SEPARATION AND LOCALIZATION OF AUDITORY AND VISUAL P300 SOURCES IN SCHIZOPHRENIA PATIENTS VIA CONSTRAINED BSS

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ABSTRACT

To separate and localize the P300 sources within the brain a robust constrained blind source separation (CBSS) algorithm has been proposed. The algorithm is an extension of the Infomax algorithm, based on minimization of mutual information, for which a reference P300 signal is used as a constraint. The reference signal forces the unmixing matrix to separate the sources of both auditory and visual P300 resulted from the corresponding stimulations. The constrained problem is then converted to an unconstrained problem by means of a set of nonlinear penalty functions. The P300 sources are then localized based on electrode – source inner products .

1. INTRODUCTION

P300 is a positive event-related potential (ERP), which occurs with a latency of about 300 ms after rare or task relevant stimuli [1]. This is particularly relevant to psychological aspects such as cognition or attention. There are two P300 sub-components that overlap at the scalp; P3b has a more centro-parietal distribution and corresponds to the classical P300 recorded within an oddball paradigm after rare and task relevant events. P3a occurs after novel events independently of task relevance and is characterized by a more frontal distribution, a shorter latency and fast habituation. The parietal and temporal cortex are involved in the generation of the auditory P3b. Concerning P3a, the superior temporal plane, the association cortices, limbic structure and frontal as well as pre-frontal cortices appear to play a major role. An increase of P300 latency with age is found for the temporo-basal but not for the temporo-superior dipoles. Figure 1 illustrates some typical P3a and P3b waves from temporo-basal and temporo-superior dipoles [1]. Attenuation of auditory and visual P300 signal can be a sign of schizophrenia. For the patients suffering from schizophrenia, the shape, amplitude, and even the position of the P300 may change. Furthermore, children of schizophrenic parents and other subjects with an enhanced risk of developing schizophrenia showed P300 abnormalities. The reduction in the amplitude of P300 is also found in patients with dementia and with affective disorders. However, the amplitude reduction of P300 is neither a sufficient nor a necessary marker of schizophrenic disorders. However, it has been clinically observed that the patients with a P300 amplitude reduction are a sub-group with neuro-developmental disorders. Moreover, the amplitude reduction is more consistent in P3b subcomponents.

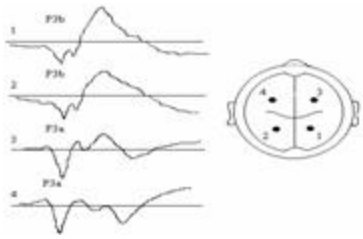


Fig. 1. Typical subcomponents of the P300 signals;) and 2) P3b, and 3) and 4) P3a signals

Blind separation of the EEG signals on the other hand, has been followed by a number of researchers [2] [3] [4]. The infomax algorithm [5] has been reported to be robust for separation of EEG signals. Some source separation problems such as signal detection and noise cancellation often expect to estimate a desired single source or a subset of sources from the mixtures. In such cases a separate function, as a constraint, has to be minimized (or maximized) in parallel with minimization of the original cost function. Exploitation of Lagrange multipliers [6] and nonlinear penalty functions [7] incorporates the constraint terms into the original cost functions thereby converting the constrained problem to an unconstrained one.

The instantaneous BSS formulation is as follows. Denote the time varying observed signals by $\mathbf{x} = [x_1(t), x_2(t), \ldots, x_n(t)]^T$ where $\mathbf{x} \in R^n$ and the unknown independent sources by $\mathbf{s} = [s_1(t), s_2(t), \ldots, s_m(t)]^T$ where $\mathbf{s} \in R^m$.

$$\mathbf{x} = A\mathbf{s} + \mathbf{v} \qquad (1)$$

and

$$\mathbf{y} = W\mathbf{x} \qquad (2)$$

Here $\mathbf{v} \in R^n$ is assumed to be a white zero mean Gaussian noise vector, $A \in R^{n \times m}$ and $W \in R^{m \times n}$ are unknown constant mixing and unmixing matrices respectively, and $(.)^T$ is vector transpose. The mixture is assumed to be over-determined (valid for usual cases), i.e. $m<n$. $\mathbf{y} = [y_1(t), y_2(t), \ldots, y_m(t)]^T$, where $\mathbf{y} \in R^m$ is the output vector. The unconstrained separation matrix can be found by finding the global minima (or maxima) of a cost function $J_M(W)$, which provides a measure of independency of the estimated sources.

