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The feasibility of a brain-computer interface functional electrical stimulation system for the restoration of overground walking after paraplegia

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Abstract

Background: Direct brain control of overground walking in those with paraplegia due to spinal cord injury (SCI) has not been achieved. Invasive brain-computer interfaces (BCIs) may provide a permanent solution to this problem by directly linking the brain to lower extremity prostheses. To justify the pursuit of such invasive systems, the feasibility of BCI controlled overground walking should first be established in a noninvasive manner. To accomplish this goal, we developed an electroencephalogram (EEG)-based BCI to control a functional electrical stimulation (FES) system for overground walking and assessed its performance in an individual with paraplegia due to SCI.

Methods: An individual with SCI (T6 AIS B) was recruited for the study and was trained to operate an EEG-based BCI system using an attempted walking/idling control strategy. He also underwent muscle reconditioning to facilitate standing and overground walking with a commercial FES system. Subsequently, the BCI and FES systems were integrated and the participant engaged in several real-time walking tests using the BCI-FES system. This was done in both a suspended, off-the-ground condition, and an overground walking condition. BCI states, gyroscope, laser distance meter, and video recording data were used to assess the BCI performance.

Results: During the course of 19 weeks, the participant performed 30 real-time, BCI-FES controlled overground walking tests, and demonstrated the ability to purposefully operate the BCI-FES system by following verbal cues. Based on the comparison between the ground truth and decoded BCI states, he achieved information transfer rates >3 bit/s and correlations >0.9. No adverse events directly related to the study were observed.

Conclusion: This proof-of-concept study demonstrates for the first time that restoring brain-controlled overground walking after paraplegia due to SCI is feasible. Further studies are warranted to establish the generalizability of these results in a population of individuals with paraplegia due to SCI. If this noninvasive system is successfully tested in population studies, the pursuit of permanent, invasive BCI walking prostheses may be justified. In addition, a simplified version of the current system may be explored as a noninvasive neurorehabilitative therapy in those with incomplete motor SCI.

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Introduction

Mobility after paraplegia due to spinal cord injury (SCI) is primarily achieved by substituting the lost function with a wheelchair [1]. However, the sedentary lifestyle associated with excessive wheelchair reliance can lead to medical co-morbidities, such as osteoporosis, heart disease, respiratory illnesses, and pressure ulcers [2]. These conditions contribute to the bulk of SCI-related medical care cost [2]. Therefore, restoration of walking after SCI remains a clinical need of high priority.

Current approaches to restoring ambulation after SCI include the use of robotic exoskeletons [3, 4] and functional electrical stimulation (FES) systems [5, 6]. These devices, however, lack intuitive able-body-like supraspinal control, as they typically rely on manually controlled switches. In addition, these systems cannot exploit the neuroplasticity of residual or spared pathways between the brain and spinal motor pools [7]. Hence, novel means of restoring intuitive, brain-controlled ambulation after SCI are needed. If successful, such novel approaches may drastically reduce SCI-related medical costs and improve quality of life after paraplegia due to SCI.

Spinal cord stimulation has recently emerged as a promising method to restore voluntary lower extremity movements to those with SCI [8, 9]. Brain-computer interfaces (BCIs), which enable intuitive and direct brain control of walking via an external device [10, 11], can be seen as an alternative approach. Surveys indicate that those with paraplegia due to SCI highly prioritize restoration of walking as a way of improving their quality of life [12, 13]. In addition, approximately 60 % of survey participants expressed willingness to undergo implantation of an invasive BCI device to restore ambulation [13]. However, before such a system can be pursued, it is necessary to establish the feasibility of brain-controlled overground ambulation. In this proof-of-concept study, we report on a noninvasive BCI-controlled FES system capable of restoring a basic form of overground walking to an individual with paraplegia due to SCI. The study advances our existing BCI systems from applications such as walking in a virtual reality environment (VRE) [14–16] and walking with a treadmill-suspended robotic orthosis [10] to overground walking [11]. If successfully tested in a population of individuals with SCI, the proposed BCI-FES system may lead to the development of a fully implantable BCI system for restoring ambulation after SCI.

Methods

Participant screening

Ethical approval was obtained from the University of California, Irvine Institutional Review Board (Irvine, CA, USA). Candidates were recruited from a population of individuals with chronic T6 – T12 SCI. They underwent several screening procedures to rule out severe spasticity, contractures, restricted range of motion, lower extremity fractures, pressure ulcers, severe osteoporosis, orthostatic hypotension, as well as affirm neuromuscular responsiveness to FES (see Additional file 1 for details). A physically active 26-year-old male with a T6 AIS B SCI, with no motor function in the lower extremities and no sensation below the injury level except for minimally preserved bladder fullness sensation, passed all the screening requirements. He provided informed consent to participate in the study. He also consented to the publication of the biomedical data and media, including photographs and videos (consent to publish was also obtained from every person featured in these photographs and videos).

Training procedure

The participant underwent BCI training to learn how to ambulate within a VRE using attempted walking and idling (i.e. relaxing) as a control strategy. This procedure also generated an EEG decoding model that was subsequently used in BCI-FES experiments. In addition, since the supraspinal areas underlying human gait can become suppressed after chronic SCI, it has been suggested that motor imagery practice may facilitate their reactivation [17]. Therefore, the purpose of the BCI-VRE training was to also facilitate the reactivation of the brain areas responsible for gait control. Finally, the participant simultaneously underwent FES training to recondition his lower extremity muscles in order to be able to stand and walk overground using a FDA-approved commercial FES system (Parastep I System, Sigmedics, Fairborn, OH).

BCI training

Similar to our prior studies [10, 15, 16], the participant first underwent a BCI screening procedure to determine if he could control the BCI in a VRE. Subsequently, he underwent BCI training in order to further master BCI-VRE control. Each BCI screening and training visit entailed the same procedure that began with a 10-min electroencephalogram (EEG) recording. During this period, the participant engaged in 30-s-long alternating epochs of attempted walking and idling while seated in his wheelchair [10, 16]. A detailed description of this procedure is given in Additional file 1.

Based on these data, an EEG decoding model was generated offline using the methods described in [10, 15, 16]. Briefly, the EEG epochs were segmented into 4-s-long trials of “Idle” and “Walk” class, transformed into the frequency domain, and their power spectral densities (PSDs) were integrated from 6 to 40 Hz in 2-Hz bins. These spatio-spectral data were then subjected to dimensionality reduction using classwise principal component analysis (CPCA) [18, 19], and discriminating features were extracted using approximate information discriminant analysis (AIDA) [20]. Note that this feature

extraction method is rooted in information theory [21] and has been extensively tested in our prior BCI studies [10, 15, 16, 22, 23]. More formally, one-dimensional (1D) features $f \in \mathbb{R}$ were extracted by:

$$f = \mathbf{T}\Phi(\mathbf{d}), \tag{1}$$

where $\mathbf{d} \in \mathbb{R}^{B\times C}$ is a single trial of spatio-spectral data (B–number of frequency bins, C–number of electrodes), $\Phi : \mathbb{R}^{B\times C} \rightarrow \mathbb{R}^m$ is a mapping from the data space to an m-dimensional CPCA-subspace, and $\mathbf{T} : \mathbb{R}^m \rightarrow \mathbb{R}$ is an AIDA transformation matrix.

