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Extraction of P300 Using Constrained Independent Component Analysis

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***Abstract*— A brain computer interface (BCI) uses electrophysiological activities of the brain such as natural rhythms and evoked potentials to communicate with some external devices. P300 is a positive evoked potential (EP), elicited approximately 300ms after an attended external stimulus. A P300-based BCI uses this evoked potential as a means of communication with the external devices. Until now this P300-based BCI has been rather slow, as it is difficult to detect a P300 response without averaging over a number of trials. Previously, independent component analysis (ICA) has been used in the extraction of P300. However, the drawback of ICA is that it extracts not only P300 but also non-P300 related components requiring a proper selection of P300 ICs by the system. In this study we propose an algorithm based on constrained independent component analysis (cICA) for P300 extraction which can extract only the relevant component by incorporating *a priori* information. A reference signal is generated as this *a priori* information of P300 and cICA is applied to extract the P300 related component. Then the extracted P300 IC is segmented, averaged, and classified into target and non-target events by means of a linear classifier. The method is fast, reliable, computationally inexpensive as compared to ICA and achieves an accuracy of 98.3% in the detection of P300.**

I. Introduction

Recently, a new technology has emerged enabling direct communication between human brain and computer, known as brain-computer interface (BCI). This is done by utilizing certain electrophysiological activities that reflect the function of the brain [1]. BCI using non-invasive means has been a subject of much research and certain natural rhythms such as alpha and beta-rhythms have been used for BCI [2][4][5]. However, the main drawback using these natural brain rhythms in BCI is that they require extensive training for controlling the natural brain waves. That is why the usage of evoked potentials (EP) for BCI is being extensively researched as they do not require subject training. P300 is a positive EP that is elicited approximately 300ms after an attended external stimulus.

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In 1988, Farwell and Donchin first introduced the idea of using P300 in BCI. They introduced some P300 detection methods for BCI such as stepwise discriminant analysis (SWDA), peak picking, area and covariance [3]. Later Donchin added discrete wavelet transform (DWT) to SWDA [6]. P300 detection usually requires extensive averaging and more the number of trials the better the accuracy and reliability of the BCI system. However, increasing the number of trials increases the processing time for detection, which is one drawback of the P300-based BCI.

Recently, independent component analysis (ICA) has been used for the extraction of P300 signals in [7] and [9]. ICA is a statistical technique that is used to separate a mixture of signals into its components provided that the components are independent of each other [8]. The main drawback of ICA is that the number of components is equal to the number of observations. Therefore, one has to apply additional signal processing methods to ascertain which components contain the P300 response. Spatially constrained ICA (scICA) is a semi-blind source separation technique which extracts only the relevant sources and has been previously used for the detection of P300 in [10]. scICA incorporates *a priori* information of the typical P300 spatial distribution. The spatial distribution is found by running ICA on the available dataset and creating a template, which is used as a single spatial constraint to constrain the mixing matrix. Hence, one has to train the spatial constraints before extracting the desired P300 sources. In this study, we propose to use constrained ICA (cICA) described in [11] and [13] for P300 extraction. The advantage of cICA is that it can extract only the relevant source blindly, without any training of the constraints being applied. The potential of cICA has already been investigated in other areas like extraction of rhythmic activity [12] and artifact rejection [13].

II. Methodology

A. Constrained ICA

ICA is a statistical technique used to separate independent sources, assuming the sources are linearly mixed. If we assume that the sources are $\boldsymbol{s(t)} = [s_1(t), s_2(t), \dots, s_n(t)]^T$ and observations are $\mathrm{x}\boldsymbol{(t)} = [x_1(t), x_2(t), \dots, x_n(t)]^T$, then the linear mixture can be represented by

