Computer Methods and Programs in Biomedicine 145 (2017) 95–102

Contents lists available at ScienceDirect

Computer Methods and Programs in Biomedicine

journal homepage: www.elsevier.com/locate/cmpb

Separation of P300 event-related potential using time varying time-lag blind source separation algorithm

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ARTICLE INFO

Article history:
Received 25 October 2016
Revised 10 March 2017
Accepted 18 April 2017

Keywords:
P300 component
Blind source separation
Schizophrenia

ABSTRACT

Synchronous averaging over time locked single-trial of event-related potential (ERP) is known as the simplest scheme to extract P300 component. This method assumes the P300 features are invariant through the time while they are affected by factors like brain fatigue and habitation. In this study, a new scheme is proposed termed as time-varying time-lag blind source separation (TT-BSS) which is upon the second order statistics of signal to separate P300 waveform from the background electroencephalogram (EEG) while it captures the time variation of P300 component. The time-lag parameter for all channels is determined by maximizing the correlation (similarity) between two successive trials. As the time-lag parameter is varying by time (trial to trial), an average is taken over the time-lag covariance matrices of all two consecutive trials. TT-BSS finally estimates a transform (separating matrix) by joint diagnolization of the covariance matrix of trials and the averaged covariance matrix of the time varying time-lag. To assess the proposed scheme, synthetic and real EEGs containing P300 are used. The EEG signals were collected from twenty schizophrenic and twenty age-matched normal subjects via 20 channels through the resting state and in presence of the oddball audio stimulus. Empirical achievements over the simulated and real EEGs imply on the superiority of TT-BSS in dynamic estimation of P300 characteristics compared to state-of-the-art counterparts such as constant time-lag BSS, constrained BSS and synchronous averaging.

1. Introduction

Human brain always generates electrical signals, termed background electroencephalogram (EEG) [1]. When the brain receives an internal or external input, a specific electrical response is added to the background EEG which is so called event-related potential (ERP) [2,3]. External events are those received by human sensors, i.e. audio or visual stimuli, while internal events are defined as mental tasks like attention, decision making, working memory, imagery movement, or performing an arithmetic task. The P300 wave [4] is an ERP which is considering to be an endogenous potential, and is appeared during cognitive processes such as decision making or categorization tasks [5]. P300 is usually obtained during the oddball paradigm, where low-probability target item is mixed with high-probability non-target items, and subjects must distinguish target item from non-target ones.

Through EEG recording [6], P00 surfaces as a positive deflection in voltage with a latency (delay between stimulus and response) between 250 to 500 ms. According to experiments reported in literature, the P300 wave is typically measured most strongly by locating the electrodes on the parietal lobe. The presence, magnitude, topography and latency of this wave are often used as metrics of cognitive function in decision making processes. While the neural substrates of this ERP component are still ambiguous [7], the reproducibility and ubiquity of this signal makes it a common choice for psychological tests in the clinic and laboratory. In the past two decades, scientific research often relies on measurement of the P300 to examine decision making [8]. As far as cognitive impairment is often correlated with modifications in the P300, this wave can be used as a measure to evaluate the various treatments on cognitive functions. In this regard, researchers have suggested the use of P300 as a clinical marker and now a large body of clinical research in the brain function assessment has been devoted to extracting and characterizing the P300 [9].

Dinteren et al. [10] recorded EEG signals of 1572 healthy subjects while they received an oddball auditory stimulus. The age of them ranged from 6 to 87, and their EEG signals were caught from the frontal and parietal lobes. After extracting P300 from these channels, they found out the developmental trajectories of frontal and parietal P300 amplitudes were significantly differed across the lifespan. They also observed that during adulthood, the amplitude

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http://dx.doi.org/10.1016/j.cmpb.2017.04.014
0169-2607/

of the parietal P300 declines with age, whereas both the frontal P300 amplitude and behavioral performance remain unaffected. It means to provide a stable behavioral performance for older participants, neurons of prefrontal part become more active to compensate for declining neural resources.

As mentioned before, P300 is generated through the cognitive recognition. In this regard, Abootalebi et al. [11] used the amplitude of P300 as an index for actual recognition of concealed information in guilty knowledge test (GKT). Their results demonstrated 86% classification accuracy in detection of guilty and innocent subjects.

Analyzing P300 gives a lot of information for automatic recognition tasks but research in this field is still in infancy. The reason of growing interests in this field are the detectability of this waveform in response to precise stimuli and it can be evoked in nearly all subjects with little variation in measurement techniques. In contrast, the negative characteristic of the P300 is its low amplitude compared to the background EEG and therefore its extraction needs some techniques like taking synchronous average over multiple recordings to remove the background activity. In the averaging process, it is assumed that the P300 has a non-variable template and its shape is constant from trial to trial. However, this assumption is failed in many cases and is not always valid. From another aspect, detecting the variation in the parameters of the P300 may contain information about the dynamic changes in cognitive processes.