A Bayesian classifier was then designed as follows:

$$f^\star \in \begin{cases} \mathcal{S}_1, & \text{if} \quad P(\mathcal{S}_1|f^\star) > P(\mathcal{S}_2|f^\star) \\ \mathcal{S}_2, & \text{otherwise} \end{cases}, \tag{2}$$

where $P(\mathcal{S}_1|f^\star)$ and $P(\mathcal{S}_2|f^\star)$ are the posterior probabilities of idling and walking classes, respectively, given the observed feature, $f^\star$. They were found using the Bayes rule $P(\mathcal{S}_i|f^\star) = p(f^\star|\mathcal{S}_i)P(\mathcal{S}_i)/p(f^\star)$, $i = 1, 2$, where $p(f^\star|\mathcal{S}_i)$ is a conditional probability density function (PDF) evaluated at $f^\star$, $P(\mathcal{S}_i)$ is the prior probability of the class, $\mathcal{S}_i$, and $p(f^\star)$ is the (unconditional) PDF. To simplify calculations, the conditional PDFs were modeled as Gaussians with equal variances. Note that this rendered the Bayesian classifier (2) linear [24]. The performance of the classifier was evaluated offline through stratified ten-fold cross-validation [25].

Each visit continued with online BCI operation, where 0.75-s-long segments of EEG data were wirelessly acquired in real time every 0.25 s using a sliding window approach. The PSDs of the EEG channels were then calculated and integrated in 2 Hz-bins for each of these segments, and used as the input for the EEG decoding model. The posterior probabilities, $P(\mathcal{S}_1|f^\star)$ and $P(\mathcal{S}_2|f^\star)$, were calculated using the Bayes rule (see above), and were averaged over a 1.5–2.0 s window to minimize false alarms and omissions [10, 15, 16]. Before online BCI operation, the BCI-VRE system was calibrated using a short procedure (see Additional file 1 for details). During each online experiment, the participant performed between one and five goal-oriented, real-time BCI walking tasks. Specifically, he was instructed to utilize attempted walking and idling to control the linear ambulation of an avatar and make sequential stops at ten designated points within the VRE [14–16]. The goal of the task (see Fig. 1) was to walk the avatar at a constant speed and complete the course as quickly as possible, while dwelling at each stop for at least 2 s. The online performances, expressed as the number of successful stops and course completion time, were compared to the results of Monte Carlo simulations to ascertain whether control of the BCI system was purposeful (details in Additional file 1). Note that despite demonstrating purposeful control during the BCI screening process, the participant continued the BCI-VRE training throughout the study. This provided the EEG decoding model for subsequent BCI-FES experiments. It also allowed the participant's BCI-VRE performance to be tracked over time and the presumed reactivation of the cortical gait areas to occur.

Fig. 1 Virtual Reality Environment. A screenshot of the VRE. The traffic cones next to the characters represent designated stops. A full point was given for dwelling at each designated stop for at least 2 s, for a total stop score of 10 points. A fraction of a point was given for dwelling between 0.5 and 2 s (proportionate to the dwelling time) and no point was given for dwelling less than 0.5 s. There was no penalty for dwelling for more than 2 s, but this increased the course completion time. As a benchmark, the course could be completed in ∼205 s with a manually controlled joystick [15, 16]

FES training

To better understand the FES training procedures, a brief description of the Parastep system's operation is first provided. Namely, the Parastep achieves ambulation by activating the quadriceps and tibialis anterior muscles. This is accomplished by placing electrode pairs bilaterally over the femoral (immediately proximal to the knee) and deep peroneal (immediately distal to the knee) nerves. Simultaneous bilateral activation of the quadriceps is used to maintain the knee extension necessary for standing, while a front-wheel walker is used for upper body stabilization. A step is achieved with the following sequence: 1. the user performs an anterior-lateral weight shifting maneuver; 2. a brief electrical stimulation is delivered unilaterally to the deep peroneal nerve while the corresponding quadriceps are deactivated, thereby eliciting a triple-flexion reflex of the leg (i.e. combination of foot dorsiflexion, knee flexion, and hip flexion); 3. the user's leg swings forward due to the anteriorly shifted center of gravity; 4. the quadriceps are reactivated to maintain a standing position. The Parastep system's adjustable parameters are the step duration (controlled manually by the subject via buttons) and

stimulation current for bilateral femoral and deep peroneal nerves. Based on these five parameters, the system generates pre-programmed stimulation sequences for walking movements.

The FDA-approved guidelines for the Parastep system require users to recondition their muscles prior to engaging in FES-mediated walking. This reconditioning also facilitates improved cardiopulmonary endurance. To this end, the participant performed strength and endurance training of the quadriceps using the FES device. Once the participant regained sufficient strength and endurance, and demonstrated the ability to stand using the FES system, the training sessions progressed to FES-assisted overground walking. This included learning the coordination of movements such as weight shifting, front-wheel walker advancement and leg swing, which facilitate FES-mediated walking. A more detailed description of these procedures is provided in Additional file 1. It should be noted that the FES training was also used to empirically determine the stimulation parameters. More specifically, the time necessary to perform the weight shifting, walker advancement, and leg swing determined the step rate. The stimulation amplitude for each femoral nerve was determined as the minimal amount of current necessary to achieve a standing posture. Similarly, the stimulation amplitude for each peroneal nerve was determined by finding the minimal current necessary to elicit an adequate triple-flexion response and step. Note that these parameters were later used in the BCI-FES experiments as described below.

The FES training continued until the participant could walk the length of the overground walking course (3.66 m) without any intervention from the physical therapist. To prevent falls and provide partial body-weight support, FES walking was performed while the participant was mounted in a body-weight support system (ZeroG, Aretech, Ashburn, VA).

BCI-FES Experiments

The BCI-FES walking experiments were initiated once the participant completed the FES training. This was accomplished by first integrating the BCI and FES systems using a dedicated microcontroller. In addition, the step rate and stimulation amplitudes (as determined above) were pre-programmed into the microcontroller such that the left and right steps cycle automatically. A motion sensor system was then developed and synchronized with the BCI-FES system for the purpose of facilitating the performance assessment. A more detailed description of these steps is provided in Additional file 1. Finally, the EEG decoding model from the most recent BCI training session was loaded into the BCI system. The participant then undertook suspended BCI-FES walking tests followed by overground BCI-FES walking tests.

Suspended walking tests

Prior to overground walking, suspended walking tests were performed to establish whether the participant could purposefully operate the BCI-FES system. First, the participant was positioned ∼1 m from a computer screen and suspended using the ZeroG support system so that his feet were ∼5 cm off the ground (see Fig. 2). This allowed the execution of BCI-FES-mediated walking and standing without having to maintain postural stability, perform weight shifting, or advance the front-wheel walker. The participant then followed 30-s-long alternating "Idle" and "Walk" visual computer cues for a total of 180 s with the goal of controlling the standing and walking functions of the BCI-FES system in real time. Finally, the participant's performance (details below) was assessed using video, BCI state, and motion sensor data.

Overground walking tests

For overground walking tests, the participant utilized the system to walk along a 3.66-m-long linear course with three cones positioned 1.83 m apart (Fig. 1). He was instructed to walk and stand at each cone for 10–20 s via verbal cues given by the experimenter. Subsequently, he used an attempted walking strategy to initiate BCI-FES-mediated walking to progress to the next cone. Note that the duration of standing at each cone was randomized to minimize anticipation by the participant. Also note that the ZeroG system was used during these tests to provide partial body-weight support and prevent falls. Overground walking tests were repeated as tolerated by the participant. Video, BCI state, and motion sensor data were recorded to assess the performance during this task.

