Brain-computer interface controlled functional electrical stimulation device for foot drop due to stroke

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Abstract— Gait impairment due to foot drop is a common outcome of stroke, and current physiotherapy provides only limited restoration of gait function. Gait function can also be aided by orthoses, but these devices may be cumbersome and their benefits disappear upon removal. Hence, new neuro-rehabilitative therapies are being sought to generate permanent improvements in motor function beyond those of conventional physiotherapies through positive neural plasticity processes. Here, the authors describe an electroencephalogram (EEG) based brain-computer interface (BCI) controlled functional electrical stimulation (FES) system that enabled a stroke subject with foot drop to re-establish foot dorsiflexion. To this end, a prediction model was generated from EEG data collected as the subject alternated between periods of idling and attempted foot dorsiflexion. This prediction model was then used to classify online EEG data into either "idling" or "dorsiflexion" states, and this information was subsequently used to control an FES device to elicit effective foot dorsiflexion. The performance of the system was assessed in online sessions, where the subject was prompted by a computer to alternate between periods of idling and dorsiflexion. The subject demonstrated purposeful operation of the BCI-FES system, with an average cross-correlation between instructional cues and BCI-FES response of 0.60 over 3 sessions. In addition, analysis of the prediction model indicated that non-classical brain areas were activated in the process, suggesting post-stroke cortical re-organization. In the future, these systems may be explored as a potential therapeutic tool that can help promote positive plasticity and neural repair in chronic stroke patients.

I. INTRODUCTION

Approximately 800,000 new stroke cases occur annually in the United States alone [1]. Advances in acute medical care have led to increased stroke survival rates, and this trend will likely continue. However, stroke survivors typically suffer from permanent motor system deficits that lead to significant disability. Conventional physiotherapies only provide limited neurological and motor function recovery, thereby rendering many stroke survivors dependent on caregivers. The societal burden of care for these individuals is expected to continue growing, particularly with increasing world population and stroke survival rates. Therefore, this situation mandates the development of novel and effective physiotherapies.

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Given the limitations of current physiotherapies, novel treatments that promote neural repair and plasticity mechanisms to elicit motor function improvements are being sought [2]. The integration of brain-computer interface (BCI) and functional electrical stimulation (FES) systems may offer long-term functional improvements in this population. It can be hypothesized that such a BCI-FES system may promote neural repair via Hebbian learning mechanisms ("neurons that fire together, wire together"), whereby the activation of post-stroke cortical areas associated with a motor behavior triggers the electrical stimulation of the corresponding lower motor neurons (via antidromic stimulation). For example, Daly et al. [3] recently reported on the development of a BCI-controlled FES system for hand grasping, which led to the improvement of hand function in a stroke survivor. This concept has also been applied to the lower extremities, where a BCI-FES system was used to control foot dorsiflexion [4]. However, the function of this system has only been tested in a population of able-bodied subjects. Here, the authors investigate the potential usability of this BCI-FES system in chronic stroke survivors with severe foot drop, and report on its successful demonstration in a single stroke subject.

II. METHODS

A. Overview

A noninvasive electroencephalogram (EEG) based BCI-FES system for foot dorsiflexion, previously developed by the authors [4], was tested in a stroke survivor with severe right foot drop. Briefly, the subject was seated in front of a computer screen, which provided instructions to alternate between sitting still (idling) and attempting to dorsiflex the impaired foot (albeit ineffectively), while EEG was recorded. EEG signals underlying both states were analyzed to develop a prediction model that can classify EEG data into either "idling" or "dorsiflexion" states. In an online test session, the subject was tasked with operating the BCI-FES system and generating BCI-FES mediated foot dorsiflexion when instructed by computer cues. The online performance of the system was assessed by calculating the cross-correlation between the decoded BCI-FES states and instructional cues.

B. Training Data Acquisition

Ethical approval to undertake this study was obtained from the University of California, Irvine Institutional Review Board. A stroke survivor (male, age 60) with right foot drop (~5° of residual dorsiflexion) due to chronic left internal capsule stroke was recruited to participate in the study.

The subject first underwent placement of a 64-channel EEG cap (MediFactory BV, Heerlen, the Netherlands). Conductive gel was applied to all electrodes and impedances were maintained at <10 KΩ by abrading the scalp with a blunt needle. The subject was then seated in front of a computer screen and directed by automated textual cues to alternate between idling (sitting still) and attempted foot dorsiflexion over a 10-min period while his EEG was recorded by a data acquisition system (NeXus-32, Mind Media, Roermond-Herten, the Netherlands). The visual cue presentation and EEG data recordings and labelings (by epochs) were controlled using custom-written Matlab (Mathworks, Natick, MA, USA) programs.

