ESTIMATION AND LOCATION TRACKING OF THE P300 SUBCOMPONENTS FROM SINGLE-TRIAL EEG

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ABSTRACT

Estimating the P300 subcomponents of Event Related Potentials (ERPs) is very important in the fields of psychiatry and neurology. The characteristics of these brain signals, such as latency, location, strength, and variation, can give useful insights of the person's condition. In particular, the signals' characteristics can aid in the diagnosis and monitoring of some specific psychiatric diseases such as schizophrenia of various stages, and can be a useful factor for their treatment. In this paper we employ a new filtering algorithm, incorporating prior knowledge of the shape of such components. Then we employ a novel localization algorithm to track the location of the P300 components trial by trial.

Index Terms— EEG, P300, source tracking, source localisation, single-trial

1. INTRODUCTION

Event-Related Potentials (ERPs) correspond to the electrical activity in the brain that occurs in response to a stimulus. They are measured with electroencephalograms (EEGs) which offer a fine temporal resolution. This allows an effective study of their time-course not available with other neuro-imaging techniques. However, spatial resolution has been limited especially when the time courses of separate brain sources overlap.

The ERP components of particular importance are the P300 subcomponents. The composite P300 wave represents cognitive functions involved in orientation of attention, contextual updating, response modulation and response resolution. It consists of multiple overlapping components, of which the two main ones are the P3a and P3b. P3a reflects an automatic orientation of attention to novel or salient stimuli independent of task relevance. Prefrontal, frontal and anterior temporal brain regions play a major role in generating P3a giving it a frontocentral distribution. In contrast, P3b has a greater centro-parietal distribution due to its reliance on posterior temporal, parietal and posterior cingulate mechanisms.

A number of techniques have been developed for the estimation of ERP signals. Blind source separation (BSS) has been used successfully for EEG separation [1] [2]. BSS extracts independent sources from the EEG without using any knowledge about the mixing process and the sources. Likewise, it simultaneously estimates the forward matrix. Another major technique is the so-called dipole method which models the brain sources as current dipoles [3]. A mathematical model is created which links the current at the dipole location to the voltage at the electrodes. Then, a Least Squares (LS) fit to the data is used to determine their parameters. These methods perform source localisation as well as source estimation. A drawback of BSS and dipole methods is that the number of sources needs to be known a priori to achieve good results. However, the MUSIC method which is based on dipole modelling does not need to know the number of sources; it scans every location in the brain to determine the presence of a dipole [4]. Another major technique namely the minimum-norm (MN) methods attempt to estimate the whole spatial topography of the underlying EEG. In contrast to the MUSIC based methods, MN methods such as LORETA [5] attempt to estimate the brain activity at every location simultaneously. The problem is traditionally ill-posed and regularisation is needed in the solution. Other techniques such as wavelets [6][7], Bayesian estimation [8][9] and LS with generic basis functions have also been used [10][11].

The method proposed in this paper uses an approximation to the prior information of the shapes of the ERP components. As it is widely observed, ERP signals are transient waves time-locked at approximate latencies after an ERP eliciting event. A good approximation for the ERP components is to model them as Gaussian spikes (with certain latencies and variances). The spikes then serve as reference signals onto which the EEG data are projected. Thus, we use the spatio-temporal information which exist in the data to find the closest representation of the reference in the data. By estimating all the existing ERP components in the data the locations of the sources are computed using a modified LS method.