Performance assessment

The subject's performances in the suspended and overground walking tests were derived based on the video, BCI state, and gyroscope data. Specifically, they were quantified by calculating the cross-correlation and information transfer rate (ITR) between the externally supplied cues and BCI-FES-mediated responses. In the suspended walking tests, the timings of the visual cues were obtained from the BCI computer. In the overground walking tests, the timings of the auditory cues were extracted from the video recordings. In both types of tests, the epochs of BCI-FES mediated responses were extracted from the gyroscope data. Similar to above, purposeful BCI-FES control was ascertained by comparing these cross-correlations to those achieved by Monte Carlo simulations (details in Additional file 1). In addition, the instances of false alarms and omissions were recorded, where a false alarm was defined as the presence of BCI-FES-mediated walking within any intended idling epoch, while an omission was defined as the absence of BCI-FES-mediated walking within any intended walking epoch. Finally, in the

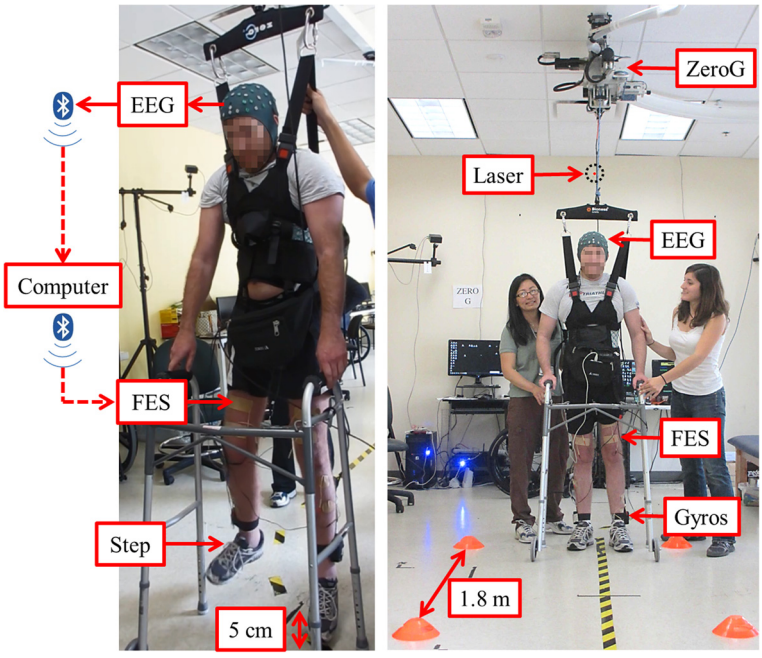

Fig. 2 Experimental setup. *Left*: The suspended walking test. In response to "Idle" or "Walk" cues displayed on a computer screen (not shown) the participant modulates his EEG by idling or attempting to walk. EEG is sent wirelessly (via Bluetooth communication protocol) to the computer, which processes the data and wirelessly sends a decision to either "Idle" or "Walk" to a microcontroller. The microcontroller (placed in the belt-pack) drives the FES of the femoral and deep peroneal nerves to perform either FES-mediated standing or walking (in place). *Right*: The overground walking test. In response to verbal cues, the participant performs BCI-FES mediated walking and standing to walk along a linear course and stop at three cones positioned 1.8 m apart. The basic components are: the BCI-FES system, motion sensor system (two gyroscopes and a laser distance meter), and the ZeroG body weight support system to prevent falls. The information flow from EEG to FES is identical to that of the suspended walking test. Note that the participant's face was scrambled due to privacy concerns

overground walking tests, the laser distance meter was used to confirm that the subject ambulated along the course and stopped at the cones.

Results

Training

The timeline of the study procedures, including the BCI and FES training, is summarized in Fig. 3. Note that while the participant obtained perfect BCI-VRE control (no omissions or false alarms) after only 11 h of BCI training, the BCI training continued until the end of the study in order to verify that the participant could maintain a high-level of BCI control. In addition, the participant completed the FES training after only 19 FES training sessions, or ~22.5 h of physical therapy, which is shorter than the Parastep manufacturer's nominal recommendation of 32 one-hour sessions.

BCI training

The performances achieved during the BCI training procedures are shown in Fig. 4. Note that the Bayesian classifier (2) achieved an offline classification accuracy significantly above the chance level (50 %) on the second visit, and a near-perfect classification accuracy by the 15th visit. This translated into a near-perfect level of control during the goal-oriented real-time BCI walking task within the VRE (Additional file 2), which is evident by the decrease in mean course completion time

Day Since Start of Study	1 to 17	22 to 38	43 to 59	75 to 117	124 to 208	214 to 256
Visit No.	1 to 4	5 to 9	10 to 14	15 to 19	20 to 24	25 to 30
Screening & Exams						
BCI Screening						
FES Screening						
BCI Training						
FES Training						
BCI-FES Testing						

Fig. 3 Timeline. Experimental time line of the study

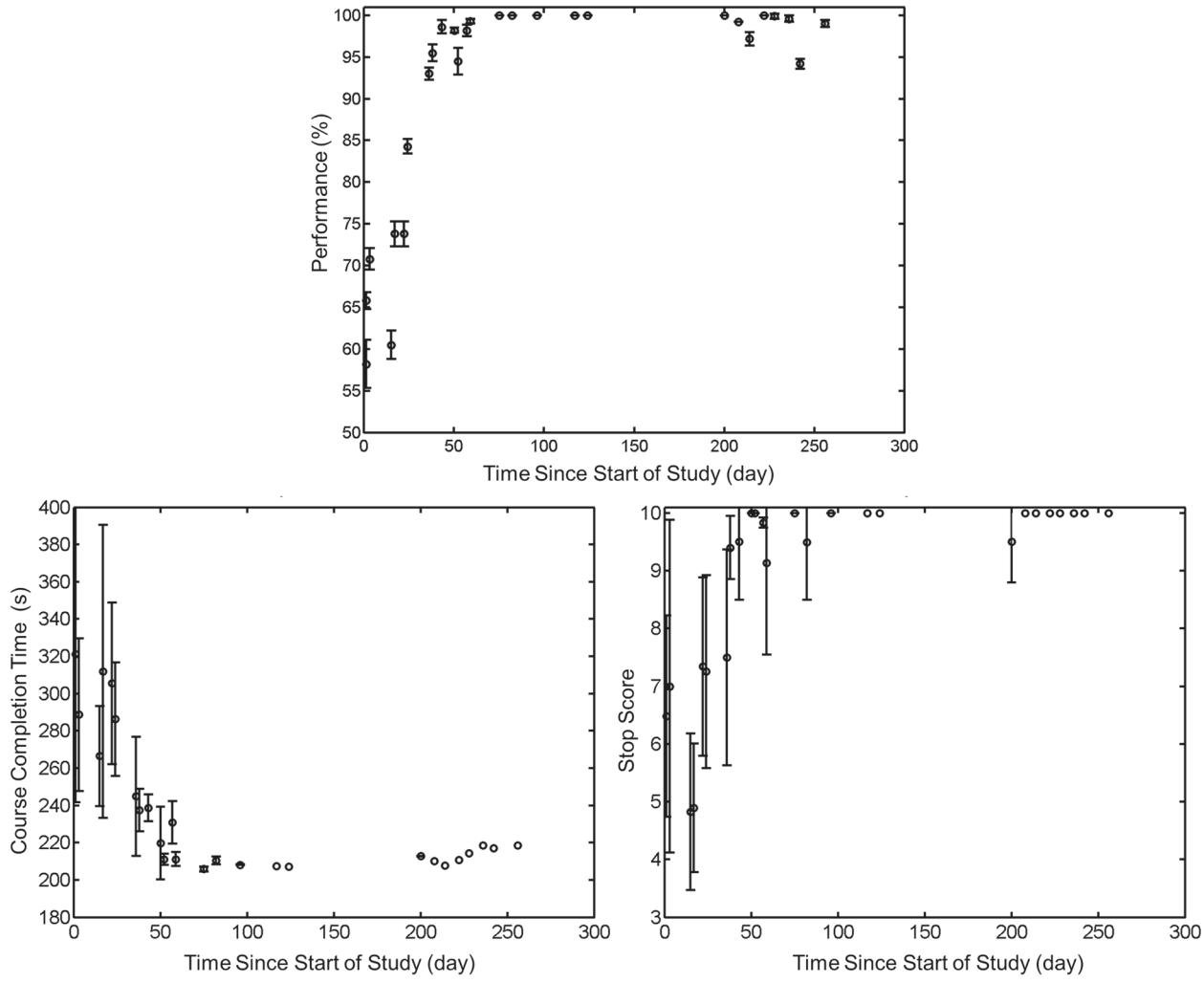

Fig. 4 BCI training performances over time. BCI training performances over time. *Top*: Offline performances (%) of the Bayesian classifier (2), as determined through the cross-validation procedure described in the BCI training section. The bar plots represent ± standard deviation (std). *Bottom*: Real-time, online BCI-VRE performances expressed as the course completion time (*left*) and successful stop score (*right*), determined as explained in Fig. 1. The bar plots represent ± std, and data points with no bars indicate that only one VRE session was performed on that day. Note that the participant performed less VRE sessions as the study progressed to make time for more BCI-FES walking sessions