Truccolo et al. [12] indicated that there exists a single-trial variability in the ERP shape due to some factors like fatigue, habituation and attention level. Therefore, mining of single-trail ERP reveals the EEG changes corresponding to the cognitive process while this information is lost when using conventional averaging for P300 extraction. Jongsma et al. [13] tried to track the dynamics of pattern-learning using single-trial ERPs. They employed a new learning-oddball paradigm presenting eight random targets (no-pattern) followed by eight regular targets (pattern). Their finding showed that tracking the dynamic structure of ERP may be useful in the understanding of learning and its different pathologies. They suggested that the implementing similar paradigms could lead to clinically useful tools for assessing the ability or speed of pattern learning in different patient groups.

Xu et al. [14] considered the problem of estimating single-trial ERPs with assumption a linear combination of multiple ERP components and an ongoing activity. They developed an iterative algorithm to estimate the ERPs in the frequency domain and the ongoing background EEG in the time domain. They illustrated the effectiveness of their method both for simulated and real data. Georgiadis et al. [15] proposed a method for single-trial dynamical estimation of ERPs using the recursive Bayesian mean square estimation updating by the Kalman filter (KF). The potentials were estimated sequentially using the previous estimations as prior information. The performance of their method was evaluated with both simulated and real P300 signals in response to auditory stimuli. Their approach provided excellent capability for the estimation of dynamic changes of ERPs parameters.

Mohseni et al. [16] presented particle filters (PFs) for the estimation of single trial ERPs. Their method was based on recursive Bayesian mean square estimation of ERP wavelet coefficients using their previous estimations as prior information. To assess the efficiency of the PFs in the noisy conditions (noise with Gaussian and non-Gaussian distribution), they added white Gaussian noise (WGN) and background EEG to the simulated ERPs. Their results were compared to that of the KF approach demonstrating the superior robustness of the PF compared to KF in the presence of the white noise.

Separation of sources consists of recovering a set of signals while only instantaneous linear mixtures are observed. In many cases, there is no available priori information about the mixing matrix, thus we have to estimate two sets of unknown parameters include source signals and the coefficients of the mixing matrix. Blind source separation (BSS) algorithms play an important role in the EEG signals processing [17,18]. In this regard, Spyrou et al. [19] employed BSS for separation and localization of the P300 sources for both visual and audio stimuli. For this purpose, they developed an effective constrained BSS algorithm which was an extension of the Infomax BSS system [20]. They considered the distance between a carefully measured P300 and the estimated sources as a constraint. Their results imply on the key role of P300 component in the diagnosis and monitoring of schizophrenic patients.

Moghavvemi et al. [21] proposed a sequential BSS-based system to extract the seizure source signal from scalp EEG and pinpoint the main location of seizure within the brain. They applied BSS algorithm to extract independent seizure sources and then scalp time-mapping process is applied to determine the main location of the extracted seizure signal within the brain. Cichocki et al. [22] applied BSS to EEG signals of patients with Alzheimer's disease (AD). They extracted EEG sources and analyzed them to detect those possibly sensitive to cortical neuronal impairment found in early stages of AD. They studied EEG recordings from 22 patients with mild cognitive impairment who later proceeded to AD. They got EEGs from 38 age-matched normal subjects and showed that the P300 sources of AD patients and healthy subjects have significant differences and classify these two groups up to 84% accuracy.

Corsini et al. [23] developed a novel approach to quantify the dynamical changes of the brain using the scalp EEG. They studied twenty sets of simultaneous intracranial and scalp EEG recordings from twenty patients with local seizure. The scalp signals were preprocessed by means of an effective block-based BSS technique to separate the underlying sources within the brain. They could significantly remove the effect of eye blinking artifacts and obtained a great improvement when the epileptic focus is not captured by the intracranial electrodes. Sameni et al. [24] proposed the application of generalized eigenvalue decomposition (GEVD) for extracting the most periodic linear mixtures from a recorded electrocardiogram (ECG) dataset. As far as ECG signal has a quasi-periodic structure, they proposed the use of time-varying period, which is updated over beat-to-beat basis, since normal ECG signals have natural deviations. Their results showed the applicability of this method for the decomposition and compression of multi-channel ECG. To distinguish the fetal ECG from the maternal one, they decomposed ECG signals, caught from the abdomen of pregnant females, and their results illustrated a great performance to extract fetal ECGs.

In this study, we have considered the temporal variation in P300 components and tries to extract them from each trial separately. To do this, we have proposed a time-varying time-lag blind source separation (TT-BSS) scheme to eliminate the unwanted contribution of the background EEG and finely extract the P300 component. In TT-BSS, the chosen time-lag has an important effect on the performance of algorithm. Since the features of P300 are varied during the signal recording, a constant time-lag cannot describe the variability of the P300. We applied a time-varying time-lag that is successively updated from a trial to another one. TT-BSS calculated time varying time-lag by maximizing the correlation (similarity) between samples in subsequent trials. The performance of the proposed approach is evaluated using both simulated and real EEG data. The real EEGs were caught from schizophrenic patients and healthy subjects when they received an auditory oddball stimulus.

The reminder of this paper is organized as follows. Section 2 presents the data collection and its specifications. In Section 3, we present BSS and its time-varying version. Experimental results and discussion are brought in Section 4, and finally, Section 5 summarize the contribution of this paper and gives an outline to the horizon of this research.

