Electroencephalography-based Motor Hotspot Detection

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Abstract: The motor-evoked potential (MEP) induced by transcranial magnetic stimulation (TMS) has been generally used to identify a motor hotspot, and it has been used as a target location for transcranial electrical stimulation (tES). However, the traditional MEP-based method needs a bulky TMS device, and it involves the empirical judgement of an expert. In this study, we propose a machine-learning-based motor hotspot identification method using electroencephalography (EEG) that is portably acquired in a tES device. EEG data were measured from ten subjects while they performed a simple finger tapping task. Power spectral densities (PSDs) were extracted from the EEG data as features, and they were used to train and test artificial neural network (ANN). The 3D coordinate information of individual motor hotspots identified by TMS were also used as the ground-truth motor hotspot locations in ANN, and they were compared with those estimated by ANN. A minimum distance between the motor hotspots identified by TMS and EEG features was only 0.24 cm, demonstrating the feasibility of our proposed novel motor hotspot identification method based on EEG features.

1 INTRODUCTION

Non-invasive brain stimulation (NIBS) is an emerging technique that applies electrical current or magnetic field to the scalp for the modulation of cortical excitability (Paulus, 2000). NIBS is divided into two types according to whether electrical current or magnetic field is used. NIBS based on electrical current is called transcranial electrical stimulation (tES) that is divided into three types: i) transcranial direct current stimulation (tDCS) (Nitsche et al., 2000), transcranial alternating current stimulation (tACS) (Herrmann et al., 2013), transcranial random noise stimulation (tRNS) (Antal et al, 2016). NIBS based on magnetic field is called transcranial magnetic stimulation (TMS) (Wassermann et al, 2001).

TMS has been widely used to identify muscle representations in the motor cortex as well as to investigate corticomotor excitability. An optimal TMS site is called as the motor hotspot, and it is generally identified based on the TMS-induced motor evoked potential (MEP).

The motor hotspot identified by TMS has been used to validate the feasibility of tES on corticomotor excitability (Cabral et al, 2015). Some studies have shown that tES is effective for motor function rehabilitation in patients with stroke, Parkinson's

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disease, amyotrophic lateral sclerosis (ALS), and so on (Hummel et al., 2006). Most tES studies have used the anodal electrode attached to the motor hotspot identified by TMS, and the cathodal electrode attached to the contralateral motor area or contralateral supraorbital area (Ferreira et al., 2019). Although TMS is an ideal tool to find the motor hotspot, a cumbersome procedure involving the empirical judgement of an expert is required to find the motor hotspot. Also, it is impractical to use a TMS device for finding the motor hotspot as a target area for tES because a TMS device is relatively bulky and heavy. A potential alternative to TMS identifying the motor hotspot is to use electroencephalography (EEG) measured while performing a motor task related to a targeted motor hotspot because EEG provides the representation information related to motor functions even though its spatial resolution is relatively low as compared to TMS. Therefore, in this study, we propose an EEG-based machine-learning approach to identify an individual motor hotspot that is used as a target location for tES.

2 METHODS

2.1 Subjects

Ten right-handed subjects (five females and five males; 25.3 ± 1.36 years) were recruited for this study. They have no history of psychiatric diseases that might affect research results. They received the information about the details of experiment procedure, and signed an informed consent for study participation. Appropriate compensation for their participation was provided after the experiment. This study was approved by the Institutional Review Board (IRB) of Kumoh National Institute of Technology (No. 6250), and was conducted in accordance with the principles of the declaration of Helsinki.

2.2 Experiment Protocols

Subjects sat on a comfortable armchair. An individual motor hotspot was first identified using TMS. The motor hotspot was defined as the TMS coil location that shows a MEP with an amplitude of at least 50 μV more than 5 out of 10 consecutive stimuli when a minimum stimulation intensity was applied. Because a target region of interest was the right first dorsal interosseous (FDI) muscle in this study, MEP was measured from the FDI muscle using Ag-AgCl disposable electrodes while single-pulse TMS was applied to a corresponding brain area (REMED., Daejeon, Korea). We searched a motor hotspot on the contralateral motor area (around C3 based on the international 10-20 system); the coil was held at approximately 45 degrees with the handle facing the rear in order for TMS to be directed perpendicular to the brain. Individual motor hotspot locations were represented in the 3D coordinate (x, y, and z) based on the vertex (Cz in the 10-20 international system) using a polhemus patriot digitizer (Polhemus Inc., Colchester, Vermont, USA). The 3D locations of individual motor hotspots were used as the ground truth, and they were compared with those identified by EEG to verify the feasibility of our proposed EEG-based motor hotspot identification approach.