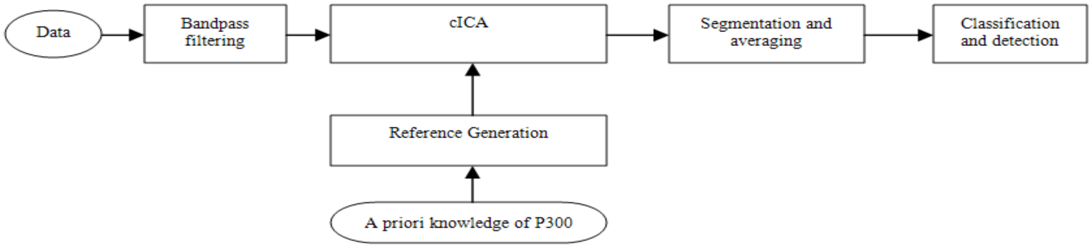


Fig. 1. Flowchart describing the steps of the P300 extraction process via cICA

$$\mathbf{x(t) = As(t)} \quad (1)$$

where $\mathbf{A}$ is the mixing matrix. The ICA finds a de-mixing matrix such that

$$\mathbf{s(t) = Wx(t)} \quad (2)$$

where $\mathbf{W} = [w_1, w_2, w_3, ..., w_n]$ is the de-mixing matrix. The problem with ICA is that the number of channels are assumed to be equal to the number of independent sources. In our problem we require only the component associated with P300. The cICA algorithm enables us to extract the required component by incorporating *a priori* information of the desired source [11]. In this case, *a priori* information is called a reference signal which carries the information of the desired source. The reference signal must be close enough to the desired signal so that the cICA can converge to the particular independent component (IC). Let the reference signal be denoted by $r(t)=[r_1(t),r_2(t),...,r_n(t)]^T$. The closeness constraint used for extraction of single IC is

$$g_i(\mathbf{w}_i) = \varepsilon(\mathbf{w}_i^T\mathbf{x}, r_i) - \xi \leq 0 \quad (3)$$

where ε is some closeness measure between the estimated output $\mathbf{w}_i^T\mathbf{x}$ and the reference signal r_i and ξ is the closeness threshold parameter. The measure of closeness used in our implementation of the algorithm is mean-squared error (MSE) and we used the same method as described in [11] to adjust the value of thresholding parameter. With the constraints in place, the constrained ICA algorithm with multi-reference comes down as follows:

$$\begin{aligned} &\textit{maximize:} \quad C(\mathbf{y}) = \sum_{i=1}^{k} J(y_i) \\ &\textit{subject to:} \quad g(\mathbf{W}) \leq 0, \quad h(\mathbf{W}) = 0 \end{aligned} \quad (4)$$

where

$$J(y_i) \approx \rho[E\{G(y_i)\}-E\{G(v)\}]^2 \quad (5)$$

denotes the ICA contrast function [8], k is the number of reference signals, $y_i = \mathbf{w}_i^T\mathbf{x}$ is the estimated output, ρ is a positive constant, v is a zero mean and unit variance gaussian variable, $G(.)=logcosh(.)$ is non-quadratic function described in [8], $g(\mathbf{W})$ is closeness constraint and $h(\mathbf{W})$ constrains the outputs to have a unit variance. We used the augmented Lagrangian approach as described in [11] to find the demixing matrix $\mathbf{W}$.

B. Dataset

We used the BCI competition 2003 dataset IIb [14] provided by the Wadsworth center for our experiment. In this dataset, the user was presented with a 6 x 6 matrix of characters. The dataset consists of 64 EEG channels in which the user's task was to focus on characters in a word that was prescribed by the investigator. For each character, the user display was as follows: the matrix was displayed for a 2.5 s period and during this time each character had the same intensity. Subsequently each row and column in the matrix was randomly intensified for 100ms. After intensification of a row or column, the matrix was blank for 75ms. Row or column intensifications were block randomized in blocks of 12. Each set of 12 intensifications was repeated 15 times for each character. Each sequence of 15 sets of intensifications was followed by a 2.5 s period, during which the matrix was blank.