2. Data description

The employed EEG signals in this section can be categorized into real and simulated data. Since in the generation of simulated signals (containing simulated P300), we use the real EEGs in the idle state, first we describe the real EEG collection and then we explain how the simulated EEGs are produced.

2.1. Acquisition of real EEG signals

Twenty patients with schizophrenia and twenty age-matched control subjects (all male) participated in this study. The group of schizophrenic patients had average age of 33.30 with standard deviation (Std) 9.52. The patients were diagnosed according to DSM-IV [25] and they were receiving a variety of standard neuroleptics medications at the time of recording. All patients were recruited from the admitted population. In contrast, the normal group included twenty healthy subjects, with average age of 33.40 and Std 9.29, and with no history of psychotic disorder. During EEG recording, each participant was seated upright with eyes open and relaxed. To avoid muscle artifact, the neck was firmly supported by the chair, and the feet were rested on a footstep.

EEG signals were recorded in two different states. In the first state (idle), the participants were seated on a comfortable chair in the resting state, they did not do any mental task. Each trial recording lasted around 2 min. In the second state, EEG signal were recorded through oddball paradigm, wherein two stimuli were presented with different probabilities in a random order. The participants were required to discriminate the infrequent target stimuli (high pitch beep) from the frequent standard stimuli (low pitch) by noting the occurrence of the target, by pressing a button. The cognitive ability of distinguishing between the low and high tones was confirmed before beginning the experiment. This cognitive experiment lasted around 20 min for each subject.

Electrophysiological data were recorded using a neuroscan 24 channel Synamps system, with a signal gain equal to 75 K (150- at the headbox). For EEG paradigms, 20 electrodes (Electrocap 10-20 standard system with reference to linked earlobes) were recorded plus vertical electrooculogram (VEOG) and horizontal electrooculogram (HEOG). The blink artifacts were corrected using an efficient technique, described in [26] and elimination of the artifacts was performed by an experienced physician through visual inspections of the recordings. In addition, the EEG signals were filtered by a band pass filter starting from 0.5 to 50 Hz. According to the international 10-20 recording system, EEG signals were recorded via 20 electrodes (Fpz, Fz, Cz, Pz, C3, T3, C4, T4, Fp1, Fp2, F3, F4, F7, F8, P3, P4, T5, T6, O1, and O2) with sampling frequency of 200 Hz.

2.2. Description of simulated EEG signals

A conventional model for the P300 estimations is the linear additive noise model [15] as described below

$$x(k) = s(k) + v(k) \qquad k = 1, 2, \ldots, N \tag{1}$$

where the response $s(k)$ shows the part of P300 activity and the rest of activity $v(k)$ shows the background EEG which is assumed to be independent of the stimulus. To generate $v(k)$, we used the EEG signals recorded in the resting state, as we explained in Section 2.1. To add the $s(k)$ to the $v(k)$, a Gaussian function was used to simulated the $s(k)$, added 300 ms after beginning of each trial. To insert the variations of P300 onto the simulated data, the amplitude and latency of the Gaussian peak are linearly decreased

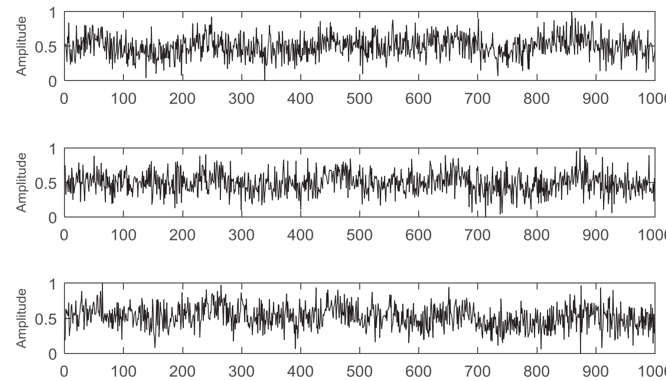

Fig. 1. The simulated signal over three channels.

through the successive trials. The amplitude, mean and variance of this Gaussian function represent the amplitude, latency and width of the P300 component, respectively. Finally, white Gaussian noise (WGN) with different intensities is added to the simulated data to show the performance of the methods in presence of noise. Fig. 1 shows the simulated data on three channels.

3. Blind source separation

Biological signal acquisition, similar to radar and sonar, is taken by an array of electrodes placed on the region of interest when there is enough evidence that something is beneath. BSS [18,27] is the solution to the problem of recovering the source signals from the observed (measured) signals where the sources and the way that they are mixed cannot be directly observed. In fact, BSS shall use a priori knowledge about the sources such as spatio-temporal decorrelation, statistical independence, sparseness, smoothness or lowest complexity to estimate sources and the mixing process [28].

