EVENT-RELATED POTENTIALS SOURCE SEPARATION BASED ON A WEAK EXCLUSION PRINCIPLE

Lan Ma[1], *Thierry Blu*[1], *and William S-Y. Wang*[2]

1. The Chinese University of Hong Kong. 2. Hong Kong Polytechnic University.

ABSTRACT

Currently, the standard event-related potentials (ERP) technique consists in averaging many on-going electroencephalogram (EEG) trials using the same stimuli. Key questions are how to extract the ERP from on-going EEG with fewer average times and how to further decompose ERP into basic components related to cognitive process. In this paper we introduce a novel Blind Source Separation (BSS) approach based on a weak exclusion principle (WEP) to solve these problems. The superior aspect of this algorithm is that it is based on a deterministic principle, which is more appropriate to analyze non-stationary EEG signals than most other BSS methods based on statistical hypotheses. The results show that our BSS algorithm can quickly and effectively extract ERPs using fewer average times than the traditional averaging methods. We show that, via BSS, we can isolate two main ERP components, which are respectively related to an exogenous process and a cognitive process, and can discriminate between the occipital lobe and the frontal lobe responses from the brain, agreeing with the classical component modeling in ERPs. Single-trial ERP separation results have demonstrated the consistency of these two main ERP components. Thus, BSS based on WEP can provide a window to better understand ERP, not only in averaging behavior, but in the complexities of moment-to-moment dynamics as well.

***Index Terms*—** Blind Source Separation (BSS), Event-Related Potentials (ERP), Electroencephalogram (EEG), Weak Exclusion Principle (WEP)

1. INTRODUCTION

When a subject's brain is presented with repetition of the same stimulus, the brain's electrical results are called Event-Related Potentials (ERPs). These can be sensed via the emplacement of electrodes on the scalp, and extracted, measured, and documented with an electroencephalogram (EEG). ERP represents a powerful tool for better understanding the human brain and its response. ERP has many potential clinical applications such as brain-computer interfaces (BCIs) and the identification of parallel neural processes [1].

The standard ERP technique currently includes artifact rejection/correction, followed by averaging the results. The square root of the number of ERP trials conducted is proportional to the Signal-to-Noise Ratio (SNR) enhancement by averaging [2]. Typically the ERP amplitude is measured in microvolts whereas the EEG amplitude is at least an order of magnitude larger. As a result, tens or even hundreds of trials are necessary to obtain a reliable ERP average waveform. The fact that so many trials are required is an obvious limitation of this method.

Nor is this the only challenging dimension of ERP research. Another is that the waveforms recorded on the scalp represent the sum of several underlying components. Decomposing the mixture into its individual components is a serious challenge; multiple components are erroneously superimposed onto the same waveform, leading researchers to label this obstacle the "Superposition Problem." These two problems are the most common impediments to the successful application of the ERP technique [3].

Blind Source Separation (BSS) is used to refer to the separation of a set of sources from mixed observations, with unknown mixing coefficients [4]. The observed EEG data are a mixture of all active sources, due to the electrodes' positioning along the scalp. The delay in transmission between source and electrode is negligible [5]. Thus, BSS methods are appropriate tools in the extraction of EEG features. The advantage of BSS in EEG analysis is that overlapping processes can be separated, making it simpler to interpret these processes [6].

The typical BSS approaches modelize the underlying source signals as stochastic processes. For example, Independent Component Analysis (ICA) represents an attempt to identify linear representations of non-Gaussian data in an effort to render its components statistically independent [7]. Thus, stationarity is required in order to guarantee the existence of a representative, or non-Gaussian, distribution of the sources. However, EEG and MEG signals are very typically non-stationary [8]. Our proposed algorithm offers a different approach. The BSS algorithm which is used in this paper is based on a deterministic principle: the weak exclusion principle (WEP). It makes no assumption of statistical independence, making it a good candidate for a model-free decomposer. This algorithm has been successfully applied to the extraction of artifacts from EEG recordings [9].

In Section 2, we present a short description of the problem of EEG blind source separation, together with a short intro-

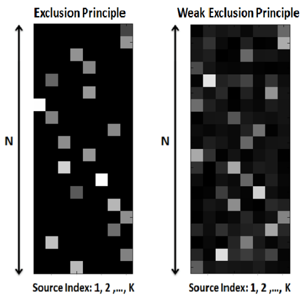

Fig. 1. Illustration of Sources which satisfy EP and WEP requirements (left and right, respectively). EP: at each time index, there is only one source activated; WEP: at each time index, one source is "significantly" larger than the others.

duction of the BSS algorithm based on WEP. Section 3 uses this approach to extract ERP from on-going EEG and further decompose ERP into basic components. Section 4 is the conclusion.