C. P300 Extraction via cICA

The main steps for our algorithm are described in Fig. 1, which are detailed as follows:

1) Bandpass Filtering: The data was bandpass filtered from 0-10 Hz because spectral analysis showed P300 to be within this frequency range.

2) Reference Signal Generation: A reference signal was generated for each of the 6 rows and columns separately. The reference signal for one particular row or column consisted of a rectangular pulse within 250 to 350 ms interval after the stimulation of that particular row or column. As each block contains 15 repetitions of each row or column so the reference signal consists of 15 pulses. So a total of 12 reference signals were generated.

3) cICA: cICA was applied on the block of data by using the reference function generated in order to detect which rows or columns elicited P300 responses. As we generated a reference signal for each row or column, hence in effect we derive 12 ICs from the cICA algorithm.

4) Segmentation and Averaging: From the beginning of stimulation of the particular row or column each IC was

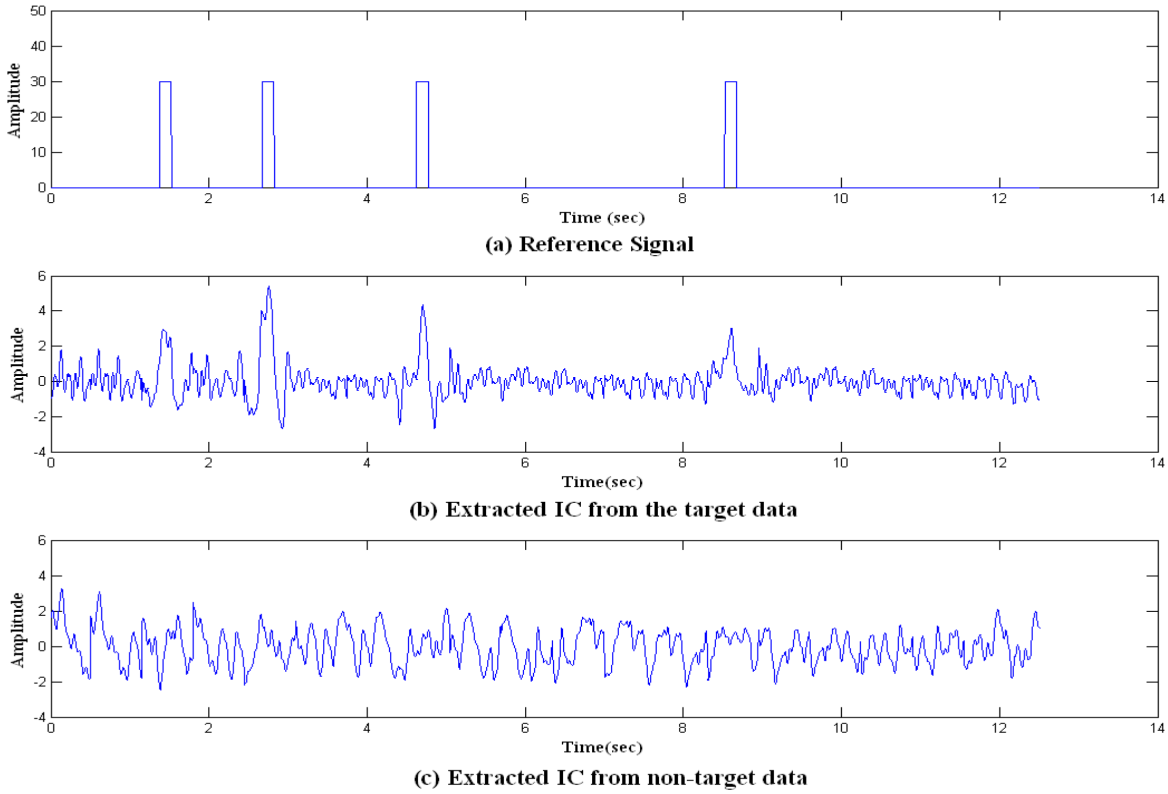
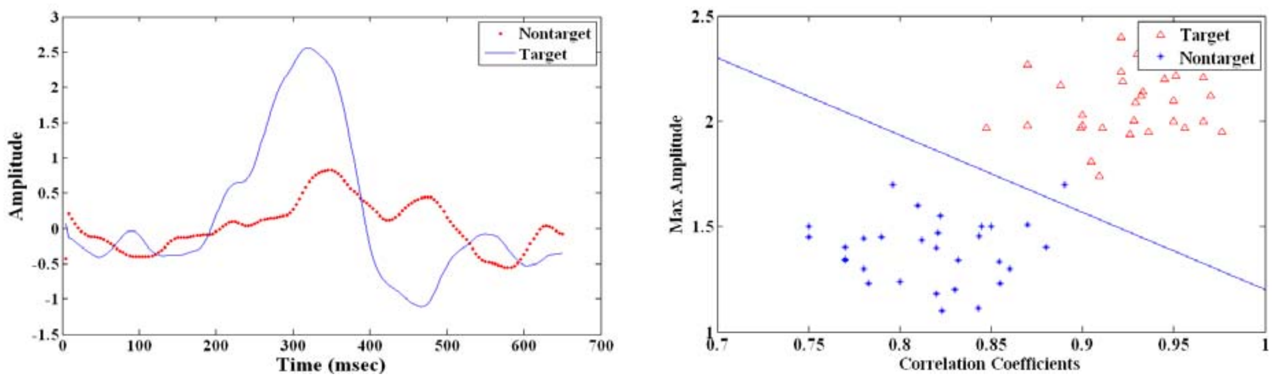


