Reduction of alpha distortion in event related potentials

K. Vanderperren[1], B. Hunyadi[2], M. De Vos[1], M. Mennes[3,4], H. Wouters[3,4], B. Vanrumste[1,5], P. Stiers[6], L. Lagae[3] and S. Van Huffel[1]

[1] Department of Electrical Engineering, Katholieke Universiteit Leuven, Leuven, Belgium
[2] Faculty of Information Technology, Pazmany Peter Catholic University, Budapest, Hungary
[3] Department of Pediatric Neurology, University Hospital Gasthuisberg, Leuven, Belgium
[4] Department of Psychology, Katholieke Universiteit Leuven, Leuven, Belgium
[5] Biosciences and Technology Department, Katholieke Hogeschool Kempen, Geel, Belgium
[6] Faculty of Psychology, Universiteit Maastricht, Maastricht, The Netherlands

Abstract — **A frequently used brain monitoring technique in cognitive neuroscience research are Event Related Potentials (ERPs). ERPs are electrical brain responses to specific sensory, cognitive and motor events in electroencephalographic (EEG) data. However, ERPs are known to have a very low signal-to-noise-ratio and suffer from artifacts present in EEG data like ocular and muscular artifacts. Another common type of distortion is alpha activity. The aim of this study is to remove this activity with different mathematical approaches.**

Classical methods like filtering and independent component analysis (ICA) do not yield good results in the reduction of alpha distortion. Therefore, we propose Parallel Factor Analysis or PARAFAC as a method for reducing the alpha activity. We will show why filtering and ICA fail to solve this problem and how PARAFAC does succeed in improving the quality of the measured ERPs.

Keywords — **Electroencephalogram, Event Related Potentials, alpha activity, Parallel Factor Analysis.**

I. Introduction

EEG data are a rough measurement of brain activity as they represent a summation of many different neural sources. Part of this neural activity are electrical potentials which occur in response to specific sensory, cognitive and motor events [1]. These potentials are called event-related potentials (ERP) and are widely used in cognitive neuroscience research.

ERPs have a very low signal-to-noise-ratio (SNR) and suffer from artifacts present in EEG data caused by non-brain (e.g. eye movements) and brain sources. In classical neuroscience research ERPs are mostly extracted by averaging over a large set of data epochs, time-locked to the onset of an event of interest. In this way the activity related to this event is emphasized, while the other activity is averaged out.

An often overlooked type of brain related distortion in ERPs is alpha activity. Alpha waves are oscillations with a frequency between 8 and 13 Hz that occur mostly when a subject is in a relaxed state. Nevertheless other studies and our own experience indicate that even alert people can show alpha activity [1]. When present, alpha waves severely diminish the ability to identify ERP components of interest, even after applying the averaging procedure.

The reduction or removal of alpha activity from the measured signal is however poorly investigated, since one mostly just replaces subjects that show alpha or rejects trials containing alpha. This is not an ideal situation since many trials might be affected, and including more trials is often not possible as experiments are preferably limited in time. In fact, longer experiments possibly induce alpha as subjects will get tired. Therefore, the aim of this study was to investigate whether mathematical techniques could provide useful solutions for the reduction of alpha activity in the EEG signal.

The simplest method to reduce alpha activity consists in applying a bandstop filter to the alpha frequency range. However, the alpha frequency band overlaps with that of several important ERP components and so filtering will remove too much of the activity of interest. A more advanced technique is Independent Component Analysis (ICA). In the last years this method has become popular for the characterization of brain activity and the removal of several types of artifacts (e.g. eye movement artifacts [2]). However, ICA can only be employed on two-dimensional data (e.g. channels and time), while it might be more interesting to study the EEG activity in three dimensions. This allows including frequency in the analysis, which might be very useful for alpha waves as they are characterized by a narrow frequency band (see above). Parallel Factor Analysis (PARAFAC) is an analysis technique that is suitable for these purposes. This technique recently made its entry in biomedical signal processing and EEG analysis (e.g. [3]). PARAFAC is suitable for the extraction of alpha waves since it can separate oscillatory signals from other activity. Here we applied both ICA and PARAFAC for the removal of alpha activity from EEG data. We evaluate the results for two types of event related

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data, namely for a cued attention paradigm and a Go/NoGo task.

II. Materials and methods

A. EEG data

Two datasets were used for the validation of the proposed methods.

The first dataset consisted of two healthy subjects who performed a cued attention paradigm during the measurements [4]. One subject showed a lot of alpha activity, the other one showed little to no alpha. Data were digitally recorded from 19 electrodes using the standard 10-20 system of electrode placement, with an online bandpass filter of 0.095-70 Hz and a sampling rate of 1000 Hz.

The second dataset comprised seven healthy children between 6 and 16 years old, of which five showed strong alpha activity. All children performed a Go/NoGo task during the EEG measurement. Data were recorded from 32 channels using the standard 10-20 system, with an online bandpass filter of 0.1-70 Hz and a sampling rate of 1000 Hz.

