EEG-triggered neuromuscular stimulation therapy for hemiplegia of the hand due to chronic stroke

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Abstract

Loss of dexterous hand function is one of the common effects of stroke. Repetitive, rehabilitative training with functionally challenging tasks have been shown to be effective in aiding hand function recovery in both acute and chronic stroke patients. Such therapeutic strategies are thought to help motor function recovery by inducing activity-dependent cortical reorganization.

Our goal is to detect hand movement intentions from the electroencephalogram (EEG) and used it to trigger electrical stimulation of the affected hand. Preliminary results suggest that EEGs can provide a reliable control signal to trigger electrical stimulation of the hand even after stroke. Movement intention was detected with a mean error rate of 18 ± 5%.

1 Introduction

Each year, more than 700,000 Americans experience a new or recurrent stroke [1]. Up to 85% of the approximately 566,000 stroke survivors experience hemiparesis of the upper extremity [2]. Mechanisms of motor function recovery post stroke are not completely understood; neural plasticity (i.e. the ability of the brain to dynamically reorganize with experience, learning, and in response to brain injury) is thought to play a major role [3]. For example, Nudo et al. reported that, in monkeys with motor cortical lesions affecting the hand, re-training of skilled hand use prevented the loss of or even enlarged the hand area representation in the cortex. This cortical reorganization was accompanied by recovery of skilled hand function [4].

A brain-computer interface (BCI) has been defined in a review as “a system for controlling a device (e.g. a computer, wheelchair or a neuroprosthesis) by human intentions, which does not depend on the brain’s normal output pathways of peripheral nerves and muscles”[5]. EEG signals provide a non-invasive method to read human motor intentions. Specifically, movement-related information is contained in the modulations over the motor areas in certain frequency bands, called the μ (8-13 Hz) and β (18-30 Hz) rhythms [6]. EEG-based BCI have been previously used to control neuroprosthetics [7], spelling devices [8] etc. For example, Pfurtscheller et al. demonstrated the functioning of an EEG-controlled hand grasp system in a person with spinal cord injury [7]. However, in this system, electrically stimulated hand grasp was controlled by the person modulating the foot area β rhythm.

The goal of this study is to determine the feasibility of EEG-triggered neuromuscular stimulation as a new therapeutic tool for stroke patients. This tool will allow testing of the hypothesis that augmenting muscle activation in response to motor intent may aid motor function recovery by facilitating and reinforcing the underlying neural mechanisms. The tool might especially benefit people with severe disability, where the disability precludes other rehabilitation methods. Preliminary data is presented here on evaluating how well EEGs can be used to predict hand movement intention after stroke.

2 Methods

2.1 Experimental setup

Participants in this study are to be at least six months post stroke, medically stable, and have hemiparesis of the hand due to the stroke. Two subjects have participated in the study so far. The first subject had a left hemisphere stroke, and the second subject had a right hemisphere stroke.
stroke. Both subjects had some residual function in the affected hand.

Subjects were fitted with a 128-channel EEG cap. Surface electromyographic (EMG) electrodes were placed on hand extensor and flexor muscles of both forearms. Subjects were seated in front of a screen, and visual cues were shown that indicated when to open or relax the affected hand (figure 1). Each block of trials consisted of 20 repetitions of actively opening the hand for 3 s followed by relaxing the hand for approximately 5 s. The duration of the ‘relax’ phase was varied to prevent the subject from predicting the next hand-open cue. At the end of each block, the subject was allowed to rest for several minutes. Six to seven blocks were performed in each session. EEG, EMG, and task cues were recorded while the person performed the tasks for later offline analysis. All experiments were done with the approval of the MetroHealth Medical Center Institutional Review Board.

Figure 1: Screen shot of one example cue indicating to relax the left hand and actively open the right (affected) hand.

