論文内容の要旨

論文題目：MEG study on the prediction of motion trajectory

(脳磁図を用いた運動軌道予測に関する研究)

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Motion is one of the most important ways for human to communicate with environments such as other people and objects. A moving process mainly bases on motion commands, which is generated from neurons in motor cortex, transferred by motor nervous system, and finally executed by voluntary muscles. Among them, motor cortex is obviously the essential part while the other two are important as well. There are patients that have clear consciousness but are not able to move their body because of injuries to their peripheral motor nerves or the muscles for execution. In these cases, Brain Computer Interface (BCI) is a possible solution. In BCI, a computer is used to replace the pathway of motion command, and artificial devices such as robotic arms are for the purpose of replacing the injured body parts. Thus BCI system can directly link brain activity to artificial devices and enable paralyzed patients to move as healthy people.

In recent years, many researchers have focused on motion system and presented several methods to control man-made devices by using motor activities. These techniques range from invasive methods such as implanted microelectrode arrays [1] and electrocorticography (ECoG) [2] to non-invasive methods such as electroencephalography (EEG) and magnetoencephalography (MEG). In invasive studies, electrodes are directly placed in certain part of brain or on the surface of brain, thus the recorded data has a very high signal to noise ratio (SNR), which is effective for investigating complicated motion. However, a surgery is needed in invasive technique so that it is risky and unstable for real application. Non-invasive studies are safer and more convenient, but the recorded brain activities are always contaminated by environmental noises and thus making it difficult to be used for motion pattern extraction. Currently, non-invasive studies on continuous motion mainly concentrate on the prediction of motion trajectory and present relatively high prediction performances [3], [4]. However, the characteristics of motor activities during this procedure remain unclear. Thus current predictions in non-invasive studies are ineffective, which is represented by large feature number and large training data set.

In this study, we developed a noise reduction method which can improve SNR of MEG single-trial data and applied it on motion prediction. Then, we used preprocessed data to investigate temporal, spectral and spatial characteristics of motion related activities. Finally, we confirmed that selected subject-dependent frequency features are really generated by motor and sensorimotor cortices and thus are effective motion-related features.

Chapter 1 introduces the background of motion researches, which includes motor system and current status of BCI. Then we talk about our measurement device (MEG), noise conditions, and data analysis method adopted in motion feature selection and prediction. Moreover, we explain the significance of our study and briefly review the whole thesis.

Chapter 2 offers an effective noise reduction method with almost no brain activity loss, which is vital for the accurate prediction of motion trajectory from single trial data. It should be noted that this method can be applied to all kinds of MEG systems, regardless of having magnetometer or not.

In this chapter, we first describe tSSS method [5] developed by Dr. Samu Taulu. This method is developed for Elekta system with both magnetometer and gradiometer, while the applications to other systems with only gradiometer type sensors are still not fully tested. We implemented tSSS algorithm on Matlab and applied it to our system (Yokogawa PQ2440R). However, signal leakage problem occurred and brain activities reduced to 1/3~1/2 after using tSSS method on our system. We discuss the possible reasons for the signal leakage and provide a solution by discriminating brain activity and interference noise from temporal information. Utilizing this process, interference noise leakage can be further suppressed and brain activity can be recovered from the leakage by signal projection.

In all of computer simulation, phantom simulation, and real brain signals application, compensation tSSS method work well as is shown in Figure 1. Compared to tSSS method, our compensation method preserves signals well and has very small reconstruction error. This suggests that the compensation tSSS is a valuable noise reduction method for single trial analysis in our gradiometer only system.

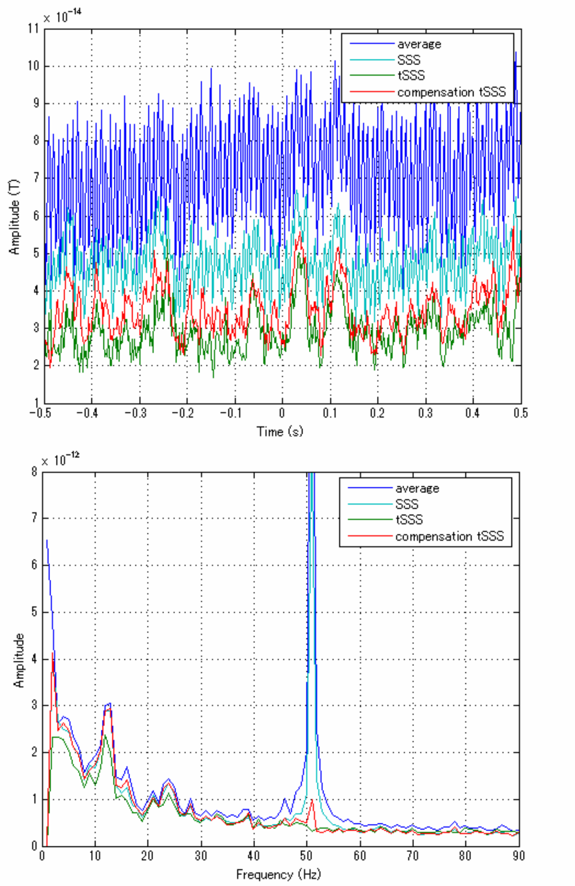

Figure 1. Noise reduction results comparison of different method on MEG raw data. The upper plot illustrates root mean square of all channels and the lower one shows corresponding FFT results.

