An Averaging Technique for the P300 Spatial Distribution

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Summary
Introduction: This article is part of the Focus Theme of Methods of Information in Medicine on “Biosignal Interpretation: Advanced Methods for Neural Signals and Images”.

Objectives: The main objectives of the paper regard the analysis of amplitude spatial distribution of the P300 evoked potential over a scalp of a particular subject and finding an averaged spatial distribution template for that subject. This template, which may differ for two different subjects, can help in getting a more accurate P300 detection for all BCIs that inherently use spatial filtering to detect P300 signal. Finally, the proposed averaging technique for a particular subject obtains an averaged spatial distribution template through only several epochs, which makes the proposed averaging technique fast and possible to use without applying any prior training data as in case of data enhancement technique.

Methods: The method used in the proposed framework for the averaging of spatial distribution of P300 evoked potentials is based on the statistical properties of independent components (ICs). These components are obtained by using independent component analysis (ICA) from different target epochs.

Results: This paper gives a novel averaging technique for the spatial distribution of P300 evoked potentials, which is based on the P300 signals obtained from different target epochs using the ICA algorithm. Such a technique provides a more reliable P300 spatial distribution for a subject of interest, which can be used either for an improved spatial selection of ICs, or more accurate P300 detection and extraction. In addition, the experiments demonstrate that the values of spatial intensity computed by the proposed technique for P300 signal converge after only several target epochs for each electrode allocation. Such a speed of convergence allows the proposed algorithm to easily adapt to a subject of interest without any additional artificial data preparation prior the algorithm execution such in case of data enhancement technique.

Conclusion: The proposed technique averages the P300 spatial distribution for a particular subject over all electrode allocations. First, the technique combines P300-like components obtained by the ICA run within a target epoch in order to obtain a averaged P300 spatial distribution. Second, the technique averages spatial distributions of P300 signals obtained from different target epochs in order to get the final averaged template. Such a template can be useful for any BCI technique where spatial selection is used to detect evoked potentials.

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1. Introduction

The P300 is an event-related potential that is visible in an EEG recording as a positive peak at approximately 300 ms from the appearance of the event (stimulus). Both P300 amplitude and latency change across the scalp by decreasing over frontal and increasing over parietal areas [1, 2]. Topographic research has been presented in [3, 4] and an overview of P300 theory can be found in [5].

The P300 has been widely used for Brain Computer Interface (BCI), a communication interface which bypasses any muscle or nerve mediation and connects a computer directly with the brain by picking up signals generated by the brain activity. Application of P300 in BCI has many variants, but in all cases the paradigm is the same: the BCI system presents the user with some choices, one at a time; when it detects a P300 potential, the associated choice is selected. A well known BCI that exploits the P300 evoked potential is certainly the BCI P3 speller device [6, 7]. The BCI P300 speller device presents to a user a matrix of letters while its columns and rows flash randomly and one at a time. The user focuses the attention on a letter of interest to be spell out. After the letter is intensified, the brain generates a P300 potential natively. As the P300 is an innate response, it does not require training on part of the user.

Several signal processing techniques have been used to investigate and recog-
nize the P300 and among these a quite natural tool seems to be Independent Component Analysis (ICA) which has been introduced in the BCI paradigm with significant results [8]. The authors were winners of the BCI Competition 2003 using carefully found fixed ICA mixing matrix. Moreover, they have used temporal and spatial selection of generated ICs enhancing P300 signal and obtaining 100% accuracy in the testing data for the BCI P3 speller device. In [9], the authors have also used spatial selections of ICs, where they compared the spatial distribution of each independent component with the most-likely spatial distribution of the P300 signal obtained by training data from BCI Competition 2003 dataset. In [10], the fuzzy logic combined with ICA was employed to obtain high accuracy with one single intensification of raw and columns of a BCI-speller.

In this paper, we aim at analyzing the P300 amplitude spatial distribution over a scalp, and a spatial distribution averaging technique based on the statistical properties of ICs is proposed. The main purpose in the recovery of the averaged topographic distribution of the P300 amplitude over a scalp is the “optimization” of P300-based BCIs through the selection of the optimal electrode set and the individuation of more informative area on the scalp for extracting P300 potentials. In addition, such an averaged spatial template can be used to improve spatial filtering required by some of the BCI techniques as those presented in [8, 9].

The paper is organized as follows. The proposed technique for the P300 spatial averaging across a scalp is presented in Section 2. Section 3 shows the results obtained by the proposed technique using the data from the BCI Competition 2003 dataset. Conclusion is outlined in Section 4.

