

## Chapter 25

# Application of Prewhitening Beamformer with Linear Constraints for Correlated EEG Signal Source Estimation

**Teruyoshi Sasayama**

*Kyoto University, Japan & Japan Society for the Promotion of Science, Japan*

**Shoji Hamada**

*Kyoto University, Japan*

**Tetsuo Kobayashi**

*Kyoto University, Japan*

### ABSTRACT

*To investigate the effect of signal correlation, the authors compared the relative abilities to estimate the source of an ERD/ERS signal among minimum variance beamformer (MVBf), linearly constrained (LC)-MVBf, prewhitening beamformer (PWBf), and LC-PWBf during the measurement of correlated signals. In numerical simulations, equivalent current dipoles were placed in the primary motor cortex to detect the modulation of  $\mu$  and  $\beta$  rhythms. It was confirmed that the location bias of LC-PWBf was smaller than that of MVBf, LC-MVBf, and PWBf. These results suggest that LC-PWBf is useful for estimating the location of signal sources that are highly correlated and have low signal-to-noise ratio.*

### INTRODUCTION

There is a growing interest in rhythmic brain activity with respect to motor, sensory, and cognitive functions measured by electroencephalograms (EEGs). Spectral decreases and increases of power

in rhythmic brain activity are called event-related desynchronization (ERD) and event-related synchronization (ERS), respectively (Pfurtscheller & da Silva). Most movement-imagery-based brain-computer interfaces (BCIs) (Graimann et al. 2010) function by detecting ERD and ERS using EEGs. For example, the ERD of  $\mu$  (8–12 Hz) and  $\beta$  (approximately 20 Hz) rhythms are observed in the

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left primary motor area (IM1), while the ERS of  $\mu$  and  $\beta$  rhythms are observed in the right primary motor area (rM1), when right-hand-movement imagery is performed (Pfurtscheller & Neuper 1997, Pfurtscheller & da Silva 1999).

Extraction of ERD/ERS signals from noisy EEGs is of interest in movement-imagery-based BCI studies. Stimulus-locked averaging is often applied to ERD/ERS signal extraction to suppress noise. However, stimulus-locked averaging suppresses not only noise but also the ERD/ERS signals.

Sekihara et al. (2006, 2008) proposed a pre-whitening beamformer (PWBF) that can suppress a large percentage of background interference, which is also suitable for extracting ERD and ERS signals. However, adaptive spatial filters, such as a minimum variance beamformer (MVBF) and a PWBF, are known to be sensitive to signal correlation. When signals are highly correlated, signal source reconstruction fails (Van Veen et al. 1997, Sekihara et al. 2002). Furthermore,  $\mu$  and  $\beta$  rhythms of rM1 and IM1 occur simultaneously, indicating that they are highly correlated.

Meanwhile, when we use MVBF, we can overcome the issue of highly correlated signals by applying linear constraints, namely a linearly-constrained (LC)-MVBF (Sekihara & Nagarajan 2008). A linear constraint for a set of voxels in a local region, which is referred to as a “cluster,” is used in order to suppress the power output from the region. One method to identify clusters involves using functional resonance imaging (fMRI) to locate regions with significant brain activity.

In this chapter, we used LC-PWBF to overcome the signal correlation issue in PWBF. To quantitatively examine their applicability to BCIs, numerical simulations were carried out to compare the estimation performances of an ERD/ERS signal location among MVBF, PWBF, LC-MVBF, and LC-PWBF.

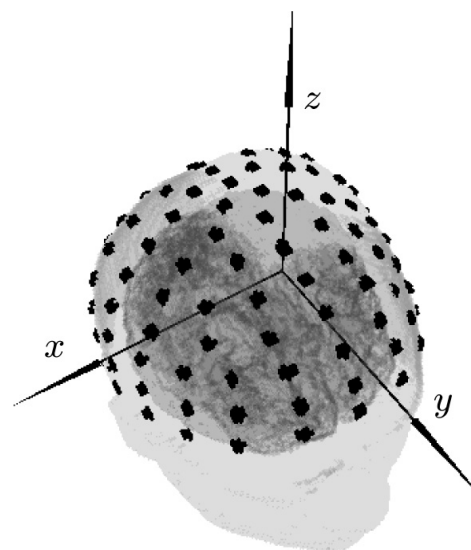
## METHODS

### EEG Electrodes and Head Model

In the following numerical experiments, we used an EEG electrode alignment from the ActiveTwo system (BioSemi Inc., Amsterdam, the Netherlands). The arrangement of electrodes follows the extended international 10-20 system (American Clinical Neurophysiology Society 2006). Figure 1 shows the arrangement of electrodes. The number of sensors  $n$  was 128.

EEG signal sources were estimated using a custom-made realistic head model that was constructed using MRI data (Sasayama et al. 2010). Realistic head models are more suitable than are concentric spherical models for EEG signal source estimation. This property is observed because the electric potential is susceptible to both the conductance and structure of head tissues (Yvert et al. 1997). The head model consists of eight types of tissue: gray matter, white matter, cerebrospinal fluid, skin, muscle, fat, skull, and eyeballs. The conductivity value of each tissue used in this chapter was the same as that reported by Hirata

*Figure 1. Head model and the arrangement of EEG electrodes*



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