A NEW BEAMFORMING APPROACH FOR THE LOCALISATION OF EVENT RELATED POTENTIALS

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ABSTRACT

The ERP signals describe the concentrated electrical activity of the brain in response to an external event. ERPs exhibit variations in latency, strength and location between various instances of the same event. Also, different population groups can show similarities in the characteristics of their ERPs and this fact is used by clinicians in diagnosis and monitoring of some specific psychiatric diseases. In this paper, we model the ERP components as transient spikes and use them as reference signals. We employ a novel localisation procedure utilising spatial notch filters and the information from the modelled ERP. The algorithm accurately localises the ERP sources within a noisy environment.

1. INTRODUCTION

ERPs correspond to the electrical activity in the brain that occurs in response to a stimulus. They are measured primarily with electroencephalograms (EEGs) which offer a fine temporal resolution and allow an effective study of their time-course not available with other neuro-imaging techniques. However, the spatial resolution is 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 localisation and estimation of the EEG signals in general. One of the most popular methods is the dipole fitting method [1] [2]. The EEG sources are modelled as current dipoles and then a least squares (LS) fit to the data is performed. Of particular interest is the multiple signal classification (MUSIC) method. This method searches for a source at a large number of possible locations. It performs a grid search employing the noise subspace of the data utilising the singular value decomposition (SVD) of the EEG data. Another group of methods are the linear constrained minimum variance (LCMV) [3] filters or beamformers [4]. The LCMV method tries to spatially filter the EEG signal so that the activity from only one location is passed. A grid search is performed to show the activity from a number of locations. Another main class of methods are the minimum norm (MN) methods [5]. These methods use the same dipole model for the sources but instead of looking for one source at a time an inverse solution is applied to the entire solution space. The inverse solution is constructed from the forward or lead-field matrix which makes the system greatly underdetermined considering that the solution space consists typically of thousands of source locations. Regularisation and smoothing methods are applied to create a unique solution [6] [7] [8] [9] [10].

The construction of the algorithm is similar to that of the LCMV spatial filter method. In the LCMV method the filter output is minimised, while the activity from one location passed. Here, we try to force the filter output to be as similar as possible to our reference ERP component while we cut off the activity from a location. It turns out that if the reference signal matches the true ERP and the true location is within our solution space (i.e is included in the grid search) then the algorithm will always attain a saddle point at the correct location. That implies that if the ERP model is not entirely true, for example, the reference has a slightly different latency or width, the algorithm will try to find the closest match between the reference signal and the extracted one.

The proposed method does not need any prior assumptions about the number of sources, and more importantly it does not require a noise subspace (i.e overdetermined; system, more sensors than sources). A number of different cases are examined for generic data and real EEG. Specifically, we examine the effect of noise and the effect of correlation between different ERP components.

2. SOURCES AND EEG MODEL

In the proposed method a head and source model is used to describe the propagation of the brain sources to the sensors. The sources are modelled as current dipoles and their propagation to the sensors is mathematically described by an appropriate forward model [11].

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

$$\mathbf{X} = \mathbf{HMS} + \mathbf{N} = \sum_{i=1}^{m} \mathbf{H}_i \mathbf{m}_i \mathbf{s}_i + \mathbf{N} \tag{1}$$

The second term of equation (1) is the matrix form of the model and $\mathbf{H}$ is a $n \times 3m$ matrix describing the forward model of the m sources to the n electrodes. It is further decomposed into m matrices $\mathbf{H}_i$ as:

$$\mathbf{H} = [\ \mathbf{H}_1 \quad \dots \quad \mathbf{H}_i \quad \dots \quad \mathbf{H}_m] \tag{2}$$

where $\mathbf{H}_i$ is an $n \times 3$ matrix whose each column describes the potential at the electrodes due to the i_{th} dipole for each of the 3 orthogonal orientations. For example, the 1_{st} column of $\mathbf{H}_i$ describes the forward model of the x component of the i_{th} dipole when the y and z components are zero. Similarly, $\mathbf{M}$ is a $3m \times m$ matrix describing the orientation of the m dipoles. Finally, $\mathbf{s}_i$ which is a $1 \times T$ vector, is the timecourse of the i_{th} dipole and $\mathbf{N}$ is the combination of the measurement noise and modelling error.