Incorporation of the constraint requires another cost function such as $J_C(W)$ to be minimized together with $J_M(W)$. The constraint term is then joined to the main objective function by using either a Lagrange multiplier or a set of penalty functions. Application of penalty functions, however, affords more opportunity to relax the constraints and exploit the possible nonstationarity of the mixtures. An overall cost function is best defined as :

$$J(\mathbf{W}) = J_M(\mathbf{W}) + kG(J_C(\mathbf{W})) \tag{3}$$

where $G(.)$ is the penalty function and k is a penalty coefficient. In the following sections a new constrained BSS method based on the original Infomax BSS system and incorporating a reference signal as a constraint is introduced for detection and localization of the P300 sources within the brain from the EEGs.

2. THE CONSTRAINED ALGORITHM

In an undetermined BSS system the estimated ICs do not necessarily represent the actual sources. This happens when EEGs are to be separated. In the development of this project we aim at separation of the scalp EEG mixtures in such away that the desired P300 signal is one of the estimated ICs. The Infomax BSS algorithm is based on minimization of the mutual information or maximization of the entropy. The Infomax cost function $J_M(W)$, can be found in the literature [5]. The unmixing matrix is recursively updated on the basis of;

$$W = arg\ \min_{\mathbf{W}}[J_M(\mathbf{w}) + kG(J_C(\mathbf{w}))] \tag{4}$$

Here $J_M(W)$ is the main objective function of the Infomax BSS algorithm and

$$J_C(\mathbf{W}) = \|\mathbf{p} - \mathbf{y}\|^2 = \|\mathbf{p} - W\mathbf{x}\|^2 \tag{5}$$

where $\mathbf{p}$ is a matrix built up of rows, each equal to the P300 reference signal. The reference signal is obtained by averaging several segments of the same electrode signal after a visual or auditory periodic stimulation. The update equation is generally denoted as

$$W(t+1) = W(t) + \Delta W(t) \tag{6}$$

where extending the NGA as in [6] we have

$$\Delta W(t) = \mu \frac{\partial J(W)}{\partial W} W^T W =$$

$$\mu\left(?\,\mathbf{I} + (1 - \frac{2}{1+\exp(W\mathbf{x})})(W\mathbf{x})^T + 2\mathbf{q}\left(\mathbf{x}(W\mathbf{x} - \mathbf{p})^T\right)^T W^T \right) W$$

Here γ is a constant, $\mathbf{I}$ is a unitary matrix. $\boldsymbol{W}$ is initialised to $\boldsymbol{W}_{init} = \mathbf{I}$ and μ is the learning rate, calculated empirically via the following adaptive criterion:

$$\mu(t) = \mu_0 \left(\frac{\alpha}{\|\mathbf{Rx}\|_F^2} + \frac{\beta}{?+\|\Delta J_C\|} \right) \tag{8}$$

where μ_0, α, β, and ζ are constants adjusted manually. In the above formulation $\mathbf{q}$ is updated iteratively based on the new $\boldsymbol{W}$ in the direction of minimizing the distance between the output ICs and the P300 reference signal i.e.

$$\mathbf{q} = k\,.\,diag\left[(W\mathbf{x} - \mathbf{p})(W\mathbf{x} - \mathbf{p})^T\right]/L \tag{9}$$

where k is the penalty parameter and L is the length of the signal. In the above analysis we ignored the effect of noise, which is inherently contained in $\mathbf{x}$. However, incorporation of the constraint into the original infomax update equation does not generally change the performance of the system in terms of noise effect. In fact, it is likely to regularize this effect.

3. LOCALIZATION CRITERION

Localization of the EEG sources has been investigated recently [3] [8] [9]. With some indeterminacy in the results we can approximate the location of the sources in the brain. Unlike the methods in [8] and [9], which consider the sources as magnetic dipoles, we consider them as the sources of isotropic propagation. Therefore the head (mixing media) model only mixes and attenuates the signals. Therefore based on Figure 1 we have

$$\|\mathbf{f}_k - \mathbf{a}_j\|_2 = d_j \tag{10}$$

where $\mathbf{f}_k$ and $\mathbf{a}_j$ refer to the source and the electrode coordinates respectively, and d_j are nonlinearly proportional to the inverse of the correlations between the estimated source k and the electrode signals. j = 1,2,3 represent the electrodes involved in calculation of the correlation values, and k = 1, 2, . . . , M, show the source numbers. In this equation all the variables except $\mathbf{f}_k$ are known. Incorporating more than three mixtures does not affect the result whereas it makes the computation more intensive. The nonlinearity stated above comes from the

