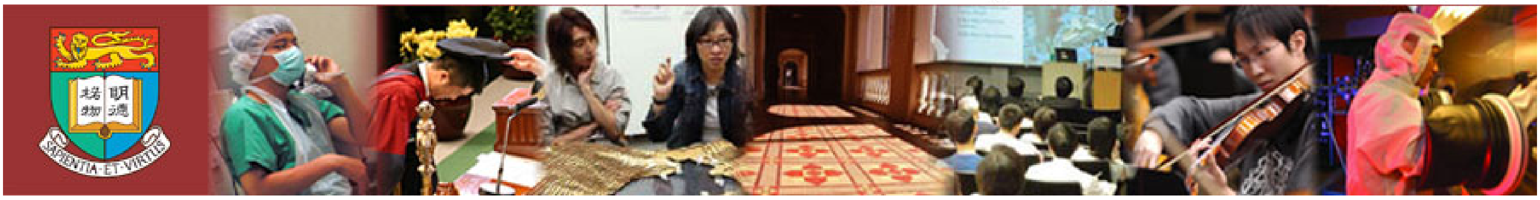

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Second Order Statistics Based Blind Source Separation for Artifact Correction of Short ERP Epochs

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Abstract- **ERP is commonly obtained by averaging over segmented EEG epochs. In case artifacts are present in the raw EEG measurement, pre-processing is required to prevent the averaged ERP waveform being interfered by artifacts. The simplest pre-processing approach is by rejecting trials in which presence of artifact is detected. Alternatively artifact correction instead of rejection can be performed by blind source separation, so that waste of ERP trials is avoided. In this paper, we propose a second order statistics based blind source separation approach to ERP artifact correction. Comparing with blind separation using independent component analysis, second order statistics based method does not rely on higher order statistics or signal entropy, and therefore leads to more robust separation even if only short epochs are available.**

Keywords **- EEG, ERP, Artifact Correction, Blind Source Separation, Second Order Statistics**

I. INTRODUCTION

Event-related brain potential (ERP) is the brain electrical response induced by presenting repeated/similar stimuli to the subject [1]. It can be captured by placing electrodes on the scalp and extracted from the measured electroencephalogram (EEG). Since the discovery of these time-locked brain activities, ERP has provided a powerful tool for cognitive studies such as attention, memory, language and motor functions.

Standard procedure for obtaining ERP includes artifact rejection/correction and then averaging. Assume the ERP components are time-locked over trials and the ongoing EEG is random with respect to the stimulus presentation, the random ongoing EEG would be suppressed but the ERP would be enhanced via the averaging process. The signal-to-noise ratio (SNR) enhancement by averaging is proportional to the square root of the number of ERP trials. Normally the ERP amplitude is in several microvolts while the ongoing EEG is in several tens of microvolts. Therefore it generally requires tens to hundreds of trials to obtain a reliable ERP average waveform.

However, in addition to induced ERP and ongoing EEG, artifact signals may also be present as additive components to the measurement. Examples of artifact are eye activities, muscle activities and power line interference, and many of them have magnitude of over 100 microvolts. Averaging may not effectively suppress this kind of unwanted signals. The simplest solution is to reject those trials in which the presence of artifact is detected (e.g. using a magnitude threshold). However, in case of large rejection rate, the number of available trials could be low and the average ERP waveform would become unreliable.

Alternatively artifact correction can extract the artifact components so that 'clean' EEG is left for further processing. In recent years, artifact correction methods were based on two common approaches, regression and blind source separation (BSS) by independent component analysis (ICA) [2]. Regression provides a relatively simple mathematical solution for ocular artifact correction by regressing measurement in eye channels to all other channels. However artifacts other than eye activities cannot be tackled. Also a certain portion of neural signal would be eliminated by the regression process due to forward propagation.

ICA decomposes the multi-channel EEG data into a mixture of statistically independent sources [3]. In case a source signal is identified as artifact, it will be ignored in the re-mixing process. The non-artifact source signals are then linearly re-mixed to obtain 'clean' EEG. In this paper, we propose similar artifact correction by blind source separation. However the separation is based on second order statistical algorithm [4,5] instead of ICA, which is higher order statistics based. This avoids nonlinear activation functions and the separation would be more robust. Also even short ERP epochs could result in reliable source separation since the algorithm involves only second order statistics.

II. METHODOLOGY

The multi-channel ERP signal $\{x_1(t), x_2(t), \ldots, x_m(t)\}$ is assumed to be a linear mixture of uncorrelated source components $\{s_1(t), s_2(t), \ldots, s_m(t)\}$,

$$\underline{x}(t) = [x_1(t) \quad x_2(t) \quad \ldots \quad x_m(t)]^T$$

$$\underline{s}(t) = [s_1(t) \quad s_2(t) \quad \ldots \quad s_n(t)]^T$$

$$\underline{x}(t) = A\underline{s}(t)$$

where A is the m x n mixing matrix, m the number of ERP channels and n the number of uncorrelated sources.