In addition to the forward model, we create a model for the timecourse of the ERP sources as well. It is well established that they exhibit transient behaviour which can be captured by a Gaussian spike. Here, we model the ERP references as:

$$\mathbf{r}_i = exp(-(t-l_i)^2/\sigma_i^2) \tag{3}$$

where l_i is the latency of the ith ERP component and σ_i is the spike width (Figure 1). The EEG then can be explained as a sum of such spikes and non ERP related activity. Generally, ERPs are not correlated with each other and occur at distinct latencies. An exception is the P3a and P3b subcomponents, which overlap slightly but their peaks are distinct. To use the reference model properly an estimation of their latencies and widths is necessary. These parameters should correspond to the true ERP shape of each component. In this work we focus on the P300 subcomponents (P3a and P3b) for which an approximate estimate is made by inspection of the data [12]. Also, many P300 templates can be found in the literature from other studies to estimate the duration of these spikes. The spike shapes do not need to be very accurate since the algorithm finds the closest match.

3. DEVELOPMENT OF THE ALGORITHM

The designed algorithm is based on spatial notch filtering and minimising the distance of the reference signal and a filtered version of the EEG. We perform a constrained optimisation technique in which the primary cost function is the euclidean distance between the reference signal and the filtered EEG:

$$f_d(\mathbf{w}) = ||\mathbf{r}_i - \mathbf{w}^T\mathbf{X}||_2^2 \tag{4}$$

The minimum point can be obtained by the classic Least Squares (LS) minimisation and is given by:

$$\mathbf{w}_{opt} = (\mathbf{X}\mathbf{X}^T)^{-1}\mathbf{X}\mathbf{r}^T \tag{5}$$

This method designs a filter $\mathbf{w}_{opt}$, which is of dimensions $n \times 1$, and gives an estimate of the reference signal that exists in the data. However, this procedure alone does not include any spatial information unless we obtain all the filters $\mathbf{w}_i$ for all the sources. This way, we can construct a matrix $\mathbf{W}$, similar to the separating matrix in an ICA framework, which could be converted to the forward matrix $\mathbf{H}$ [12]. In this work we wish to estimate the location of a source which matches our reference signal without having to estimate the $\mathbf{w}$ filters for other sources.

If we use a constraint function such as:

$$f_c(\mathbf{w}) = \mathbf{w}^T\mathbf{H}(p) = \mathbf{0} \tag{6}$$

where $\mathbf{H}(p)$ is the forward matrix of a dipole at location p and perform a grid search over a number of locations then the algorithm will point to the true location of the reference signal (as shown later). Note that $\mathbf{H}(p)$ denotes the forward matrix at location p while $\mathbf{H}_i$ denotes the forward matrix of source i at some location. Such a constraint function can be thought of as a spatial notch filter. A spatial notch filter will remove any signal coming from a specific location. The stopband behaviour of the filter will depend on the number of electrodes and the spacing between the sources in the grid. By imposing such a constraint to the original cost function we force the filter output to have minimum energy from a particular location.

Practically, we design an adaptive beamformer which scans a number of locations and tries to find the closest match to our reference signal. However, at the same time, we are testing for the absence of the reference signal. This expresses the main novelty of this work. When the proposed beamformer scans a particular location it tries to match the reference signal while placing a null in that particular location. If the reference signal does not originate from that location the beamformer will try to find the closest match but will be influenced by the three degrees of freedom (one degree of freedom for each orthogonal dipole) that have been used by placing the null in that location. So, the solution will differ from the optimum filter that extracts the reference with minimum error. In this case, our adaptive beamformer will not be equal to $\mathbf{w}_{opt}$ of equation (5). The $\mathbf{w}_{opt}$ filter places nulls to the locations of the undesired sources (assume $\mathbf{r}_j$ is our desired source at location $\mathbf{H}_j$):

$$\mathbf{w}_{opt}^T\mathbf{H}_i = \mathbf{0} \quad i = 1...m \,\text{and}\, i \neq j \tag{7}$$

where j refers to the position of the desired source. At some point during the grid search, the forward matrix $\mathbf{H}(p)$ is going to take the value of the forward matrix of source j, our desired source. At this point $\mathbf{H}(p) = \mathbf{H}_j$, which will place another null in the location of our desired source. So, at this point our beamformer $\mathbf{w}$ satisfies:

$$\mathbf{w}^T\mathbf{H}_i = \mathbf{0} \quad i = 1...m \tag{8}$$

Hence, the only result of the filter will be a zero signal, which can only be obtained by a filter equal to the null vector. That is because we have cancelled out all other signals. This happens only when the beamformer points to the location of our desired source. For any other location, the beamformer will try to do its best according to the conditions imposed by the constraint. So, we steer our beamformer over a number of locations and at some point it will fail to give any output (i.e. it is equal to the null vector). That location will be the location of the desired signal. In other words, the optimum point of the process is where the algorithm fails to find a solution.

We will now show that for the correct reference and location the filter $\mathbf{w}$ is forced to zero. The constrained problem can be posed as:

$$min \quad f_d(\mathbf{w}) \quad \text{subject}\, to \quad f_c(\mathbf{w}) = \mathbf{0} \tag{9}$$

This constrained problem can be converted to an unconstrained optimisation procedure by using Lagrange multipliers. Consequently, equation (9) is converted to:

$$F(\mathbf{w}) = f_d(\mathbf{w}) + f_c(\mathbf{w})\mathbf{q} = ||\mathbf{r}_i - \mathbf{w}^T\mathbf{X}||_2^2 + \mathbf{w}^T\mathbf{H}(p)\mathbf{q} \tag{10}$$

where $\mathbf{q}$ is a 3×1 vector of Lagrange multipliers. The derivative of $F(\mathbf{w})$ w.r.t. $\mathbf{w}^T$ is:

$$\frac{\partial F(\mathbf{w})}{\partial \mathbf{w}^T} = \frac{\partial}{\partial \mathbf{w}^T}\{\mathbf{r}\mathbf{r}^T - 2\mathbf{r}\mathbf{X}^T\mathbf{w} + \mathbf{w}^T\mathbf{X}\mathbf{X}^T\mathbf{w} + \mathbf{w}^T\mathbf{H}(p)\mathbf{q}\} \tag{11}$$

where i has been omitted for simplicity. This becomes:

$$\frac{\partial F(\mathbf{w})}{\partial \mathbf{w}^T} = -2\mathbf{r}\mathbf{X}^T + 2\mathbf{w}^T\mathbf{X}\mathbf{X}^T + \mathbf{q}^T\mathbf{H}(p)^T \tag{12}$$

To obtain the minimum we set equation (12) to zero and obtain:

$$\mathbf{w}^T = \frac{1}{2}\left(2\mathbf{r}\mathbf{X}^T - \mathbf{q}^T\mathbf{H}(p)^T\right)\mathbf{C}_x^{-1} \tag{13}$$

where $\mathbf{C}_x = \mathbf{X}\mathbf{X}^T$ is the covariance matrix of $\mathbf{X}$. If we substitute equation (13) to equation (8) we obtain:

$$\mathbf{w}^T\mathbf{H}(p) = \frac{1}{2}\left(2\mathbf{r}\mathbf{X}^T - \mathbf{q}^T\mathbf{H}(p)^T\right)\mathbf{C}_x^{-1}\mathbf{H}(p) = 0 \tag{14}$$

which will give us the Lagrange multipliers $\mathbf{q}$:

$$\mathbf{q}^T = 2\mathbf{r}\mathbf{X}^T\mathbf{C}_x^{-1}\mathbf{H}(p)(\mathbf{H}(p)^T\mathbf{C}_x^{-1}\mathbf{H}(p))^{-1} \tag{15}$$

Now, we substitute that into equation (13) and we obtain the full expression for the filter:

$$\mathbf{w}^T = \left(\mathbf{r}\mathbf{X}^T - \mathbf{r}\mathbf{X}^T\mathbf{C}_x^{-1}\mathbf{H}(p)(\mathbf{H}(p)^T\mathbf{C}_x^{-1}\mathbf{H}(p))^{-1}\mathbf{H}(p)^T\right)\mathbf{C}_x^{-1} \tag{16}$$

which splits into two parts; the first part is the solution to the primary cost function $f_d(\mathbf{w})$ and the second part is due to $f_c(\mathbf{w})$:

$$\mathbf{w}^T = \mathbf{w}_{opt}^T - \mathbf{r}\mathbf{X}^T\mathbf{C}_x^{-1}\mathbf{H}(p)(\mathbf{H}(p)^T\mathbf{C}_x^{-1}\mathbf{H}(p))^{-1}\mathbf{H}(p)^T\mathbf{C}_x^{-1} \tag{17}$$

