31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Single Trial Independent Component Analysis for P300 BCI System

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***Abstract*—A Brain Computer Interface (BCI) is a device that allows the user to communicate with the world without utilizing voluntary muscle activity (i.e., using only the electrical activity of the brain). It makes use of the well-studied observation that the brain reacts differently to different stimuli, as a function of the level of attention allotted to the stimulus stream and the specific processing triggered by the stimulus. In this article we present a single trial independent component analysis (ICA) method that is working with a BCI system proposed by Farwell and Donchin. It can dramatically reduce the signal processing time and improve the data communicating rate. This ICA method achieved 76.67% accuracy on single trial P300 response identification.**

I. Introduction

As human beings, we possess a wonderful ability of communicating with other people in the world. A healthy person can express his or her ideas, feelings and desires by speech, gesturing or writing. This communicating ability makes our daily life easy and enjoyable. However, there are some people being locked in their body for different reasons. They are fully conscious and aware of what is happening in their environment but totally lose their control over any voluntary muscles. Locked-in people are not able to communicate with other persons via traditional communication method. Fortunately, with the development of neuroscience and computer science, researchers have designed a lot of different brain computer interfaces to help locked-in people get their basic communicating ability back [1].

BCI is a channel established between the human brain and computer or other electronic equipments for communication and control purpose. To implement a reasonable and practicable brain computer interface there are two major prerequisites have to be fulfilled: 1. Signals that reliably describe several distinctive brain states have to be available, 2. These signals must be easily extracted and classified on-line [2]. Electroencephalography (EEG) signals meet these two prerequisites and they can be easily, noninvasively recorded, making EEG currently the best candidate for BCI system construction. There are two general types of BCI systems that have been developed by researchers using EEG as the information carriers and can be described as: Type 1: initiative BCI system [3][4][5], and Type 2: passive BCI system [6][7]. Initiative BCI system requires the subjects to learn to produce self-regulated, stable EEG signal, such as alpha or mu rhythm. This learning process will take several weeks and since there are only two states, on and off, available, it is not effective when performing multiple choices tasks. For the passive BCI system, the subjects will be given auditory or visual stimuli and generate response (event related potential) to those stimuli. The Event Related Potential (ERP) can be classified after several signal processing processes and used to identify the subjects' intent. One of the well-designed passive BCI systems, known as P300 speller, was proposed by Farwell and Donchin [6] in 1988. This BCI system utilizes the P300 component of the ERP to allow locked-in individuals to communicate without using any neuromuscular function. The P300 BCI speller presents a selection of characters arranged in a 6×6 matrix. The subject focuses attention on one of the 36 character cells of the matrix in which each row or column is being intensified in a random sequence. The row and column intensifications that intersect at the attended cell represent the target stimuli, which occur with a probability of 1/6. The rare presentation of the target stimuli in the random sequence of stimuli constitutes an Oddball Paradigm [8] and will elicit a P300 response to the target stimuli. With proper P300 feature selection and classification, the attended character of the matrix can be identified and communicated [9]. This BCI system has been widely used by researchers with different signal processing techniques including Stepwise Linear Discriminant Analysis (SWLDA) [9], Support Vector Machine (SVM) [10], Matched Filter [11] and Wavelet Analysis [12]. Our research is also based on P300 speller.

Although all the techniques mentioned above demonstrated notable performance, Dean J Krusienski *et al.* [13] conclude that SWLDA is the most accurate and practical processing method on data collected using the P300 speller paradigm. However SWLDA and other techniques share the same drawback. They need to average at least several trials to remove the background noises and enhance the magnitude of P300 response before applying the P300 classifier on EEG signal. This time consuming step greatly slows down the whole signal processing and therefore makes them not suitable for the online P300 classification with single trial. We need a fast and reliable processing technique that can perform the online P300 analysis accurately for effective communication. It becomes our motivation of designing algorithms of P300 analysis based on Independent Component Analysis (ICA).