Offline analysis of all data was performed using the Matlab toolbox EEGLAB [5]. Data were filtered using a 30 Hz digital lowpass filter and eye artifacts were removed using ICA. Epochs were extracted from 200 ms before until 800 ms after stimulus presentation and baseline removal was performed based on the interval from 200 ms before until the stimulus onset.

B. Independent Component Analysis

ICA is a signal processing technique that can be used to recover independent sources from a set of simultaneously recorded signals that result from a linear mixing of the source signals [6]. The ICA model is described as:

$$x(t) = A \cdot s(t) \tag{1}$$

with s(t) the vector of source signals, x(t) the vector of measured mixtures and A the mixing matrix. The ICA algorithm succeeds in retrieving the source signals from the measured data by assuming that the sources are mutually independent.

In this study, the decomposition is done with Second-Order Blind Identification (SOBI) [7]. This ICA approach relies on stationary second-order statistics and was applied to all our data epochs. The alpha related sources were identified based on their frequency spectrum. Afterwards every epoch was reconstructed without its alpha sources.

C. Parallel Factor Analysis

PARAFAC is a multidimensional decomposition technique that can decompose the EEG signals into a series of distinct atoms. Every atom is characterized by a certain time course, spatial distribution and spectral behavior and ideally represents a distinct brain source. The data is presented by the sum of these atoms as follows:

$$S_{dft} = \sum_{k=1}^{N_k} a_{dk} \cdot b_{fk} \cdot c_{tk} + E \tag{2}$$

with N_k the number of atoms, a_{dk}, b_{fk} and c_{tk} the space, frequency and time signatures of every atom and E the model error.

To obtain the three-dimensional structure, all epochs were normalized and put through a digitized continuous wavelet transform (CWT) with a Morlet wavelet [8]. After this, PARAFAC was applied to extract a certain number of components with each a specific time, space and frequency signature. Alpha atoms were identified based on their spectral signature and spatial distribution, which is typically posterior for alpha activity. After removal of these alpha atoms, epochs can be rebuilt according to equation (2). As the epochs are still in three-dimensional form, an inverse wavelet transform has to be applied [9]. The corresponding denormalization constant was determined in a heuristic way as 0.11.

D. Validation criteria

A first validation criterion is based on the spectral content before and after alpha removal. The presence of alpha activity is quantified on channel Pz with the ratio of spectral power in the alpha range (8-13 Hz) on the power in the whole frequency spectrum (0-30 Hz).

A second validation criterion assesses the quality of the event related potentials using the SNR of the components of interest. The SNR was defined as the ratio of the amplitude of the peak under study (the signal) and the standard deviation of the baseline (the noise).

III. Results

Both SOBI and PARAFAC were only applied to the six subjects with severe alpha distortion. However, the validation criteria were also computed on the original data of the subjects with only little alpha, to serve as an indication of good quality data.

For every subject, SOBI was computed for all epochs and in the majority of the epochs 2 to 5 components were

removed. With PARAFAC, all epochs were decomposed in 2 and 3 components and in both cases the alpha atoms were identified and removed. An example of such an alpha atom and its time, space and spectral signature, is given in Fig. 1.

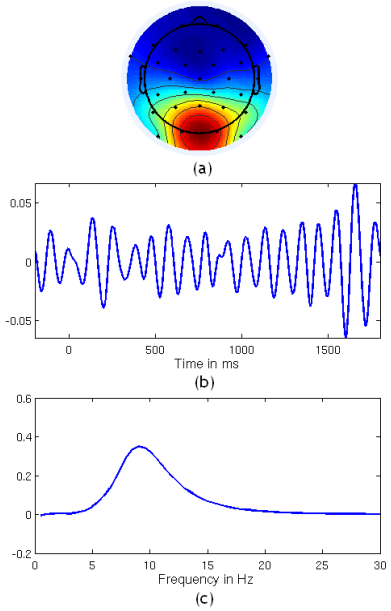

Fig. 1 Example of one PARAFAC atom representing alpha with (a) the potential distribution on the scalp; (b) the time course in ms; (c) the frequency spectrum in Hz.

In Table 1 the ratio of alpha power before and after removal of the alpha activity is shown for SOBI as well as for PARAFAC with 2 and 3 components. For the alpha-free subjects the ratios were 6.25% for the attention related task and 5.52% and 2.76% for the Go/NoGo task.

Table 1 Ratio of alpha power to total power (in %) before and after artifact removal in the entire dataset

Subject	Original	ICA (SOBI)	Parafac 2	Parafac 3
Subject 1 (attention)	23.35	9.11	6.42	7.46
Subject 2 (Go/NoGo)	26.41	18.68	12.65	9.87
Subject 3 (Go/NoGo)	17.80	6.88	7.87	6.82
Subject 4 (Go/NoGo)	17.28	9.71	7.15	6.43
Subject 5 (Go/NoGo)	13.71	6.31	3.31	3.07
Subject 6 (Go/NoGo)	10.00	3.66	2.04	1.81

This first validation criterion only checks to what extent the alpha distortion is removed from the data. The second validation criterion, the SNR verifies whether the quality of the underlying data is improved.

