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Generation of Spatial Filters by ICA for Detecting Motor-related Oscillatory EEG

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Abstract—**To detect the imagined limb movement from EEG for the use in BCI, the increase (ERS) and decrease (ERD) of the band power of the EEG originated from the sensorimotor cortex are commonly used. A spatial filter using neighboring channels is generally applied to the measured EEG for detecting such brain activity related to the motor imagery. However, the configuration and location of the spatial filter have been selected by the empirical method on trial-and-error basis. In this study, we recorded the EEG during motor imagery of left hand, right hand and feet from five subjects, and the ICA (independent component analysis) was applied to discover the spatial filters for extracting event-related EEG components of the motor imagery. It was suggested that the application of ICA might offer the experimenters appropriate local spatial filters, or at least, the "initial guess" for designing or selecting custom local spatial filters.**

I. Introduction

To realize the EEG-based BCI (brain-computer interface) using motor imagery, the increase and decrease of the EEG band power (event-related synchronization/desynchronization, ERS/ERD) at mu, beta or gamma frequency range are extracted and detected to specify the limb of which the user imagined the movement [1].

These EEG components are originated from the sensorimotor cortex, and can be extracted by applying the spatial filter, which is defined as the weighted sum of the EEG data measured simultaneously from multiple electrode sites.

The spatial filter with sparse and localized weight distribution (local spatial filter), e.g. bipolar montage and the Laplacian filter, is useful to extract the localized cortical EEG activities. As these local filters use only a few or some electrodes, the application of these filters can reduce the number of EEG channels for detecting motor imagery. However, the local spatial filter should be optimized by the large-scale numerical analysis to test all the places and combinations of the electrodes.

In this study, a method to optimize the location and the configuration (distribution of the weight values) of the local spatial filter for detecting EEG activities during motor imagery in a semi-automatic manner was proposed. It was shown that the local spatial filters to extract EEG components related to motor imagery could be generated by applying ICA (independent component analysis) to the measured EEG data.

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II. Spatial filters for BCI

The spatial filter has been used to reduce artifacts and far-field potentials and to extract specific brain activations from measured EEG data. The common spatial pattern (CSP) filter is one of the efficient spatial filters. The CSP filter is designed so as to maximize the classification accuracy of the multidimensional data [2, 3, 4, 5]. In general, the weights of the CSP filter are widely distributed in space.

The spatial filter with sparse and localized weight distribution (local spatial filter) has been generally used to extract cortical near-field potentials. The Laplacian filter and bipolar montage are commonly used as local spatial filters [6, 7, 8]. In case of the practical use of BCI, the electrodes used in the spatial filter should be as less as possible. The local spatial filter is suitable for such purposes.

Before applying such local spatial filters, the proper selection of the local spatial filter should be done for extracting the target cortical activities from EEG. The selection could be determined by the location and the configuration (distribution of weight values in space).

McFarland et. al compared the performances of spatial filters to extract motor-related mu and beta EEG oscillations. It was shown that the large Laplacian filter (gap between the center electrode and surrounding electrodes: 6 cm) and the CAR (common average reference) filter marked better results than a small Laplacian filter (gap: 3 cm) or a standard ear-reference (monopolar) [6]. The bipolar montage configuration is also known to be effective and is widely used to extract motor-related brain responses [7, 8].

When using the local spatial filters on the practical BCI, all the possible locations of the local spatial filter should be tested, and the best location should be chosen by the large-scale numerical analysis.

Moreover, such local spatial filters are pre-defined to obtain the derivatives or partial derivatives at the center point from the measured EEG voltages, and the configurations are symmetric or isotropic in space. However the source area of the target EEG activity may have a distribution in space and the source distribution may be anisotropic or atypical. That means that configurations of such pre-defined local spatial filters might not be optimal to extract cortical EEG activities.

III. Methods

In this study, the ICA was tested to generate and discover the appropriate configuration and the proper location of the local spatial filter to extract motor-related cortical EEG.