2.2 Feature extraction

**Initial Signal Processing:** EEG signals from 43 channels, spanning the sensorimotor areas were collected at 1200 Hz, 16 bit resolution (Pentusa, Tucker Davis Technologies). Offline, the EEG data were downsampled and spatially filtered by common average referencing. EEG signals were then filtered into seven frequency bands between 1-35 Hz, each 5 Hz wide. A time series of log-mean-squared values of each frequency band was calculated every 50 ms using overlapping 1 second windows of data. This resulted in a total of 301 channel/frequency-band combinations (43 channels x 7 bands).

2.3 Classification

The processed signals were used to train a Gaussian kernel support vector machine (kSVM) to classify hand open/closed states [9]. The trained kSVM was then used to identify novel data, which were not used for training. Classifier performance was quantified using mean cross validation error (CVE) [10].

2.4 Identifying the most useful signals

The processed signals were ranked according to their usefulness for predicting intended hand movement using the kappa parameter (κ) [9]. κ is a numeric rank based on how well a particular data set can be used to classify between two or more classes relative to chance (equations below). In order to compute κ, the kSVM classifier is trained with data from each channel frequency-band combination. The trained kSVM classifier is then used to classify novel data from the same combination. The proportion of the total number of data points that is classified correctly and wrongly is computed to obtain the confusion matrix H. The process is then repeated for all 301 channel frequency-band combinations.

\[
p_o = \sum H_{oo} \\
p_e = \frac{\sum n_{oo} n_{eo}}{N \times N} \\
\kappa = \frac{p_o - p_e}{1 - p_e}
\]

Where,

\(p_o = \) Accuracy, \(p_e = \) Chance expected agreement (0.5 for our two-class data).
\(N = \) Total number of samples available.
\(n_{oi}, n_{io} = \) column, row sum of the confusion matrix.

2.4 Classifier refinement

The kSVM classifier was then retrained by using multiple channel/frequency-band combinations together to classify hand open/closed state. Ten different groups were tested consisting of the top 10%, 20%, etc. up to 100% of the possible 301 channel/frequency-band combinations (ranked based on their individual κ parameters). The mean CVE was calculated for each group.

3 Results

3.1 Regions predictive of hand movement
Figure 2: Mean kappa rank over all seven frequency bands tested for each electrode location. The EEG electrode locations are shown as black dots. Top is subject 1, and bottom is subject 2.

3.2 Performance of the classifier

<table>
<thead>
<tr>
<th>Subj.</th>
<th>Day</th>
<th>CVE All</th>
<th>N%</th>
<th>CVE Best N%</th>
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<tr>
<td>1  1</td>
<td>0.13±0.04</td>
<td>60</td>
<td>0.11±0.01</td>
<td></td>
</tr>
<tr>
<td>1  2</td>
<td>0.13±0.03</td>
<td>100</td>
<td>0.13±0.03</td>
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<td>1  3</td>
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<td>90</td>
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<tr>
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<td>0.21±0.04</td>
<td>70</td>
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<tr>
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</tr>
<tr>
<td>mean</td>
<td>0.19±0.05</td>
<td>75±19</td>
<td>0.18±0.05</td>
<td></td>
</tr>
</tbody>
</table>

Table 1: ‘CVE All’ indicates the five fold cross validation error rate achieved by the classifier when information from all channels and frequencies were used to build the classifier. ‘CVE Best N%’ indicates the lowest error rate over any combination tested. ‘N%’ indicates the % of channel/frequency-bands that resulted in the lowest error when used in combination.

4 Discussion and Conclusions

The ability of the classifier to consistently detect hand moving/relaxed states on different days from people with hand hemiparesis following a cortical stroke suggest that EEG-triggered neuromuscular stimulation therapy may be possible in the future. EMG contamination of the EEG signal appeared to have a detrimental effect on classification and was particularly strong in the first two sessions with subject two. Efforts to reduce EMG contamination in session three resulted in a marked improvement in classifier performance. We are currently working to improve classifier performance with real-time EMG artefact rejection and alternate methods of signal processing.

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References