fact that the head is not a homogenous region. In a spherical model of the head we may consider three main layers; brain, skull, and scalp for which the thickness is known. The conductivity of the skull, σ_{skull}, is from 10 to 100 times less than those of the brain and the scalp i.e. $10\sigma_{scalp} < \sigma_{brain} = \sigma_{scalp} < 100\,\sigma_{skull}$. In order to incorporate the non-homogeneity and ensure that there will be a solution to equation (10) within the brain region, these values have to be nonlinearly mapped and normalized such that all the estimated sources fall within the brain region. In addition we assume that we have the solution for some certain EEG sources such as normal Delta rhythm.

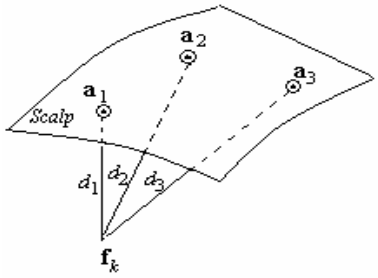
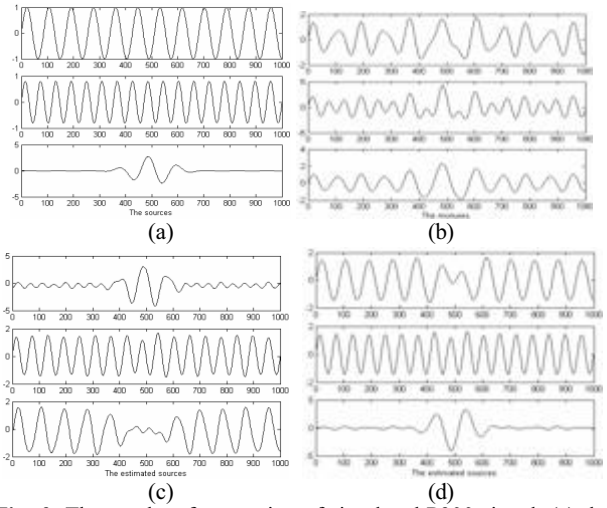


Fig. 1. Scalp model including three electrodes, and the location of the source to be identified (assuming the head is homogenous)

4. EXPERIMENTAL RESULTS

In this part the proposed CBSS algorithm is applied to the simulated as well as real EEG data. The sampling frequency is 200 sample/sec. The data is pre-whitened and $\boldsymbol{W}$, the separation matrix is initialised to $\mathbf{I}$. The P300 reference signal is achieved by temporal averaging of each electrode signal. This signal is then used as a reference for updating the unmixing matrix.

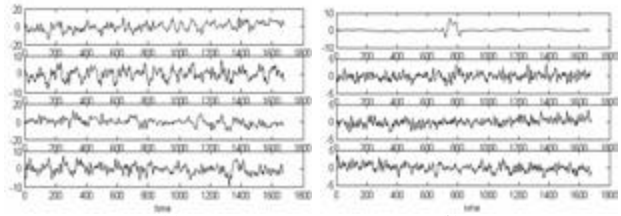


(a) (b)

(c) (d)

Fig. 3. The results of separation of simulated P300 signal; (a) the original sources, (b) the mixtures, (c) the estimated sources using the traditional and (d) the estimated sources using the constrained Infomax algorithms; all plots are amplitude vs. time.

The algorithm attempts to minimize the Euclidian distance between the output of CBSS and the reference P300. In the first experiment only three mixtures including the P300 have been modelled and used. Figure 3 compares the results of separation using traditional Infomax BSS algorithm and those of the proposed constrained technique. The convergence of the system proved to be faster than that of the well-known NGA-based joint diagonalization criterion. Also the Euclidean distance between the estimated P300 output and the P300 reference was smaller with CBSS. In the next experiment the reference P300 signal has been estimated from the mixtures by temporal averaging the signal. The period of the stimuli is ten seconds and it lasts for 0.5 second. We avoid any eye blinking or other artefacts. Figure 4 shows the results of separation of the P300 signal for a schizophrenia patient.



(a) (b)

Fig. 4. The results of separation of a real P300 signal in a schizophrenia patient, using the constrained Infomax algorithm; (a) the EEGs and (b) the separated signals using CBSS, the top signal is the separated P300 (only 4 out of 10 signals have been displayed here).