2. Spatial Distribution from Selected Sources

In this section, we introduce a novel technique to estimate the information about P300 spatial distribution by using the ICA algorithm. The ICA algorithm is essentially performed by finding uncorrelated components that maximize a non-Gaussianity measure among the components [11, 12]. In [8], the ICA algorithm has been used to detect P300 signal wherein the ICA mixing matrix has been estimated by the P300 data enhancement technique. This technique artificially concatenates a sufficient number of target epochs from the training data set and it is performed off-line, prior the P300 BCI experiments, in order to find the ICA mixing matrix. Unlike the technique based on the P300 data enhancement, the proposed approach requires only few target epochs to find out the most-likely P300 spatial distribution. This provides a possibility to use the proposed technique even without training data set. Additionally, the algorithm cannot be affected by the occasional inconsistency of the solution obtained by the ICA algorithm which happens when the ICA is not sometimes capable to separate the components within one target epoch especially when the epochs are short in data. This is because the proposed algorithm exploits all P300-like components, which might be even found manually, to obtain an averaged P300 spatial distribution within one target epoch.

Suppose a vector $x$ of $m$ measurements is obtained from labeled data (i.e., one single target epoch), where $m$ is the number of electrodes used for the measurements, and the ICA algorithm is applied to $x$. The intensities of the components are taken for electrode Cz, which is allocated according to the international 10/20 electrode allocation system (Figure 1). An example of obtained ICs is given in Figure 2.

Temporal selection of an independent component is based on the knowledge that a P300 component averages 300 ms after the excitation of the external stimulus and most likely has a peak around 310–350 ms. From Figure 2, one can select independent components $s_8$, $s_{10}$, $s_{15}$ and $s_{16}$ being most likely the P300 signal or a part of the P300 pattern.

Spatial selection additionally exploits the prior knowledge on the P300 signal. It is known that the P300 signal appears most intensively across the vertex region, e.g. at Cz, Fz, Pz, C3 and C4 electrode allocations, and it is usually the most intensive at Cz. Examples of temporal and spatial selection

![Figure 1](image-url)  
Electrode designation and channel assignment numbers (Sharbrough, 1991)
of P300-like components are presented in [8] and [9].

Considering the spatial distribution of each component given in Figure 3, one can select \( s_{10} \) as the most likely P300 independent component. When only one component is selected then its spatial distribution can be extracted by the values of the component correspondent column of the mixing matrix \( A \), e.g. for component \( s_{10} \) we have \( a_{10} = (a_{1,10}, a_{2,10}, \ldots, a_{m,10})^T \).

The component \( s_{16} \) is also included and combined with \( s_{10} \) as shown in upper Figure 4 since it fits both temporal and spatial criteria (Figure 2 and Figure 3). When two P300-like ICs are selected, the question is how to combine the information on the spatial distribution of each selected vector to calculate the spatial distribution of their linear combination (Eq. 1)

\[
P = c s_{300} = a_{10} s_{10} + a_{16} s_{16}.
\]

The vector \( c \) represents the desired spatial distribution of P300 signal within the current epoch, and \( s_{300} \) is the unique component which the ICA algorithm would extract after the first run in an ideal case, wherein the ICA is capable to separate P300 signal.

In order to derive the final expression for the spatial distribution averaging of two components, we have to recall the constraints imposed on the ICA algorithm result, the unit variance

\[
E[ss^T] = I,
\]

and the mutual orthogonally resulted by mutual statistical independence of two components, which is the core constraint of the ICA algorithm [11, 12]

\[
E[s_i s_j^T] = 0, \ i \neq j.
\]

We can reformulate the goal of finding the spatial distribution of P300 as the computation of the coefficients of the new vector \( c \) such that variance of \( s_{300} \) is also unitary as in case of ICs \( s_i \) obtained by the ICA. After the variance operator is performed to the left and the right hand side of Eq. 1, recalling the constraint (Eq. 3) we obtain

\[
c c^T = a_{10} a_{10}^T + a_{16} a_{16}^T,
\]

where \( c c^T \) is a diagonal matrix containing squares of the values hidden in the vector \( c \). For the sake of clarity, we consider only one electrode \( i \) among all measurement allocations, where \( i = 1, \ldots, m \) and \( m \) is the number of electrode sites. By doing this, the matrix equation (Eq. 4) becomes a scalar equation

\[
c_i = a^2_{i,10} + a^2_{i,16}.
\]

