[n] = s[n] + r_k[n]$, where $s[n]$ is the signal P300 and $r_k[n]$ the noise, each record has a length of $1\leq n\leq N$, coherent averaging is done among the k -th epochs or records [16]. Although the coherent averaging is of great acceptance, it is essential to clarify that it has limitations. The most important is that it considers the evoked potential signal is repeated exactly the same in each era, this in most cases it is not true [17], in addition to assume that the noise is Gaussian and zero mean.

In this work we propose an algorithm based on coherent averaging that we call *Coherent Self-Averaging,* a method of analysis in the time to clean time series of white noise, the algorithm takes the signal and generates a straight line between samples separated by a value m, the resultant signal returns to enter again the algorithm, we call this process *epoch* such a way that the resulting signal becomes the input signal by K epochs. This method is applied to simulated signals P300 with different SNR and compared with the traditional method.

II. Methods

A. Method of Coherent Averaging (CA)

The records can be pre-processed with the coherent averaging or synchronized, one of the most commonly used techniques in the estimation of the wave P300, is to average

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the potential registered synchronized with the application of the stimulus. The (1) represents the coherent averaging, where $x_k[n]$ is the k-nth epoch of potential registered, *s[n]* isthe signal P300 with length $1 \leq n \leq N$,$r_k[n]$ is the *k*-nth signal with noise variance $\sigma^2$and *K* is the total number of epochs.

$$y_K[n] = \frac{1}{K}\sum_{k=1}^{K} x_k[n] = s[n] + \frac{1}{K}\sum_{k=1}^{K} r_k[n] \qquad (1)$$

In this context $r_k[n]$ is considered as the sum of random stationary signals with different variances, which are added by defining a resulting variance σ^2. For each time instant *n*, the term noise may be interpreted as an estimator of the average value of a sample of *K* data. Such average results in a new random variable that has the same average value and a variance σ equal toσ^2/K resulting in an improvement in the SNR by a factor of $\sqrt{K}$[16].

However, the method requires a large number of records or eras, which in practice are not necessarily identical, synchronous with a stimulus and are contaminated not only white noise but also of noise produced by other electrophysiological signals and motion artifacts.

B. Definition of the Coherent Self-Averaging (CSA)

For a time signal with N samples $\{x_0[n]: 1 \leq n \leq N\}$, given *m*, form the sequence $X_{1i}^n$with length N, such as:

$$X_{1i}^{n}[i, i+1, \dots, i+m] = \{p_m(i, i+1, \dots, i+m) + b_m\}, \qquad (2)$$

with $i = 1, 1+m, \dots, N-m$

And $X_{1j}^{n+1}$with length N, such as:

$$X_{1j}^{n+1}[j, j+1, \dots, j+m] = \{p_m(j, j+1, \dots, j+m) + b_m\}, \qquad (3)$$

with $j = 2, 2+m, \dots, N-m$

where *m* represents the number of consecutive samples of x_0, p_m is the slope of line formed between *n* and *n*+*m* signal $x_0$and b_m is the cut-off point on the vertical axis of line formed between *n* and *n*+*m*.

Taking to, X_{1i}^nandX_{1j}^{n+1}find the average of the values in each *n* sample of vectors with length N.

$$x_k[n] = \frac{X_{ki}^{n}[n] + X_{kj}^{n+1}[n]}{2} \qquad (4)$$

where k = 1, 2,…,K and represents the epochs of the coherent self-averaging.

C. Records Simulated

In this work were used ERP simulated signals generated a signal P300 (see Fig. 1). A wave with variable amplitude, negative peak in 100ms and predominant positive peak near the 300ms, with a sampling frequency of 1000 Hz. White noise was added at different times, each set of records with different relationship SNR, in all cases the noise was of magnitude greater than that of the simulated signal ERP.

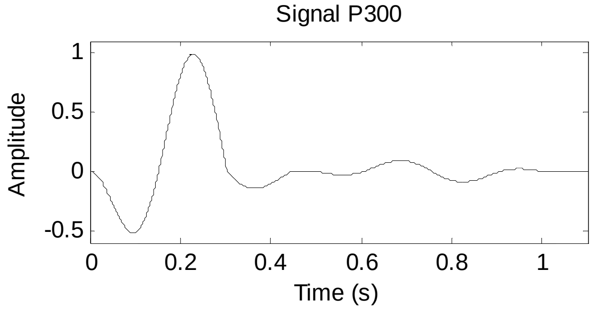

Fig. 1 Simulated Signal P300

D. Procedure

Applied the averaging method consistent (*coherent averaging* CA) with different eras: 100, 200, 300 and 400 to each group of records with different SNR. Four groups with 400 records each were analyzed: Group 1 with SNR of -10.7587dB (approx. 1:3), Group 2 with SNR of -16.7965dB (approx. 1:7), Group 3 with SNR of -24.7591dB (approx. 1:17) and Group 4 with SNR of -30.7662dB (approx. 1:34).

