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An Improved P300 Extraction using ICA-R for P300-BCI Speller

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Abstract— **In this study, a new P300 extraction method is investigated by using a form of constrained independent component analysis (cICA) algorithm called one-unit ICA-with-reference (ICA-R) which extracts the P300 signal based on its prior temporal information. The main advantage of this method compared to the existing ICA-based method is that the desired P300 signal is extracted directly without requiring partial or full signal decomposition and any post-processing on the outcome of the ICA before the P300 signal can be obtained. Since only one IC is extracted, the method is computationally more efficient for real-time P300 BCI applications. In our study, when tested on the BCI competition 2003 dataset IIb, the current state-of-the-art performance is maintained by using the one-unit ICA-R. Besides that, the ability of the method to visualize P300 signals at the single-trial level also suggests it has potential applications in other types of ERP studies.**

I. INTRODUCTION

In recent years, a new emerging technology known as Brain-Computer Interface (BCI) has been developed. This technology utilizes specific neural signals to facilitate communication and control between humans and computers. One of the widely used neural signals for BCI is P300, a kind of event related potential (ERP) which appears as a positive wave and normally occurs 300 ms after attending to a rare stimulus. In P300 BCI, it is a requirement to have a fast and reliable ERP detection response which requires shorter training periods and instantaneous interaction between humans and computers. However, detecting a P300 signal directly from raw EEG is still a challenging task because of the non-stationarity nature of the signal and the noise contamination from ongoing background EEG activities. As a result, this has led to the emergence of research which aims at finding an effective way to extract P300 signals such that the background EEG is attenuated and the P300 signal can be easily detected.

Different types of single-trial ERP extraction techniques have been proposed over the years. One of the more successful techniques is Independent Component Analysis (ICA). The ability of ICA in extracting P300 signals has been successfully demonstrated in [1]. In addition, the application of ICA has resulted in a remarkable breakthrough in classification performance for early P300 BCI [2]. However, the implementation of ICA is impractical for real-time situations due to the fact that traditional ICA does not extract the desired ERP in a straightforward manner. After decomposition, it often requires manual selection of the extracted source signals [1][3][4] or manipulation of the ICA subspace [2] before the ERP can be extracted successfully. Hence, different approaches for guiding the selection have been proposed to overcome this weakness. One of the increasingly popular method is constrained ICA (cICA) which extracts the desired signal by utilizing prior information of the signal such as the spatial pattern [5] and the time course of the desired signal [6]. The application of such an ICA with promising results has been reported in the biomedical signal processing fields such as artifact rejection [7] and rhythmic activity [8].

Lately, a similar effort is also proposed for the P300-BCI speller [9] where a variant of cICA named ICA-with-Reference (ICA-R) [6] is applied for P300 extraction. In [9], assuming that a traditional 6 x 6 P300 speller matrix of characters is used, 12 reference signals are first generated with rectangular pulses to represent a 250-350 ms time region of a row/column stimulation in a character signal block. Twelve independent components (ICs) are then extracted by performing ICA-R on the given signal block using the 12 reference signals. Since there will be two reference signals that coincide with the P300 signal waveform from the target row and column, the extracted ICs that correspond to the target row and column will contain the P300 signal. Thus, to identify the target row and column, one EEG epoch is extracted from each IC according to the onset of the row/column stimulation it represents. Then, a classifier is applied for P300 detection. Although the described method can achieve a decent classification performance in P300 detection and only extract a subset of ICs compared to traditional ICA-based method, the requirement of applying ICA-R exhaustively on each testing data makes it less attractive for real-time BCI applications.