The problem occurs when at least one of the projection coefficients \( a_{i,10}, a_{i,16} \) is negative since we can not easily determine the sign of \( c_i \). In order to cover this critical case, each column that projects the selected P300-like IC and has at least one negative value is shifted so to have all values greater or equal to zero; the linear combination extracted from Eq. 1 and the scalar equation (Eq. 5) becomes now

\[
c_i s_{300} = a_{i,10} s_{10} + a_{i,16} s_{16} = P_i.
\]
Equations 6 and 9 imply
\[ c_i \min^{s_{P300}} = a_{\min, 10} s_{10} + a_{\min, 16} s_{16} = P_i \min. \quad (10) \]

If we perform the expected value operator \( E \), which finds the mean value, on both sides of Equations 9 and 10, we have
\[ c_i E[s_{P300}] = E[P_i], \quad (11) \]
\[ c_i \min E[s_{P300}] = E[P_i \min]. \quad (12) \]

If we divide left and right-hand sides of these last two equations, the second relation among \( c_i \) and \( c_i \min \) is found and it is given by
\[ c_i = \frac{c_i \min E[P_i]}{E[P_i \min]}. \quad (13) \]

It should be stressed that if \( E[P_i] = 0 \) then \( c_i = 0 \) follows from Equation 11, since the time domain shape of a P300 signal implies \( E[s_{P300}] \neq 0 \). Recalling first relation (Eq. 8), the final expression for \( c_i \) becomes as can be seen in Figure 5 (Eq. 14).

A singular case arises when \( E[P_i] = E[P_i \min] \). This case happens if there exists such \( i \) that all i-th projection coefficients of columns \( a_{10} \) and \( a_{16} \) are \( a_{i, 10} = a_{\min, 10} \) and \( a_{i, 16} = a_{\min, 16} \) simultaneously. This is the case when the i-th projection coefficients of two vectors are negative and the corresponding coefficient \( c_i \) can be easily obtained by
\[ c_i = -\sqrt{a_{i, 10}^2 + a_{i, 16}^2}. \quad (15) \]

The result can be generalized in accordance to the presented example. Suppose that within the data there is a P300 signal, and the ICA algorithm is performed separating \( m \) ICs \( s_i \). If it is possible to select \( \kappa \) P300-like signals among those components (\( \kappa \in \{1, 2, \ldots, m - 1\} \) where \( m \) is usually equal to 2, 3 or 4) then the spatial distribution of the appropriate linear combination is hidden in the vector \( c \) as follows.

**Proposition 1:** The spatial distribution of the evoked P300 signal within a target epoch could be obtained by
\[ c_i = \frac{\sqrt{\sum_j (a_{i,j} - a_{\min,j})^2} E[P_i]}{E[P_i] - E[P_i \min]} \]
if $E[P_i] \neq E[P_i^{\min}]$, otherwise $c_i = -\sqrt{\sum_{j=1}^{n} a_{i,j}^2}$, where $P_i = E[\Sigma_{j=1}^{n} a_{i,j} s_j]$ and $P_i^{\min} = E[\Sigma_{j=1}^{n} a_{i,j}^{\min} s_j]$.

The middle and bottom figures in Figure 6 show an example of the proposed spatial averaging for two selected P300-like components. Similar procedure can be conducted to average the spatial distributions obtained by two different target epochs. The only difference comparing to the result given by Proposition 1 is that the variance operator of two linearly combined P300 components will have an additional term, covariance of two components which can be easily computed, since the two P300 components, coming from two different target epochs, might not be statistically independent.

3. Results

Figure 7 gives the comparison between the two averaged spatial distributions obtained by data enhancement and the proposed method using 20 target epochs. The results show that the distributions are quite similar, in which the correlation coefficients is $\rho_{12} = 0.987$. The obtained similarity suggests that the proposed method can be used for the purpose of spatial selection of the ICs as in [9]. The experiments also show that the values computed by the proposed technique for P300 spatial distribution averaging converge after only several target epochs for each electrode allocation. Figure 8 shows the spatial averaging progress for four arbitrarily selected electrodes.

4. Conclusion

The proposed approach estimates the P300 spatial distribution for a particular subject and it does not require any artificial data preparation as in case of the data enhancement technique. The P300 selection within a target epoch can be made even manually taken all P300-like components into account. This is important in case where the ICA is not able to fully separate P300 signal into only one component. This gives additional reliability to the proposed method making it almost insensitive to the possible ICA execution inaccuracies and inconsistence.

In this work, we have not aimed at getting an improved spatial filtering method but at providing an analytical procedure for finding an averaged P300 spatial distribution template for each subject individually. By using such a procedure one can improve...
any of spatial filtering techniques, which can be used for BCI purposes. Developing a spatial filter based on prior information on P300 spatial distribution is a focus of our current research.

References


Figure 8 Progress of spatial averaging