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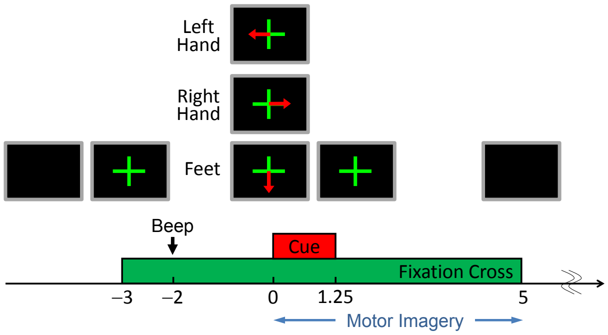

Figure 1. Timing of a trial in the experiment.

Five subjects with normal motor abilities were requested to imagine the movements of their left hand, right hand or feet for five seconds.

The time chart of a trial in the experiment is shown in Figure 1. The instructions to subjects (Figure 1, upper) were displayed on the LCD display in front of the subjects. Three seconds after showing the green fixation cross, a red arrow was presented as a cue for 1.25 seconds. During the period between the onset of the cue (t = 0 s) and the offset of the fixation cross (t = 5 s), subjects were instructed to imagine the movement of the subjects' own limb, which was instructed by the direction of the red arrow (left: left hand, right: right hand, down: both feet). On each trial, the limb to be imagined was changed in a random order. For each subject, 6 sessions each of which consisted of 30 trials were conducted (totally 180 trials, 60 trials/limb).

EEG during motor imagery was recorded from Ag-AgCl electrodes placed over 32 positions (see e.g. Figure 2 (a), left) at the sampling frequency of 2 kHz. The reference and the ground electrodes were placed on right and left earlobe, respectively.

After resampling the recorded EEG data to 100 Hz, the following three kinds of local spatial filters were applied and the performances to extract the EEG activities related to the motor imagery were compared.

(1) Bipolar filter: Bipolar re-reference was applied. Voltage difference of the pairs of nearest neighboring anterior and posterior electrodes was calculated, e.g. Cz – FCz.

(2) Laplacian spatial filter: A 2-D isotropic measure of the second spatial derivative of the voltage distribution. It is approximated using the center and the surrounding electrodes by the following equation.

$$V_i^{LAP} = V_i - \frac{1}{N}\sum_{j\in \boldsymbol{S_i}} V_j \quad (1)$$

where V_i and V_i^{LAP} are the measured and the Laplacian filtered signal at i th channel, $\boldsymbol{S_i}$ is a set of the first nearest neighbor electrodes of i th channel, and N is the number of the first nearest neighbor electrodes ($N = 4$).

(3) ICA spatial filter (local filter generated by ICA): ICA was applied to obtain the unmixing matrix and the independent EEG components. The FastICA algorithm [9] was used in this study. Each row of the unmixing matrix is defined as the distribution of the weight value (configuration) of the ICA filter. The topographic distributions of the weights of the ICA filters were visually inspected, and the independent components obtained by the ICA filters were analyzed. The ICA filters which had the spatially-localized distribution near the sensorimotor cortex and were relevant to motor imagery were selected and used for further analysis.

Time-frequency ERS/ERD maps of the EEG after applying one of the local spatial filters were computed. The ERS/ERD was calculated by the following equation [1].

$$\mathrm{ERS/ERD} = \frac{A(t)-R}{R} \times 100[\%] \quad (2)$$

The relationship between the EEG responses extracted by the local spatial filters, and the location and the configuration (distribution of weight values) of the local spatial filter, were evaluated.

IV. Results and Discussion

A. Local Spatial Filter Generated by ICA

It was shown that the local spatial filters which can extract the EEG components related to motor imagery were generated by applying ICA.

One of the examples of the analysis to apply two types of the local spatial filters to the same data is shown in Figure 2. Figures 2 (a) and 2 (b) show the results of a bipolar filter, and the ICA filter generated from the same data, respectively. Both spatial filters extracted the increase (ERS) of the higher beta-band oscillation (24 – 30 Hz) during feet motor imagery (Figures 2 (a) and 2 (b), center and right). From the spatial configuration of the ICA filter (Figure 2 (b), left), one location with positive weight (Cz) and one with negative weight (FCz) could be found. This configuration is similar to a bipolar filter at the vertex area, which is commonly used for EEG-based BCI to detect feet motor imagery [8].

