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EEG-based Brain-Computer Interface to a Virtual Walking Avatar Engages Cortical Adaptation

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***Abstract*—Recent advances in brain-computer interface (BCI) technologies have shown the feasibility of neural decoding for both users' gait intent and continuous kinematics. However, the cortical adaptation and the dynamics of cortical involvement in human upright walking with a closed-loop BCI in virtual environment (VE) have yet to be demonstrated. To address explore this possibility, we designed a closed-loop BCI to allow users to control a virtual avatar to walk using their encephalography (EEG). Delta band EEG (0.1 – 3 Hz) was used as the main feature in prediction. Our results demonstrate the feasibility of using a closed-loop BCI to learn to control a walking avatar. The average decoding accuracies (Pearson's r values) across all subjects increased from (Hip: 0.18 ± 0.31; Knee: 0.23 ± 0.33; Ankle: 0.14 ± 0.22) on Day 1 to (Hip: 0.40 ± 0.24; Knee: 0.55 ± 0.20; Ankle: 0.29 ± 0.22) on Day 8. Source localization revealed significant differences in cortical network activity between walking with and without closed-loop BCI control of the virtual avatar. This current study demonstrates the feasibility of using a closed-loop EEG-based BCI-VR to trigger cortical adaptation, promoting cortical involvement, and monitoring cortical activity from non-invasive EEG. Our system may be relevant for neurological gait rehabilitation as a clinical tool for post-stroke physical training and clinical assessment.**

Keywords— Electroencephalography (EEG), Brain-computer interface, BCI-VR system, human walking

I. INTRODUCTION

Recent studies show that EEG recorded during walking contains different features from EEG during standing, and is coupled with the gait cycle [1, 2]. For example, Bradford et al showed electrocortical activities (obtained from EEG recordings) distinguishes between uphill and level ground walking [3]. Different EEG features were also found when comparing active to passive walking in a robotic device [4], and walking with different attention levels [5]. Growing evidence suggests that EEG contains rich information about human walking.

Recent advanced BCIs have shown the feasibility of decoding human motor intent and lower limb kinematics from EEG signals. The underlying decoders in most of these studies are classifiers, which make discrete prediction of among a few states. For example, Bulea et al. decoded sitting and standing intentions from scalp EEG signals [6]. EEG-control of a lower-body exoskeleton was also reported in [7].

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Continuous decoding, or regression, is commonly used in invasive BCI settings. Kinematics of bipedal walking in rhesus monkeys was decoded with high accuracy using implanted microwire arrays [8]. Continuous 3D control of an robotic arm was achieved with a human subject [9]. However, it is difficult to translate the same invasive technology to walking because of the complexity resulting from constant movement. Our group has then shown the feasibility of using EEG to infer continuous kinematics during walking in human subjects in both offline [10, 11] and real-time [12, 13] settings. Additionally, the linear envelope of surface electromyography (EMG) signals during walking was also reconstructed [14, 15]. Moreover, we have shown that motion artifacts are negligible at the gait speeds used in our studies and which are relevant for gait rehabilitation [16].

The real-time feedback of BCIs is traditionally provided through some kind of robotic device such as an exoskeleton [17], yet VR-based rehabilitation is an provides unique benefits [18]. VR creates an interactive and cost-effective environment that ensures patient engagement and motivation to improve performance. An fMRI study showed that VR intervention is effective on triggering cortical reorganization and associated locomotor recovery [19].

We have previously shown that subjects learned to control a walking avatar using BCI under normal and alter visuo-motor perturbations over several days [12]. In this study, we used source localization analysis to compare cortical network activity between waling with and without closed-loop BCI control. We hypothesized that the closed-loop EEG-based BCI-VR system enhances cortical involvement in human treadmill walking, and triggers cortical networks involved in error monitoring and motor learning. This work is a further step toward the development of a novel training paradigm using BCI-VR system for improving the efficacy of rehabilitation.