We now proceed to show that if $\mathbf{r}$ corresponds to a source $\mathbf{s}_j$, which is uncorrelated with the other sources, and the forward matrix $\mathbf{H}_j$ is included in the grid search, then $\mathbf{w}$ will be forced to zero. This happens only for the conditions mentioned above. Consider the product $\mathbf{r}\mathbf{X}^T$ (ignore the noise for the moment) which is:

$$\begin{aligned}\mathbf{r}\mathbf{X}^T &= \mathbf{r}\Big(\sum_{i=1}^{m}\mathbf{H}_i\mathbf{m}_i\mathbf{s}_i\Big)^T \\ &= \mathbf{r}\sum_{i=1}^{m}\mathbf{s}_i^T\mathbf{m}_i^T\mathbf{H}_i^T\end{aligned} \tag{18}$$

So if the sources are uncorrelated then we get:

$$\mathbf{r}\mathbf{X}^T = \mathbf{r}\mathbf{s}_j^T\mathbf{m}_j^T\mathbf{H}_j^T \tag{19}$$

By substituting that into equation (17) we get:

$$\mathbf{w}^T = \mathbf{w}_{opt}^T - \mathbf{r}\mathbf{s}_j^T\mathbf{m}_j^T\mathbf{H}_j^T\mathbf{C}_x^{-1}\mathbf{H}(p)(\mathbf{H}(p)^T\mathbf{C}_x^{-1}\mathbf{H}(p))^{-1}\mathbf{H}(p)^T\mathbf{C}_x^{-1} \tag{20}$$

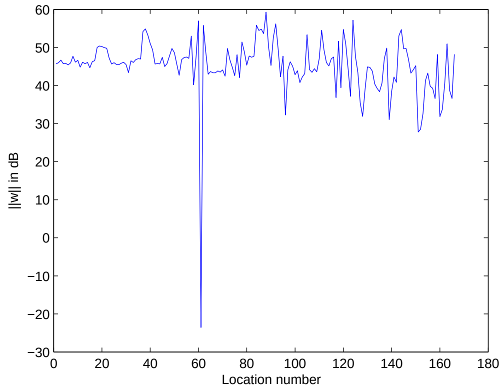

Figure 1: Localisation plot for one source uncorrelated with other sources in a noise free environment. The location number refers to a geometrical location within the brain.

Now, at some point during the grid search the matrix $\mathbf{H}(p)$ will take the value of $\mathbf{H}_j$ which will give through equation (20) the following:

$$\begin{aligned}\mathbf{w}^T &= \mathbf{w}_{opt}^T - \mathbf{r}\mathbf{s}_i^T\mathbf{m}_i^T\mathbf{H}_j^T\mathbf{C}_x^{-1} \\ &= \mathbf{w}_{opt}^T - \mathbf{r}\mathbf{X}^T\mathbf{C}_x^{-1} \\ &= \mathbf{w}_{opt}^T - \mathbf{w}_{opt}^T = \mathbf{0}\end{aligned} \tag{21}$$

So, $\mathbf{w} = \mathbf{0}$ only for the location corresponding to the desired signal. A measure of how close $\mathbf{w}$ is to the null vector will point to the correct location. The procedure is to calculate equation (17) for all locations obtained from a forward model and choose the solution with $\mathbf{w}$ closest to the null vector. The closeness measure we use is the norm of $\mathbf{w}$ since it reflects the distance of $\mathbf{w}$ to the origin which is the null vector.

4. EXPERIMENTAL RESULTS

In this section we apply the algorithm to a simulated EEG signal containing a number of ERP components and at the end we localise the P3a and P3b from real EEG data.