and increase in successful stop score. The EEG decoding models resulted in spatio-spectral features that converged to similar frequencies and brain areas across visits (see Additional file 1). A sample of these features is depicted in Fig. 5, where areas under electrodes CP3, CPz, and CP4 were deemed by the decoding model as important for classification of attempted walking and idling. Note that these areas approximately correspond to the motor and somatosensory cortices. Spectral analysis confirmed the physiological basis of these features, as event-related synchronization (ERS) was observed at CP3 and CP4 in the low-β band (13 – 16 Hz), and event-related desynchronization (ERD) was observed at CPz in the high-β band (23 – 28 Hz).

FES training

The participant typically performed one or two FES training sessions per week. The progression of his FES training is described in detail in Table 1 below. After the visit 19, he demonstrated proper overground walking using the Parastep system. During this training period, it was empirically determined that the participant required 4 s to perform each FES-mediated step. This step rate was programmed into the microcontroller, as explained in the BCI-FES Experiments subsection above. It was also determined that for the suspended walking test, the participant required a nominal stimulation of 120 mA at the femoral nerve, and 50 mA at the deep peroneal nerves. These values were somewhat higher for the overground walking

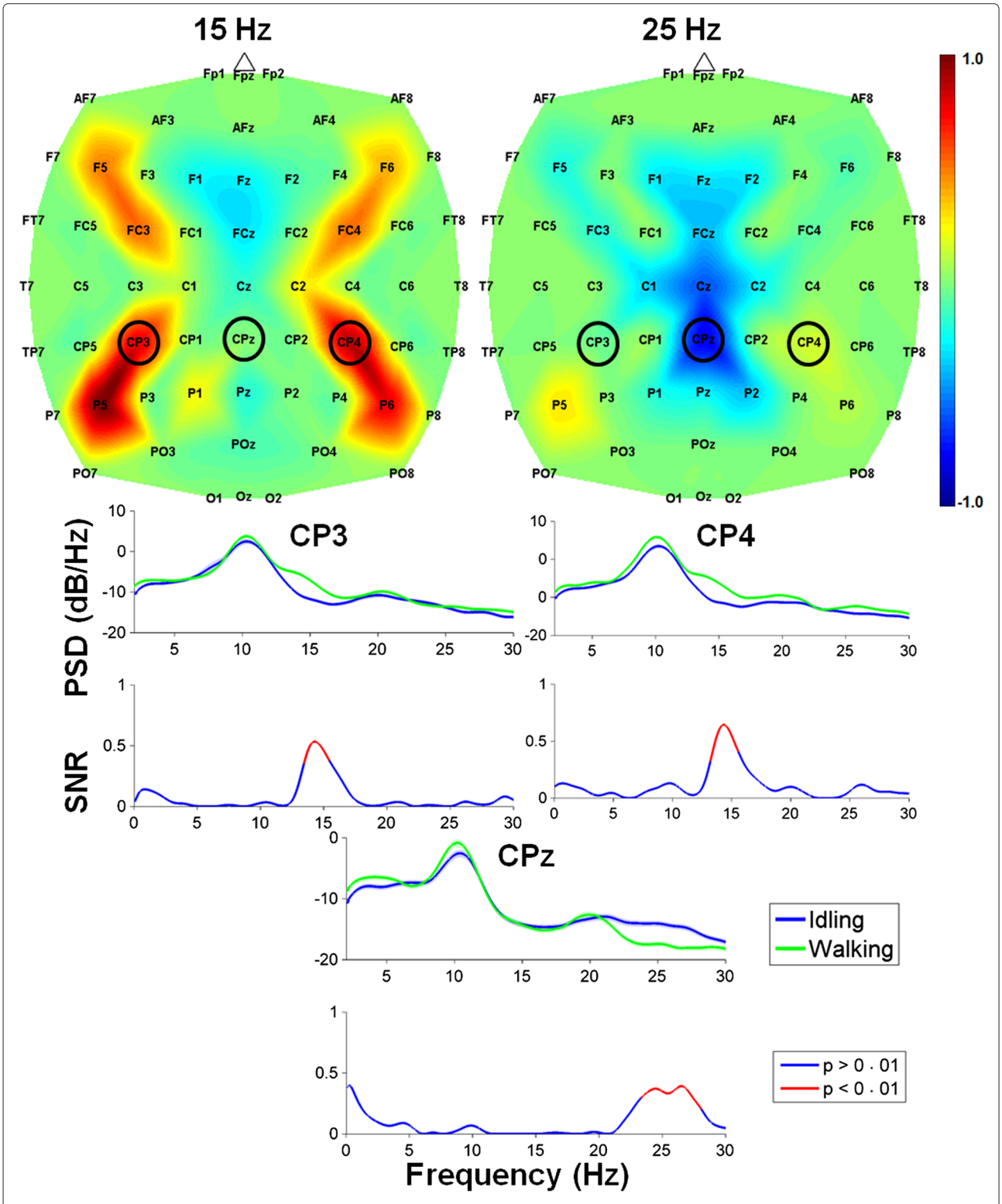

Fig. 5 EEG feature extraction maps. *Top*: Feature extraction maps obtained by a combination of CPCA and AIDA for classification of attempted walking versus idling. The spatial distribution of features is shown for the frequency bands centered at 15 Hz and 25 Hz, where the features with values close to ±1 are more important for classification. The maps were generated from data collected during the last visit. *Bottom*: Log power spectral density (PSD) during idling (blue) and walking (green) at electrodes CP3, CPz, and CP4, where shaded regions represent error bars. Underneath the PSD plots are the corresponding signal-to-noise ratio (SNR) plots with significant SNRs ($p < 0.01$) represented by red lines. Note the event-related synchronization (ERS) in the 13–16 Hz range (at CP3 and CP4) and event-related desynchronization (ERD) in the 23–28 Hz range (at CPz)

Table 1 FES training activities across visits. The participant required 19 visits (∼22.5 h of physical therapy) to comfortably walk 3.66 m

Day since start of study	1 – 17	22 – 38	43 – 59	75 – 117
Visit no.	1 – 4	5 – 9	10 – 14	15 – 19
	FES screening, strength training, standing endurance	Standing, posture and alignment	Weight-bearing support, balance, weight shifting	Front-wheel walker management, stepping, locomotion

tests, namely, 130 mA for the femoral nerve, and 70 mA and 60 mA for the left and right deep peroneal nerves, respectively. These stimulation parameters were also used for subsequent BCI-FES tests.

During FES training, the participant experienced a sprain of the left ankle, which was caused by his outside activities. This condition was resolved after one week of rest and periodic icing. The participant also experienced occasional light headedness during his initial attempts of FES-mediated standing and walking. However, this was no longer an issue after the participant progressed to BCI-FES-mediated walking. No other adverse events were observed.