2. PROPOSED METHOD

We model the EEG signal as an $n \times T$ matrix (n is the number of electrodes and T is the number of time samples):

$$\mathbf{X} = \mathbf{HS} = \Sigma_i \mathbf{h}_i \mathbf{s}_i \quad (1)$$

where $\mathbf{H}$ is the $n \times m$ forward matrix of the m sources $\mathbf{s}_i$. The sources $\mathbf{s}_i$ are considered as the ERP components that are directly relevant and time-locked to the stimulus. They are thought to have a transient spiky shape. We need to design m filters $\{\mathbf{w}_i\}$ (note that we do not know the number of sources beforehand) that satisfy:

$$\mathbf{s}_i = \mathbf{w}_i^T \mathbf{X} \quad (2)$$

This can be achieved if each filter $\{\mathbf{w}_i\}$ is designed to minimise:

$$\mathbf{w}_{opt} = \arg\min ||\mathbf{s}_i - \mathbf{w}_i^T \mathbf{X}||_2^2 \quad (3)$$

which, however, requires some prior knowledge about the shape of the sources $\mathbf{s}_i$. In this work we model the sources as:

$$\mathbf{s}_i = exp(-(t - \tau_i)^2 / \sigma_i^2) \quad (4)$$

where τ_i is the latency of the ith source and σ_i its width. The width is chosen as the average width of the P3a and P3b subcomponents and it does not have to be accurately estimated since the LS solution (3) will find the closest match.

2.1. Estimating the source signals

To estimate the sources $\mathbf{s}_i$ we create a large number of reference signals $\mathbf{r}_l = exp(-(t - l)^2 / \sigma^2)$ each having a latency at a different time sample. Hence, we create T of those references (Figure 1).

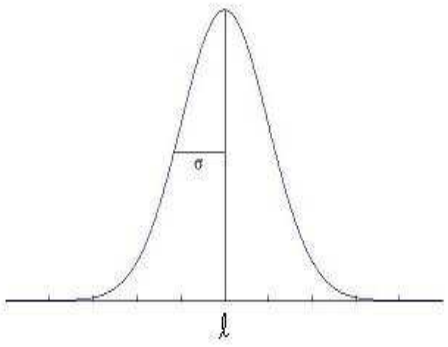

Fig. 1. Gaussian spike used to model the ERP components

Then we compute T (note that $T \gg m$) filters such as:

$$\mathbf{w}_l^T = \arg\min ||\mathbf{r}_l - \mathbf{w}_l^T \mathbf{X}||_2^2, \quad \mathbf{y}_l = \mathbf{w}_l^T \mathbf{X} \quad (5)$$

We assume that the signals $\mathbf{y}_l$ which have a similar latency to a true source $\mathbf{s}_i$ correspond to that source only. Also, since the ERP components have distinct latencies we expect the signals $\mathbf{y}_l$ to be grouped in m clusters, equivalent to the number of sources. To cluster the T signals $\mathbf{y}_l$ we use the following algorithm:

for i=1 to T

- measure $l(i)$, the latency of $\mathbf{y}_i$
- if $l(i) - l(i-1) < \beta$, then $\mathbf{y}_i$ and $\mathbf{y}_{i-1}$ belong to the same group, β is a threshold selected empirically
- if $l(i) - l(i-1) > \beta$, then $\mathbf{y}_i$ belongs to a different group than $\mathbf{y}_{i-1}$

Then, within each group we average all the signals $\mathbf{y}_i$ to obtain c signals $\mathbf{y}_c$, and it is expected that $c = m$. Note that the obtained sources can be the scaled versions of the original sources $\mathbf{s}_i$ because their scales depend on the amplitude of the reference signals.

This procedure extracts spike-like waves from the data. The main advantage is that by sweeping all the data at relatively small intervals, every spike-like wave will be extracted. This coincides with ERP signals, which are known to have transient waveforms. Also, this method is robust to differences in the modelling of the spikes. It extracts the sources which are most similar to the reference signal.