II. MATERIALS AND METHODS

A. Experimental setup and protocol

Twelve healthy individuals (7 males, 5 females, aged from 19 to 29) participated in this study. The experiment procedures were approved by the Institutional Review Board at the University of Houston and consented by all subjects. Each subject was instrumented with 64-channel EEG cap, three goniometer sensors on each leg, and three wireless inertial measurement units (IMUs). The subjects were instructed to have two minutes (mins) of standing still on a treadmill in the beginning and end of each trial. In the remaining period, the subjects walked on a treadmill at one mile per hour (mph) while looking at an avatar displayed eye-level on a monitor placed in front of the treadmill. The movements of the avatar's left leg in the sagittal plane followed the subjects' movements precisely all the time by using the data from goniometer sensors placed at hip, knee, and ankle joint. However, the avatar's right leg was driven either by goniometer sensors (*Gonio-ctrl*) or predicted joint angles from BCI system (*BCI-ctrl*) depending on the protocol. In addition to the *Gonio-ctrl* and *BCI-ctrl* phases, visual kinematic perturbation was also introduced to the first four subjects to explore the cortical adaptation. Details for experimental setup and experimental protocol can be found in our previous studies [12].

B. *Real-time closed-loop EEG-based BCI decoder*

We developed a custom C++ software to stream and synchronize EEG and goniometer data in real-time manner. The software was also designed to implement signal pre-processing and predict joint angles from EEG. EEG were band-pass filtered at delta (0.1 – 3 Hz) in real time to get delta band. Previous studies showed this band contains most power in joint angle signals [13, 20].

Non-linear relationship between neural activities and lower limb kinematics may challenge the linear Wiener decoder in real-time applications [10, 21]. A complex model-based approach [22, 23], or non-linear state approximation using unscented Kalman filter [10, 21] could be used to capture this non-linearity. Another challenge of closed-loop EEG-based BCI is the non-stationary property of EEG signals [24]. Osborn et al. recommended implementing a closed-loop decoder adaptation (CLDA) for invasive neural decoding of hand kinematics of non-human primates [25]. This algorithm constantly updates the neural decoder after a certain interval (pre-defined) by retraining the decoder using the most updated training data. In this study, CLDA-UKF was used as the neural decoder to predict lower limb kinematics of human walking in real-time. Details for this algorithm can be found in our previous studies [12, 13].

C. *Offline EEG signal processing and source localization*

The offline EEG analysis were performed in Matlab R2016a (The MathWorks, MA) and EEGLAB [26]. Fig. 1 shows a flowchart for the EEG signal processing. EOG channels were first removed and the remaining EEG signals (60 channels) were high pass filtered at 0.1 Hz. Corrupted EEG channels were rejected based on criteria in [1]. The remaining EEG channels were then re-referenced by subtracting to their common average. Next, artifact subspace reconstruction (ASR) was applied to remove high amplitude artifacts (e.g., eye blinks, muscle burst) [27]. After this step, EEG data were down-sampled to 100 Hz and Infomax ICA was applied.

EEG electrodes were aligned to a standard MNI brain model by using 3D position data obtained from a Captrak system. We then computed equivalent current dipole that matched to the scalp projection of each independent component (IC) source by using a standard three-shell boundary element head model included in the DIPFIT toolbox [26]. Only ICs in which the equivalent dipoles explained > 80% of variance of the IC scalp projections were retained for further analysis. Next, we visually inspected each IC scalp projection, its equivalent dipole's location, and its power spectra and removed ICs that related to non-brain artifacts (e.g., eye blink/movement, neck muscle). We generated feature vectors (which include power spectra, IC scalp projections, and dipole locations) from the remaining ICs and used the k-means algorithm (k = 7) to obtain IC clusters across subjects. ICs that were outside three STD range of cluster centroids were grouped into a special cluster and removed as outliers.