It took a signal randomly from each group and you have applied the method of self-coherent averaging (*coherent self-averaging* CSA), taking to *m=2*, with different iterations to called *epochs*, similar to CA. The SNR of selected signals in each group are: Group 1 signal with SNR of -10.1793dB, Group 2 signal with SNR of -16.7254dB, Group 3 signal with SNR of -24.9165dB and Group 4 signal with SNR of -30.7423dB.

The SNR of each process were obtained and compared both graphically and quantitatively.

TABLE I
SNR WITH THE METHOD CA

	SNR (dB) GROUP1	SNR (dB) GROUP 2	SNR (dB) GROUP 3	SNR (dB) GROUP 4
Original Signal	-10,7587	-16,7965	-24,7591	-30,7662
Epoch 100	9,8119	2,8641	-4,4697	-11,0494
Epoch 200	11,7402	6,5137	-1,5535	-7,7764
Epoch 300	14,5992	7,9601	-0,1642	-6,6453
Epoch 400	15,9329	8,8693	2,1331	-6,1792

TABLE II
SNR WITH THE METHOD CSA

	SNR (dB) GROUP1	SNR (dB) GROUP 2	SNR (dB) GROUP 3	SNR (dB) GROUP 4
Original Signal	-10,1793	-16,7254	-24,9165	-30,7423
Epoch 100	3,6763	-3,3303	-7,9913	-15,3594
Epoch 200	4,5248	-2,7482	-6,5304	-11,5639
Epoch 300	5,0008	-2,3647	-5,9438	-8,6151
Epoch 400	5,3759	-2,0539	-5,5902	-6,3310

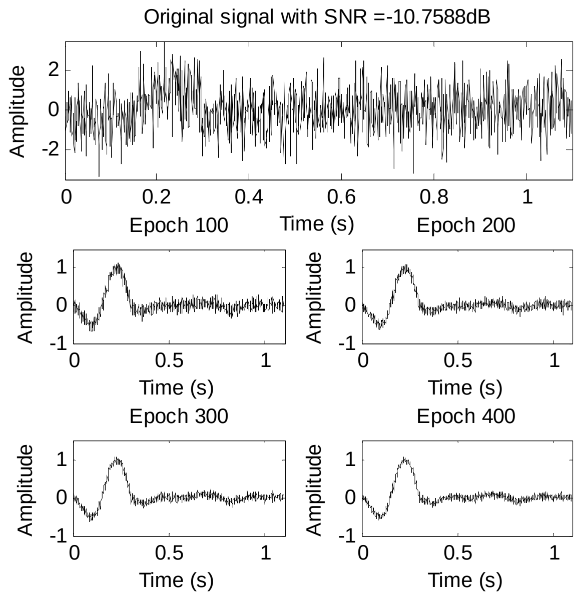

Fig. 2 A record of the Group 1, the results of the implementation of the method CA in the epochs 100, 200, 300 and 400

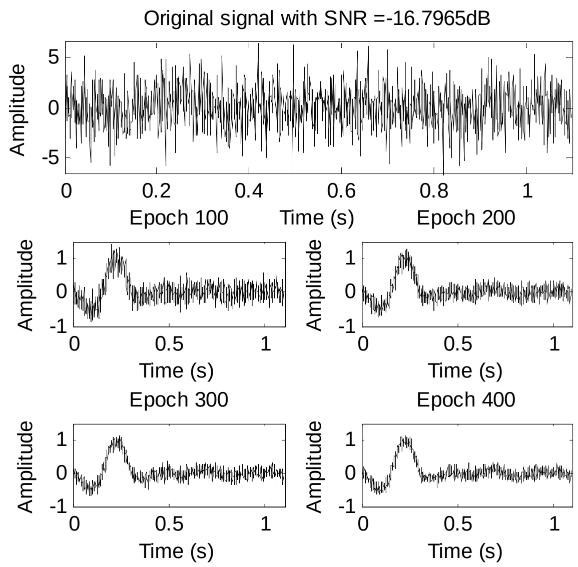

Fig. 3 A record of the Group 2, the results of the implementation of the method CA in the epochs 100, 200, 300 and 400

III. Results

With the method CA was obtained an increase in the SNR in all groups. In Figs. 2 and 3 are distinguished the P300 wave in each epoch 100, 200, 300 and 400 respectively. In Figs. 4 and 5 the P300 wave is less clear and is different for every time a positive wave in the period of latency. Table I shows SNR values in each epoch and each group.