Suspended walking tests

Once the BCI and FES training were completed, the suspended walking experiments were performed on visits 20 and 21 (Additional file 3). The performance metrics of these tests, including the cross-correlation and lag, number and duration of false alarms and omissions, and the ITR, are presented in Table 2. The participant achieved a very high level of control during this task, as evidenced by cross-correlations as high as 0.957 and ITRs as high as 3.643 bit/s with no false alarms or omissions. The subject's performance in both of the suspended walking tests was purposeful ($p < 0.01$), according to the criterion outlined in Additional file 1.

Overground walking tests

Given the promising results above, the participant started the overground walking tests on visit 20 (immediately after the first suspended walking test), and continued these tests until the end of the study (visit 30). In total, 30 overground walking tests were performed over a 19-week period (see Fig. 2). Between one and six overground walking tests were performed on each visit, with each test having an average duration, written in the format mean (standard deviation), of 3.234 (0.743) min. Over time, the participant was able to perform more tests per visit (see Additional file 1). An average cross-correlation between experimenter's verbal cues and BCI-FES response (i.e. leg movement recorded by gyroscopes, see Fig. 6 and Additional file 4) was 0.775 (0.164) with a 2.861 (4.229) s lag. Note that ∼60 % body-weight support was applied throughout these tests. This value was chosen since it approximates the contribution of the upper body in the total body weight. It was also found to be comfortable for the participant and adequate to prevent falls via the ZeroG's fall detection algorithm.

The participant had an average of 2.333 (2.039) false alarms (Table 3) and no omissions across all overground walking tests and visits. Comparison to the Monte Carlo simulations also revealed that all 30 overground walking tests were performed with purposeful control ($p < 0.01$). Furthermore, he was able to achieve ITRs similar to the suspended walking tests. In particular, he had an average ITR of 2.298 (0.889) bit/s across all overground walking tests, with a maximum ITR of 3.676 bit/s achieved during the second overground walking test on the 28th visit (see Fig. 6). Finally, no adverse events were observed during BCI-FES-mediated overground walking.

Table 2 The subject's performances in the suspended walking tests

Visit no.	ρ	Lag (s)	ITR (bit/s)	FA	FA duration (s)	OM
20	0.917	3.00	3.041	1	1.75	0
21	0.957	4.25	3.643	0	0	0
Avg.	0.937	3.630	3.342	0.500	0.880	0

Cross-correlation (ρ), lag, and ITR between the cues and the participant's FES-mediated walking are shown. The number of false alarms (FA), FA duration, and number of omissions (OM) are also shown

Discussion

This study represents the first demonstration of an individual with paraplegia due to SCI purposefully operating a noninvasive BCI-FES system for overground walking in real time. The participant initially operated the system while being completely suspended, and subsequently translated this skill to an overground walking condition. He achieved a high level of control and maintained this level of performance during a 19-week period. These results provide a proof-of-concept for direct brain control of a lower extremity prosthesis to restore basic overground walking after paraplegia due to SCI.

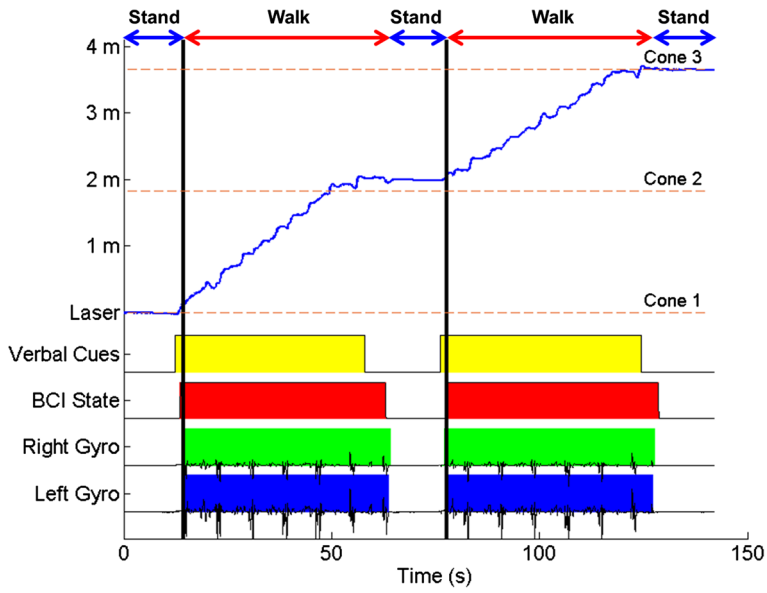

Fig. 6 Representative space-state-time plot. The best overground walking test results (data from the 2nd test on the 28th visit). The beginning and end of yellow blocks mark the onset of the "Walk" and "Idle" verbal cues, respectively, given by the experimenter. Red blocks represent periods when the BCI system was in the walk state; otherwise, the system is in the idle state. Green and blue blocks represent leg movements recorded by the gyroscopes. The laser signal (blue trace) represents the space-time plot, i.e. the participant's position within the course as measured by the laser distance meter. Note that there is a delay between the onset of the "Idle" cue and the BCI idle state. This latency includes the time required for the participant's cognitive processing and EEG to change, as well as the time required for BCI processing. The discrepancy between the onset of the idle state and gyroscope signals is due the fact that transitions from the walk to idle state can be decoded at any time during the pre-programmed 4-s step cycle. For example, if the state transition occurs during an uninterruptible leg swing, the participant will finish the leg swing despite the BCI system being in the idle state (e.g. the first green block). If, on the other hand, the state transition occurs after a leg swing, the leg will be stationary even before the system enters the idle state (e.g. the second green block). Finally, the discrepancy between the gyroscope signals and the distance meter is due to the participant only progressing when the front-wheel walker is advanced, which happens once every 4 s. Hence, all the leg movements prior to walker advancement will be registered by the gyroscope, however, they will not contribute to a position change

The decoding models for real-time BCI control yielded EEG classification features that were spatially distributed over the motor and somatosensory cortices. A bilaterally-distributed ERS in the low-β band (13 – 16 Hz) and a centrally-distributed ERD in the high-β band (23 – 28 Hz) were especially prominent. These findings are consistent with prior studies [26, 27], where foot motor imagery resulted in an ERS primarily over the hand representation areas, and an ERD over the foot representation area. These phenomena were observed in both the μ (8 – 12 Hz) and β (13 – 30 Hz) bands, and are thought to represent an activation of foot representation area with simultaneous inhibition of networks underlying hand movements [26, 27].

Table 3 Cross-correlation (ρ) between verbal cues and gyroscope movement, ITR, number of false alarms, and false alarm rate for the 30 overground walking tests performed. Note that the false alarm rates were calculated using the total idling duration. No omissions occurred during any overground walking session

$n = 30$	Average	Std. Dev.	Best
ρ	0.775	0.164	0.987
Lag (s)	2.861	4.229	2.742
ITR (bit/s)	2.298	0.904	3.676
FA	2.333	2.073	0
FA Rate (FA/s)	0.043	0.039	0

The best session results (on the 28th visit) are shown in the last column

The participant achieved and maintained a high level of performance during the BCI-VRE, suspended walking and overground walking tests. In comparison to the suspended walking conditions, there was a notable increase in the false alarm rate during overground walking. This drop in performance could be explained by an increase in EEG noise produced by movements, such as postural stabilization or weight shifting. Nevertheless, the false alarm rate decreased toward the end of the study, presumably due to the participant's better understanding of the task as well as practice with operating the BCI. Anecdotally, the participant was also able to carry a light conversation during these experiments without interfering with the function of the system. This robustness in real-time control, together with a high-level of performance

sustained across months, indicates that BCI-FES mediated restoration of basic walking function after SCI is feasible.