4.1 Simulated EEG

The efficiency of the algorithm is investigated for different scenarios. We obtain a forward model using the **BrainStorm** software [13]. We create seven Gaussian pulses in seven different locations with random orientations, peaking at different latencies and we use seven electrodes. We consider several different cases in order to evaluate the effect of noise and correlation between sources. The source we are looking for is originally placed at location numbered 61. For the simple case of no noise and uncorrelated sources we get Figure 1 which correctly localises the source. In Figure 2 we show that even in the case of correlation the source is correctly localised.

The performance of the algorithm can be affected by the orientation of the dipole while the other parameters are fixed. For example, in the previous plot the sources had the same location, orientation and power for all the cases. What varied, was the noise power and their cross-correlation. The next case to consider is a statistical performance of the algorithm for various random orientations. We do that because

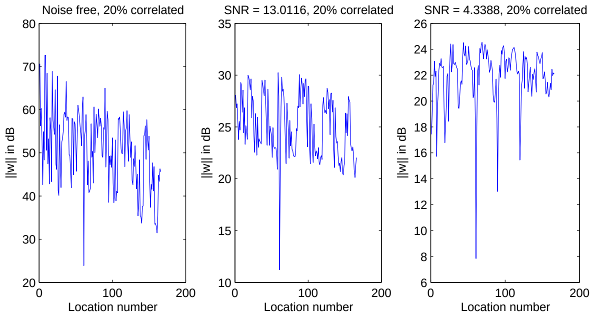

Figure 2: Localisation plot for one source 20% correlated with other sources, for different SNR.The source is correctly localised for all three cases.

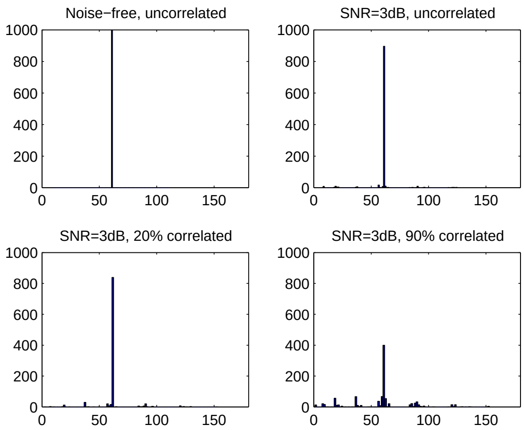

Figure 3: Histogram of the location for four cases. For the worst-case scenario (90% correlation 2dB SNR) the algorithm localises the source with 40% accuracy. For 20% correlation and 3dB SNR it localises with 84% accuracy which is slightly less of the 3dB SNR, uncorrelated case with success rate of 90%.

the performance of the algorithm is affected by the dipole orientation. Figure 3 shows the histogram of estimated locations for 1000 different dipoles randomly oriented for four different cases. In Figure 4 we show the succesfull localisation probability versus the SNR (really high SNR cases are not shown).

5. CONCLUSIONS

In this paper we developed an algorithm for the localisation of the P300 subcomponents. We modified the LS approach where we use a desired signal and a spatial notch filter. The desired signal is designed based on prior knowledge of the shape of the P300 subcomponents. The algorithm is in fact a special kind of beamformer and is a constrained version of the original LS solution. It points to the correct location when we have a suitable model of the actual sources and the sources are uncorrelated. As seen by section IV correlation between sources and increased noise can degrade the performance of the algorithm but even in those cases the algorithm achieves high localisation accuracy.

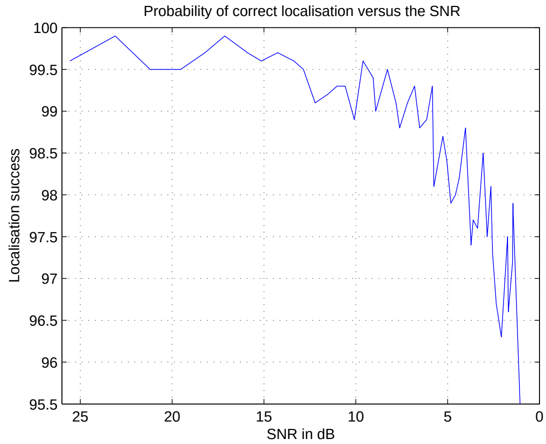

Figure 4: Here we show the probability of correct localisation for various SNRs. The purpose is to evaluate the performance of the algorithm for different orientation of the sources. We used the same noise sequence for 1000 different orientations and various SNR values.

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