BSS has several applications in decoding and extracting the underlying of biological signals. Since EEG signals have narrow bandwidths and low sampling frequency; therefore, the mixing process can be assumed instantaneous, it means that the source signals receive to the sensors at the same time. EEG signals (observed data) in a BSS process can be linearly reconstructed by sources in addition to considering a measurement noise as

$$x(k) = As(k) + n(k) \qquad k = 1, 2, \ldots, N \tag{2}$$

where $x(k)=[x_1(k), x_2(k),\ldots, x_m(k)]^T$, m is the number of electrodes (sensors), $N$is the number of recorded samples, $x_i\ (k)$ is the EEG signal at ith channel and $s(k)=[s_1(k), s_2(k),\ldots, s_n(k)]^T$, where n is the number of source signals. The element a_{ij} of the matrix $A \in R^{m\times n}$ is the mixing coefficient from jth source to ith electrode and $n(k)$ is an additive noise, which compensates $x_i(k)$ the difference between $x(k)$ and $As(k)$. The separation is performed using an $n \times m$ matrix, W, which uses only the information about $x(k)$ to reconstruct the original source signals as illustrated below

$$y(k) = Wx(k) \quad \text{where} \quad y(k) \approx s(k) \tag{3}$$

In general, the task of BSS is to estimate the separating matrix W for obtaining original source signal $s(k)$, $k=1, 2, \ldots, n$, given the measured signals $x(k)$, $k=1, 2, \ldots, m$. If sources have temporal structures, therefore each source has non-vanishing temporal correlation [18]. In this way, less restrictive conditions such as second-order statistics can be used to estimate the mixing matrix and sources in comparison with statistical independence [29,30]. The algorithms based on the time-delayed covariance matrices are probably the simplest ones for blind separation of sources with temporal structure since the problem can be converted to eigenvalue decomposition problem.

The algorithm for multiple unknown signals extraction (AMUSE) [17] as a famous second-order statistics BSS algorithm has a degree of similarity to the known principal component analysis (PCA) [31]. Nevertheless, AMUSE employs both PCA and singular value decomposition (SVD) in two separate stages. In the first stage, standard PCA is applied to whiten the data as described below

$$x_1(k) = Qx(k) \tag{4}$$

$$Q = R_x^{-1/2} = (V\Lambda V^T)^{-1/2} = V(\Lambda)^{-1/2}V^T \tag{5}$$

where $R_x = E\{x(t)x^T(t)\}$ shows standard covariance matrix, $x(t)$ is the EEG signal observed at all electrodes in time t. In the second step, SVD is applied for time-delayed covariance matrix of the pre-whitened data.

$$R_{x_1}(\tau) = E\{x_1(t+\tau)x_1^T(t)\} = U\Sigma V^T \tag{6}$$

where time-lag τ usually sets to 1, Σ is diagonal matrix with decreasing singular values and U, V are orthogonal matrices of left and right singular vectors. Finally, AMUSE estimates the separating matrix as

$$W = U^T Q \tag{7}$$

In this study, the employed version of BSS exploits both the second-order statistics and temporal structure of sources. In the following sections, we describe the schemes that are implemented in this research. At first, the BSS using constant time-lag for eliciting the P300 component is explained. Next, the proposed time-varying time-lag and the constrained BSS are described respectively.

3.1. Constant time-lag BSS

Parra et al. [32] showed that linear BSS can be formulated as a GEVD. In this method, the separating matrix is obtained by the GEVD that simultaneously diagonalize the covariance matrix of the observations and an additional symmetric matrix whose form depends on the particular assumptions. In the first step, two covariance matrices are estimated as

$$R_x(0) = E\{x(t)x^T(t)\} \tag{8}$$

$$R_x(\tau) = E\{x(t+\tau)x^T(t)\} \tag{9}$$

where $x(t)$ is the EEG signal observed at all electrodes in time t, and τ shows the constant time-lag. Moreover, to assure the symmetry of $R_x(\tau)$ and the realness of its eigenvalue, the following step is required in practice

$$R_x = (R_x + R_x^T)/2 \tag{10}$$

In the second step, GEVD is applied to ($R_x(0)$, $R_x(\tau)$) matrix pair, and find the matrices U and D as

$$U^T R_x(0) U = D \tag{11}$$

$$U^T R_x(\tau) U = I \tag{12}$$

where D is the diagonal generalized eigenvalue matrix corresponding to the eigenmatrix U, with real eigenvalues sorted in ascending order on its diagonal. U is a transformation that simultaneously diagonalizes $R_x(0)$ and $R_x(\tau)$. Finally, the source signals are reconstructed as

$$y(t) = U^T x(t) \tag{13}$$

This method is named constant time-lag BSS in this study and Table 1 shows all stages of this algorithm. We set the constant time-lag τ to the time differences between two stimuli.

3.2. Time-varying time-lag BSS

It is evident that in practice, P300 wave varies through time, and consequently its characteristics deteriorates from trial to trial [12]. Variations of the P300 parameters links to several factors such as fatigue, caution, etc. In this paper, to digest the P300 variation, a time varying approach is proposed to finely extract the P300 from each separate trial. The time-lag τ_t is updated at each trial in order to finely locate the P300 interval at each trial. The time-lag τ_t is applied for estimation of time delayed covariance matrix of the EEG signals as follow

$$R_x(\tau_t) = E\{x(t+\tau_t)x^T(t)\} \tag{14}$$

where sample at the time instant t is compared with the sample $t+\tau_t$ in the successive trials, and τ_t is estimated by maximizing the correlation (similarity) between two consecutive trials during 250– 500 ms after stimuli. Since the main power of P300 component is in delta range [19], for better estimation of time-lag τ_t, the EEG signals are filtered in the delta band (0– 4 Hz). This time-lag determines the correct interval of P300 and time-lag is updated accordingly. The TT-BSS algorithm extracts a desired P300 signal from a set of multichannel recordings by simultaneously diagnolize the time delayed covariance matrix and standard covariance matrix of scalp EEG trials. Table 2 shows all stages of the proposed TT-BSS algorithm.