Future studies will focus on testing the function of this system in a population of individuals with SCI. If successfully tested in a larger population, this system may represent a precursor to invasive BCI systems for overground walking. Namely, the cumbersome nature of the current noninvasive system makes its adoption for restoration of overground walking unlikely. This limitation can potentially be addressed by a fully implantable BCI system, which can be envisioned to employ invasively recorded neural signals, such as electrocorticogram or action potentials, as well as implantable spinal cord stimulators [8] or FES systems [28]. Such a fully implantable system would eliminate the need to mount and unmount the equipment, such as an EEG cap, bioamplifier and a computer, thereby making the implantable system more practical and aesthetically appealing. Using an invasive system may also be the only viable approach to deliver cortical stimulation for restoring lower extremity sensation during walking. Nevertheless, the noninvasive system presented here may become a safe test bed to determine which individuals are good candidates to receive these invasive neuroprostheses, once they become available. Furthermore, a simplified future version of the current system may be applied as neurorehabilitative therapy for those with incomplete SCI, whereby residual connections between the brain and spinal motor pools may be strengthened through activity-dependent plasticity mechanisms [29]. In summary, the system reported here represents an important step toward the development of technologies that can restore or improve walking in individuals with paraplegia due to SCI.

Additional files

Additional file 1: Appendix. A supplementary document with additional details, as indicated throughout the body of this report. (PDF 8171 kb)

Additional file 2: Virtual reality training. The participant is engaged in using idling and attempted walking to control the linear walking of an avatar in a virtual reality environment. (MP4 10,240 kb)

Additional file 3: Suspended walking test. The participant is suspended in the air using the ZeroG system. In response to idle/walk cues, the participant utilizes idling/attempted walking to active/de-activate the FES system. (MP4 6144 kb)

Additional file 4: Overground walking test. The participant follows verbal cues from the experimenter, and utilizes attempted walking to perform BCI-FES mediated walking towards the next cone in the course. He then uses idling to stand and dwell until instructed to start walking towards the next cone. (MP4 8878 kb)

Competing interests

CEK received salary from HRL Laboratories, LLC. (Malibu, CA). The authors declare that they have no competing interests.

Authors' contributions

CEK integrated the BCI-FES system, built the motion sensor system, conducted the experiments, performed the data analysis, and wrote the manuscript. PTW implemented the BCI software, assisted with integrating the BCI-FES system, and provided technical support. CMM assisted with the experiments. CCYC provided physical therapy and assisted with the experiments. AHD oversaw and conceived the study, recruited patients, assisted with integrating the BCI-FES system, and assisted with experiments. ZN oversaw and conceived the study, designed the signal processing algorithm, and assisted with the experiments. All authors read and approved the final manuscript.

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Appendix: The Feasibility of a Brain-Computer Interface Functional Electrical Stimulation System for the Restoration of Overground Walking after Paraplegia

The following sections will provide additional details on the methods and results of the study.

1 Methods

1.1 Inclusion/Exclusion Criteria

Individuals with paraplegia due to spinal cord injury (SCI) were recruited according to the following inclusion criteria: age over 18; SCI level between T6 and T12; complete motor paraplegia (AIS A or B) or severe paraparesis (AIS C) due to SCI, resulting in the inability to walk; stable vertebral column to allow upright position; able to provide informed consent prior to the initiation of study; and able to provide transportation to the experimental site. The exclusion criteria were as follows: osteoporosis; prior or current lower extremity fractures; inability to tolerate functional electrical stimulation (FES); inability to control the electroencephalogram (EEG)-based brain-computer interface (BCI) system; presence of any electronic implant (e.g. pacemaker); presence of pressure ulcers; frequent autonomic dysreflexia; orthostatic hypotension; poor truncal control; severe spasticity or contractures; orthopedic malformations that may prevent proper use of the FES system; any neuromuscular disease; cauda equina syndrome; or pregnancy.

To ascertain compliance with the above criteria, candidates underwent several screening and imaging exams. More specifically, these procedures were performed to ensure the participants' ability to safely tolerate the FES and weight bearing during overground walking. In addition, a BCI system integrated with a virtual reality environment (VRE) [1–3] was used for BCI screening in order to ensure that participants could operate the BCI system in real time.

1.2 Screening and Imaging

The candidates were first subjected to neurological and orthopedic exams. Subsequently, a dual energy X-ray absorptiometry (DEXA) scan of the entire body was performed to rule out the presence of severe osteoporosis. In addition, the X-rays of hips, femurs, knees, tibias, fibulas, and ankles, were obtained to rule out fractures and/or lower extremity deformities. Candidates were excluded from the study if they exhibited severe osteoporosis or lower extremity stress fractures.

To rule out orthostatic hypotension, a tilt-table exam was performed using standard clinical practices. Within 5 min of gradual or immediate elevation to 90°, participants must not have exhibited symptoms of orthostatic hypotension such as: a drop in systolic blood pressure by more than 20 points, a drop in diastolic blood pressure by more than 10 points, a pulse increase of more than 30 beats/min, lightheadedness, presyncope, or syncope.

To determine the candidates' neuromuscular responsiveness to FES and whether it causes any adverse events (e.g. autonomic dysreflexia, pain), a brief test was performed. To this end, the electrodes of a FDA-approved, commercial FES system (Parastep I System, Sigmedics, Fairborn, OH) were placed bilaterally over the quadriceps, tibialis anteriors, and gluteal muscles. The candidates' ability to generate effective, FES-mediated muscle contractions without discomfort or adverse events was observed and assessed.

1.3 BCI Screening and Training

EEG Recording

EEG was recorded by a 64-channel, actively-shielded EEG cap (Medi Factory, Heerlen, The Netherlands) mounted on the participant's head. The electrode impedances were reduced to <10 KΩ using conductive gel and scalp abrasion. The EEG data were acquired by a NeXus-32 bioamplifier (Mind Media, Roermond-Herten, The Netherlands) at a sampling rate of 256 Hz. They were wirelessly transmitted to a BCI computer via a Bluetooth communication protocol, and re-referenced with respect to a common average reference. Due to the limitations of the amplifier's wireless transmission protocol, only 24 channels of data were acquired (see Figure 1). Note that this subset of channels was selected because they cover the motor cortex and other brain areas where information pertinent to attempted walking is likely to be located. Also note that these channels are less prone to motion and electromyogram (EMG) artifacts.

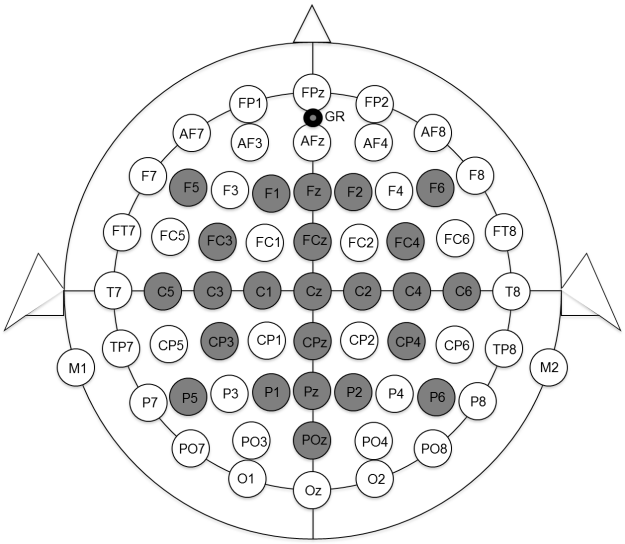

Figure 1: The schematic of a 64-channel EEG cap with electrodes arranged according to the 10–10 International Standard. The subset of channels used in the study is shown in gray.

While seated in a wheelchair, the participant engaged in 30-s-long alternating epochs of attempted walking and idling (relaxation) as guided by textual computerized cues (see Figure 2). EEG data underlying attempted walking and idling epochs were then labeled by an auxiliary signal generated using a secondary data acquisition system (MP150, Biopac, Goleta, CA). NeXus-32 and MP150 systems were synchronized using a common pulse train. The participant was instructed to remain still during the entire procedure, and his movement was monitored by the experimenter. If overt movements were observed, the entire training procedure was repeated.