ICA is a type of blind source separation method which can break a mixed signal down to statistically independent

Manuscript received April 7, 2009. This work was supported in part by the Multidisciplinary Research Graduate Education Enhancement Initiative Computational Tools for Discovery Thrust funding of University of South Florida.

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components by maximizing their non-Gaussianity. The components are related to different features of the signal. We can map them and determine which ones are connected with P300. In other words, ICA has the ability to reveal the hidden features even if they are buried in the background noise. This ability makes it possible to detect P300 via a single trial. In this article, we discuss an ICA based single trial P300 classification algorithm that has shown 76.67% accuracy for target identification in our study.

II. METHOD

2.1 Data Acquisition

The subject sat upright in front of a P300 speller, focused attention on a specified letter of the matrix on the display and silently counted the number of times the target character intensified, until a new character was specified for selection. The EEG was recorded using a cap (Electro-Cap) embedded with 16 electrode locations distributed over the entire scalp. The EEG was band pass filtered 0.1–60 Hz and amplified with an amplifier (20,000×), digitized at a rate of 160 Hz.

2.2 Data Structure

The rows and columns were intensified for 75 ms with 100 ms between intensifications. Because of the delay of P300 occurrence, the EEG signal segments from 175 ms to 350 ms following each intensification are used as our experiment segments. 480 segments from each channel including 80 from target flash (the intensification of row or column that contains the desired character) and 400 from non-target flash (the intensification of row or column that does not contain the desired character) were extracted for the offline analysis.

Table 1: The EEG data structure in our experiment

Total number of EEG segments	480×16	Segment length	175 ms
Sampling Frequency	160 Hz	Number of samples in each segment	28
Intensification Duration	75 ms	Interval Time	100

2.3 Processing Flow

The processing flow used in this work is given in Fig 1.

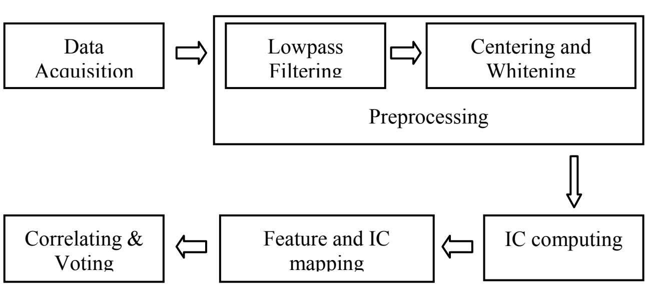

Fig 1: The processing flow

The details of the sub-blocks are discussed in the following sections.

2.4 Preprocessing

a. All the extracted EEG signals from the 16 channels (electrodes) are low pass filtered to remove the background noise with cut-off frequency setting as 10Hz.

b. Before the independent components (ICs) of the EEG signals being computed, the observed vector x of EEG signals need to be centered and whitened to make its components uncorrelated and their variances equal unity. The whitening transformation is done by using the eigenvalue decomposition (EVD) of the covariance matrix $\varepsilon\{xx^T\}=EDE^T$, where E is the orthogonal matrix of eigenvectors of $\varepsilon\{xx^T\}$ and D is the diagonal matrix of its eigenvalues. The whitening can now be expressed as:

$$\tilde{x} = ED^{-1/2}E^T x \tag{1}$$

If we express x as:

$$x = As \tag{2}$$

where s is the independent components vector and A is the linear transformation from s to x, then we have:

$$\tilde{x} = ED^{-1/2}E^T As = \tilde{A}s \tag{3}$$

It can be easily verified that the new transformation matrix $\tilde{A}$ is orthogonal. Hence the number of parameters needs to be estimated reduced from n^2 (the number of elements in the original matrix A) to about n(n-1)/2 ($\tilde{A}$ contains only n(n-1)/2 degree of freedom) [14].