In this paper, we investigate an implementation of the ICA-R algorithm for P300 extraction that is computationally more efficient than the one reported in [9]. Firstly, as in previous implementations, we propose to apply ICA-R only during the training phase. Secondly, instead of using ICA-R with 12 reference signals as in [9], which resulted in 10 redundant and unrelated ICs being extracted together with the target ICs, we propose to use one-unit ICA-R [6] to extract specifically the P300 IC. This is done by using a single reference signal to indicate the expected time span of the target P300 signal. Then, during the detection stage, assuming that the characteristic of P300 signals does not change across sessions, the demixing vector obtained from the training phase is applied on each test data to extract the P300 signals. The advantages of using the proposed method are: 1.) Since ICA-R is only performed during the training

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stage, the method is faster than [9], 2.) Given that only one IC is required to be extracted, the proposed one-unit ICA-R method requires less computation compared to [9] and other traditional ICA-based methods, 3.) Since the extraction is directed at the P300 signal, there is no post-processing step as in traditional ICA-based method [2][3][4] before an IC can be used.

II. METHODOLOGY

A. One-unit ICA-with-Reference (ICA-R)

ICA is a type of blind source separation technique that recovers a set of source signals from a set of measured signals. It assumes the measured signals, $\mathbf{x}(t) = [x_1(t), x_2(t), ..., x_N(t)]^T$ are linear instantaneous mixtures of source signals, $\mathbf{s}(t) = [s_1(t), s_2(t), ..., s_N(t)]^T$, and that there are equal number of measured signals and source signals, such that $\mathbf{x}(t)$ can be defined as $\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t)$ where $\mathbf{A}$ is the mixing matrix. Assuming the source signals are statistically independent, traditional ICA tries to find a demixing matrix, $\mathbf{W}$ to recover all the source signals such that the source, $\mathbf{s}(t) = \mathbf{W}\mathbf{x}(t)$ are maximally independent. Each resultant source signal is also known as an independent component (IC). In our case, since only the P300 signal is of interest, the full ICA decomposition is unnecessary.

Here, a one-unit ICA-R algorithm is chosen to find a demixing vector, $\mathbf{w}$, such that an IC, $y(t) = \mathbf{w}^T\mathbf{x}(t)$, that is closest to our desired signal is recovered by incorporating prior information of the desired signal which is carried inside a reference signal, $r(t)$. For simplicity of formulation, the time index, t is omitted in the following.

The cost function of a one-unit ICA-R based on the approximation of negentropy [10] is defined as [6]:

$$\max_{\mathbf{w}} \quad J(\mathbf{w}) = [E\{G(y)\} - E\{G(v)\}]^2$$
$$s.t. \quad g(\mathbf{w}) = \varepsilon(y, r) - \xi \leq 0, h(\mathbf{w}) = E\{y^2\} - 1 = 0 \quad (1)$$

where $G(.)$ can be any non-quadratic function as given in [10], $E\{.\}$ is the time average of samples, v is a Gaussian variable with zero mean and unit variance, g($\mathbf{w}$) is the closeness measure between the extracted signal, ξ is the threshold of closeness measure, y and reference signal, r. h($\mathbf{w}$) is the equality constraint which ensures $J(\mathbf{w})$ and $\mathbf{w}$ are bounded.

In this paper, the augmented Lagrangian approach for the cost function in (1) derived by [6] is applied. The contrast function, $G(y) = log(cosh(y))$ is chosen for negentropy estimation and the mean square error (MSE) is used for the closeness measure where $g(\mathbf{w}) = E\{(y - r)^2\} - \xi$. In traditional ICA, the column of a mixing matrix, $\mathbf{A} = \mathbf{W}^{-1}$ usually conveys the topographic information of an IC. However, this spatial pattern cannot be obtained in one-unit ICA-R by inverting $\mathbf{w}$. Hence, in this paper, the least square estimate of a spatial pattern (or mixing vector), $\mathbf{a}$, from an IC is used:

$$\mathbf{a} = \frac{\mathbf{X}y^T}{yy^T} \quad (2)$$

B. Design of a Reference Signal

The design of a reference signal is crucial when trying to extract a signal using ICA-R. To ensure the quality of extraction, the reference signal needs to match the desired signal as close as possible. One of the commonly used method is generating rectangular pulses to coarsely represent the time course of a desired signal [6][7]. In our study, a similar approach is adopted. First, during training, the time span of the P300 signal is first decided and adjusted based on the P300 time region found by the K-means clustering algorithm which segmented the grand-average of target minus non-target multi-channel responses into P300 and non-P300 time regions. Then, a reference signal is generated by using rectangular pulses to represent the time span of the P300 signal in a target trial. A simple illustration of the reference signal is shown in Fig. 1. An overview of the training and testing scheme using the proposed method as a pre-processing tool is shown in Fig. 2.