Fig. 2. (a) A part of reference signal showing 4 pulses (b) Corresponding extracted IC from target data (c) Corresponding extracted IC from non-target data



(a) (b)

Fig. 3. (a) Comparison of averaged segment containing P300 and non P300 signals (b) Plot of feature space with a linear classifier

segmented into 15 epochs of 650 ms intervals and averaged.

5) P300 Detection: Each averaged segment was correlated with a P300 template. The correlation coefficients and maximum amplitude of the averaged segment were used as features to classify the events into the target and non-target events.

A linear classifier was designed which was able to classify the target and non-target events successfully. The feature with the classification boundary is illustrated in Fig. 3(b).

III. Results

Before the application of cICA, the existence of P300 was confirmed by averaging target and non-target events at the electrode channel Cz. Fig. 2(a) shows a portion of the reference signal generated for a specific row or column. The extracted components by using the cICA algorithm are illustrated in Fig. 2(b) and Fig. 2(c). The extracted IC containing P300 responses is shown in Fig. 2(b). It can be seen from the figure that P300 can be extracted quite effectively using this technique. Fig. 2(c) shows the extracted IC for the non-target event. In order to increase the reliability and the accuracy of the algorithm we segment the target events into 15 epochs and perform averaging to improve the SNR. Fig. 3(a) shows a comparison of the resulting P300 from the extracted signal after averaging, for both target and non-target events. Using this algorithm, we were easily able to separate the target and non-target events by the means of a simple linear classifier, as illustrated in Fig. 3(b). The linear classifier was trained with 10 target and 10 non-target events. We used 30 target and 30 non-events in the testing phase and achieved a 98.3% accuracy. Accuracy can be increased if a more complex classifier was used.

IV. Discussion and conclusion

Our P300 extraction based on cICA gives better performance as compared to other methods such as ICA. In the conventional ICA, signal is decomposed into several components depending on the number of multichannel observations and most of them do not contain P300 information. In our algorithm, cICA converges only on that independent component containing P300 information, thereby reducing the computation needed to extract P300 signal without compromising the reliability and accuracy of P300 detection and extraction. With a typical Pentium IV personal computer, ICA takes about 45 seconds to extract all the components whereas cICA run on the same data can extract the desired component in only 2 seconds. Hence, we can achieve a better communication rate by using, the cICA method in a P300-based BCI system which will be tested in our future work.

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