2.2. Scalp maps

To estimate the scalp maps (the columns of the forward matrix $\mathbf{H}$) we use the following novel procedure. First we compute $\mathbf{R}$ as the cross-correlation between the data matrix and the output sources matrix:

$$\mathbf{R} = \mathbf{XY}^T = \mathbf{HSY}^T \quad (6)$$

where $\mathbf{Y}$ is a matrix whose rows are the signals $\mathbf{y}_c$. The estimated sources $\mathbf{Y}$ can be written as $\mathbf{Y} = \mathbf{DS}$, where $\mathbf{D}$ is a diagonal matrix describing the scaling of each of the sources:

$$\mathbf{D} = \begin{pmatrix} d_1 & 0 & 0 & 0 & 0 \\ 0 & d_2 & 0 & 0 & 0 \\ 0 & 0 & . & 0 & 0 \\ 0 & 0 & 0 & . & 0 \\ 0 & 0 & 0 & 0 & d_c \end{pmatrix} \quad (7)$$

If we multiply $\mathbf{R}$ by the autocorrelation matrix of $\mathbf{Y}$ we can obtain a scaled version of the scalp maps:

$$\begin{aligned} \mathbf{RR}_y^{-1} &= \mathbf{HSY}^T(\mathbf{YY}^T)^{-1} \\ &= \mathbf{HD}^{-1}\mathbf{YY}^T(\mathbf{YY}^T)^{-1} = \mathbf{HD}^{-1} \end{aligned} \quad (8)$$

The permutation does not have any effect on the solution since the ordering of the sources is arbitrary. Hence, the i_{th} scaled scalp map will correspond to the scaled i_{th} source.

2.3. Least-Squares estimation of the position of the source

We now show how to calculate the position of the source using the modified LS method. The first step is to convert the elements of the $\mathbf{H}$ matrix to estimates of the distances between the electrodes and the sources. We use an isotropic

propagation model of the source where it attenuates with the $3rd$ power of the distance [12]. To convert to distances we perform the following operation:

$$r_j = \frac{1}{h_j^{1/3}} \tag{9}$$

where h_j is the j_{th} elemement of a specific column of the **H** matrix. The point **q** is the solution to the following Least-Squares problem:

$$E(\mathbf{q}, M) = \sum_{j=1}^{n} [M||\mathbf{q} - \mathbf{a}_j||_2 - r_j]^2 \tag{10}$$

where we know $\mathbf{a}_j$ depicts the positions of the electrodes, with r_j as the scaled distances and $E(\mathbf{q})$ is the squared error. The factor M denotes the scaling that arises from the algorithm as discussed in the previous section and also from the fact that our model (10) did not consider the electrical properties of the head. We desire to minimise the error function and it should ideally be zero. The derivatives with respect to **q** and M are:

$$\nabla E_{\mathbf{q}} = 2 \sum_{j=1}^{n} (\mathbf{q} - \mathbf{a}_j)(M^2 - M \frac{r_j}{||\mathbf{q} - \mathbf{a}_j||_2}) \tag{11}$$

$$\nabla E_M = 2 \sum_{j=1}^{n} M||\mathbf{q} - \mathbf{a}_j||_2^2 - ||\mathbf{q} - \mathbf{a}_j||_2 r_j \tag{12}$$

We employ an iterative procedure to estimate **q**:

$$\mathbf{q} = \mathbf{q} - k_1 \nabla E_{\mathbf{q}} \tag{13}$$

and

$$M = M - k_2 \nabla E_M \tag{14}$$

where k_1 and k_2 are the learning rates. The solutions of **q** and M are unique with an appropriate number of electrodes. The proof is omitted due to lack of space.

3. EXPERIMENTAL RESULTS

The EEG data were recorded using a Nihon Kohden model EEG-F/G amplifier and Neuroscan Acquire 4.0 software. EEG activity was recorded following the international 10-20 system from 15 electrodes. The reference electrodes were linked to the earlobes. The impedance for all the electrodes was below 5kΩ, sampling frequency Fs=2kHz and the data were subsequently bandpass filtered (0.1-70Hz).The stimuli presented were designed to elicit both the P3a and P3b subcomponents.