Since the sources are assumed uncorrelated, therefore for all τ and $i \neq j$,

$$E[s_i(t)s_j(t+\tau)] = 0.$$

A. Second Order Blind Source Separation by AMUSE [4]

The correlation matrix of $\underline{x}$ is first computed as

$$R_x = E[\underline{x}\underline{x}^T]$$

SVD of R_x is then performed,

$$R_x = U_x D_x V_x^T$$

The whitened signal $\underline{y}(t)$ can therefore be estimated as below,

$$\underline{y}(t) = D_x^{-\frac{1}{2}} U_x^T \underline{x}(t)$$

With chosen time delay τ, correlation matrix of $\underline{y}(t)$ is computed as

$$R_y(\tau) = E[\underline{y}(t)\underline{y}^T(t+\tau)]$$

SVD of R_y is then performed as,

$$R_y = U_y D_y V_y^T$$

The estimated source signals are therefore extracted by,

$$\hat{\underline{s}} = D_y^{-\frac{1}{2}} U_y^T \underline{y}(t)$$

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B. Artifact Rejection in the Source Domain

With a number of separated sources $\underline{s}(t)$, the multi-channel ERP $\underline{x}(t)$ is then be decomposed as

$$\begin{aligned}\underline{x}(t) &= A\underline{s}(t)\\ &= [\underline{a}_1 \quad \underline{a}_2 \quad \ldots \quad \underline{a}_n][s_1(t) \quad s_2(t) \quad \ldots \quad s_n(t)]^T\\ &= \sum_i \underline{a}_i s_i(t)\end{aligned}$$

artifact rejection can then be performed on the separated sources, since some of those are artifacts .

A threshold h is first chosen for the rejection process. For all the n sources, the following criterion is justified,

$$\max(|\underline{a}_i s_i(t)|) > h$$

where $\max(|.|)$ is the maximum absolute value of the matrix elements.

If the criterion is matched, the source signal will be classified as artifact and will be rejected in the remixing process.

III. Results and Discussion

ERP data was collected from the 16-channel NeuroScan EEG system, with subjects attending a visual spatial search experiment. The objective of the experiment is to study the ERP before (pre-test) and after (post-test) intensive mental workload, which is outside the scope of this paper. Electrode positions were based on the 10-20 International system including the Fp1, Fp2, F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, T3, T4, O1, Oz, O2 channels, left and right earlobe referenced. 200ms pre-stimulus and 1000ms post-stimulus raw ERP data were segmented for further analysis.

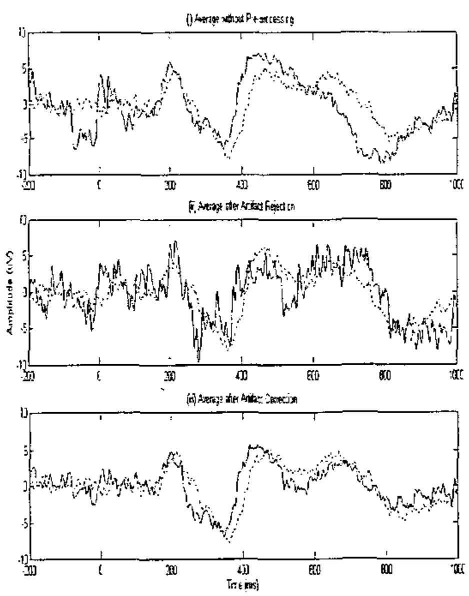

Fig.1. Pre-test (solid) and post-test (dotted) Cz ERP obtained by averaging (i) without pre-processing; (ii) after artifact rejection; (iii) after artifact correction by second order BSS.

Three different procedures were performed for comparison: average without any pre-processing, average after artifact rejection in the raw ERP domain, and average after artifact correction (i.e. artifact rejection in the separated source domain). The amplitude threshold h was chosen as 100uV. Averaged ERP waveform from Cz is plotted in Fig.1.

Looking at Fig.1(i), we can observe that significant distortion appeared if no artifact rejection/correction is performed before averaging. The distortion is obvious around the pre-stimulus baseline region, where no ERP deflection should appear. In Fig.1(ii), the ERP waveform is relatively noisy. This is because the rejection rate of the artifact rejection process for that session is higher than 80%. As a result, the number of clean ERP trials for averaging is small such that the averaged waveform is still highly contaminated by ongoing EEG. The peaks and troughs are relatively clearer in Fig.1(iii) and comparison between the pre- and post-test waveform is more confident.

IV. Conclusion

Artifact correction for ERP by second order statistics based blind source separation is proposed. We compared the ERP waveforms obtained by different averaging procedures and found that our proposed method has the best performance. Without artifact rejection/correction, the distortion to the ERP waveform is significant even when hundred of trials are being averaged. Artifact rejection by amplitude thresholding might lead to large rejection rate so that ongoing EEG cannot be effectively suppressed. With the introduction of source separation process, the amplitude thresholding can be migrated from the raw EEG domain to the transformed source domain. As a result, only artifact components will be rejected instead of whole EEG epochs. This prevents useful measurements from being discarded. Compared to other BSS approaches such as ICA, second order statistics based approach allows more robust and yet computationally more efficient estimation.

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