To measure motor-task-specific brain activity, 64 EEG electrodes were mounted on the scalp using the international 10-20 system (Figure 1), and the location of the EEG electrodes were also represented in the 3D coordinate as that of the motor hotspot identified by TMS-induced MEPs. The ground and reference electrodes were attached on Fpz and FCz, respectively. The EEG data were sampled at 1,000 Hz using a multi-channel active electrode EEG acquisition system (actiChamp, Brain Products GmbH, Gilching, Germany) while each subject performed a motor task that presses a button 30 times using a right index finger whenever a red circle appeared in the center of a monitor (Figure 2). The subjects were given enough rest in the middle of the experiment to avoid fatigue whenever they wanted. In addition, they were instructed to remain relaxed during the experiment without any movements to prevent unwanted physiological artifacts.

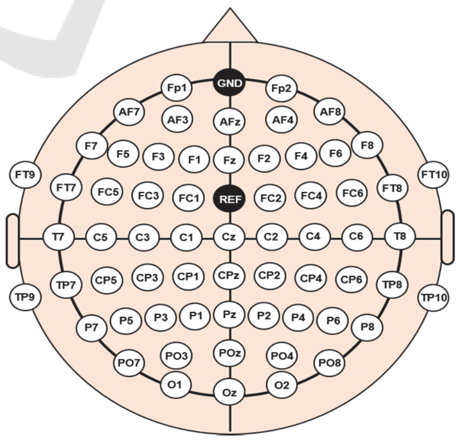

Figure 1: Electrode positions used for recording EEG data.

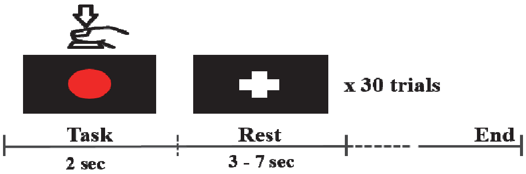

Figure 2: Experimental paradigm.

2.3 Data Analysis

EEG data were analysed using the MATLAB (MathWorks, Natick, MA, USA). The raw EEG data were down-sampled into 200 Hz. We applied common average reference (CAR) and bandpass filtering between 0.5 and 50.5 Hz (zero-phase third-order Butterworth filter) sequentially to the down-sampled data. We also applied multiple artifact rejection algorithm (MARA) based on independent component analysis (ICA) to the filtered data in order to remove physiological artifacts.

After the EEG preprocessing, we epoched the EEG data between -0.5 and 0.5 sec based on an onset time when a subject pressed a button for each trial. Power spectral density (PSD) was estimated for each trial and each channel using the fast Fourier transform (FFT), and the PSDs of six frequency bands were calculated (delta:1 – 4 Hz, theta: 4 – 8 Hz, alpha: 8 – 13 Hz, beta: 13 – 30 Hz, gamma: 30 – 50 Hz, full: 1 – 50 Hz). To identify the motor hotspot based EEG, a multi-layer feedforward artificial neural network (ANN) was trained and tested using EEG PSD features (Figure 3). The input labels of the ANN were the 3D coordinate information of the motor hotspots identified by TMS, and the outputs were their corresponding 3D coordinate information produced by the ANN based on the EEG PSD features. A 10-fold cross-validation was performed with early stopping to prevent overfitting. The distance between the 3D coordinates of the motor hotspots identified by TMS and EEG was calculated using Euclidean distance, which was defined as the error distance. The mentioned procedure was performed for each frequency band (delta, theta, alpha, beta, and gamma) and the whole frequency band (full) to find an optimal EEG frequency band to extract PSD features.