C. Prediction Model Generation

The prediction model was generated as described in [4]. Briefly, training EEG data underwent automated artifact rejection to remove EEG channels with excessive electromyogram (EMG) activity. This typically resulted in the exclusion of "hatband" electrodes. The epochs of EEG corresponding to "idling" and "dorsiflexion" states (as determined by the labeling signal) were then transformed into the frequency domain using Fast Fourier Transform (FFT), and their powers were calculated over 2-Hz bins. To facilitate subsequent classification, the data underwent dimensionality reduction using a combination of classwise principal component analysis (CPCA) [5], [6] and approximate information discriminant analysis (AIDA) [7]. More formally, the resulting 1D spatial-spectral features were extracted by:

$$f = T_A \Phi_C(d) \qquad (1)$$

where f is the feature, $d \in \mathbb{R}^{B \times C}$ are single-trial spatio-spectral EEG data (B-the number of frequency bins, C-the number of retained EEG channels), $\Phi_C : \mathbb{R}^{B \times C} \to \mathbb{R}^m$ is a piecewise linear mapping from the data space to the m-dimensional CPCA-subspace, and $T_A : \mathbb{R}^m \to \mathbb{R}$ is an AIDA matrix transform. These techniques exploit information-theoretic class separability measures [8], [9], and their detailed descriptions can be found in [6], [7]. A linear Bayesian classifier:

$$f^\star \in \begin{cases} \mathcal{I}, & \text{if} \quad P(\mathcal{I}|f^\star) > P(\mathcal{D}|f^\star) \\ \mathcal{D}, & \text{otherwise} \end{cases} \qquad (2)$$

was then designed in the feature domain, where $P(\mathcal{I}|f^\star)$ and $P(\mathcal{D}|f^\star)$ are the posterior probabilities of "idling" and "dorsiflexion" classes, respectively. The performance of the Bayesian classifier (2), expressed as classification accuracy, was then assessed by performing 5 runs of a stratified 10-fold cross-validation [10].

Finally, the optimal frequency range $[F_L, F_H]$ was found by increasing the lower and upper frequency bounds (in 2-Hz steps) and repeating the above procedure until the classifier performance stopped improving (details in [4]). The parameters of the prediction model, including the optimal frequency range, the feature extraction mapping, and the classifier parameters, were then saved for future real-time EEG analysis during online BCI-FES operation. The

signal processing algorithms were implemented into the BCI software and optimized for real-time operation [4].

D. Online Signal Analysis

During online operation of the BCI-FES system, EEG data were acquired in 0.5-sec long, non-overlapping segments in real time. The power spectral densities of the retained EEG channels were calculated and used as the input for the above signal processing algorithm. Finally, the resulting 1D spatial-spectral features were used to calculate the posterior probabilities of "idling" and "dorsiflexion" states.

E. Calibration

The BCI-FES system for foot dorsiflexion is a binary state machine with "idle" and "dorsiflexion" states. The state transition rules are dependent upon the posterior probability averaged over the 3 most recent segments (1.5 sec) of EEG data, $\bar{P}(\mathcal{D}|f^\star)$. The state transitions were governed by comparing $\bar{P}(\mathcal{D}|f^\star)$ to two thresholds, T_I and T_D. Specifically, the system transitioned from "idle" to "dorsiflexion" ("dorsiflexion" to "idle") state when $\bar{P} > T_D$ ($\bar{P} < T_I$), respectively. Also, when $T_I \leq \bar{P} \leq T_D$, the system remained in the current state.

The values of T_I and T_D were determined through a calibration procedure. The system was set to run in the online mode (with no FES) while the subject was asked to alternate between idling and attempted dorsiflexion over $\sim$2 min. A histogram of $\bar{P}$ was generated, and then used by the experimenter to empirically determine T_I and T_D.

F. Online BCI-FES System Evaluation

Prior to online evaluation, the subject was fitted with a pair of self-adhesive surface electrodes over the approximate course of the deep peroneal nerve in the right lower leg (affected by foot drop). Electrode placement and FES parameters were adjusted until FES-induced contraction of the tibialis anterior (TA) muscle resulted in $\sim$15° of foot dorsiflexion. The FES electrodes were connected to a commercial FES system that was interfaced with a computer [4]. Finally, a custom built electrogoniometer [11] was applied to the right foot dorsum to measure BCI-FES dorsiflexion response during online evaluation.

In a single online session, the subject was tasked to perform 10 alternating 10-sec long epochs of idling and BCI-FES mediated dorsiflexion of the affected foot. This task was directed by automated computer cues displayed on the screen. Ideally, during "idle" epochs, the subject would sit still and the BCI-FES system would provide no electrical stimulation. During "dorsiflexion" epochs, the subject would attempt dorsiflexion and the system would ideally detect the associated EEG changes and respond by delivering stimulation to elicit foot dorsiflexion. The BCI state transitions throughout the online session were used to evaluate the online performance. Finally, the subject attempted this task for a total of 3 online sessions.