After separation, the estimated highlighted component is localized through the following steps: (a) The correlation values are inverted and normalized between 0 and 1, (b) A nonlinear μ-law function, with $100>\mu>25$, is used for transformation of the correlation values, (c) The transformed values were scaled into between 12 mm and the radius of the head, as d_j, and (d) The solution to the following least square problem was obtained [10]:

$$\min S(\mathbf{f}_k) = \min \sum_{j=1}^{3} \left\{ \left\| \mathbf{f}_k - \mathbf{a}_j \right\|_2 - d_j \right\}^2, \ \mathbf{f}_k \in R^n \qquad (11)$$

Although by following the above steps still we may have different solutions to equation (12), in all the cases auditory and visual P3a subcomponents are consistently localized in two different regions of the brain. For a head phantom, in more than 95% of the cases an exact localization of the sources has been achieved. Both P3a and P3b signals are localized around the temporo-superior dipoles and temporo-basal dipoles respectively.

In another experiment the auditory and visual P300 have been analysed separately. 64-electrode settings were used. In Figure 5 a reference segment for Visual stimulation has been given by temporal averaging. In

Figure 6 the inner product of this signal and the electrode signals are calculated. The horizontal axis shows the electrode number in the same order as the conventional EEG electrode setting.

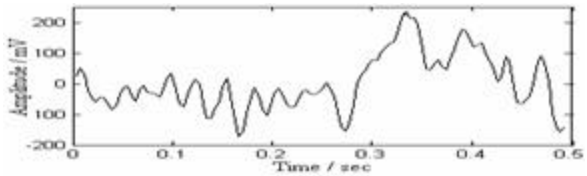


Fig. 5. The estimated visual P3a signal using CBSS.

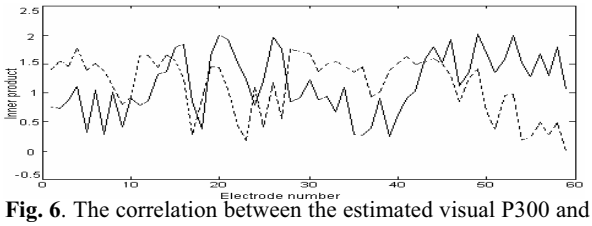


Fig. 6. The correlation between the estimated visual P300 and the electrode signals; horizontal axis shows the electrode number. Two different trials have been recorded.

In another experiment a reference signal for auditory P300 has been obtained by temporal averaging (Figure 7). Similarly, the correlation between this signal and the electrode signals are calculated and displayed in Figure 8. Comparing Figures 5 and 7 it can be concluded that the latency for visual P300 is more than for auditory P300. Also Figures 6 and 8 clearly show that the auditory and visual P300 sources are located in two different regions within the brain. Higher SNR, Less Euclidean distance of the desired output with the reference, and faster convergence concluded.

5. CONCLUSIONS

A new CBSS method has been developed and used for separation and localization of the auditory and visual P300 sources . The algorithm is an extension of original Infomax algorithm, for which a reference P300 signal is used as a constraint. The constrained problem is then converted to an unconstrained problem by means of nonlinear penalty functions weighted by the penalty terms. As a result, both auditory and visual P300 can be separated and well localized. In addition it is shown that the latency for above two P300 signals is different. The method is an effective tool in investigation of the schizophrenia disease (as well as some other neurological disorders such as Alzheimer's) in neurophysiology and psychiatry departments.

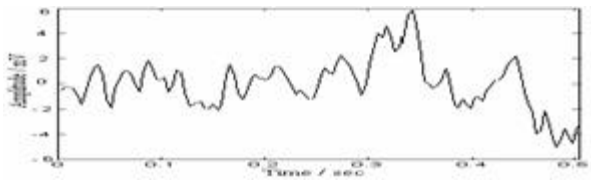


Fig. 7. The estimated auditory P3a signal.

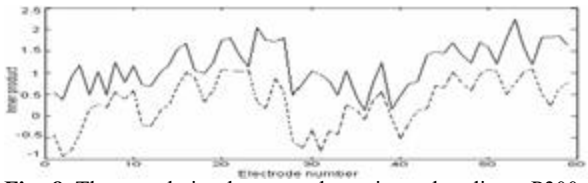


Fig. 8. The correlation between the estimated auditory P300 and the electrode signals; horizontal axis shows the electrode number. Two different trials have been recorded.

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