3.3. Constrained BSS

Constrained BSS [19] is an extension of Infomax BSS algorithm. It incorporates the Euclidean distance between the estimated sources and a reference P300 signal as constrain into the original Infomax cost function [20] to ensure that the desired P300 source is one of the estimated sources. Therefore, the constrained problem is written as

$$\max J_m(W) \text{ subject to } J_C(W) = 0 \tag{15}$$

where J_m and J_C are the Infomax and the constrained cost functions, respectively. The Infomax cost function is defined as follows

$$J_m(W) = I(z, x) = H(z) - H(z|x) \tag{16}$$

where $I(z, x)$ is the information between the inputs (x) and the outputs (z), $H(z)$ is the entropy of the output and $H(z|x)$ is the conditional entropy of the output assuming a known input. The constrained cost function is defined as

$$J_C(w_i) = \sum_{t=1}^{P} (y_i(t) - r(t))^2,\ i = 1, 2, \ldots, m \tag{17}$$

where $r(t)$ is the reference signal (obtained by frame averaging of the ERP over a number of trials) and $y_i(t)$ is the ith output at time t. There are still two unknown parameters include: the matrix W and the matrix of the Lagrange multipliers Λ. The constrained BSS finds W and Λ adaptively via the following relation

$$\begin{aligned} W_{t+1} = W_t + \mu\Big(\mathrm{I} + \big(1 - (1+\exp(W_t x))^{-1}\big)(W_t x)^T \\ - 2\Lambda\big(x(W_t x - P)^T\big)W_t^T\Big)W_t \end{aligned} \tag{18}$$

$$\Lambda = \rho\ \mathrm{diag}\big((Wx - P)(Wx - P)^T\big) \tag{19}$$

where μ is the learning rate to adapt the unmixing matrix, ρ is a scale factor for the Lagrange multiplier matrix, and P is a matrix whose rows contain the reference P300 signal.

4. Experimental results and discussion

In this section, results of the proposed method on the synthetic and real EEG signals are presented.

Table 1
The constant time-lag BSS algorithm.

1. Estimate two covariance matrix

$$R_x(0) = E\{x(t)x^T(t)\}$$

$$R_x(\tau) = E\{x(t+\tau)x^T(t)\}$$

where to assure the symmetry of $R_x(\tau)$ and the realness of its eigenvalue, we use $R_x = (R_x + R_x^T)/2$

2. Apply GEVD to $(R_x(0), R_x(\tau))$ matrix pair, and find the matrices U and D as

$$U^T R_x(0) U = D$$

$$U^T R_x(\tau) U = I$$

where D is the diagonal generalized eigenvalue matrix, and U shows the corresponding eigenmatrix. U is a transformation that simultaneously diagonalizes $R_x(0)$ and $R_x(\tau)$.

3. Reconstruct the source signal as

$$y(t) = U^T x(t)$$

Table 2
The TT-BSS algorithm.

1. Estimate standard covariance matrix

$$R_x(0) = E\{x(t)x^T(t)\}$$

2. For each two consecutive trials

   - Estimate time varying time-lag τ_t by maximizing correlation between these two trials in delta frequency range
   - Estimate time delayed covariance matrix as

$$R_x^i(\tau_t) = E\{x(t+\tau_t)x^T(t)\}$$

3. Take an average over the time-lag covariance matrices of all two consecutive trials

$$\tilde{R}_x(\tau_t) = \frac{\sum_{i=1}^{T-1} R_x^i(\tau_t)}{T-1}$$

where T shows number of trials and to assure the symmetry of $\tilde{R}_x(\tau_t)$ and the realness of its eigenvalue, we use $\tilde{R}_x = (\tilde{R}_x + \tilde{R}_x^T)/2$

4. Apply GEVD to $(R_x(0), \tilde{R}_x(\tau_t))$ matrix pair, and find the matrices U and D as

$$U^T R_x(0) U = D$$

$$U^T \tilde{R}_x(\tau_t) U = I$$

where D is the diagonal generalized eigenvalue matrix, and U shows the corresponding eigenmatrix. U is a transformation that simultaneously diagonalizes $R_x(0)$ and $\tilde{R}_x(\tau_t)$.