The steps to reconstruct the sources and compute the locations are:

1. Choose the width σ, and the number of reference signals to be created, maximum T
2. Compute the filters $\mathbf{w}_l$, each corresponding to a reference signal
3. Measure the latency of each output signal $\mathbf{y}_l$, group them in c clusters according to the algorithm in the previous section, and average the signals within each cluster
4. Measure the latency, compute the scalp maps for the averaged outputs of each cluster
5. Compute the locations of the desired components

3.1. Single-Trial P300 estimation

In this section we estimate the P300 subcomponents (for 40 trials) for a schizophrenic patient and for a control subject (Figure 2). Then, we compute their average latencies and the standard deviation of the latencies (Table 1). Lastly we compare their locations (Figures 3 and 4). Table 1 shows that the latency of the patients P300 is larger than for the control subject. The P3b's standard deviation from the mean is bigger for the patient than for the normal subject. Regarding their locations, the clusters are more distinct for the schizophrenic patient's P3a and P3b than for the normal subject's.

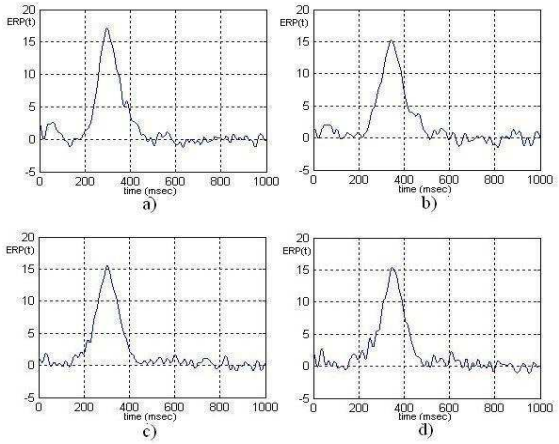

Fig. 2. The average of the obtained P3a and P3b signals for a patient, a) and b), and a control subject, c) and d).

Table 1. Mean and standard deviation of the latencies for the obtained components.

	mean P3a	mean P3b	σ_{P3a}	σ_{P3b}
Patient	297.5	344	12.3	13
Control	303	348	11.2	15.6

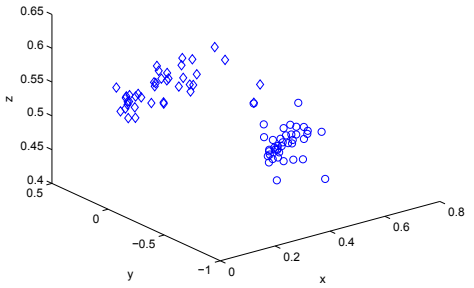

Fig. 3. The locations of the P3a and P3b for a patient are shown in this figure. The diamonds represent the P3a and the circles the P3b. The x axis denotes right to left, the y axis the front to back, z axis is up to down. The distinct clustering is evident.

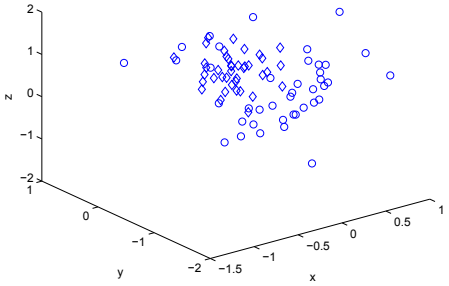

Fig. 4. The locations of the P3a and P3b for a normal subject are shown in this figure. The diamonds represent the P3a and the circles the P3b. The close clustering can be seen easily.

4. CONCLUSIONS

A novel filtering and localisation algorithm for the P300 subcomponents from single-trial EEGs has been developed here. The approach iteratively projects adaptively generated reference signals onto ERP data. The method was used to compare the characteristics of the P3a and P3b for a control and a schizophrenic patient. It was found that firstly, the average latency for the schizophrenic patient was less than the normal subject's. Secondly, the spread of P3b was more for the patient. Finally, it was found that the locations of the P3a and P3b were more distinct from trial to trial for the schizophrenic patient.

5. REFERENCES

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