Quantifying movement intentions with multimodal neuroimaging for functional electrical stimulation-based rehabilitation

Min-Ho Lee*, Bum-Joo Kim* and Seong-Whan Lee

Functional electrical stimulation (FES) is a common rehabilitation method for the purpose of recovery of paralyzed muscle by means of sequential electrical stimulation. Reports indicate that active participation by the patient, as opposed to simple stimulation, leads to improved recovery when using FES and other rehabilitation techniques. In this paper, we investigate the neurophysiological effect of an active participant's intention in the FES rehabilitation task. To observe the difference in brain signal between intentional and involuntary movement during FES, electroencephalography and near-infrared spectroscopy were simultaneously measured in the motor cortex area. The result showed that the presence of intention affects the activation of the brain significantly in both hemodynamic responses (near-infrared spectroscopy) and electrical (electroencephalography) patterns, and the accuracy of classification between passive and active mental states during FES was 85.3%. Our result implies the possibility to quantify motivation, or active participation, during rehabilitation, which has not been considered a measurable value in the rehabilitation field. ***NeuroReport*** **27:61–66**

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Introduction

Brain computer interfaces (BCIs) are systems that benefit from brain information for the purpose of controlling a computer application or devices [1]. Combining assistant devices, such as a robotic arm, exoskeleton system, or functional electrical stimulation (FES), the rehabilitation process can be enhanced significantly. However, to achieve better motor learning or rehabilitation effect, engaged cognitive processing is essential; effortless repetition of certain tasks does not guarantee sufficient results [2].

To overcome this problem, a goal-oriented training program has been adopted [3]. By setting a clear goal to achieve, participants were more engaged in the training program; thus, they paid more attention toward each training task [4]. Moreover, motivation and feedback influences the brains reward system during rehabilitation training in the basal ganglia [5]. Goal setting encourages cognitive processes to activate and causes meaningful change in both the training result and physiological modification as evidenced in motor skill acquisition [6,7].

Although goal-oriented training can elicit purposeful participation, it is still unclear whether it is effective for every participant in every trial. Indeed, results gained by rehabilitation procedures today tend to vary at considerable levels. That is, the same procedure may obtain a very successful result in some participants, but may not be as successful for the others. This large participant variance is because of many variables, such as physiological cause, differences in participants, and motivation of the participant. In terms of motivation, the difficulty in maintaining a high concentration level for certain tasks has been well established, and rehabilitation training is not an exception. The aim of this study is to develop a strategy to overcome this obstacle of varying concentration levels during a patient's rehabilitation.

To ensure fully engaged patients, it is first necessary to develop a system to monitor their level of engagement during the rehabilitation task. As attention and engagement is a cognitive process, brain signals will most likely capture the information that we need. However, to our knowledge, there has not been any research that distinguishes the brain activation difference between active participation and effortless involuntary movement during rehabilitation. To investigate this difference, simultaneous measurements of electroencephalography (EEG) and near-infrared spectroscopy (NIRS) were recorded during FES rehabilitation tasks. EEG is the most commonly used device in the context of non-invasive BCIs that measures scalp voltage fluctuations, which result from the neuronal activity. While NIRS depends on focal changes in cerebral blood flow, i.e. on concentration

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changes of the chromophores deoxygenated and oxygenated hemoglobin following neuronal activity [8]. From the multimodal neuroimaging data, we observed clear activation patterns in both electrical and hemodynamic responses by FES-based rehabilitation tasks; furthermore, we evaluated the difference in EEG signal according to the engagement state of the participants and attempted to distinguish them by applying machine learning methods. The result was promising as performance of the classifier was above 80% on average for all classifications and suggests the possibility of quantifying the amount of engaged processing during training.