5. Reconstruct the source signal as

$$y(t) = U^T x(t)$$

4.1. Results on the simulated data

First, the three compared algorithms are applied to the simulated data without any WGN, in this case, only background EEG is considered as noise. Second, WGN with signal to noise ratio (SNR) equals to −5 dB, is added to the simulated data. In this case, both background EEG and WGN are considered as additive noise to P300. We filter the reconstructed sources within delta frequency band since the main power of the P300 component is in the delta frequency range. The result of constant time-lag, the suggested TT-BSS and constrained BSS for extracting the simulated P300 wave from background EEG are shown in Figs. 2 and 3. Mean square error (MSE) for three mentioned algorithms is calculated and presented in Table 3. Our results over the synthetic (simulated) data showed that the proposed time-varying algorithm is a suitable tool for estimation of the P300 wave compared to constant time-lag algorithm especially when the WGN is added.

4.2. Results on the real data

We have recorded EEG signals of twenty schizophrenic patients and twenty age-matched normal subjects through the oddball paradigm, as we explained in Section 2.1. To demonstrate the effectiveness of the proposed algorithm, the conventional averaging method is implemented. The number of oddball stimulus for each subject was about 80, and we took an average of the event-related data temporally over 80 trials (correspond to 80 events) in order to enhance the quality of the P300 waveform. Fig. 4 shows the grand averaging process of all subjects on Fz, Cz and Pz channels for two mentioned groups.

Table 4 shows the mean and Std of amplitude and latency for P300 component in the two mentioned groups using averaging technique. Our results shows that P300 effect size is smaller in amplitude ($p\text{-}value = 0.0004$) and longer in latency ($p\text{-}value = 0.0861$) in schizophrenic patients compared to normal subjects. Our

Table 3
The MSE between real and reconstructed sources.

	MSE Without Gaussian noise	MSE With added WGN (SNR = – 5 dB)
Constant time-lag BSS	0.0399	0.1537
TT-BSS	0.0394	0.1140
Constrained BSS	0.0424	0.0915

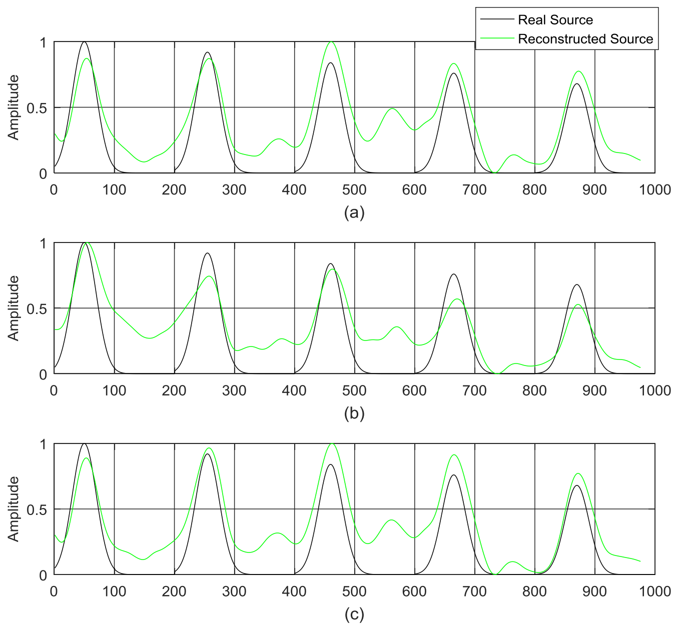

Fig. 2. The extracted P300 component for (a) TT-BSS, (b) Constant-lag BSS, (c) Constrained BSS.

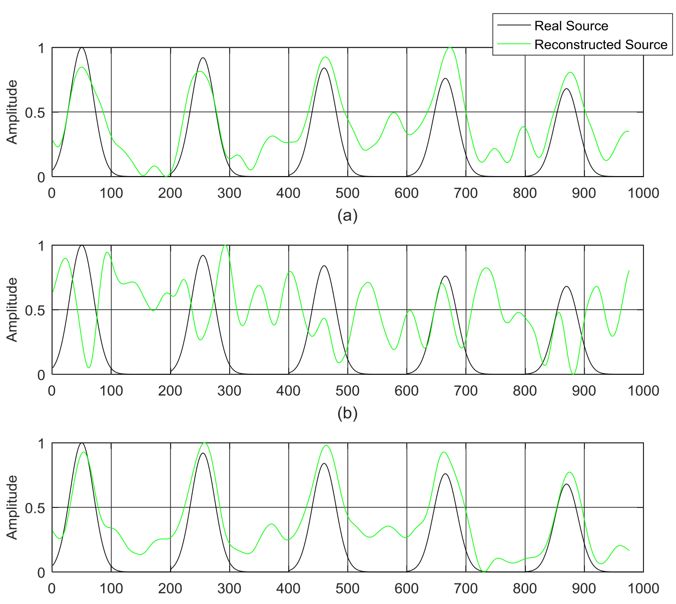

Fig. 3. The extracted P300 component with added WGN with SNR = – 5 dB for (a) TT-BSS, (b) Constant-lag BSS, (c) Constrained BSS.

Table 4
The mean and Std of amplitude and latency for P300 component.