Calibration

Similar to our previous studies [2–4], the real-time BCI system was implemented as a binary state machine (see Fig. 3), which is governed by comparing the temporally averaged posterior probabilities $\bar{P}(\mathcal{S}_1|f^\star)$ and $\bar{P}(\mathcal{S}_2|f^\star)$ to state transition thresholds, T_I and T_W. To reduce erroneous state transitions during real-time, online operation, the values of T_I and T_W were determined through a short calibration procedure. Briefly, the BCI was set to run in the online mode (with the VRE turned off) while the participant alternated between idling and attempted walking for ∼5 min, as prompted by verbal cues from the experimenter. The underlying EEG data were analyzed offline as explained in the main text, and the average posterior probabilities were calculated. Initially, the thresholds were set as $T_I = \text{median}\{P(S_2|f^\star \in S_1)\}$ and $T_W = \text{median}\{P(S_2|f^\star \in S_2)\}$. Note that this procedure is likely to yield T_I and T_W such that $T_I < T_W$. Also note that this asymmetric threshold structure reduces the participant's mental workload [2]. Finally, the values of T_I and T_W were fine-tuned in a brief familiarization session.

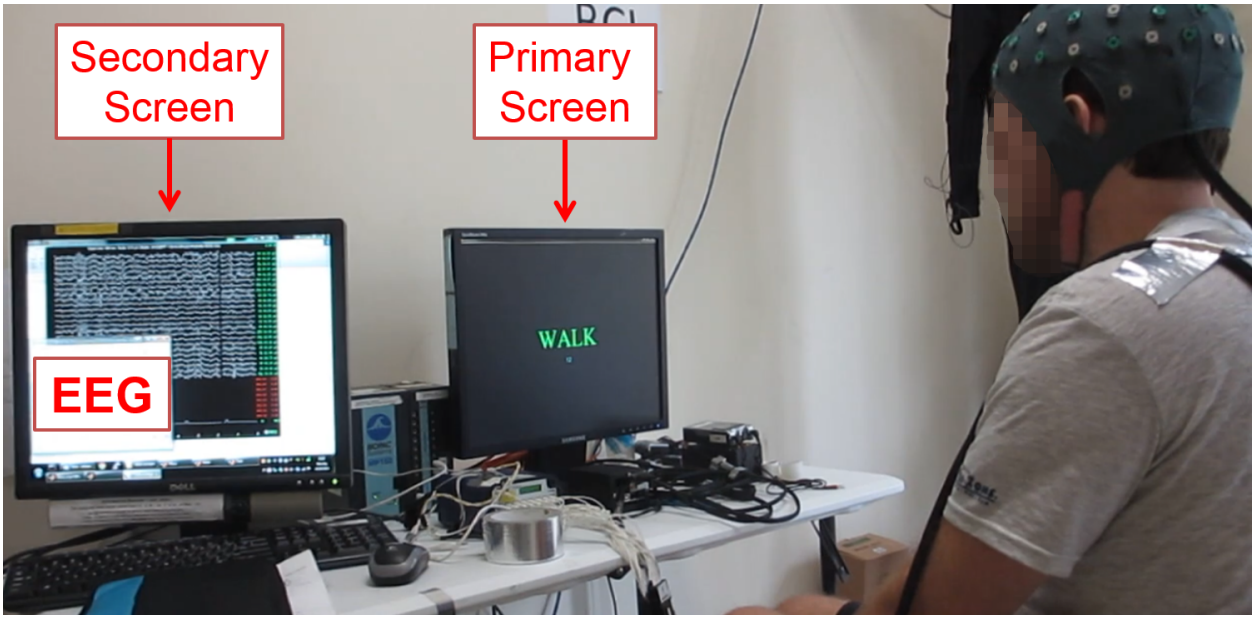

Figure 2: The participant undergoing the BCI training procedure performs attempted walking and idling in response to computer cues shown on the primary screen. Note that the secondary screen (used by the experimenter) was angled such that the participant could not be distracted by it. Also note that the participant's face was scrambled to protect his privacy.

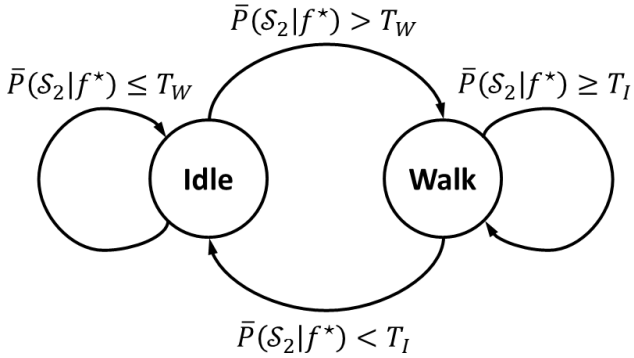

Figure 3: A state machine with the idle and walk states, and state transition rules defined by comparing the average posterior probability of walking, $\bar{P}(\mathcal{S}_2|f^\star)$, to T_I and T_W. For example, if the system is in the idle state and $\bar{P}(\mathcal{S}_2|f^\star) > T_W$, the system transitions to the walk state. Note that since $\bar{P}(\mathcal{S}_1|f^\star) = 1 - \bar{P}(\mathcal{S}_2|f^\star)$, the state transition rules can be expressed as a function of $\bar{P}(\mathcal{S}_2|f^\star)$ only.

Performance Assessment

Since BCI-VRE tasks were performed without externally supplied cues, the ground truth was not known, and therefore the participant's online performances were assessed using the stop score and course completion time [1–3]. To ascertain whether these performances were purposeful, they were compared to the results of Monte Carlo experiments. More specifically, the task was simulated by randomly drawing posterior probabilities and feeding them into the state machine described in the previous section. For this purpose, the threshold values, T_I and T_W, matched those used in the online BCI-VRE tasks. This resulted in a randomly generated sequence of Idle and Walk states, from which the stop score and completion time were calculated. The above procedure was repeated for a total of 1,000 simulation runs, and from these simulated performances, a 2D probability density function (PDF) was estimated using the Parzen window method [5]. Through the subject's online performance point, defined by a successful stop and completion time pair, an iso-PDF contour was drawn. The volume under the PDF outside of this contour was then found by numerical integration, which effectively defines the p-value of the following null hypothesis: "the subject's performance is not different from that of random walk." A performance was deemed purposeful if the empirical p-value of the corresponding Monte Carlo simulation was <0.01.

1.4 FES Training

The participant performed strength and endurance training of his lower extremity muscles, with the goal of being able to bear ∼85% of his body weight in an upright position. These exercises were performed both on site, with the assistance of a physical therapist, and at home. To accomplish this goal, the participant first performed knee extension exercises by having FES applied to his quadriceps. The exercise was repeated with a gradually increasing resistance, which was achieved by attaching ankle weights. Once the participant was able to fully extend the leg with ankle weights equivalent to 10% of his body weight, the strengthening exercise transitioned to FES-mediated standing. These procedures were performed with the help of the physical therapist. To maintain quadriceps strength and endurance, the participant performed daily at-home FES exercises. These consisted of repetitive 10–15-s-long FES-mediated knee extensions while wearing ankle weights. The exercise was terminated after the quadriceps fatigued. In addition, the participant performed FES-mediated foot dorsiflexion exercises for 10–15 s, and repeated this procedure until his tibialis anterior muscles fatigued.

Upon completing the strengthening exercise, the overground gait training began. Its focus was on learning the specific coordination of movements that are necessary for FES-mediated standing and walking. This included mastering the following actions:

1. Standing posture: ability to use FES to stand up from a sitting position, and maintain a proper anterior-posterior/left-right alignment while standing.