Chapter 3 presents a study on 1-D continuous motion using a tool bar. This study offers a successful feature selection method for arm motion trajectory prediction and confirms the efficiency of compensation tSSS method in continuous motion prediction.

In this study, we applied a non-invasive MEG study on 4 BCI-untrained subjects' continuous motion. In the task, BCI-untrained subjects were asked to perform continuous motions using toolbar and both subjects' brain activity and motion position were recorded simultaneously. We calculated the spectrum of brain activity below 100 Hz and investigated the correlation between brain activity

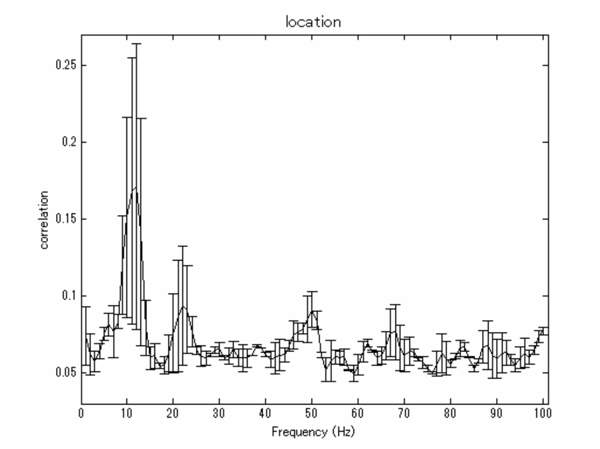

Figure 2. Correlation between actual motion and the spectral amplitudes of MEG from sensors over motor cortex, averaged across four subjects.

spectrum and motion parameters. From the correlation results shown in Figure 2, we considered 9-14 Hz which has a relatively high correlation value as motion related frequency feature. Then, we adopted different channel selection models and time-windows, and determined proper features using prediction performance evaluated by multivariate linear regression. By using these motion related features, we offered an effective motion trajectory prediction with an acceptable correlation coefficients (average value across all subjects is 0.32, $p < 0.001$) on the single trial data preprocessed by compensation tSSS method. This indicates that using well-selected motion related feature, non-invasive methods can also achieve accurate prediction on continuous untrained limb motion as invasive methods. Moreover, compensation tSSS preprocessed data provides a significant higher prediction performance than original tSSS preprocessed data which specifies that compensation tSSS provides a higher SNR and performs better than original tSSS method on our MEG system.

Chapter 4 reconsiders the experiment in Chapter 3 and investigates correlation between motion trajectory and each frequency below 100 Hz for each subject. The difference between subjects is compared and subject-dependent frequency bands are selected for single trial prediction.

Table 1. Comparison of prediction performance results using tSSS and compensation tSSS method, fixed model, main subject-dependant model and combined model. The result is shown as mean ± standard deviation (SD) of all subjects.

Single-trial data	**tSSS**	**Compensation tSSS**
Fixed frequency	0.23 ± 0.14	0.32 ± 0.14
Single subject-dependant	0.27 ± 0.11	0.40 ± 0.10
Combination of subject-dependant	0.31 ± 0.08	0.47 ± 0.10

In this study, we concentrated on spectral amplitudes of MEG and tested several ways of frequency band selection to further improve the prediction. From the correlation between spectral amplitude and motion trajectory, we extracted several subject-dependent frequency bands, which range from μ (8-16Hz) and β rhythm (18-24Hz) to low frequency δ rhythm (5-7Hz) and some part of high frequency γ bands (30-50Hz, 60-70Hz). Compared to fixed frequency band (9-14 Hz) mentioned in Chapter 3, subject-dependent frequency band offers a better prediction performance, as is listed in Table 1. In addition, the combination of two or three subject-dependent frequency bands further improves the prediction performance and this improvement is significant for most of subjects. From the prediction performance of all subjects, we concluded that using correlation based feature selection method, single-trial MEG data can also predict continuous motion well (r = 0.47) with few features (less than 100).

Chapter 5 focuses on the robustness of different motion cycles and devices, and reveals the spatial patterns of motion related frequency features. The source level analysis provides the evidence that such selected frequency features are motion related activities come from motor cortex and sensorimotor cortex.

To test the robustness of our feature selection method, we performed similar motion using a different device (trackball) in task 1. The prediction result confirms that our feature selection method works equally well on different devices which indicates a robustness of different devices. In task 2, we considered a different motion cycle without visual guidance and confirmed the efficiency of our feature selection method on different motion cycle, which shows a robustness of different motion. As there is no visual guidance, the selected features are verified to be from motion brain activities. From further contour map and source estimation studies, it is also confirmed that the sources of frequency features selected by our method are really located in the contralateral motor cortex and sensorimotor cortex.

Chapter 6 summarizes all the studies in this paper and discusses the future research directions.

In this paper, we firstly discussed the interference noise condition and developed compensation tSSS method to effectively suppress the noise in single trial MEG data. Then we investigated on continuous motion and designed a motion related feature selection method which greatly reduces feature number in motion trajectory prediction. By combining several subject-dependent frequency bands, a successful prediction is provided with single trial MEG data. Further contour map and source analysis confirm these features come from motor cortex and thus are motion related features.

Our study reveals detailed characteristics of motion related activities which are consistent to ECoG and EEG studies. It also provides a guidance to select features and achieves a successful single trial motion prediction. The high quality prediction demonstrates that non-invasive measurement can predict motion comparably well as invasive measurement such as ECoG. Also, the prediction of arm movement trajectory in our study provides a possibility of controlling external prosthetic devices.

Reference:

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