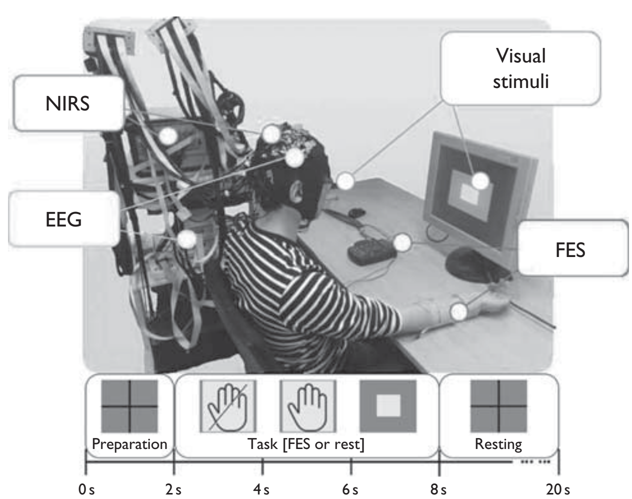
Methods

Experimental paradigm

Experiment setup

The experimental task was performed under two different session conditions – idle FES (no participant engagement with FES stimulus), active FES (participants engaged with FES stimulus), and rest (resting state with no FES stimulus). There were three runs for each session, and each run consisted of 50 trials, 25 for the given task and 25 for rest, making 75 task trials for each session. The experimental paradigm is shown in Fig. 1. In the idle FES session, FES stimulation was administered to induce a grasping motion, but participants were instructed not to pay any attention toward the FES stimulation. In the active FES session, participants were instructed to proactively pay attention to the stimulation and engage in sensorimotor imagery of grasping task without actually moving.

Fig. 1



Experiment environment and paradigm. The EEG and NIRS signals were simultaneously recorded during the FES stimulus. The participant was instructed on three conditions of tasks (active FES, idle FES, and rest) by visual stimuli on a monitor. EEG, electroencephalography; FES, functional electrical stimulation; NIRS, near-infrared spectroscopy.

Five healthy individuals participated in this experiment; all of them were male and right-handed. The participants sat in a comfortable chair with armrests and were instructed to relax their arms. To induce the passive movement, their right arm was placed on the desk in front of them and tightly fixed with an arm band to prevent any unexpected movement or detachment from the FES electrodes. The participants were asked to stay still during the experiment, but could request a pause to the instructor whenever they wanted. The entire experimental setup and concepts of the neurofeedback system have been uploaded onto YouTube (*https://youtu be/qLUUqS6jiDw*).

Data acquisition

EEG and NIRS brain signals were simultaneously measured and recorded from the participants during the experiment. EEG was recorded from the scalp using a multichannel EEG BRAINAMP (Brain Products, Gilching, Germany) amplifier. The signal was obtained from 24 different Ag/AgCl electrodes densely located in the sensory-motor area (SMA). The NIRS equipment (NIRScout Extended; NIRx Medizintechnik GmbH, Berlin, Germany) measured the hemodynamic activity of the brain with 10 sources and eight detectors, resulting in 24 NIRS channels. The EEG electrodes and the NIRS channels (consisting of sources and detectors) were designed to be in overlapping positions in accordance with the international 10–20 system and covered the SMA of the head (to specify, FC1, FC2, FC3, FC4, FCC1h, FCC2h, FCC3h, FCC4h, FCC5h, FCC6h, C1, C2, C3, C4, FCP1h, FCP2h, FCP3h, FCP4h, FCP5h, FCP6h, CP1, CP2, CP3, and CP4). The electrodes of the FES equipment (Motionstim 8; Medicine Electronics, Hamburg, Germany) were placed on the Extensor digitorum communis and Flexor digitorum superficials of the participants' right arm.

Data analysis

NIRS analysis

The analysis of NIRS data was carried out offline. Concentration changes in hemoglobin were calculated according to the modified LambertBeer law. This procedure converted attenuation changes measured by the NIRS system into concentration changes of Oxy Hb and Deoxy Hb [9]. NIRS data were low-pass filtered at 0.2 Hz using a one-directional filter method, namely, a third-order Butterworth filter. A baseline interval was defined from 1 to 0 s before stimulus onset and its mean was subtracted from each trial. This baseline was obtained to make all NIRS signals gather at the same starting point, normalizing their relative variance of amplitude.

The data were than divided into epochs from 0 to 14 s after the stimuli onset, grouped according to the task: rest, idle FES, and active FES. The processed NIRS data were used to assess the significance of signal difference between the tasks using a one-way analysis of variance and a *t*-test in all channels.

EEG analysis

For the EEG data, the time interval was chosen to be between 750 and 4500 ms after stimulus onset. A common approach in sensory-motor rhythm-based BCI research is to estimate participant-dependent band-pass filters from training data established heuristic. This heuristic depends on the Laplacian spatial filter to reduce the volume conduction effects in the EEG signals. After applying the temporal filter to the data, common spatial patterns were used as spatial filters [10]. Log variances of the temporally and spatially filtered data were calculated as features.

Linear discriminant analysis was adopted as the classifier. The classifiers were produced for all binary task comparisons: rest versus idle FES, rest versus active FES, and idle FES versus active FES. All parameters of frequency-spatial filters and linear classifier were estimated solely on the training set of each cross-validation step. Validation was performed by a cross-validation with a 10-fold chronological split.