2.5 Independent Component Analysis

Independent component analysis (ICA) is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals. It is a good solution for the Blind Source Separation (BSS) problem. For example, two speakers (S_1 and S_2) speak simultaneously in a room with two recorders (R_1 and R_2) recording their speech at different location in the room. The recorded signals, $R_1(t)$ and $R_2(t)$, can be expressed like this:

$$\begin{aligned} R_1(t) &= a_{11}S_1(t) + a_{12}S_2(t) \\ R_2(t) &= a_{21}S_1(t) + a_{22}S_2(t) \end{aligned} \tag{4}$$

If we know the values of a_{11}, a_{12}, a_{21} and a_{22}, we can solve these equations for S_1 and S_2. Unfortunately these weights (a's) are unknowns and these equations can only be solved under the assumption that S_1 and S_2 are independent non-Gaussian signals by Independent Component Analysis. This is a famous example of "cocktail party" problem. Obviously, EEG signal analysis is a type of "cocktail party" problem. The electrodes "record" the mixed EEG signal at different locations around the scalp. Therefore, it is reasonable to apply ICA on EEG signal to identify those independent sources and map them to P300.

There are a lot of ICA algorithms available, such as Infomax[15], JADE[16] and FastICA[17]. All of them can successfully compute the independent components by maximizing the non-Gaussianity or *negentropy*, which is a measurement of non-Gaussianity [18], of the ICs. In our research, we choose FastICA to perform ICA because it converges much faster than other algorithms with high reliability.

We use the average of 400 of preprocessed 175ms EEG signals from non-target flash as the "standard non-target flash" signal, denoted as x_{nt}. Similarly, the average of 80 preprocessed EEG signals from target flash is set as the "standard target flash" signal, denoted as x_t. By applying FastICA, the independents components vector s and the mixing matrix A of x_t can be computed and expressed as:

$$x_t = A_t s_t \tag{5}$$

The vectors in s_t are used as the "standard independent components set" of the EEG signal and A_t is used as the "standard coefficients matrix" showing the activation status of the ICs underlying in x_t. Here we made an assumption that the EEG signal from target flash contains more components than those from non-target flash. This is reasonable since the EEG signal of target flash is constituted of "background noise" and P300 response while the EEG signal of non-target flash is constituted of "background noise" only. By substituting s_t and x_{nt} in equation (2), we can solve for A_{nt} that shows the activation status of the ICs underlying in x_{nt}. We inspected A_{nt} and A_t and noticed the significant differences between them. The coefficients of some ICs are much larger in A_t than they are in A_{nt}. It implies that some of the ICs in the standard ICs set are strongly related to P300 response.

This conclusion was confirmed by inspecting 480 individually computed activation matrices A of 80 target and 400 non-target flashes. Most of them somehow follow the "activation pattern" mentioned before. In this work, we selected 3 ICs with the largest difference of their coefficients in A_{nt} and A_t as the P300 related ones. The activation status of these 3 ICs in different channels will be used as the feature for P300 identification.

2.6 Correlation Method and Majority Vote Scenario

In our experiment, 16 ICs were computed and 3 of them, IC 2, 4 and 11, were considered having strong relation to P300. Their "activation pattern" in all the 16 channels of the standard target/non-target flash are investigated and recorded as the reference pattern of target/non-target flashes. For an unknown incoming flash, its activation matrix will be computed and the "activation pattern" of IC 2, 4, and 11 will be extracted. If it is a target flash, the activation pattern of the P300 related ICs should be more similar to the target reference pattern, otherwise the activation pattern should be more like the non-target reference pattern. We use Pearson product-moment correlation coefficient ρ as the measurement for the similarity.

$$\rho = corr(i, r) \tag{6}$$

where i is a vector that represents the activation status of a chosen IC of an incoming signal, r is a vector that represents the activation status of the same IC in the target or non-target reference. According to the distribution of the correlation value ρ, we can appropriately choose the threshold value t *that maximizes the* correct target/non-target identification rate. We performed 1 and 3 ICs based identification in this work. The general classifying criteria can be expressed as:

$if \sum_j \rho_j \geq t$, the incoming signal is a target, otherwise it is a non-target. (7)

where j = 1 or 3, ρ_j is the correlation value according to the *j-th* P300 related IC. For 1 IC (IC4) based identification, t was set as 0.2 and for 3 ICs (IC2, IC4 and IC11) based identification, t was set as 0.5. (All the threshold values were chosen by maximizing the correct identification rate. Different subjects may have different threshold values according to their individual ρ *distribution.*)

Other than directly summing the correlation values from corresponding ICs, we also use 3 P300 related ICs to vote according to the following voting criteria:

If $\rho_1 \geq t_1$ vote for target, otherwise vote for non-target.