2. EEG BLIND SOURCE SEPARATION APPROACH BASED ON A WEAK EXCLUSION PRINCIPLE

2.1. Mathematical Model of EEG Blind Source Separation

The problem of EEG blind source separation is formulated as follows: Stacking Mixtures (EEG signal) in an $N \times K$ matrix $\mathbf{X}$ (N: time samples, K: the number of electrodes), we would like to unmix them as a linear combination of K sources. Mathematically, we would like to find the $N \times K$ matrix $\mathbf{S}$ describing the time-samples of the sources and the mixing $K \times K$ matrix $\mathbf{A}$ such that

$$\mathbf{X} = \mathbf{SA}; \text{ or, more visually, } N \overset{\leftarrow K \rightarrow}{\boxed{\mathbf{X}}} = N \overset{\leftarrow K \rightarrow}{\boxed{\mathbf{S}}} \times K \overset{\leftarrow K \rightarrow}{\boxed{\mathbf{A}}} \qquad (1)$$

BSS divides the EEG data into two parts: $\mathbf{S}$ (the time course of the sources) and $\mathbf{A}$ (fixed spatial patterns in the sensor space). Complicated modeling of the signal sources' physical properties is not required; nor is modeling of the head conductivity distribution.

2.2. Blind Source Separation Approach Based On A Weak Exclusion Principle

In this paper, we applied the BSS algorithm based on the weak exclusion principle (WEP), which is detailed in our previous paper [9]. We also tested the algorithm performance using

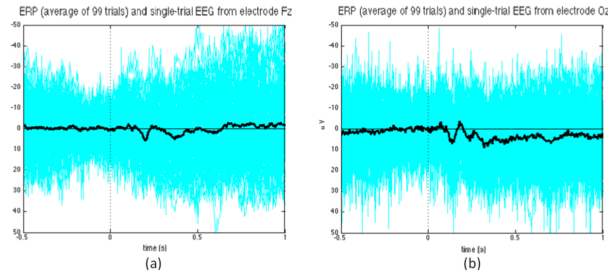

Fig. 2. Illustration of average ERP amplitude is much smaller than on-going EEG. Black line: ERP from one electrode (an average of 99 trials); Blue line: Each single trial EEG signal of the 99 trials. (a) From electrode Fz. (b) From electrode Oz.

simulated data in the previous paper. The principle, briefly put, which underlies the Exclusion Principle (EP) is that:

An $N \times N$ matrix $\mathbf{S}$ is exclusive, *iff* for all row index $i \in [1, ...N], \mathbf{S}_{ij} \neq 0 \Longrightarrow \mathbf{S}_{ij'} = 0, for\ \forall j' \in [1, ...K] \setminus j$.

Less strictly, the Weak Exclusion Principle (WEP) assumption is that, at each time instance, the EEG signal is dominated by one source which is larger than the others (by at least a factor of 2). Thus, the other sources do not need to be non-activated at all. Visually, two examples of sources which satisfy EP and WEP requirements, respectively, are shown in Fig.1.

3. BLIND SOURCE SEPARATION OF EEG FOR THE ANALYSIS OF EVENT RELATED POTENTIALS

The dataset is taken from a visual stimulation task online dataset. EEG data was acquired at 2048 Hz from 64 BioSemi active electrodes placed according to the international 10-20 system [10]. The data we used for separation was from one subject, which has had 99 trials.The EEG signal was down-sampled to 200Hz and band-pass filtered from 4 Hz to 40 Hz. We performed an eigenvalue decomposition first on the EEG data and kept the components that can represent 90% variance to decide the source number. Here we want to point out that this eigenvalue decomposition procedure was not used for the purpose of de-noising, but rather, to algebraically reduce dimensions.

The algorithm is very fast. It was implemented in Matlab (The Mathworks, Inc., Natick, Massachusetts, USA) and run on an Apple laptop with a 2.7 GHz Intel Core i5 processor. The computation time for one-time separation is around 0.57 seconds.

Fig. 2 illustrates that ERP amplitude of the order of several microvolts while the ongoing EEG is significantly larger. From the ERPs, we can see that different electrodes have different ERP waveforms. The standard ERP plots cannot integrate the global information.