Five surrounding locations with negative weights (C1, C2, CP1, CPz and CP2) were also observed from this ICA filter. The configuration of the spatial filter that consists of Cz and these five surrounding electrodes is similar to the Laplacian filter. By comparing the performance of the ICA filter with the bipolar filter, it was found that the generated ICA filter is more suitable to extract ERS activities during feet motor imagery. These observations suggest the configuration of the ICA filter is like the combination of the bipolar and the Laplacian filters.

It was also found that the time courses of the beta-band EEG power are different between these two spatial filters (Figures 2 (a) and 2(b), center and right). This might suggest that the EEG components extracted by the two filters are different, even though the centers of these two filters are located at the vertex area.

It was shown that, instead of analyzing the data to specify the location and type (configuration) of the spatial filters by the empirical method on trial-and-error basis, ICA could be used to generate the local spatial filter to extract the oscillatory EEG activities which were related to the motor imagery. Moreover, though all the types or the spatial filter should have been tested on the previous method, the application of ICA could also discover the appropriate configuration of the spatial filter (distribution of weight value in space), even if it had an anisotropic or atypical configuration.

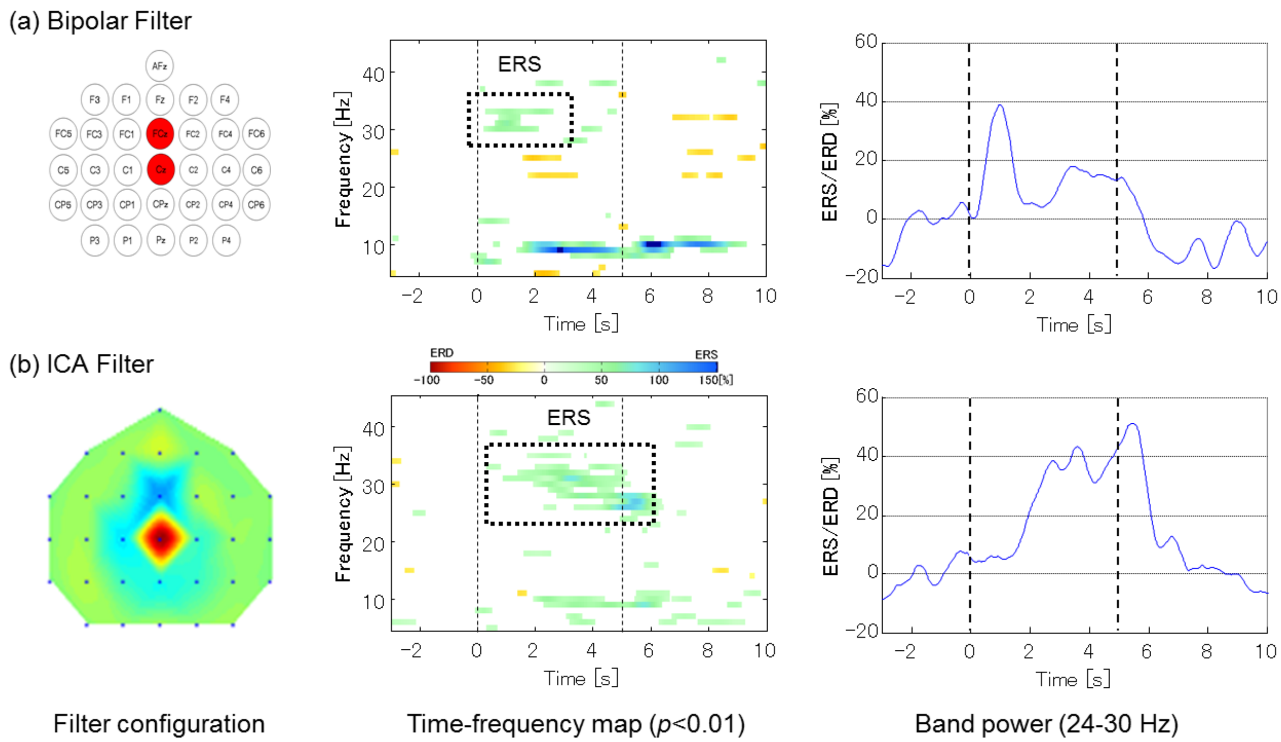

Figure 2. Examples of local spatial filters and the properties of EEG components extracted from the same data.