3 RESULT

Figure 4 presents a representative example from one subject, showing the 3D coordinate locations of motor hotspots identified by TMS (red) and EEG PSD features (blue). The detected motor hotspots are

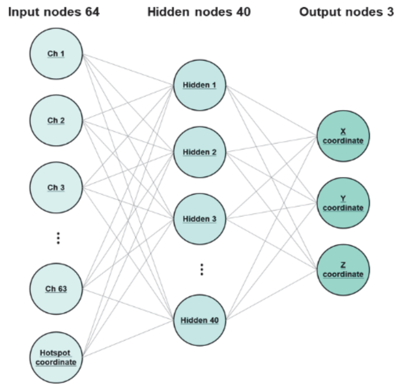

Figure 3: Schematic diagram of an ANN model used to find motor hotspots based on EEG features.

located in the contralateral motor area of the right index finger, and the motor hotspot locations identified by TMS and EEG PSD features are close to each other (0.65 cm).

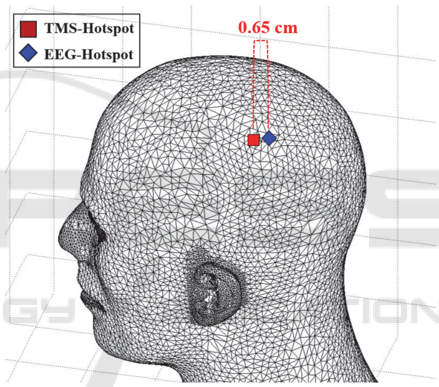

Figure 4: 3D coordinate information of motor hotspots identified TMS (red) and EEG PSD features (blue).

Figure 5 shows the mean error distances for each frequency band. A minimum error distance of 0.24 cm was obtained when a full band was used to extract PSD features (1.09 ± 0.38 cm for delta, 0.89 ± 0.43 cm for theta, 0.85 ± 0.46 cm for alpha, 0.43 ± 0.31 cm for beta, and 0.35 ± 0.34 cm for gamma).

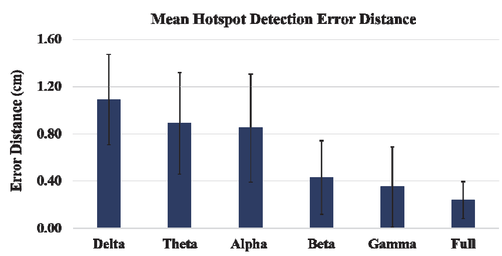

Figure 5: Mean error distances for each frequency band.

Individual error distances for each frequency band are presented in Table 1.

Table 1: Motor hotspot error distances of each subject for each frequency band.

Subject	Delta	Theta	Alpha	Beta	Gamma	Full
S1	0.82	0.92	0.31	0.13	0.03	0.11
S2	1.31	0.91	0.81	0.28	0.18	0.16
S3	0.73	0.87	0.35	0.28	0.17	0.25
S4	0.38	0.52	0.47	0.15	0.08	0.22
S5	1.22	0.71	0.48	0.33	0.16	0.09
S6	1.69	1.02	1.39	0.64	0.69	0.17
S7	1.36	0.51	1.30	1.10	0.74	0.30
S8	0.97	0.57	1.10	0.23	0.26	0.21
S9	1.03	0.89	0.72	0.39	0.15	0.21
S10	1.39	2.00	1.55	0.76	1.03	0.65
Mean	**1.09**	**0.89**	**0.85**	**0.43**	**0.35**	**0.24**
± Std.	**0.38**	**0.43**	**0.46**	**0.31**	**0.34**	**0.16**

4 CONCLUSIONS

In this study, we proposed an EEG-based novel motor hotspot identification algorithm using machine learning technique to provide a target location for tES without using TMS. A minimum distance between motor hotspots identified by TMS-induced MEP and EEG features was 0.24 cm when using a full frequency band information. As a tES electrode size is generally bigger than 1 cm, it is expected that the motor hotspot identified by EEG features could be covered by a tES electrode with a small error distance. However, additional tES experiments should follow to verify the feasibility of our proposed motor hotspot identification method based on EEG on corticomotor excitability.

Instead of using a TMS device, an EEG device is required to apply our proposed machine-learning-based motor hotspot identification method. Note that it is possible to integrate an EEG device to a tES device with retaining its portability, and a commercially available tES/EEG device already exists (e.g., NeuroElectronics Starstim). Thus, we expect that the EEG-based hotspot detection algorithm will facilitate use of tES, in particular, for home-based tES treatment. One limitation of our algorithm is that TMS was used to find the 3D coordinates of motor hotspots. Thus, we will develop an advanced method that use the 3D coordinates of motor hotspots identified by TMS to construct a motor hotspot identification algorithm, after which it uses only EEG features to find individual motor hotpots for new subjects.

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