III. EXPERIMENTS

A. Dataset

To study the performance of our proposed method, the BCI competition 2003 dataset IIb for P300 speller is used [11]. In this dataset, a 6 x 6 matrix comprising 36 characters was presented to a subject where the subject was instructed to focus on characters in a word that was given by the investigator. For each run, each row and column was randomly intensified for 100 ms followed by a resting period of 75 ms, resulting in up to 12 different stimulations. Later, a total of 15 runs were performed for each character. When a row/column highlights a character that the subject is focusing on, a P300 signal occurs in the EEG signal. Hence, the objective in this dataset is to predict the correct character by identifying the row epoch and column epoch which contains a P300 signal.

B. Procedures

1) Data preparation: There are in total three sessions of EEG data in the given dataset. For training, six characters from the first two parts of Sessions 10 were used. For testing, the remaining part of Session 10 and 11 were combined to form *Test1* (36 characters) while Session 12 was used as *Test2* data (33 characters). This is so that the results can be compared to [2] and [9].

2) Training phase: Before training, the two parts in the training data were combined to form a continuous multi-channel EEG signal. The training signal was then bandpass-filtered between 0.1-10 Hz, centered and pre-whitened before ICA-R was applied to estimate the demixing vector, $\mathbf{w}$. During training, the extracted IC was segmented into EEG epochs of 525 ms starting from stimulus onset. Based on the given class label, a linear SVM classifier [12] was trained on these EEG epochs which is a vector of 126 time samples.

3) Testing phase: In the testing phase, a P300 signal was extracted from each test epoch by applying the whitening vector and demixing vector which were obtained in the training phase. To predict a character, the classifier was applied onto the extracted signal. The row and column epoch

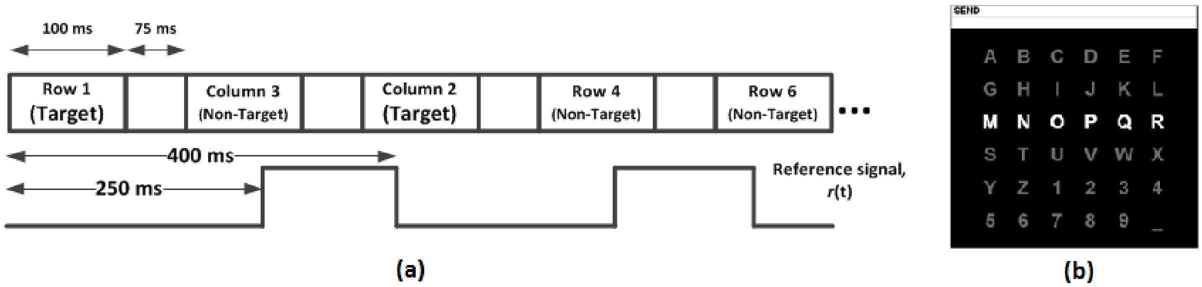

Fig. 1. (a) Generation of rectangular pulses as a reference signal for one-unit ICA-R, (b) P300-BCI interface used in BCI Competition 2003 [11]