Results

The first aim of this study was to highlight the neurophysiological difference between engaged and passive involuntary movement. The second objective was to establish the classifier on the basis of this evidence, which would be able to evaluate the intention or engagement status of the participant toward the passive movement stimulation.

Brain signal analysis

Stronger hemodynamic activity in the left hemisphere, specifically the C3 area, was found in FES tasks compared with resting states (Fig. 2b). Moreover, block-averaged hemodynamic activity during the active FES task showed higher activation in the overall area compared with idle FES in all participants (Fig. 3). Activities are restricted to the motor cortex area and no strong activation was represented during the resting state, proving that this effect is strongly related to the activation of the motor cortex in the SMA.

Cortical activation does occur during the idle FES task, evidenced by higher Oxy Hb concentrations compared with the resting state. The deoxy Hb concentration decreases as Oxy Hb increases, which is another typical pattern of cortical activation in hemodynamics [11].

Statistical analysis between tasks was also carried out. A one-way analysis of variance between tasks showed that there is statistical significance between each task for most participants, even between idle FES and active FES (Fig. 3, $^{*}P<0.05$, $^{***}P<0.01$). However, a result that showed significance between all three tasks was rare; only two participants showed such a significant difference. The results for all participants except one, nonetheless, showed significant differences between binary comparisons, being rest versus idle FES, rest versus active FES, and idle FES versus active FES. They had at least one channel that showed a significant difference between idle FES and active FES in the NIRS signal. However, one participant showed no significance in this comparison, indicating that the brain signal patterns were not significantly different from all channels for all tasks. As discussed later, this resulted in low classification performance during idle FES versus active FES comparison.

An event-related potential was evident throughout the task session. Compared with the resting state, strong depression of the signal in 10–14 Hz was observable in most of the participants (Fig. 2a). It was also clear that this component was stronger in the motor-related cortical area in the left hemisphere. It did not show, however, evident power difference as the NIRS signal showed in block average analysis.

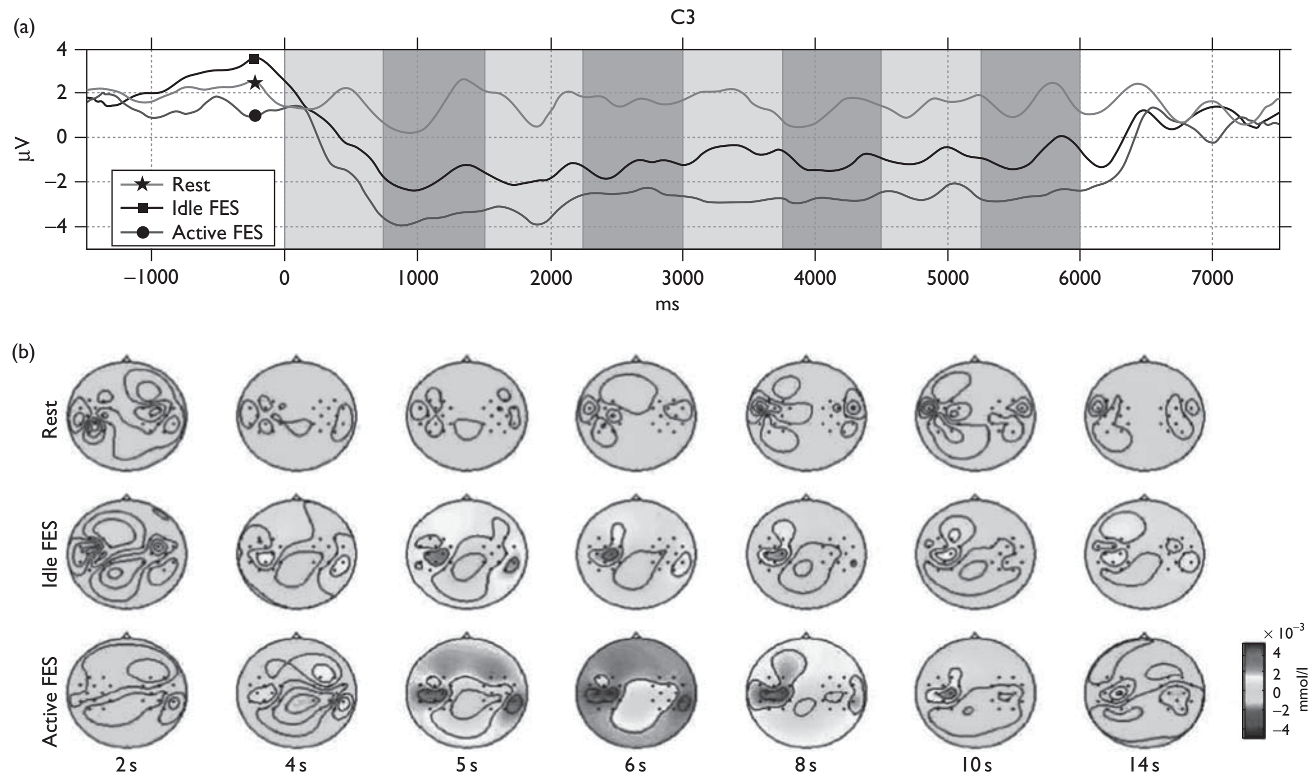
The EEG signals are applied to estimate a classification performance because of its high temporal resolution. All averaged classification results were above 80%. The highest performance was 91.2%, shown in the classification between resting versus active FES. Rest versus idle FES showed accuracy much above chance level, similar to idle versus active FES (Table 1). However, classification between idle FES versus active FES yielded high variance among the results.