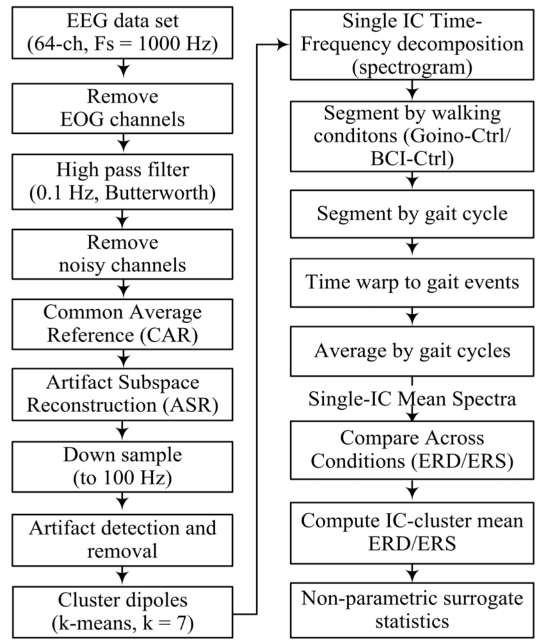

Fig. 1. Flowchart illustrates offline EEG processing and source localization

Time-frequency decomposition (spectrogram) was performed for each IC in the clusters (window length of 500 ms, maximum overlap) across the whole trial. The full-length spectrogram was then segmented into gait cycles, which were detected from kinematic data, and linearly time-warped to the average gait cycle length so that right heel-strikes were aligned at the same median latency. Individual epoch spectrograms were concatenated for each cluster in each walking conditions (*Gonio-ctrl* and *BCI-ctrl*). Subtraction was performed on the spectrograms from these two conditions. The difference spectrograms were masked for significance ($\alpha = 0.05$) with bootstrapping that randomly shuffled 200 surrogate data.

III. RESULTS

A. *Real-time decoding accuracies improved with training*

We observed the improvement of real-time decoding accuracy across trials. Fig. 2. shows the average real-time decoding accuracies across all subjects increased from (Hip: 0.18 ± 0.31; Knee: 0.23 ± 0.33; Ankle: 0.14 ± 0.22) on Day 1 to (Hip: 0.40 ± 0.24; Knee: 0.55 ± 0.20; Ankle: 0.29 ± 0.22) on Day 8.

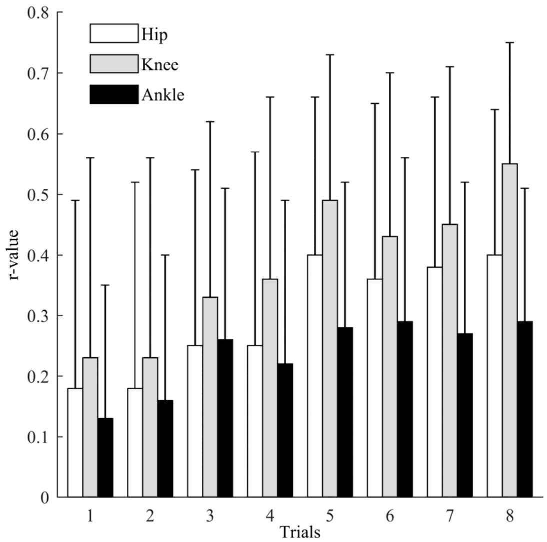

Fig. 2. Pearson's r values for all subjects across 8 days of training.

B. *Spectral power difference between walking with and without BCI-control of the walking avatar*

Source localization revealed seven cortical IC clusters: anterior cingulate cortex (ACC), superior temporal gyrus (STG), posterior parietal cortex (PPC), inferior parietal lobe (IPL), inferior frontal gyrus (IFG), and occipital lobe (OL). Here, we focus on findings for ACC, PPC and OL. Fig. 3 shows the difference spectrograms for these clusters between walking with and without BCI control of the avatar, *BCI-ctrl* and *Gonio-ctrl*, respectively. The significant differences in the spectrograms were obtained by using a non-parametric bootstrapping technique with random shuffling.