	Amplitude	Latency
Normal group	0.9362 ± 0.0480	370.75 ± 33.22
Schizophrenic group	0.8292 ± 0.1064	395 ± 50.7833

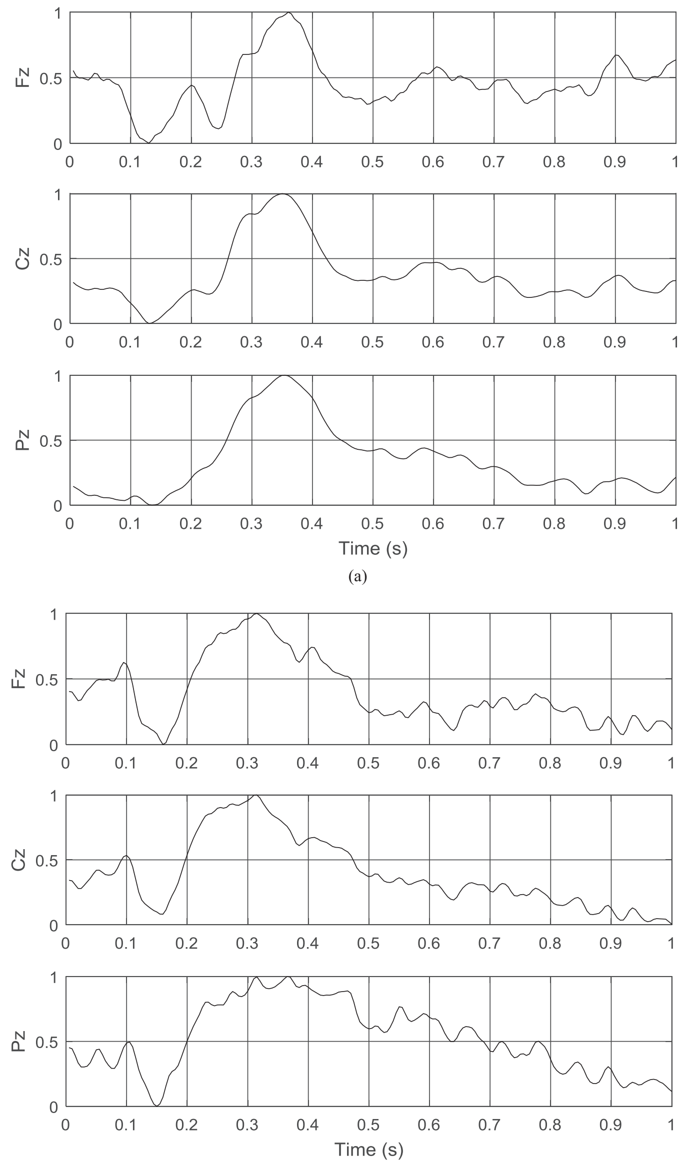

Fig. 4. The averaging process on Fz, Cz, Pz channels for (a) normal participants and (b) schizophrenic patients.

findings showed that the schizophrenia disorder affects the amplitude and latency of P300 component and in line with previous study [33] that conducted a systematic search for articles published between 1983 and 2003 that compared P300 features of schizophrenic patients to the control group. Their results showed that the patient group displays a trend for amplitude reduction and latency delays.

The assumption in the averaging is that the task-related cognitive process does not change through the time, especially from trial to trial. However, it is shown this assumption is not always valid. It seems that the observation of variation in the parameters

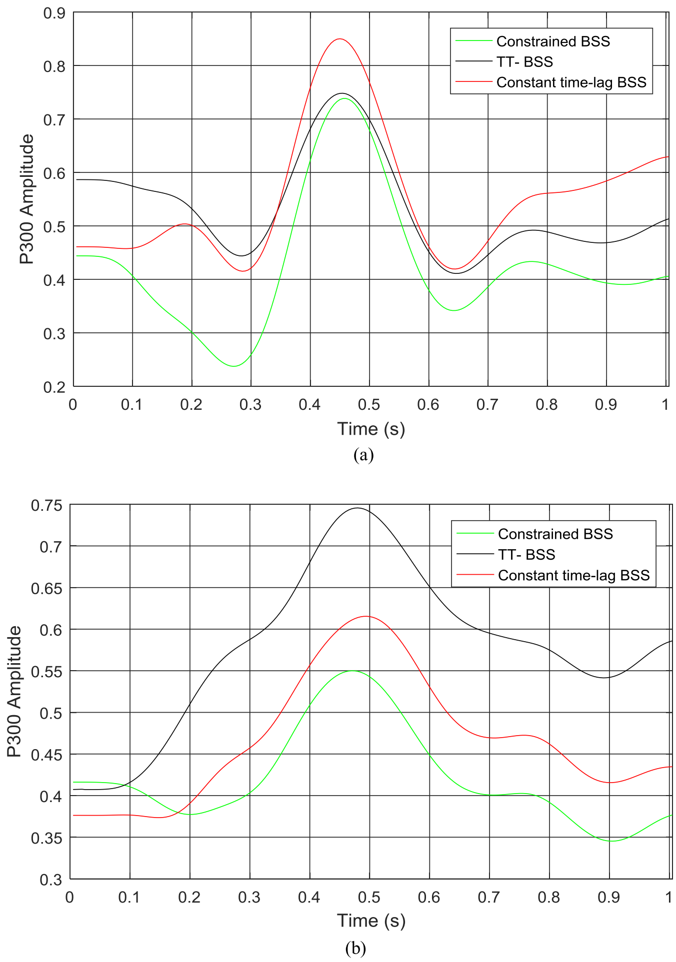

Fig. 5. The extracted P300 component for (a) a normal subject, (b) a schizophrenic patient.

