Automatic Identification of Independent Components Representing Sensorimotor Mu Rhythms

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Introduction:

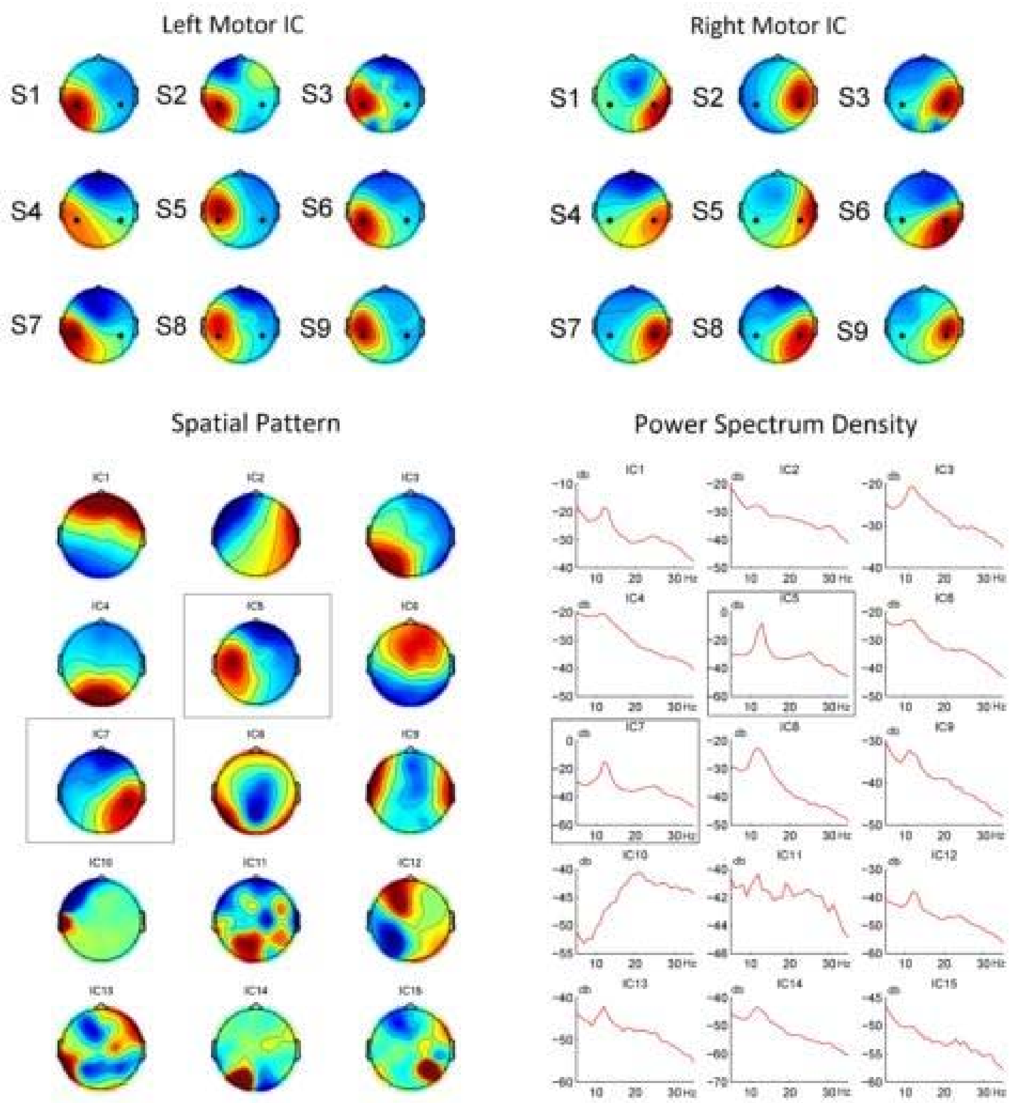
Independent Component Analysis (ICA) has shown a good capability in separating the scalp electroencephalogram (EEG) signals into functionally independent sources, such as neural components and artifactual components (Jung et al., 2001). Due to its superiority in EEG source separation, ICA has been widely applied to EEG research (Vigario et al., 2000). However, due to the lack of knowledge of selection criteria, the identification and interpretation of independent brain components is currently time-consuming and needs subjective selection (Viola et al., 2009). For example, in brain-computer interface (BCI) studies, the identification of the sensorimotor mu component was always performed manually, and therefore significantly reduces the practicality of ICA in online BCI applications. This study develops an automatic approach for identifying motor components from different subjects who participated in a BCI experiment using motor imagery.

Methods:

We recorded 32-channel EEG signals from nine healthy volunteers (six males and three females, aged between 22 and 25) in an online BCI experiment, where the left- and right-hand imagery movements were designated to control vertical cursor movements on the screen (Wang et al., 2007).
For each subject, ICA was used to decompose the scalp EEG signals using the EEGLAB toolbox (Delorme and Makeig, 2004). This study used two criteria to characterize motor-related components after ICA: (1) the spatial pattern, which suggests the source location of the component, should be consistent with the expected scalp projection of the sensorimotor cortex on each hemisphere; (2) the power spectrum density (PSD) of the component should match the typical spectral profile of the mu rhythms. According to these criteria, the motor ICs were first selected manually, providing an objective basis for evaluating the proposed automatic method.
This study defined three quantitative parameters to characterize the motor IC on each hemisphere: (1) distance between the equivalent dipole, which was obtained using DIPFIT plugin in EEGLAB, and the group mean of dipoles of the motor ICs; (2) correlation between IC's spatial pattern and the group mean of spatial patterns of the motor ICs; (3) EEG power ratio of the mu rhythm (12-15Hz) to its neighbors in the frequency band of 15-20Hz. For each parameter, an index could be obtained for each IC by sorting the values of the parameter across all ICs. The index reflects the similarity between an IC and a motor component. The identification of the motor components combined these parameters to calculate a weighted sum as a motor index. The IC, which had the smallest motor index, was selected as the motor IC. The left and the right motor IC was considered separately.

Results:

In this study, all subjects were able to control the BCI by regulating the amplitude of the mu rhythms on both hemispheres. As expected, two typical motor ICs, which represented brain activities originating from the left and right motor areas, were extracted by ICA. Figure 1 shows spatial patterns of the manually selected motor components from all subjects.
The ICs identified by the proposed automatic approach were exactly the same as those selected manually. Both spatial pattern and PSD features contribute to the successful identification of the motor components. When considered separately, the three parameters resulted in 17, 16, and 14 ICs same as the manually selected ICs respectively. Figure 2 shows spatial projections and PSDs of all independent components for a sample subject. According to the calculated motor index, IC5 and IC7 were identified as the two motor components.



Conclusions:

These results demonstrated that the proposed method provides an efficient and objective way of identifying independent brain components, which can significantly facilitate the employment of ICA in EEG signal analysis, especially the implementation of an online BCI system.

Motor Behavior:

Brain Machine Interface

Abstract Information

References

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