A Small, Portable, and Battery-Powered Brain-Computer Interface System for Motor Rehabilitation

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***Abstract*— Motor rehabilitation using brain-computer interface (BCI) systems may facilitate functional recovery in individuals after stroke or spinal cord injury. Nevertheless, these systems are typically ill-suited for widespread adoption due to their size, cost, and complexity. A small, portable, and extremely cost-efficient (<$200) BCI system was created using a custom EEG amplifier array, a commercial microcontroller and touchscreen. The system's performance was tested using a movement-related task in 3 able-bodied subjects with minimal previous BCI experience. The custom amplifier array performed similarly to a commercial array (maximum of ρ=0.85). The BCI's average decoding accuracy across subjects (76.9%) was comparable to that of full-size BCI systems. Small, portable, and inexpensive BCI systems like this one will facilitate the use of BCI-based movement rehabilitation in the stroke and spinal cord injury populations.**

I. Introduction

Millions of individuals in the US are afflicted by motor impairments caused by stroke and spinal cord injury (SCI) [1], [2], [3], [4], [5]. These impairments can lead to serious health problems and lost productivity for the affected individuals [1], [5]. While motor recovery in stroke and SCI survivors plateaus after six months post-injury despited standard rehabilitative therapies [5], [6], [7], recent studies suggest that the use of brain-computer interfaces (BCIs) in post-stroke movement therapy (assisted by a robot or electrical stimulation) may promote motor recovery [8], [9], [10], [11]. This approach could potentially be applied to SCI motor rehabilitation, as it has already been shown that BCIs can be used effectively by subjects with paraplegia and tetraplegia [14], [15].

While current BCI systems offer robust performance, they are inappropriate for use outside the clinic or research laboratory due to their size, cost, and lengthy setup time. This is problematic, since the general consensus in motor rehabilitation is that the best therapies are those that can be done often and at home [16]. For BCIs to be a practical rehabilitative option, they must be readily available as small, portable, low-cost systems. These systems must, at least, consist of electroencephalographic (EEG) amplifiers as well as a processing unit that translates these brain signals into control commands for an output device. While commercial amplifier systems are available for purchase, they can be expensive and bulky. Additionally, both commercial and research amplifiers generally require a desktop or laptop computer [17], [18], [19] for signal processing. Thus, these BCI systems are neither small nor truly portable and require extensive setup. The few research BCI systems that can utilize an embedded processing unit for real-time BCI use are expensive, overly complex, or too bulky [20], [21]. In order to meet our goals (simple, compact, portable, and low-cost), we designed and tested a BCI system for motor rehabilitation that utilizes a custom 4-channel EEG amplifier, a commercial microcontroller, and touchscreen (see Fig. 1).

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II. Methods

A. Hardware Design

A custom 4-channel EEG amplifier (Fig. 2) was designed and fabricated (Smart-Prototyping, NOA Labs, Kowloon, Hong Kong) and paired with an Arduino Mega microcontroller (Arduino, Ivrea, Italy) and touchscreen with on-board microSD card (Seeed Studio, Shenzhen, China). Each EEG channel of the amplifier array consists of 3 stages (instrumentation amplifier followed by two operational amplifiers). This cascade includes active high-pass (corner frequency of 1.59 Hz) and low-pass (corner frequencies of 33.86 Hz and 32.88 Hz respectively) filters. The minimum total gain of the amplifier is 26400$\times$, with >80 dB common mode rejection ratio. Further noise reduction is achieved using a driven right leg (DRL) circuit and by exploiting active shielding on the EEG cap. The number of channels was chosen to be 4 to reduce the board size and production costs without compromising performance. Unpublished analysis of stroke and SCI data from previous studies [9], [14] suggests that BCI performance does not deteriorate significantly until <4 channels are used. The entire amplifier array was implemented as a shield for the Arduino Mega microcontroller board to facilitate easy integration of the components. A portable 5V battery was used to power the system. The entire assembly (see Fig. 1) is small (7.5$\times$10$\times$3 cm) and costs less than $200 (excluding the EEG cap).

To validate the fidelity of the custom amplifier array, EEG was simultaneously amplified and recorded from three able-bodied subjects using the custom array and a commercial EEG amplifier array (BIOPAC Systems, Goleta, CA). Subjects were fitted with a commercial 64-electrode EEG cap, and impedances were reduced to <10 kOhm for 6 electrodes

Fig. 1. A picture of our BCI system with an EEG cap and a portable 5V battery. The BCI system and battery cost <\$200. The touchscreen, with built-in microSD slot, snaps onto a shield with the custom amplifier array which snaps onto a commercial microcontroller. EEG signals from the subject are amplified by the custom array and sent directly to the microcontroller for processing, BCI decoding, and effector output.

(Cz, CPz, C1, and C2, referenced to AFz, with DRL feedback to M2) using conductive gel. Note that the electrodes used were expected to cover the foot motor areas in able-bodied individuals. EEG signals from Cz (referenced to AFz) were amplified using both the custom and commercial systems, and then recorded at 4 kHz by a commercial MP150 system (BIOPAC Systems, Goleta, CA) over a period of 50 s. Signals amplified by the commercial system were subjected to software filters using the same parameters as the those of the custom array. Finally, the Pearson correlation between signals from both systems was calculated.