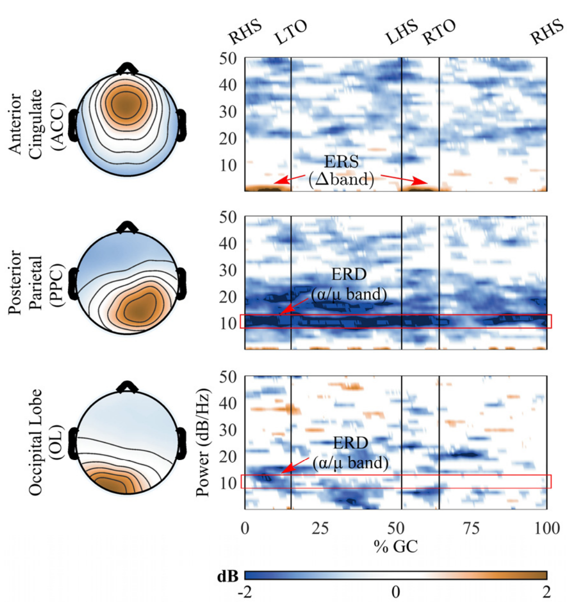

Fig. 3. Spectral power difference between walking on a treadmill with and without BCI control of a walking avatar. The red rectangles illustrate sustained ERD in the alpha/mu band. Non-parametric bootstrapping technique with random shuffling was used for the comparison, $\alpha = 0.05$.

IV. Discussion

We showed the feasibility of building a real-time decoder for users to control the leg movement of a virtual avatar using their EEG. We then demonstrated the feasibility of controlling the avatar via a closed-loop BCI and monitoring cortical activity using non-invasive EEG [12]. Source localization analysis revealed significant differences in cortical activity between walking with and without closed-loop BCI control. Specifically, we found sustained α/μ (8-13 Hz) suppression in the PPC and OL, while less sustained but still significant decreases (ERD) were observed in the β band (14-30 Hz) band across all the clusters. Our results also showed significantly increased cortical activity in the low frequency bands, Δ (0.1-3 Hz), in the ACC area with respect to the control condition (*Gonio-ctrl*).

We observed that the subjects were able to adapt the avatar's gait patterns controlled via the closed-loop EEG-based BCI. The improvement of real-time decoding accuracies in 8 days of training suggests that with practice, subjects gained more control of the walking avatar by using their brain signals [12]. This finding supports the view that the visuomotor adaptation can be triggered directly from brain activity and thus the proposed system can also be used as a platform to examine cortical plasticity in the human brain.

Significant decreased power (ERD) in the α/μ and β bands have been showed in recent studies when participants were actively involved in the walking tasks [4, 27]. Bulea et al. suggested that the ERD in the α/μ and β bands indicate increased cortical involvement when participants walked on an active treadmill or with increased gait speed. The ERD in these bands were also found in the sensorimotor areas when walk-assisting robot users engaged in active walking as opposed to being carried by the machine. Furthermore, numerous studies have shown that the ERD in these bands is correlated with higher neuronal activation due to increased task demand. Therefore, our results indicate that walking while controlling an avatar using a real-time closed-loop BCI-VR system enhances cortical involvement in the gait task.

While ERD in the α/μ and β bands associated with increasing task demands, the low frequency band power in the ACC is known to increase (ERS) in response to increasing task demands [28]. Previous studies also showed θ oscillations of EEG signals correlated with task difficulty [29], error monitoring and learning processes, and memory and decision making. Interestingly, a study from Womelsdorf et al reported that local field potential theta-activity in ACC of macaque monkeys holds the core functions in cognitive control processes and in error monitoring [30]. fMRI studies with human individuals also showed evidence for a direct relation between ACC activity and error detection and behavioral adjustment, and the online monitoring of performance [31]. This result could be an indication that using a BCI-VR promotes cortical network activity involved in error monitoring and motor learning.

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