If $\rho_2 \geq t_2$ vote for target, otherwise vote for non-target.

If $\rho_3 \geq t_3$ vote for target, otherwise vote for non-target.

where ρ_1, ρ_2 and ρ_3 are correlation values that correspond to IC2, IC4 and IC11 respectively. t_1=0.3, t_2=0.2 and t_3=0.34. The majority vote of them will determine the label of an incoming EEG signal.

III. Results and Discussion

The results of our experiment are shown in Table 2, Table 3 and Table 4.

Table 2: Result of 1 IC (IC 4) based correlation method

Category	Correctly Classified	Incorrectly Classified	Total	Accuracy	Error Rate
Target	21	9	30	70%	30%
Non-target	19	11	30	63.3%	36.7%

Table 3: Result of 3 ICs (IC 2, 4, and 11) based correlation method

Category	Correctly Classified	Incorrectly Classified	Total	Accuracy	Error Rate
Target	23	7	30	76.7%	23.3%
Non-target	21	9	30	70%	30%

Table 4: Result of 3 ICs (IC 2, 4, and 11) based voting

Category	Correctly Classified	Incorrectly Classified	Total	Accuracy	Error Rate
Target	23	7	30	76.7%	23.3%
Non-target	22	8	30	73.3%	26.7%

The 1 and 3 ICs based correlation method and 3 ICs based voting scenario were tested by 60 EEG signals including 30 from non-target flash and 30 from target flash. For 1 IC based correlation method, with t = 0.2, we achieved 70% and 63.3%

accuracies for target and non-target identification, respectively. For 3 ICs based correlation method, with $t = 0.5$, these accuracies increased to 76.67% and 70%, respectively. The majority voting scenario provided the best identification accuracies of 76.67% and 73.3% for target and non-target, respectively. In our research we prefer to reduce the type II error because if we fail to identify a target flash, the identification process can be repeated till the target successfully identified. But if a signal is falsely identified as "Target", this error will not be realized until the final character selection. Considering this, we may reduce the type II error by decreasing the t value. However, the tradeoff is that the processing time will increase due to repetition. The P300 based single trial ICA algorithm significantly reduces the processing time by removing the time consuming step due to "averaging" used in other algorithms. Furthermore, our algorithm will stop and start the next "Target searching" whenever it hits a "Target". Thus the expecting target identifying time is given by $\varepsilon(t) = 3.5\ flashes = 175\times3.5 = 612.5\ ms$, which is approximately 1/10 of the best processing time achieved by SWLDA [19]. Moreover, in the comparison of bit rate according to Wolpaw's definition [20], our method achieved 129.4 bits/min while SWLDA achieved 33.8 bits/min.

There is still room for improving the processing speed and accuracy by optimizing the algorithm. For example, we can weigh the voters or modify the voting rule to improve the performance of voting. In our experiment, we made an assumption that the P300 response occurs between 175 ms and 350 ms following a target flash, which is not true for some subjects because in some cases P300 shows up in the 350 ms to 500 ms range. This problem can be solved by using appropriate flashing and interval time. The P300 related ICs may vary in each individual subject, both in number and "pattern". We need to study more cases to test the robustness of this method. We are planning to optimize our algorithm by applying appropriate filter during preprocessing, solving the non-stationary problem [21] and involving statistical models in our future work. Our goal is to further improve the accuracy of the single trial P300 analysis algorithm to make it more suitable for real-world applications and clinical use.

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