B. Signal Acquisition

Using the same EEG cap setup as above, subjects underwent a 4-min training session, in which they followed alternating 6 s-long cues on the touchscreen to relax or dorsiflex their right foot. EEG signals were sampled at 256 Hz per channel by the microcontroller. Using a custom, highly-optimized C++ program, two bandpass filters were then applied in software to this input to resolve the α (8-12 Hz) and β (13-30 Hz) band signals. The average power of the 8 output signals (4 channels x 2 frequency bands) during the last 5 s of each cue was calculated and stored on the microSD card. This training data (8 dimensions $\times$ 40 epochs) was used to create a classifier that could distinguish relaxing from dorsiflexing using only EEG (modeled closely on the classifier from [22]).

C. Classifier Design

First, principal component analysis was used to reduce the number of dimensions of the training data while ensuring that $\geq$99.7% of the overall variance was still explained. The resulting lower dimensional data was then subjected to linear discriminant analysis to find the 1-D projection that maximized class separability. The data in this optimal 1-D subspace was then used to find the parameters for a naive Bayesian classifier that calculates the posterior probability of dorsiflexing (P_D). These transformations and classifier parameters were stored on the microSD card for subsequent real-time BCI operation. Ten-fold cross-validation was also run on-board to estimate the accuracy of the classifier.

A binary state machine using two thresholds, T_1 and T_2, translated P_D into one of two states: relaxing or dorsiflexing. If $P_D < T_1$, the system predicted the relaxed state; if $P_D > T_2$, the system predicted the dorsiflexed state. Otherwise, the system defaulted to the last predicted state. These thresholds were determined using a 1-min calibration session, where P_D was calculated every 0.5 s while subjects followed alternating 6-sec cues to idle or dorsiflex their right foot. Using a grid search, T_1 and T_2 were chosen such that the accuracy of the predicted states was maximized.

D. Real-Time BCI Testing

Subjects participated in 4-6 trials (120 s each) where they followed alternating 6-s cues to relax or dorsiflex their foot. The BCI system analyzed their EEG signals using the subject-specific classifier generated above to predict the

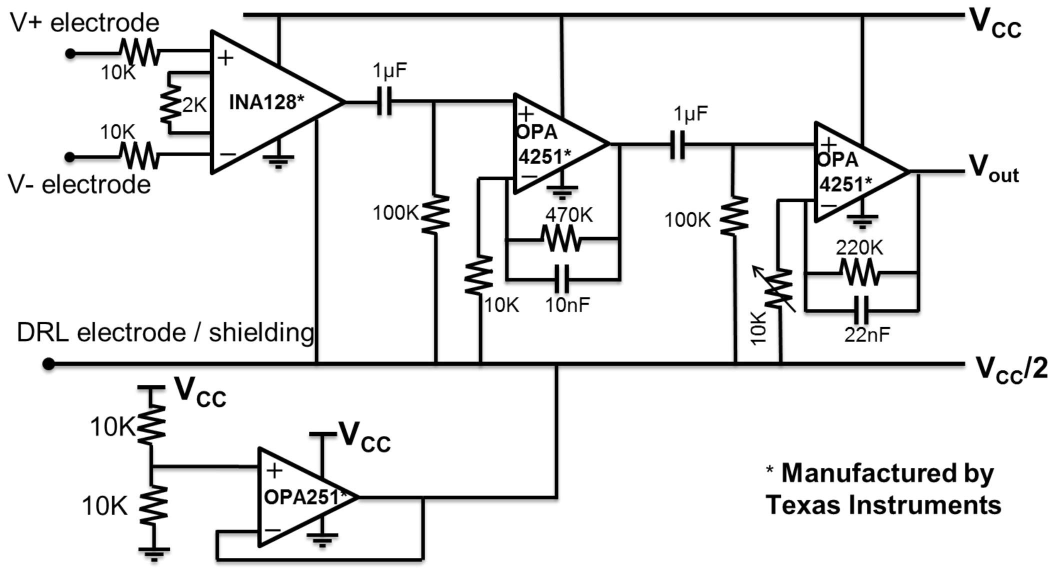

Fig. 2. The schematic of a single channel from the custom amplifier array. Note presence of 3 amplifier stages with high-pass and low-pass filters. Environmental noise is further attenuated using a DRL circuit and active shielding. The 4-channel system was implemented as a shield for a microcontroller.