Fig.3 shows ERP from electrode Fz and Oz, with average time as 99 trials, 20 trials and 10 trials respectively. As the

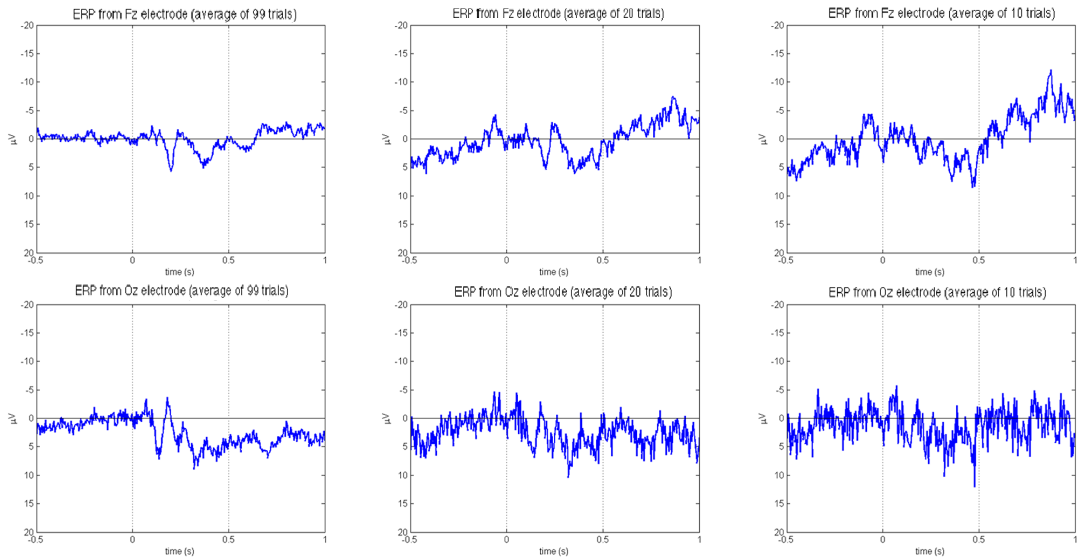

Fig. 3. ERP from electrode Fz and Oz, with average time as 99 trials, 20 trials and 10 trials separately. As the average times decrease, the SNR of the ERP curves drops and ERPs become harder to observe.

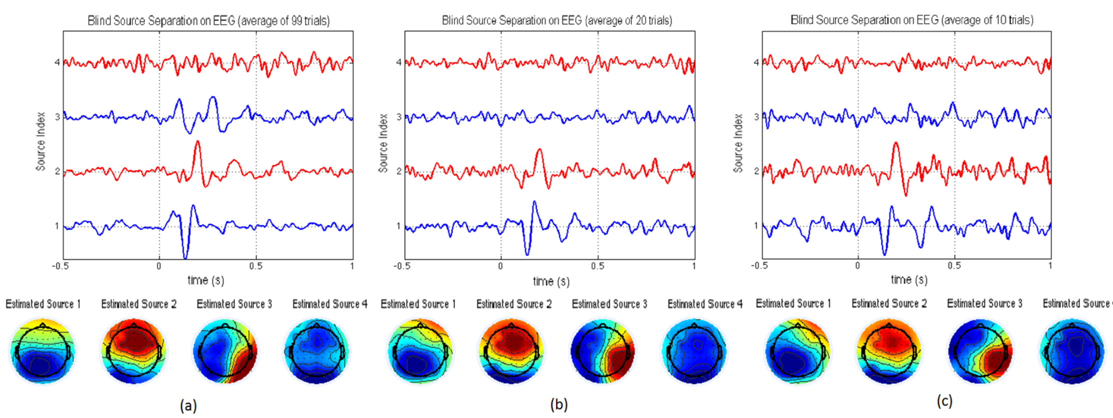

Fig. 4. Blind Source Separation based on Weak Exclusion Principle (WEP) to extract the ERPs, with average time as 99 trials, 20 trials and 10 trials separately. As the average times decrease, the main separated sources remain stable.

average time decreases, the SNR of the ERP signal drops.

Fig.4 shows the performance of BSS on EEG to extract the ERPs under different average times. Here it is necessary to note that the sources are ranked in a descending order. That is to say, the first source represents the largest variance in this dataset. Because of the nature of the BSS source reconstruction problem, the scale of the topographies is not the same as the real signal scale. However, it reflects landscapes of the separated sources.

From the separation results we can see that after dimension reduction, there are in total four main sources. The first source shows a strong activity in the occipital lobe and the time course of this source shows that its peak is around 100ms-130ms after the onset of the visual stimulation. This may relate to an exogenous process, which is well known as N100. The second source shows a strong activity in the frontal lobe and the time course of this source shows that its peak is around 200ms after the onset of the visual stimulation. This may relate to a cognitive process. These two sources represent the largest variance of the EEG signals. As the average times decrease, the two main separated sources remain stable.

Fig.5 shows several single-trial EEG separation results compared with the average of 99 trials ERP. The results demonstrated the consistency of the separation. We can still observe the two main ERP components via single-trial separation. It shows that BSS provides a window to understand not only averaging behavior, but the complexities of moment-to-moment dynamics as well.

