Probabilistic Enhancement of EEG Components Using Prior Information of Component-Related Spatial Correlation

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***Abstract*— We propose a probabilistic scheme to enhance the target component of electroencephalogram (EEG) using a multi-channel Wiener filter with time-variant spatial correlation matrices estimated using maximum *a posteriori* (MAP) estimation.**

I. INTRODUCTION

Independent component analysis (ICA) is a widely used method for improving EEG signal-to-noise ratios [1]. It works well under the assumption that the number of sources is equal to or less than the number of sensors, which is questionable in the context of EEG. Sakanashi, et al [2] proposed a probabilistic audio separation scheme using a Wiener filter in which time-variant spatial correlation matrices of each components are estimated using the maximum likelihood criterion. We apply this scheme to enhancement of the target EEG signal component, and improve its performance by setting prior distributions to spatial correlation matrices and using MAP criterion for parameter estimation.

II. OBSERVATION MODEL

Following previous work's observation model [2], we denote the complex amplitude of an observation multi-channel EEG signal in the time-frequency domain as $\mathbf{x}(n,f) = [\mathbf{x}^{(1)}(n,f), \cdots, \mathbf{x}^{(J)}(n,f)]^\top$ and that of its k-th component as $\mathbf{c}_k(n,f) = [\mathbf{c}_k^{(1)}(n,f), \cdots, \mathbf{c}_k^{(J)}(n,f)]^\top$ where n is the index of a time frame, f is that of a frequency bin and J is the number of EEG channels. We assume that $c_k(n,f)$follows a multivariate complex Gaussian with a zero mean vector as follows:

$$p(\mathbf{c}_k(n,f)) = \mathcal{N}(\mathbf{c}_k; \mathbf{0}, v_k(n,f)\mathbf{R}_k), \tag{1}$$

where $v_k(n,f)$ is the degree of activeness of the k-th component in (n,f) and $\mathbf{R}_k$ is a spatial correlation matrix that represents the correlation between EEG channels. Therefore, the likelihood of the observation signal is written as

$$p(\mathbf{x}|\theta) = \prod_{n,f} \sum_{k=1}^{K} \alpha_k \mathcal{N}(\mathbf{x}(n,f); \mathbf{0}, v(n,f)\mathbf{R}_k). \tag{2}$$

where $\theta = \{\alpha_k, v_k(n,f), \mathbf{R}_k\}_{k=1}^{K}$, and α_k is the probability of k-th component's being active in each (n,f).

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III. MAXIMUM A POSTERIORI ESTIMATION OF SPATIAL CORRELATION MATRICES

We assume a situation where features of the target component is known; e.g., the ERP of P300 component needs to be enhanced as the target component in some applications. Therefore, we can set the prior distributions of each $\mathbf{R}_k$ as

$$p(\mathbf{R}_k^{-1}|\mathbf{\Psi}_k) = \mathcal{W}(\mathbf{\Psi}_k, q), \tag{3}$$

where $\mathcal{W}$ is Wishart distribution. $\mathbf{\Psi}_k$ and q are hyper parameters which are determined in advance using prerecorded EEG signals. We estimate parameters that maximize following posterior probability using the EM algorithm,

$$p(\mathbf{R}|\mathbf{x}, v, \alpha) = \prod_{n,f} p(\mathbf{x}(n,f)|\theta) \prod_{k} p(\mathbf{R}_k^{-1}|\mathbf{\Psi}_k) \tag{4}$$

where $\mathbf{R} = \{\mathbf{R}_1, \cdots, \mathbf{R}_K\}$. Each components's time-variant spatial correlation matrix is given as follows:

$$\mathbf{R}_{\mathbf{c}_k}(n,f) = m_k(n,f) v_k(n,f) \mathbf{R}_k. \tag{5}$$

where $m_k(n,f)$ is the posterior probability.

IV. ENHANCEMENT WITH WIENER FILTER

We construct a multi-channel Wiener filter and enhance the target components [2],

$$\mathbf{c}_k(n,f) = \mathbf{R}_{\mathbf{c}_k}(n,f) \left(\sum_{k=1}^{K} \mathbf{R}_{\mathbf{c}_k}(n,f) \right)^{-1} \mathbf{x}(n,f). \tag{6}$$

V. EXPERIMENTAL EVALUATION

A subject participated in an experiment of the oddball paradigm using a 27 channel EEG. By our proposed method, the S/N ratio is improved (see Fig.1) and the accuracy of pattern recognition (200 standard stimuli v.s. 50 target stimuli) was improved from 64% (raw) to 79% (proposed).

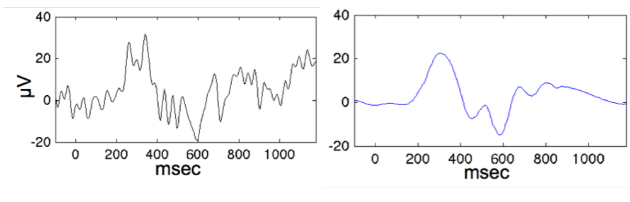

Fig. 1. Raw signal (left) and after the proposed method (right)

REFERENCES

[1] A.Hyvarinen, J.Karhunen, and E.Oja. Independent component analysis. Vol. 46. John Wiley Sons, 2004.

[2] R.Sakanashi, et al. "Comparison of superimposition and sparse models in blind source separation by multichannel Wiener filter." Proc. APSIPA, 2012