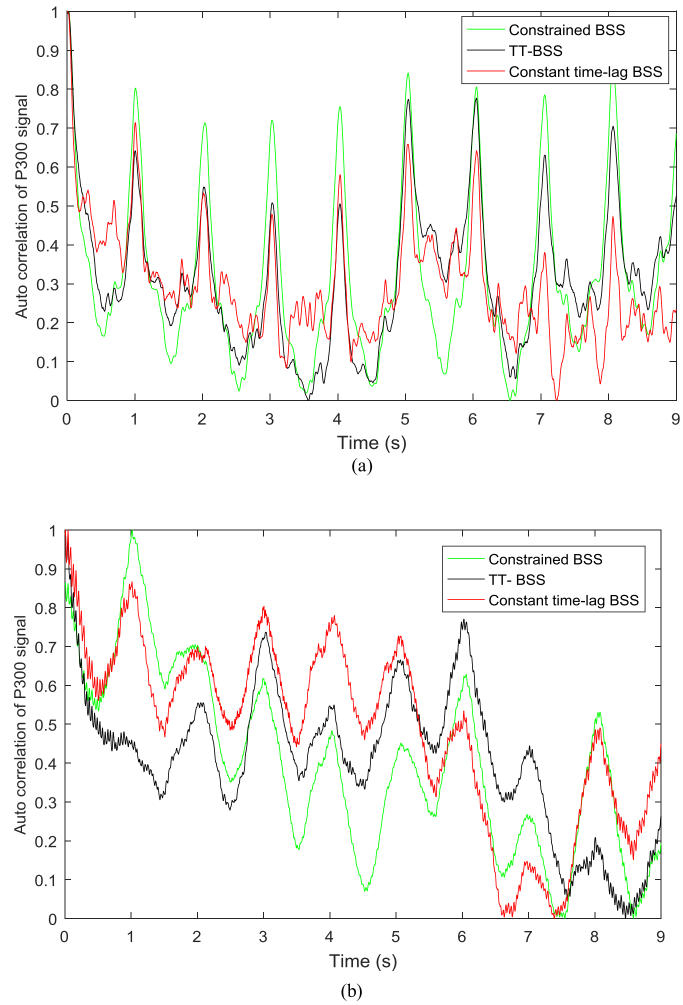

Fig. 6. Autocorrelation of P300 component for (a) a normal subject, (b) a schizophrenic patient.

of the ERP permits the dynamic assessment of changes in cognitive process. Therefore, constant time-lag BSS, TT-BSS and constrained BSS are applied for separation of P300 from the unwanted contribution of the on-going background activity of the brain. The separated sources by three mentioned algorithms are filtered since the main power of the P300 component is in the delta frequency range. Figs. 5 and 6 show the estimated P300 (single trial) and its autocorrelation for a healthy and a schizophrenic subject respectively. Fig. 5 indicated that the latency of the P300 component for schizophrenic patient is longer than the healthy subject. Our result is in line with Table 4 where it is shown that the P300 latency is increased in schizophrenia disorder.

There are important points that must be taken into account when comparing the TT-BSS and constrained BSS methods.

I. Since the temporal structure of P300 has rich information, the TT-BSS uses relevant features upon second-order statistic of data to recover the P300 sources while constrained BSS tries to minimize the mutual information, searching for sources that are maximally independent. In this study, less restrictive conditions such as second-order statistics is used to estimate the separating matrix and sources in comparison with the assumption of statistical independence among the sources.
II. The proposed approach uses a time-delayed covariance matrix. In fact, physiologists are not familiar with the interpretation of independent components extracted from multichannel recordings, but they are interested in temporal structure that are repeated in each trial.
III. The TT-BSS scheme consists of time-lag detection step, covariance matrix calculation, and a single step of GEVD. Therefore this method imposes lower computational burden in comparison with the iterative constrained BSS algorithm.
IV. The constrained BSS needs some parameters (W_0, Λ, μ, and ρ parameters) to be selected according to specific requirements. However the most important problem in this algorithm is finding the time varying time-lag.

5. Conclusion and future work

In this study, TT-BSS is proposed for the separation of P300 from the background EEG. Since sources of P300 have temporal structure, the performance of algorithms based on second-order statistics of data in the estimation of original sources is usually acceptable. TT-BSS imposes the less restrictive constraint compared to the statistical independence condition while its execution is faster than BSS based iterative methods. Our results empirically prove that the proposed scheme is able to digest the natural variation of the P300 parameters for revealing the dynamic changes in the brain system of the schizophrenic patients compared to normal subjects, in response to cognitive tasks. As a future work, using the filtered covariance matrices is suggested to enhance the results. Moreover, TT-BSS can be applied to other ERP components to assess which processing stage in the brain is affected in patients with cognitive disorders.

Acknowledgment

The authors of this paper present a special thanks to Dr. Gregory W. Price who has given us his database including EEG of normal and schizophrenic participants.

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