Basic research for the realization of online MEG using SSD

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Abstract

Neurofeedback systems have been found to be effective in the clinical rehabilitation of paralysis. However, most systems exist only for use with EEG, which is cumbersome to apply to patients and has lower spatial resolution than MEG. Furthermore, the best practices for neural data feature extraction and feature selection are not well established. The inclusion of the best performing feature extraction algorithms is critical to the development of clinical neurofeedback systems. Using simultaneously collected MEG and accelerometer data before and during 10 spontaneous finger movements, we performed an in-depth comparison of independent components analysis (ICA) and spatio-spectral decomposition (SSD) algorithms for their individual abilities to isolate movement-relevant features in brain activity. Having restricted raw data to that from sensorimotor rhythm (SMR) frequencies in select MEG sensors over sensorimotor cortex, we compared ICA and SSD components using: (1) 2D topographies, (2) activations over time, (3) and correlations with accelerometer data at both 0ms and 60ms time delays. SSD performed more quickly and produced components that were more highly correlated with the behavioral data than ICA. We will discuss these results and suggestions for application to neurofeedback systems. In particular, we will present detailed visualizations of SSD results and discuss potential strategies and pitfalls for feature selection.

Keywords: Magnetoencephalography, Spatio-spectral decomposition, Morlet wavelet transform, Neurofeedback

1. Introduction

For diseases that affect brain function, such as strokes, immediate treatment with medication and surgery is important, but post-onset rehabilitation also plays a critical role in the wellbeing of patients.

One of the techniques used for non-invasive brain function evaluation is magnetoencephalography (MEG)[1-

[2]. MEG has high temporal resolution as well as high spatial resolution, and it is commonly used clinically for epilepsy diagnosis and rehabilitation[10]. Without the ability to monitor a patient's relevant brain activity in real time during rehabilitative exercises, efficient rehabilitation cannot occur.

The purpose of this study was to evaluate the use of spatio-spectral decomposition (SSD) of real-time MEG data during spontaneous movement[3-6]. Performance was evaluated by comparing SSD results to the results from a standard analysis technique, independent components analysis (ICA). SSD completed decomposition faster than did ICA, with the SSD analysis completed about 270 times faster in the preliminary experiment. In addition, as shown in Table 1, the correlation with the accelerometer data (shifted by 60[ms] to account for the time difference between neural motor planning and actual motor execution) was also stronger for the most highly correlated SSD component as compared to the most highly correlated ICA component. Our results indicated that SSD outperforms ICA in the context of feature extraction for online, real-time MEG analysis; therefore, we present our investigation of the SSD components and conclude with suggestions for feature selection.

Table 1. The correlation with the accelerometer data and ICA or SSD.

	60[ms]
1st ICA	0.71
2nd ICA	-0.18
3rd ICA	-0.55
4th ICA	-0.07
5th ICA	0.35
1st SSD	0.15
2nd SSD	-0.89
3rd SSD	-0.13
4th SSD	0.47
5th SSD	-0.45

2. Experiment

The data were collected using a full-head 306-channel magnetoencephalograph (Vectorview, Elekta-Neuromag, Helsinki, Finland) at a sampling frequency of 1000 [Hz]. In order to reduce power supply noise and other interference, measurements were taken inside a magnetic field shield room (1 [kHz] shielding rate 55.2 [dB]). The participant was a healthy person who attached an acceleration sensor to the middle finger of his left hand and performed ten spontaneous flexion (i.e., bending) and extension (i.e., relaxing) movements of the indicated finger as shown in Fig.1 (hereinafter referred to as "the task"). The accelerometer data indicated the start and duration of flexion and extension.

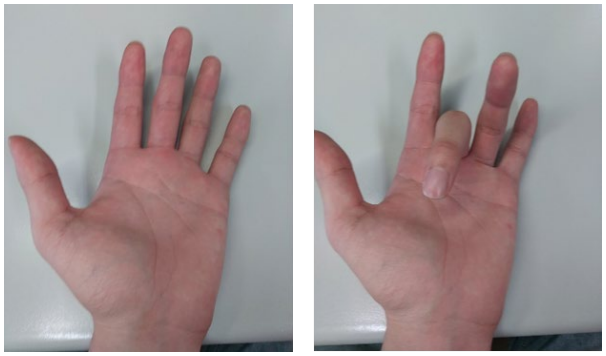


Fig.1: The spontaneous flexion (bending) and extension (relaxing) movements.

3. Analysis Method

After collecting the raw MEG data from all 306 channels, we sub-selected 26 gradiometers corresponding to the right sensorimotor cortex (SMC) and performed ICA and SSD analyses[7-8], which each identified components within the largest cited frequency band for sensorimotor rhythm (SMR)[9], 8-30 [Hz]. As presented in Table 1, we calculated Pearson correlations between the time-adjusted accelerometer data and each of the top five components from ICA and SSD. We calculated the SSD topographies about 20 seconds and then performed a Morlet wavelet transform to examine frequency power over time (Fig.2). In addition, in order to increase the signal-to-noise ratio (SNR), the wavelet analysis was performed on task-locked averaged components to indicate average brain activity in the final 2 seconds before flexion start. There were 10 tasks completed over 20 seconds at irregular intervals.