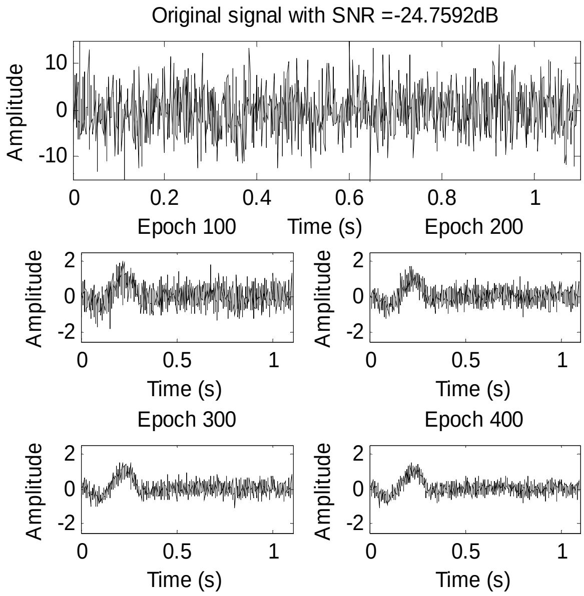

Fig. 4 A record of the Group 3, the results of the implementation of the method CA in the epochs 100, 200, 300 and 400

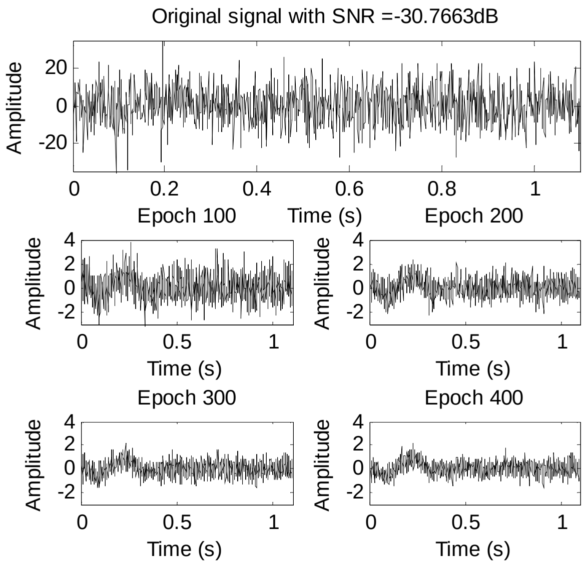

Fig. 5 A record of the Group 4, the results of the implementation of the method CA in the epochs 100, 200, 300 and 400

The implementation of the method CSA to each signal from each group also showed an increase of the SNR. In Figs. 6 and 7 the P300 wave is clearly distinguishable, in addition to this there is a decrease in the white noise, as well as its frequency. In Figs. 8 and 9 the P300 wave is not distinguishable. Table II shows the SNR values in every epoch and in every group.

In all cases the epoch400 showed the best results.

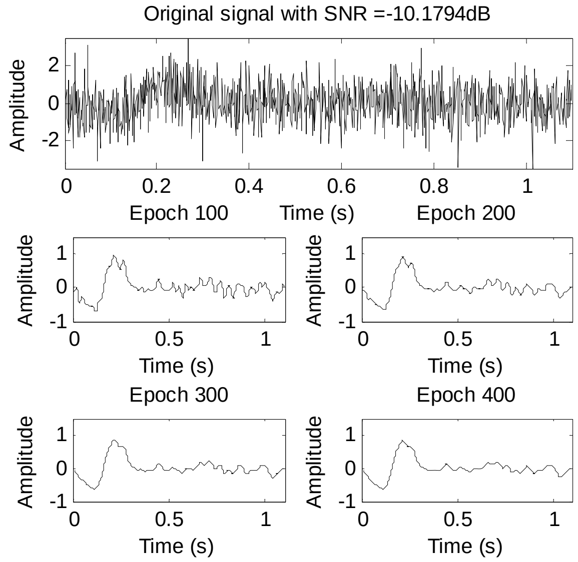

Fig. 6 A record of the Group 1, the results of the implementation of the method in the CSA epochs 100, 200, 300 and 400