For the Go/NoGo task one of the most important peaks is certainly the N2. Therefore, the SNR is computed as the ratio of the amplitude of this N2 in NoGo trials (where it is more pronounced) and the standard deviation of the prestimulus interval. The N2 is defined as the largest negative deflection between 200 and 350 ms after stimulus onset on frontocentral channels (Fz, Cz, FC1 and FC2). Table 2 shows the SNR for all Go/NoGo datasets with severe alpha distortion before and after alpha removal with our different methods. The two alpha-free subjects with Go/NoGo data showed SNRs of 5.80 and 8.44.

Table 2 SNR of N2 peak in averaged NoGo trials of Go/NoGo task

Subject	Original	ICA (SOBI)	Parafac 2	Parafac 3
Subject 2 (Go/NoGo)	2.09	2.63	3.34	2.19
Subject 3 (Go/NoGo)	4.20	4.08	4.94	5.06
Subject 4 (Go/NoGo)	4.89	5.88	8.68	12.2
Subject 5 (Go/NoGo)	1.64	1.21	1.23	1.49
Subject 6 (Go/NoGo)	3.42	3.17	4.61	4.84

For the other dataset, we take the P3 as the peak of interest and define it as the largest positive deflection between 250 and 600 ms after stimulus onset on parietal channels. The original SNR was 3.56, for ICA 3.42 was measured and PARAFAC with 2 and 3 components gave an SNR of 3.81 and 3.76 respectively. The alpha-free subject for this task had an SNR of 13.06.

IV. Discussion

Table 1 reveals that with all methods the alpha power is severely reduced. However, the values are lower in the case of PARAFAC and fit closer to the range of the alpha-free subjects. Only in subject 2 none of the methods seems to remove all alpha activity.

According to the SNR, all subjects, except for subject 5, benefit from the PARAFAC approach to remove alpha distortion. ICA is also valuable for some subjects, but has lower SNRs than PARAFAC.

To explain the difference in ICA results between the subjects, we also looked at the sources retrieved with ICA. It was noticed that for many subjects, the algorithm did not succeed in separating sources that only contain activity in the alpha band. This is probably due to the fact that ICA sources are required to be mutually independent. In this sense, PARAFAC is a better choice for alpha removal since it does not require this independency.

In Fig. 2 one can see the grand average ERPs for both Go (green) and NoGo (blue) trials on channel Cz before and

after alpha removal with PARAFAC. The prestimulus interval, which should ideally be zero, is clearly better after artifact removal. However, the amplitude of the N2 (bigger in NoGo than in Go trials) decreases after alpha removal. This seems to indicate that the increase in SNR might be due mainly to an improvement of the prestimulus interval.

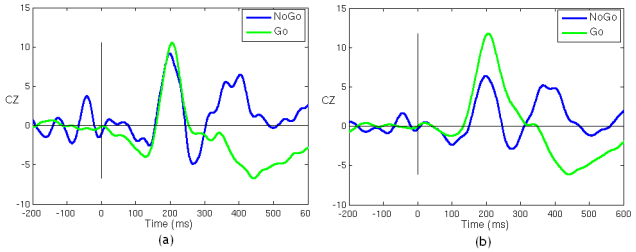

Fig. 2 Grand average ERP for Go (green) and NoGo (blue) trials on channel CZ; (a) before artifact removal; (b) after PARAFACwith 3 components

Another problem arises when one is interested in the P1. This is a positive deflection around 100 ms after stimulus onset, especially present on posterior channels. The P1 not only has a potential distribution similar to the one of alpha activity, but also has a frequency around 10 Hz, which is in the middle of the alpha interval. Therefore, removing alpha will reduce the quality of the P1 peak to a great extent.

Another possible explanation for the difficulty of removing alpha might be the fact that ERPs and alpha are not fully independent. This idea is not yet widely accepted in ERP research, but some people argue that ERPs are dependent on brain state (e.g. [10]). Since alpha is one of the factors that determine this brain state, its removal might decrease the ERP quality.

V. Conclusions

Alpha distortion can be a serious problem for the quality of ERP components. However, most studies overlook this issue by removing all severely damaged trials. Because this is not an ideal situation, the aim of this paper was to reduce the alpha activity with advanced mathematical decomposition techniques. For this purpose both ICA and PARAFAC were used and validated on different datasets.

Although the amplitude of some ERP peaks might be reduced, we believe that PARAFAC is a useful tool in the removal of alpha distortion. It is able to separate the alpha activity in a distinct atom and to increase the SNR of our data.

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