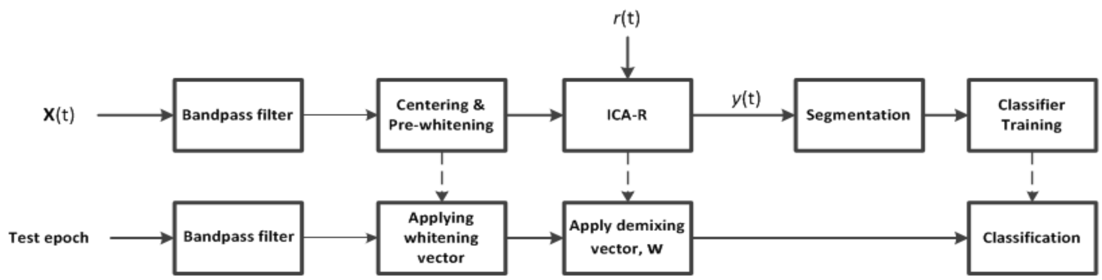

Fig. 2. An overview of the training and testing scheme which uses a one-unit ICA-R as the pre-processing tool

with the highest classifier score were chosen to infer the character. This step was repeated by using different number of epochs for averaging.

IV. RESULTS AND DISCUSSION

A. *Qualitative Examination*

Firstly, the reliability of the proposed ERP extraction algorithm for determining the desired P300 IC will be examined using the data described in Section III. After segmenting and averaging the ICs from the training and test data for the target and non-target signals, the averaged signal waveforms are shown in Fig. 3. It can be seen that each IC from the three sessions successfully captures the P300 signal in their respective target epochs. In addition, the normalized spatial patterns of the extracted ICs from these sessions also matches with the spatial characteristics of the P300 signal which has its peak located within the central region. These results demonstrate the reliability of recovering the desired P300 signal directly using a one-unit ICA-R with a single reference signal. Moreover, by using a common demixing vector estimated from the training session, the algorithm is still capable of extracting the desired P300 signals across the other test sessions, demonstrating its robustness. Fig. 4 shows the single-trial target responses from the ICs for the different sessions. It reveals that the P300 signals are nonstationary which further explains the need to deploy a longer rectangular pulse for the reference signal.

B. *Quantitative Examination*

By applying the training and testing scheme shown in Fig. 2, it is revealed that the predicted character often changes between the target character and its surrounding

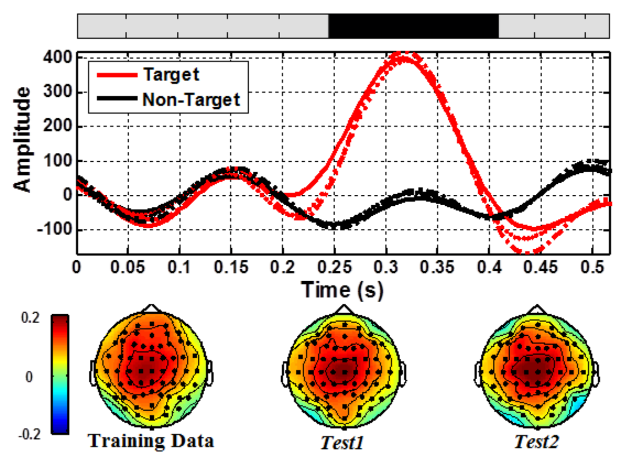

Fig. 3. Top plot - The P300 time region (Black) on the grand average of target minus non-target multi-channel responses of training data obtained by K-means clustering algorithm. Middle plot - Normalized averaged target and non-target epochs of the ICs extracted by applying whitening vector and demixing vector on Training data (Solid line), *Test1* (Dotted line) and *Test2* (Dash-Dotted line). Bottom plot - Normalized scalp pattern corresponding to the extracted IC from Training data, *Test1* and *Test2*.

characters although the character had been correctly predicted in an earlier run. This is likely caused by the crossover of the intensification which affects the neighbouring characters. To reduce this external effect, the sequence of 15 repetition runs were randomized for each character before the averaging operation. The number of epochs used for averaging ranges from one to 15 and for each test set, we generated up to 200 datasets by resampling using the permutation method taken for each available n-tuple (where n = 1,2,...,15) set. The resulting classification results using all 64 channels are plotted in Fig. 5. We achieved a mean