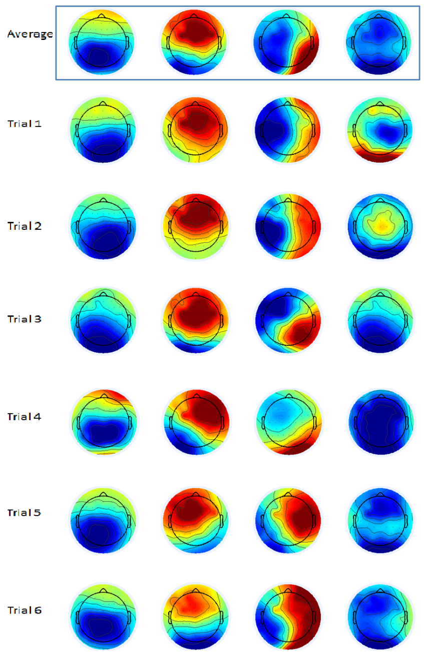

Fig. 5. Single-trial EEG separation results compared with the average of 99-trials separation results. The results demonstrate the consistency of the separation.

4. CONCLUDING REMARKS

The results presented in this paper use the BSS algorithm based on WEP, and do not require any statistical assumption of the type of source of the evoked fields. These results show some interesting features that seem to agree with the traditional ERP components, namely that the proposed algorithm can quickly and effectively extract ERPs using fewer average times.

One disadvantage of the standard ERP procedures is its failure to integrate all the electrodes information, the "global" information. By performing BSS based on WEP, we can isolate two main ERP components, related to an exogenous process and a cognitive process, respectively, and can discriminate between the occipital lobe and the frontal lobe responses from the brain. Single-trial separation results have showed the consistency of these two main ERP components.

Furthermore, BSS on the level of single-trials provides a window to understand not only averaging behavior, but the complexities of moment-to-moment dynamics as well, which may be useful in regards to online signal analysis, including brain-computer interfaces.

5. ACKNOWLEDGMENT

This work was supported by GRF 14200114 awarded to Thierry Blu of the Chinese University of Hong Kong and GRF 14611615 awarded to William S-Y. Wang of the Hong Kong Polytechnic University.

6. REFERENCES

[1] Sandra K Loo, Agatha Lenartowicz, and Scott Makeig, "Research review: Use of eeg biomarkers in child psychiatry research–current state and future directions," *Journal of Child Psychology and Psychiatry*, vol. 57, no. 1, pp. 4–17, 2016.

[2] Sander Nieuwenhuis and Mischa De Rover, "Event-related potential," *Encyclopedia of Psychopharmacology*, pp. 642–647, 2015.

[3] Julia Lechinger, Tomasz Wielek, Christine Blume, Gerald Pichler, Gabriele Michitsch, Johann Donis, Walter Gruber, and Manuel Schabus, "Event-related eeg power modulations and phase connectivity indicate the focus of attention in an auditory own name paradigm," *Journal of neurology*, pp. 1–14, 2016.

[4] Arnaud Delorme, Terrence Sejnowski, and Scott Makeig, "Enhanced detection of artifacts in eeg data using higher-order statistics and independent component analysis," *Neuroimage*, vol. 34, no. 4, pp. 1443–1449, 2007.

[5] Nguyen Linh-Trung, Adel Belouchrani, Karim Abed-Meraim, and Boualem Boashash, "Separating more sources than sensors using time-frequency distributions," *EURASIP Journal on Applied Signal Processing*, vol. 2005, pp. 2828–2847, 2005.

[6] Pierre Comon, "Independent component analysis, a new concept?," *Signal processing*, vol. 36, no. 3, pp. 287–314, 1994.

[7] Arnaud Delorme and Scott Makeig, "Eeglab: an open source toolbox for analysis of single-trial eeg dynamics including independent component analysis," *Journal of neuroscience methods*, vol. 134, no. 1, pp. 9–21, 2004.

[8] Alexandre Gramfort, Daniel Strohmeier, Jens Haueisen, Matti S Hämäläinen, and Matthieu Kowalski, "Time-frequency mixed-norm estimates: Sparse m/eeg imaging with non-stationary source activations," *NeuroImage*, vol. 70, pp. 410–422, 2013.

[9] Lan Ma, Thierry Blu, and William SY Wang, "An eeg blind source separation algorithm based on a weak exclusion principle," in *Engineering in Medicine and Biology Society (EMBC), 2016 IEEE 38th Annual International Conference of the*. IEEE, 2016, pp. 859–862.

[10] Michael X Cohen and K Richard Ridderinkhof, "Eeg source reconstruction reveals frontal-parietal dynamics of spatial conflict processing," *PLoS One*, vol. 8, no. 2, pp. e57293, 2013.