The classification accuracy of EEG was higher than expected. Classification between idle FES and active FES seems reasonable enough for some participants, given the highest accuracy of 92.7%. However, there was one participant (participant b) with very low performance during classification of idle FES and active FES – close to chance level. As we will describe later, this participant was the one who failed to generate distinct signals between tasks in NIRS measurement. For the others, it is noticeable that rest versus active FES produced the highest performance. Idle FES versus active FES classification lost a consequential amount of performance because of the one participant with low performance because it yielded a high SD, and yet it still remained above chance level.

Discussion and conclusion

The EEG classification result appears promising. All participants showed significantly high performance in rest versus task classification. Moreover, we successfully classified the EEG signals between idle FES and active FES states. This strongly implies that there are significant activation pattern differences between these two tasks and that they are distinguishable. As both task conditions had stimulation of FES, it was clear that

Fig. 2



(a) Event-related desynchronization (ERD) analysis. The EEG signal in motor-related frequency (1014 Hz) was observed. C3 and C4 channels during positive FES and resting state are compared. (b) Block average scalp map of each tasks in NIRS oxy Hb from 0 to 14 s after stimulation. Stronger and longer lasting amplitude change was observable in active FES compared with idle FES. The activation area was highly restricted around C3, implying intense activation of the motor cortex during the task. The significance level differed among participants, but all except one of them showed a significant result in the C3 area, at least showing a difference between rest and the stimulation tasks. This corresponds with the classification result as they show distinct results between rest and stimulation tasks, but one failed to show meaningful accuracy differentiating idle and active FES. EEG, electroencephalography; FES, functional electrical stimulation; NIRS, near-infrared spectroscopy.

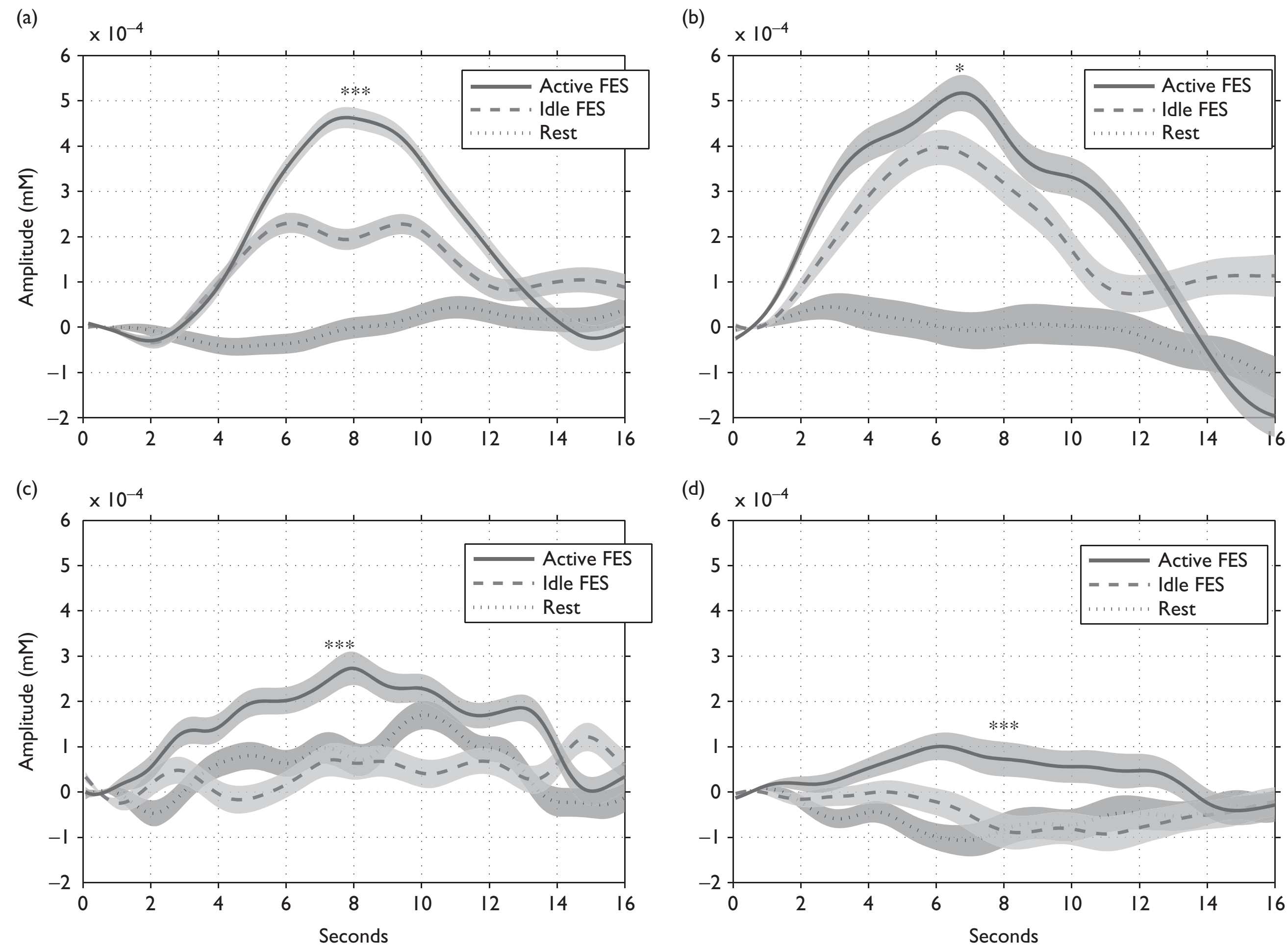
engagement in sensorimotor imagery could be effectively shown during involuntary movement.