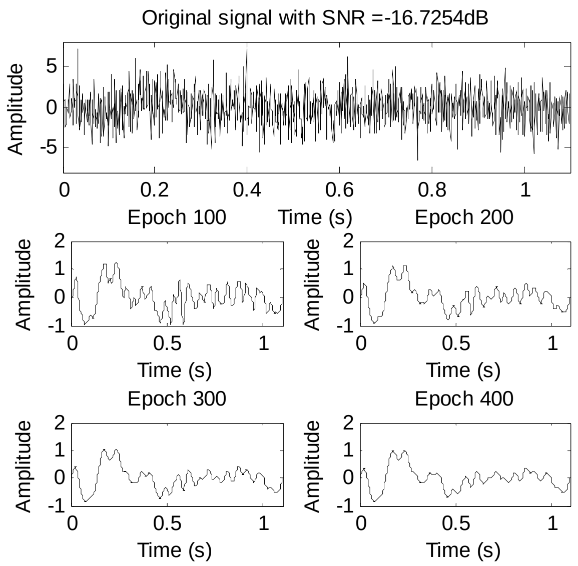

Fig. 7 A record of the Group 2, the results of the implementation of the method in the CSA epochs 100, 200, 300 and 400

IV. Conclusion

The two methods were increased in the SNR. However, the best results showed the method CA. The advantages of the coherent self-averaging (CSA) compared to the traditional method is that you only need a signal and not hundreds of signals, avoiding long training sessions for signals in the BCI system and immediate recognition of the signal hidden in the white noise. In other words, the characteristics in the time domain are extracted directly from the signal.

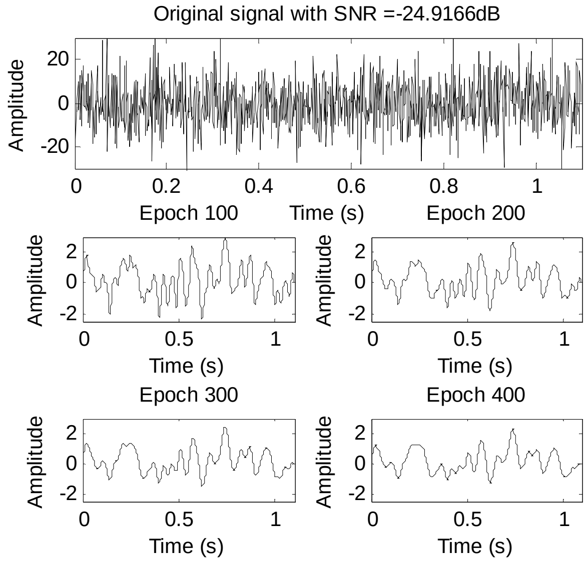

Fig. 8 A record of the Group 3, the results of the implementation of the method in the CSA epochs 100, 200, 300 and 400

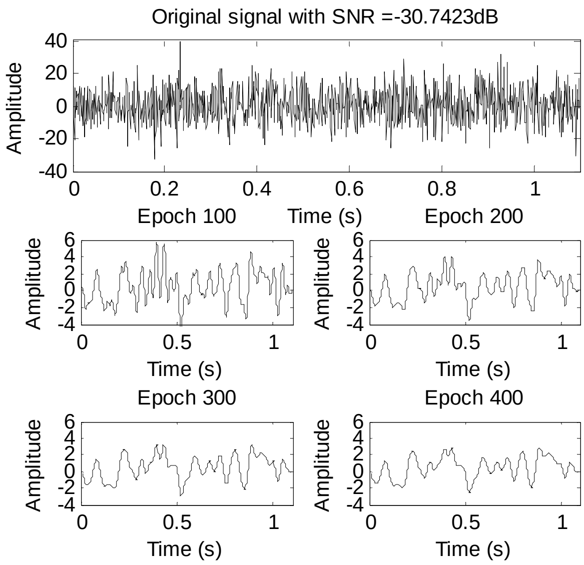

Fig. 9 A record of the Group 4, the results of the implementation of the method in the CSA epochs 100, 200, 300 and 400

In the CSA, increasing the number of iterations or "epochs" you can overcome the low values displayed in front of the CA. In addition the variation of the m-value may cause unwanted effects in the resulting signal.

Method CSA for not making any transformation is easy to deploy and requires little computational load. In addition, it can be used in time series of any kind where suspected contamination of white noise.

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