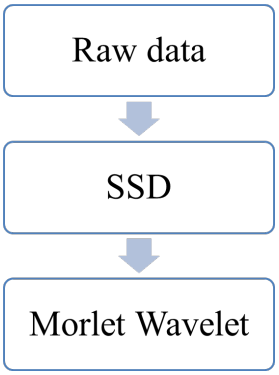


Fig.2: The flow of analysis method

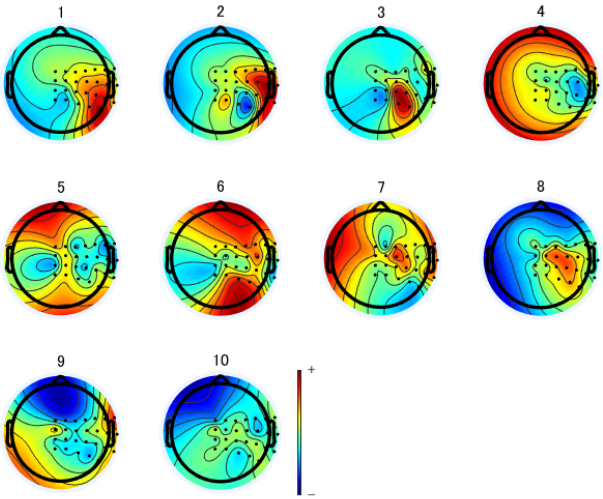
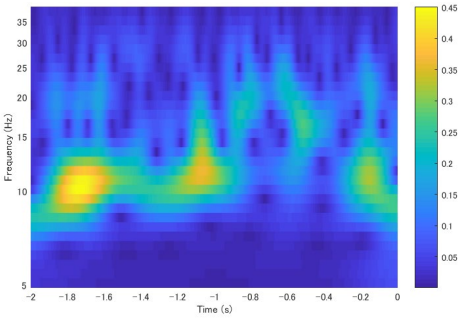
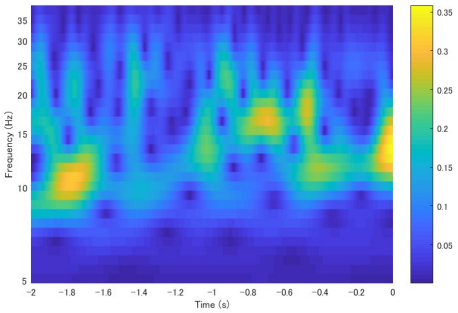


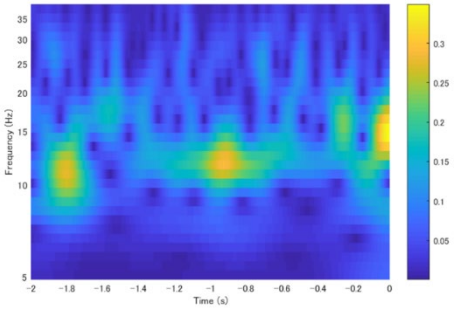
Fig.3: The results of Topography using SSD



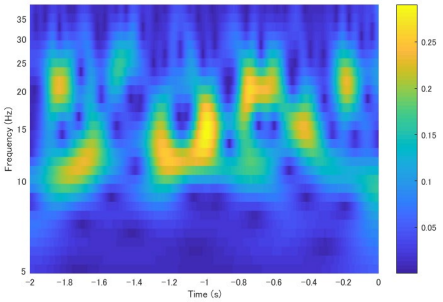
2nd SSD



3rd SSD



4th SSD



5th SSD

Fig.4: The results of the across-task averaged second, third, fourth and fifth SSD components

4. Results

From the results of topography (Fig. 3), the first eight SSD components showed activity localized around the right SMC. As shown in Fig. 4, the across-task averaged third and fourth SSD components had higher SMR band power immediately preceding the task. The pattern of activity observed in the SMR frequency band across task instances indicated that the first four SSD components

captured artifactual activity (e.g., movement activity). In the averaged component as well as across task instances, steady activity during the two seconds preceding flexion was observed at 12-13 [Hz] in the fifth SSD component.

5. Conclusion

In this paper, we performed offline MEG data analysis during flexion and extension of the middle finger of the left hand in order to investigate the use of SSD in online, real-time MEG analysis.

There are several key points to take away regarding the automation of feature selection in this context. First, the SSD component with the highest correlation to accelerometer data (comp. 2, r = -0.89) was, in this case, indicative of muscular noise reaching the MEG sensors rather than indicating neural activity as desired. Second, the component most likely to indicate relevant neural activity (comp. 5) was, in addition to not being the most highly correlated with accelerometer data (r = -0.45), also not the first component (i.e., it was not the component with the strongest eigenvalue or largest SNR). Finally, when only considering a few trials (i.e., at the beginning of neurofeedback rehabilitation) or particularly noisy data, using averaging techniques can lead to incorrect feature selection due to the extreme amplitude of artifacts and the components that capture them. Therefore, a component to use for patient feedback cannot be selected based solely on having the highest average SMR power, the highest correlation with behavioral data, or the highest eigenvalue.

Future study will include the same analysis for SSD components 6-8, which show promising topographies. Furthermore, we will investigate the usefulness of baseline correction in component selection and of logarithmically scaled components as features in unsupervised learning.

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