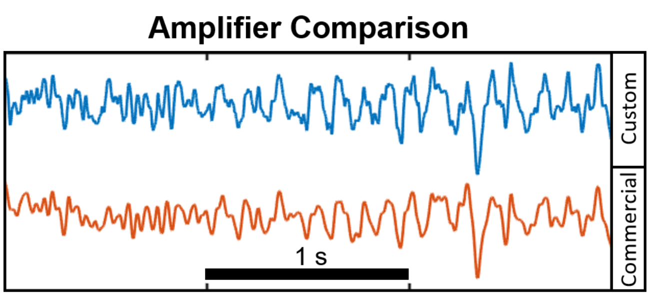

Fig. 3. A 3-s example of EEG data from S1 when amplified with the custom array (blue) and a commercial array (orange).

subject's movement state (relaxed or dorsiflexed) every 0.5 s. In order to prevent noisy state transitions, the mode of the last 3 predictions determined the final BCI output. Visual feedback was provided in the form of an LED that was controlled by the BCI output. The performance of the system was assessed as the percentage of correctly identified outputs.

III. Results

Three able-bodied subjects participated in the study. The correlation between the custom and commercial amplifiers during a 50 s recording for S1, S2, and S3 was 0.85, 0.84, and 0.73 respectively. A representative 3-s example of EEG from S1 amplified by both systems is provided in Fig. 3. BCI decoding results for S1-3 are provided in Table I. In addition, a representative example of S1's training data in the original 8-D and the final 1-D subspace is provided in Fig. 4. Note that even with the limited processing capacity of an Arduino Mega, classifier generation, cross-validation, and threshold calibration each took <20 s to perform.

TABLE I

Summary of BCI testing results for three able-bodied subjects.

Subject	Cross-Validation Accuracy	Number of Trials Completed	Average Trial Accuracy
S1	97.5%	4	78.9%
S2	95%	6	78.8%
S3	100%	5	73.0%

IV. Discussion and Conclusions

A custom amplifier array was designed, manufactured, and paired with a commercial microcontroller and touchscreen to create a BCI system that decoded movement-related EEG changes. Despite the disparate characteristics of the hardware and software filters used, the custom amplifier array performed similarly to its more expensive commercial counterpart. Moreover, it produced clean EEG signals that enabled acceptable BCI decoding in 3 inexperienced able-bodied subjects. The observed real-time decoding accuracies (76.9% on average) were comparable to previous studies in able-bodied individuals [23] and stroke survivors [9] that utilized full-size BCI systems with longer training times and significantly more EEG channels. Any reduction in the number of EEG channels used also reduces setup time and makes BCI therapy more appropriate for frequent, at-home use. Specifically, the setup time for this BCI system was <10 mins for all subjects. Additionally, the decoding accuracies reported here do not consider the system's lag ($\geq$1 s) due to smoothing across the last 3 predicted BCI states. Note that a large amount of environmental noise was present during S3's training and subsequent trials. This may explain the decreased correlation between the custom and commercial amplifier arrays and the decreased BCI decoding

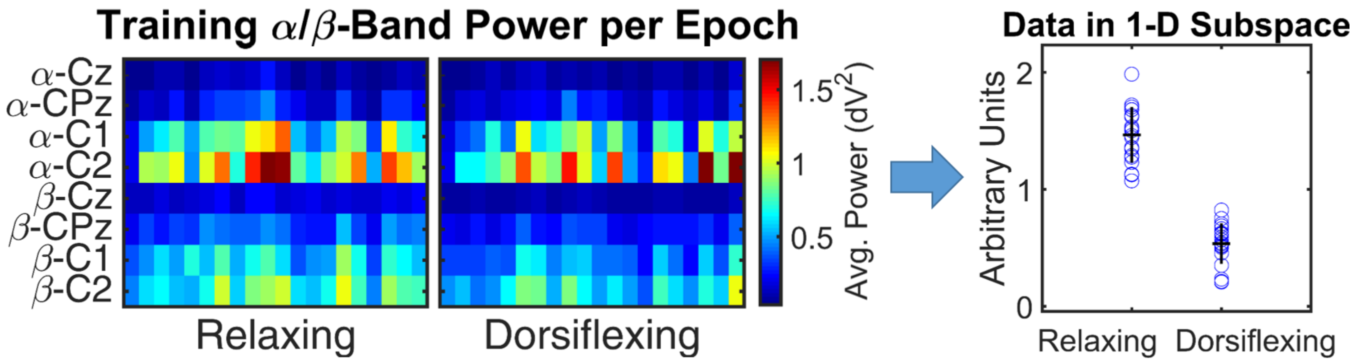

Fig. 4. Left: The original 8-D training data collected from S3 during relaxing and dorsiflexing epochs and stored on the microSD card. Right: The training data after it was projected onto the most-separable 1-D subspace. The mean (horizontal bar) and standard deviation (vertical bars) for each state is provided. Note that the training data from the relaxed and dorsiflexed states do not overlap in this 1-D subspace.

performance for this subject.

In summary, we demonstrated that a small, simple, and inexpensive BCI system could accurately decode the movement state of 3 able-bodied users from EEG signals. We expect that this system can be used easily and effectively by both stroke and SCI survivors without significant loss of performance compared to expensive, full-size BCIs. Additionally, our BCI system can be paired with portable and cost-efficient end effectors, such as commercial functional electrical stimulators, to produce a simple and accessible BCI-based movement therapy for stroke and SCI survivors. Future directions include testing the system with motor-imagery-based control strategies, as well as in people with stroke and spinal cord injury.

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