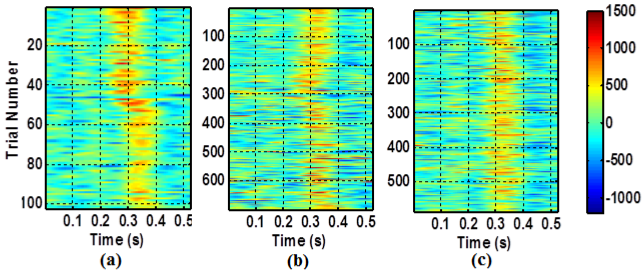

Fig. 4. Single-trial target responses from extracted IC on (a) Training data (b) *Test1* and (c) *Test2* whereby only target responses which had previous and upcoming two stimulations belong to non-target were used.

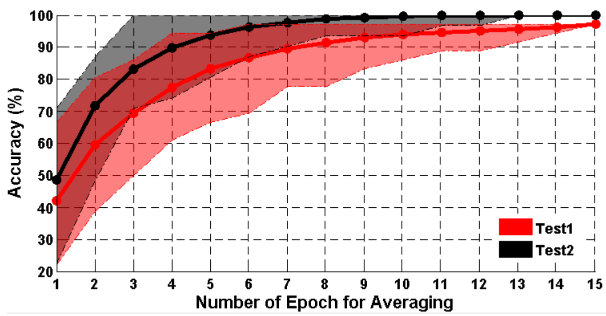

Fig. 5. Classification performance on *Test1* (Red) and *Test2* (Black) based on BCI competition 2003 dataset IIb with the shaded region represents the min-max boundary of an accuracy curve.

accuracy performance of 84% (min of 67% and max of 94%), 94% (min of 86% and max of 97%) and 97%[1] for 5, 10 and 15-averaged trials respectively for the *Test1* data. This compares favourably with the method using ICA-R with 12 references repetitively reported in [9] with accuracies of 90%, 96% and 97% over the same number of averaged trials respectively. On the other hand, when compared to the traditional ICA-based method used by the winner of BCI competition 2003 [2], our method requires an average of 8 trials to reach 99% accuracy while the best performance achieved by [2] is using 5 trials if manual selection of the starting point is allowed.

C. Computational Analysis

To analyse the computational performance of the different ICA-based methods, a further test is performed by running each method on a segment of continuous EEG signals that is taken from all the four character "A" in *Test1*. The reason for this step is that the method in [9] requires its reference signals to represent only specific target row/column stimulations. The resulting EEG segment consists of 64 channels and 32110 time samples. The tested methods are (1) one-unit ICA-R, (2) ICA-R with 12 references [9] and (3) Infomax-ICA [13] (to represent traditional ICA). The CPU is an Intel Xeon E3-1230 processor running at 3.2 GHz with 8GB RAM. The time taken for one unit ICA-R, ICA with 12-references and Infomax-ICA in P300 extraction after 50 iterations are 0.33 s $\pm$ 0.01 s, 3.02 s $\pm$ 0.05 s and 58.06 s $\pm$ 13 s respectively. It can be clearly seen that computational time increases whenever the partial and full signal decomposition step are required as in [9] and the traditional ICA-based method. In contrast, since only one IC is extracted, the one-unit ICA-R is the most computation efficient of the three methods.

[1]No min-max accuracy figure since all available 15 epochs were used

V. CONCLUSIONS

A P300 extraction method using one-unit ICA-R is investigated for P300-BCI and tested against existing ICA-based methods on the publicly available P300 speller dataset. Compared to [9], our results showed that fast and reliable P300 extraction can be achieved by using demixing vector from one-unit ICA-R in the training stage without exhaustively applying ICA-R with 12 references onto every single test data. Besides that, since only the desired P300 IC is extracted, the one-unit ICA-R requires less computational time compared to any existing ICA-based method while maintaining the current state-of-the-art classification performance. In addition, the ability of the method to visualize signals in the single-trial level also suggests it has potential applications in other types of ERP studies.

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