The online performance was assessed by the following criteria: 1. Cross-correlation between BCI-FES decoded states
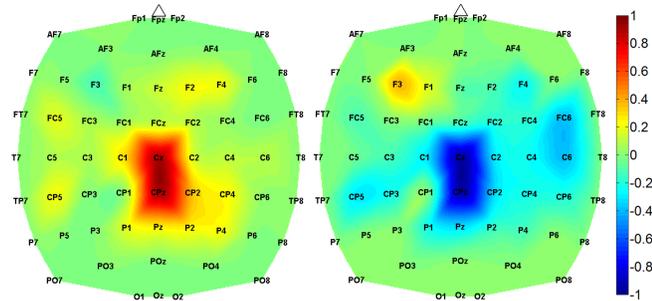
Fig. 1. CPCA-AIDA feature extraction map at the 20–22 Hz bin. Values close to +1 and -1 indicate brain areas of importance for classifying EEG data into "idling" and "dorsiflexion" classes. Since feature extraction mapping is piecewise linear, there are two maps for two classes.
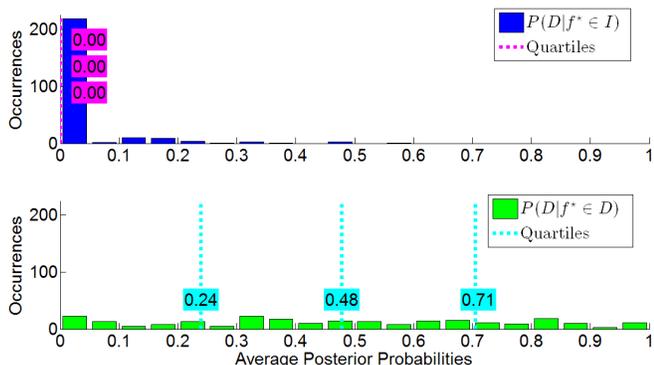

Fig. 2. Histograms of the averaged posterior probabilities, $\bar{P}(D|f^\star)$, during "idling" (top) and "dorsiflexion" (bottom) states.
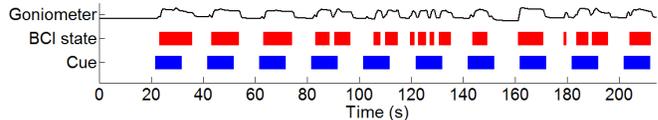

Fig. 3. A representative online session: Blue blocks correspond to instructional cues to attempt dorsiflexion; Red blocks mark epochs of BCI-FES dorsiflexion states; Black trace shows the corresponding goniometer trace, which confirmed effective dorsiflexion each time a red block is present. Note that small dorsiflexion movements are detected by the goniometer immediately prior to larger displacements. These represent the subject's attempted, although impaired, dorsiflexion prior to the BCI-FES response.

Note that the maximal cross-correlation was found at a time lag of 1.5–2 sec. These results are statistically significant (p $< 10^{-4}$) when compared to 10,000 Monte Carlo simulation trials (generated with 50% chance classification accuracy), indicating that purposeful BCI control was attained.

TABLE I

THE PERFORMANCE FOR EACH ONLINE SESSION. $\rho^\star$ IS THE MAXIMAL CROSS-CORRELATION BETWEEN THE BCI-FES RESPONSE AND THE COMPUTER CUES AT THE CORRESPONDING TIME LAG. OMISSIONS AND FALSE ALARMS ARE ALSO REPORTED FOR EACH SESSION.

Session	$\rho^\star$	Time Lag (sec)	Omissions	False Alarms
1	0.63	1.84	0	3
2	0.54	2.00	0	3
3	0.62	1.65	0	2
Average	0.60	1.83	0	2.67

and the instructional cues; 2. The number of omissions, defined as the failure to activate BCI-FES mediated dorsiflexion during a "dorsiflexion" cue; 3. The number of false alarms, defined as the activation of the BCI-FES mediated dorsiflexion during an "idle" cue.

III. RESULTS

A. Offline Performance

The subject underwent training data collection and analysis as described Section II. The average offline classification accuracy was 98.8% with a standard deviation (SD) of 0.4%, with EEG features most relevant for classification being the power in the 15–25 Hz band in the mid-central and mid-centroparietal areas. Representative topographic distribution of features is shown in Fig. 1.

B. Online BCI-FES Performance

Upon the calibration session, histograms of the posterior probability $\bar{P}(\mathcal{D}|f^\star)$ were plotted (Fig. 2), and the threshold values T_I and T_D were empirically chosen as 0.15 and 0.35, respectively.