B. Classification Accuracy of the Filtered EEG Data

The performances of the spatial filters were evaluated by the pattern classification accuracy.

The feature vector at time t was calculated as follows. The power spectrum value at the frequency of 5, 6, … , 40 Hz (36 dimensions) was obtained by applying FFT to the data extracted by a 1-second rectangular time window ($t - 0.5 \sim t + 0.5$ [s]) after filtering by one of the local spatial filters. For each type of the three kinds of local spatial filters, power spectrum values calculated from the selected three locations (left hand, right hand and foot area on the sensorimotor cortex) were concatenated to one vector ($36 \times 3 = 108$ dimensions) and it was used as a feature vector for pattern classification. The time window was shifted for every 100 ms to obtain the feature vectors at each time period.

As the bipolar filters, Cz-FCz, C3-FC3 and C4-FC4 were selected, and the electrodes located at Cz, C3 and C4 were selected as the center electrodes of the Laplacian filters (see Figure 3 (a) and (b), respectively). As the ICA filter, three filters with local weight distribution which was located near Cz, C3 and C4, were visually inspected and selected.

The pattern classification to discriminate the class Rest and each of the Task classes (left hand, right hand and feet) was tested at each time. All the epoch data (totally 180 trials) were used for both sample and test data. The feature vectors at time $-1.9 \sim -1.0$ s and $1.1 \sim 4.0$ s were used as the sample data on class Rest and Task, respectively. All the feature vectors taken from the same subject at all the time period were used for test data. The Mahalanobis distances between a test data and the sample data of Rest and three Task classes were calculated, and the test data was classified to the nearest class.

Figure 3 shows the result of the pattern classifications using the bipolar, Laplacian and ICA filters on one of the subjects. The examples of the ICA filters generated from the EEG data are shown in Figure 3 (c). The peak weights were located at the corresponding motor area (areas around C4, Cz, C3 on left hand, feet, right hand motor imagery, respectively). The configurations for left and right hand motor imagery were almost isotropic and were similar to the Laplacian spatial filter. But the ICA filter for feet motor imagery was anisotropic, and unlike the Laplacian filter, more than one electrode location had peak weight values.

The classification accuracies for each imagery task (left hand, right hand and feet) of a subject are shown in Figure 3 (d). It was shown that the classification accuracy increased from about 2 seconds after the onset of the cue. The maximum accuracies of pattern classification were more than 0.9 on feet movement imagery task, and about 0.8 on left and right hand movement imagery task. From this subject, the ipsilateral as well as the contralateral activation of the motor-related mu oscillation was observed. The low accuracy of pattern classification on left and right hand movement imagery might be due to the similarity of the spatial distributions of the frequency components of EEG during motor imagery.

The accuracy before starting motor imagery task (i.e. false positive rate) was high on feet movement imagery task. This means it was relatively difficult to distinguish the feet movement imagery class and the rest state. The false positive rates of Laplacian and ICA filters were lower than that of bipolar filter. During motor imagery ($0 \sim 5$ s), the accuracies of pattern classification were almost the same for the three local spatial filters, but the result by bipolar filter was a little bit lower than those by Laplacian and ICA filers.