NIRS also succeeded in measuring a hemodynamic difference between the two tasks. The NIRS results differed between participants. Some showed a significant distinction between all tasks in a single channel, but most of them showed a significance in only two tasks. As shown in Fig. 3, the results showed four different circumstances around the C3 area. Yet, it was clear that the differences in three out of four circumstances led to high classification accuracy; only one participant showed low performance in classification.

It is true that not all participants showed marked contrast between tasks. This is not only the case in this study. In fact, the term BCI illiteracy is commonly used to describe a population not capable of inducing a brain signal strong enough to grant a classifier for differentiation. Moreover, as our participants were all novel to any BCI paradigm before, they might find difficulty in making difference between two tasks. As rehabilitation is a process with a long period of training, participants with enough time may show a clear difference between two conditions, providing enough information for rehabilitation.

The significance of this study lies in the possibility of classifying the participant's activation of sensorimotor imagination with neurophysiological information. Motivation, engagement, or active participation during rehabilitation has been a variable that was hard to define. Given that strong engagement of cognitive processes results in better rehabilitation, this measure can provide additional information on a patient's variability in recovery for clinical practitioners [2]. With the evidence of neurological change as an indicator of more effective rehabilitation, the present study shows how a previously unreliable assessment of patient engagement can be identified more accurately. This result could conceivably guide both patients and therapists to maximize the result of rehabilitation training. However, the analyzing routines presented here have been solely validated offline with health participants. Our future work will extend our

Fig. 3



Oxygenated hemoglobin concentration. All data were obtained around the C3 area. (a) The best-performing participant; all tasks were significantly different from one another. (b) The case when FES tasks, idle FES and active FES, were distinguishable from the resting state, but not significantly different from each other. (c) Another case similar to this; however, this time, only positive FES is significantly different from others. Even in the C3 area, a graph similar to (d) was found. The differences between tasks were not significantly different from another. The participant with this result was unable to distinguish idle FES versus positive FES.* and ***Indicates the significant level corresponding to $P<0.05$ and $P<0.01$ between the active FES and the idle FES line. FES, functional electrical stimulation.

Table 1 Classification accuracy (%) for individual participants as well as their mean

Participants	Rest versus idle FES	Rest versus active FES	Idle FES versus active FES
a	89.6	94.4	92.7
b	82.6	91.3	55.6
c	93.0	98.0	86.0
d	71.2	81.2	98.7
e	93.3	90.0	93.3
Mean	85.9 ± 9.3	91.0 ± 6.3	85.3 ± 17.1

FES, functional electrical stimulation.

research to a real-time RES rehabilitation system with patients.

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Conflicts of interest

There are no conflicts of interest.

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