After correct FES electrode placement was confirmed, the subject underwent the online BCI-FES evaluation task, and the resulting BCI response was recorded (see Fig. 3). The overall performances are summarized in Table I. The average maximal cross-correlation between the computer cues and the subject's BCI-FES response over 3 sessions was 0.60.

IV. DISCUSSION

At the time of writing, this study demonstrates the first successful BCI operation of a lower extremity FES system by a stroke survivor with foot drop. Acquisition of purposeful online control was immediate, and the performance was comparable to those of able-bodied individuals [4].

The offline classification accuracy of 98.8% was superior to those of able-bodied individuals (average: 92.5%) [4]. The feature extraction maps demonstrated that the EEG β-band power in the mid-central and mid-centroparietal areas was the most informative for classifying attempted dorsiflexion of the stroke-affected foot. They also indicate a posterior displacement (electrode CPz) and expansion of the foot representation area when compared to able-bodied individuals (electrode Cz) [4]. This deviation from classical foot motor representation is likely due to post-stroke cortical reorganization and is consistent with Green et al. [12]. It is also noteworthy that the data-driven machine learning approach employed here was able to map the brain physiological changes after chronic stroke. This implies that the current technique can potentially be used as a brain mapping tool.

The subject attained purposeful online control of the BCI-FES system on the very first session. The average $\rho^\star$ achieved by this stroke subject was 0.60 (SD $=$ 0.05), which was comparable to that of able-bodied individuals (0.67, SD $=$ 0.07, $n = 5$), albeit in a contralateral control paradigm [4]. In addition, subjects in both studies had no

omissions. However, when compared to [4], where all but one of the able-bodied subjects had no false alarms, this stroke subject had 2–3 false alarms in each online session. The higher false alarm rate could be caused by post-stroke abnormalities of EEG, particularly its increased complexity and randomness, as documented in [13]. These phenomena may also be responsible for the many "breaks" observed during the "dorsiflexion" states (Fig. 3). Alternatively, discontinuous BCI-FES dorsiflexion may also be attributed to neurophysiological changes induced by central fatigue (due to repetitive motor tasks after central nervous system injury [14]) or by peripheral fatigue (due to prolonged FES stimulation [15]). Other factors such as the subject's lack of familiarity with the system and incomplete understanding of the assigned task may also be postulated.

Despite this increased noisiness in the performance, the stroke subject was able to immediately attain purposeful control of the BCI-FES system following a short (∼15 min) training/calibration session. Given that this is a single-subject study, the feasibility of applying this system to a population of stroke subjects as well as performance benchmarks need to be established. If usability can be generalized to a stroke survivor population with foot drop, the future envisioned application will be to employ the BCI-FES dorsiflexion system as a rehabilitation tool in a seated physiotherapy to improve dorsiflexion. It is hypothesized that after prolonged BCI-FES operation, Hebbian plasticity mechanisms will help improve the connection between the post-stroke motor cortex and spinal cord motor pools, leading to permanent improvements in foot dorsiflexion, and ultimately, gait function.

To translate the BCI-FES dorsiflexion system into a rehabilitative tool for stroke survivors with foot drop, several problems must addressed. Specifically, there exists a latency between the initiation of movement and BCI response, and idle epochs contain a fair number of false alarms. Given that the hypothesized mechanism of inducing neural repair via BCI-FES operation is Hebbian plasticity, it will be favorable to shorten this latency and reduce the number of false alarms. Reducing the latency between the initiation of movement and BCI-FES response will help better time-lock the activation of the relevant post-stroke motor cortex with peripheral nerve stimulation. Steps such as decreasing the posterior probability averaging window (currently 1.5 sec) or increasing the refresh rate (currently 2 Hz) may ameliorate this problem, but an increase in the number of false alarms can be expected as a trade-off. False alarm stimulation by the device during idling epochs can result in user frustration, early fatigue of the TA muscle, and possibly elicit maladaptive plasticity. Hence, eliminating false alarms during idling periods will also be critical to facilitate a future BCI-FES based physiotherapy. However, increased EEG entropy after stroke may render this problem unavoidable without "locking-out" stimulation during the idle periods. Finally, the amount of time necessary to apply the EEG cap may prohibit the application of this system as a physiotherapy due to a significant increase in cost. Reducing the number of EEG channels to a subset of useful electrodes, as suggested by Fig. 1, as well as future use of dry electrodes are possible time- and cost-saving measures.

V. Conclusion

In summary, this case report indicates that the BCI-FES dorsiflexion system is promising for applications toward stroke rehabilitation. The EEG signal processing techniques employed here can facilitate online BCI operation with minimal supervision despite altered post-stroke physiology and cortical re-organization. The online BCI performances of this stroke subject were comparable to those of able-bodied individuals. However, future work must be done to test this system across a population of individuals with foot drop due to stroke in order to establish generalizability, set performance benchmarks, and address the system's limitations.

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