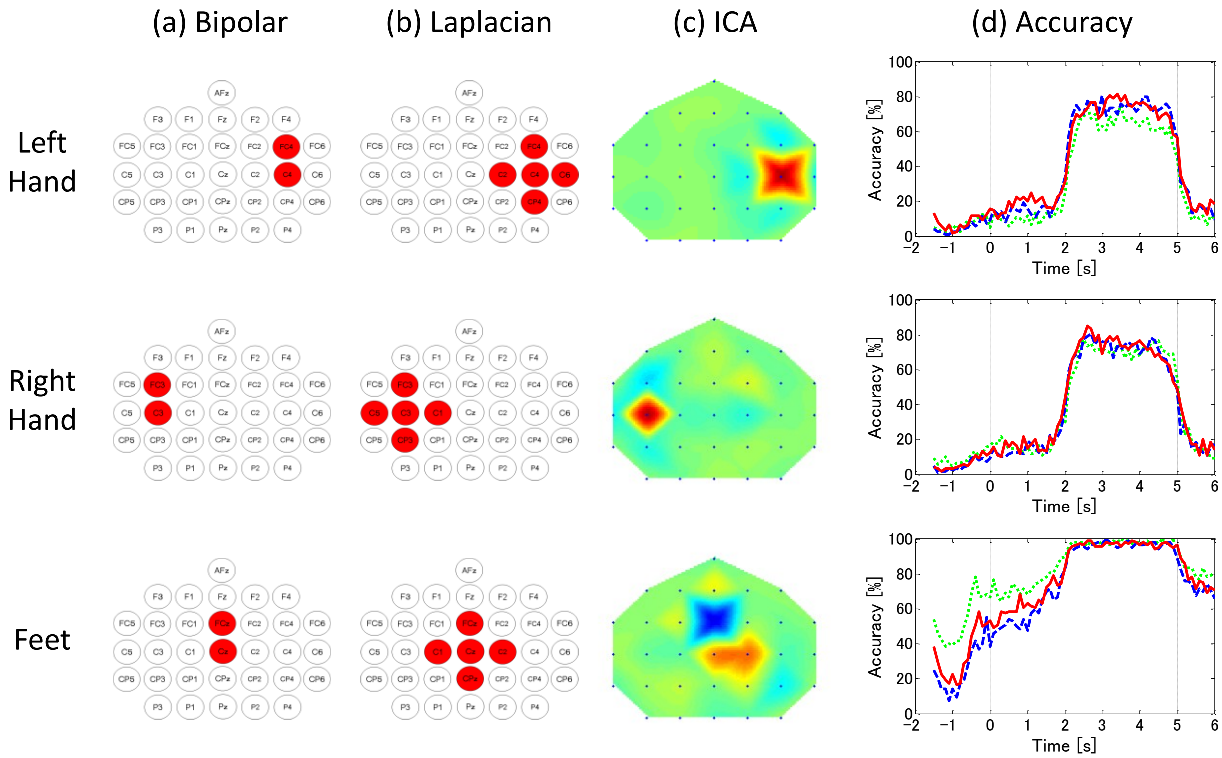

Figure 3. Selected local spatial filters (a)-(c) and the classification accuracies after filtering. Green, blue and red lines denoted classification accuracies with bipolar, Laplacian and ICA filters, respectively.

V. Discussion

It was shown that the local spatial filters could be generated by applying ICA to the measured EEG data. These ICA filters were located near the left hand, right hand and feet areas in the motor cortex. It was also shown that the spatial distributions of the generated ICA filters with local distributions were similar to the bipolar filter or Laplacian filters. And the anisotropic or atypical distributions of the ICA filters were also observed. Moreover, the performances of these ICA filters were comparable to those of pre-defined Laplacian filters, and were better than those of bipolar filters.

The purpose to apply ICA to the measured EEG data was to estimate the appropriate location and scale (number of electrodes needed) of the local spatial filters to detect EEG components related to motor imagery. From these results, it was suggested that the application of ICA might offer the experimenters appropriate local spatial filters, or at least, the “initial guess” for designing or selecting custom local spatial filters. The application of ICA could avoid the empirical method on trial-and-error basis and the large-scale data analysis to determine the local spatial filters for each individual subject on the BCI system based on motor imagery.

In this study, the unmixing matrix of ICA was used to determine the abstract spatial distribution of the ICA filter. The pruning of the electrode locations with small weight values should be investigated to discover the closely optimal configuration of the local spatial filters.

VI. Conclusion

For improving the EEG-based BCI to detect motor imagery, the application of ICA to EEG data to extract motor-related oscillatory EEG activities was proposed and tested. The detailed investigation of the application of ICA to obtain the optimal location and configuration of the local spatial filter was left for further study.

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