2. Weight-bearing support: FES-mediated standing with ∼85% of body weight supported by the legs and ∼15% supported by the arms through the front-wheel walker.

3. Weight transfer: ability to shift body weight in the anterior-posterior direction for advancement and ability to shift body weight to the supporting leg.

4. Stepping: the ability to perform FES-mediated toe off, swing through, and heel strike.

5. Front-wheel walker management: proper placement of the walker during both standing and walking in order to facilitate upper body stability and advancement.

1.5 BCI-FES Integration and Motion Sensor Development

To determine the participant's intention, the wirelessly acquired EEG data (see Section 1.3) were analyzed in real time by the BCI computer, which executed the EEG decoding model from the latest BCI training session. These decisions were then sent to a microcontroller unit (MCU, Arduino, SmartProjects, Turin, Italy) via wireless communication (Bluetooth Mate Silver, Sparkfun Electronics, Boulder, CO). Using digital relays (Relay shield V2.0, Seeed Technology Inc., Shenzhen, China), the MCU was interfaced with the "left step," "right step" and "stand" switches of the Parastep system. Finally, a custom C++ program was uploaded to the MCU to execute an automatic, cyclic stepping pattern in order to induce walking at the

pace determined in the FES training sessions. It should be noted that the MCU only executed these stepping commands when the Walk state was decoded. When the Idle state was decoded, the MCU activated the digital relays responsible for the standing function.

A motion sensor system was developed to facilitate the real-time performance assessment of the BCI-FES system. To accomplish this, two gyroscopes (L3G4200D, STMicroelectronics, Geneva, Switzerland) and a laser distance meter (411D Laser Distance Meter, Fluke Corporation, Everett, WA) with a custom digitizer (LR3 Laser Rangefinder Interface, Porcupine Electronics LLC., Cedar Park, TX), were integrated with a secondary Arduino MCU. An auxiliary signal was generated by this MCU and sent to NeXus-32 in order to synchronize the EEG and motion sensor data for subsequent analyses. The MCU also transmitted gyroscope, laser, and synchronization data to the BCI computer in real time via a Bluetooth communication protocol (Bluetooth Mate Silver). For convenience, the MCUs, NeXus-32, and Parastep's Battery Pack and Stimulator Unit, were placed in a backpack/belt-pack worn by the subject (see Fig. 2 in the main text), while the distance meter was mounted on the trolley of a body-weight support system (ZeroG, Aretech LLC, Ashburn, VA).

1.6 BCI-FES Performance Assessment

Suspended Walking

The performances achieved in suspended walking tests were evaluated by performing cross-correlation and information transfer rate (ITR) analyses on the aligned BCI, motion sensor, and video data. The cross-correlation between the computer cues (representing the ground truth) and BCI-FES-mediated walking/idling was calculated for a range of latencies (lags), and the maximal temporal correlation, ρ, and optimal lag were determined. In addition, false alarm and omission rates, as well as the duration of these errors, were calculated. A false alarm was defined as the initiation of a BCI-mediated walking response within an intended idling epoch. Conversely, an omission was defined as the absence of a BCI-mediated walking response when the intention was to walk. Finally, the ITR (bit/s) was calculated as [6]:

$$\mathrm{ITR} = B\,\mathcal{I}(\mathrm{D},\mathrm{T}) \tag{1}$$

where B is the number of decisions per unit of time (4/s in this study) and $\mathcal{I}(\mathrm{D},\mathrm{T})$ is the mutual information between the true state of the nature, T, as determined by the computer cue, and the state, D, decoded by the computer. Note that the variable T has been lagged according to the value found in the cross-correlation analysis. The mutual information was found as:

$$\mathcal{I}(\mathrm{D},\mathrm{T}) = H(\mathrm{D}) - H(\mathrm{D}\,|\,\mathrm{T}) \tag{2}$$

where $H(\mathrm{D})$ is the entropy of the decoded variable and $H(\mathrm{D}\,|\,\mathrm{T})$ is the conditional entropy of the decoded variable given the true state of the nature. The first term in (2) can be calculated as:

$$H(\mathrm{D}) = -\left[p(\hat{\mathrm{I}})\log_2 p(\hat{\mathrm{I}}) + p(\hat{\mathrm{W}})\log_2 p(\hat{\mathrm{W}})\right]$$

where $p(\hat{\mathrm{I}})$ and $p(\hat{\mathrm{W}})$ are the probabilities of decoding the Idle and Walk states, respectively. Assuming equal prior probabilities, $p(\mathrm{I}) = p(\mathrm{W}) = 0.5$, we have:

$$p(\hat{\mathrm{I}}) = \frac{1}{2}\left[p(\hat{\mathrm{I}}\,|\,\mathrm{I}) + p(\hat{\mathrm{I}}\,|\,\mathrm{W})\right] \quad \text{and} \quad p(\hat{\mathrm{W}}) = \frac{1}{2}\left[p(\hat{\mathrm{W}}\,|\,\mathrm{I}) + p(\hat{\mathrm{W}}\,|\,\mathrm{W})\right]$$

where $p(\hat{\mathrm{W}}\,|\,\mathrm{I})$ is the probability of a false alarm, $p(\hat{\mathrm{I}}\,|\,\mathrm{W})$ is the probability of an omission, and $p(\hat{\mathrm{I}}\,|\,\mathrm{I})$ and $p(\hat{\mathrm{W}}\,|\,\mathrm{W})$ are the probabilities of correctly decoded Idle and Walk states, respectively. The calculations in (2) can be completed after assuming equal priors and realizing that [6]:

$$H(\mathrm{D}|\mathrm{T}) = \frac{1}{2}\left[H(\mathrm{D}\,|\,\mathrm{T}=\mathrm{I}) + H(\mathrm{D}\,|\,\mathrm{T}=\mathrm{W})\right]$$

where the conditional entropy terms are given by:

$$\begin{aligned} H(\mathrm{D}|\mathrm{T}=\mathrm{I}) &= -\left[p(\hat{\mathrm{I}}\,|\,\mathrm{I})\log_2 p(\hat{\mathrm{I}}\,|\,\mathrm{I}) + p(\hat{\mathrm{W}}\,|\,\mathrm{I})\log_2 p(\hat{\mathrm{W}}\,|\,\mathrm{I})\right] \\ H(\mathrm{D}|\mathrm{T}=\mathrm{W}) &= -\left[p(\hat{\mathrm{I}}\,|\,\mathrm{W})\log_2 p(\hat{\mathrm{I}}\,|\,\mathrm{W}) + p(\hat{\mathrm{W}}\,|\,\mathrm{W})\log_2 p(\hat{\mathrm{W}}\,|\,\mathrm{W})\right] \end{aligned}$$

To ascertain whether the subject's performances in the suspended walking tests were purposeful, Monte Carlo simulations were performed. More specifically, the subject's performance in each suspended BCI-FES walking test was compared to the outcomes of 10,000 Monte Carlo simulation runs, and an empirical p-value was calculated. Similar to [4], each Monte Carlo run used the following auto-regressive model:

$$\begin{aligned} &X_{k+1} = \alpha X_k + \beta W_k \quad X_0 \sim U(0,1) \\ &Y_k = h(X_k) \end{aligned} \tag{3}$$

where X_k is a state variable, $W_k \sim U(0,1)$ is uniform white noise, Y_k is the simulated posterior probability (see defined in Section 1.3), and h is a piecewise linear saturation function that ensures $Y_k \in [0,1]$. The coefficients α and β were then determined so that the mean and lag-one correlation coefficient of the sequence $\{Y_k\}$ match those of the posterior probability sequence, $\{P_k\}$, observed in the online tests, i.e.:

$$\begin{aligned} &\alpha = \rho \\ &\alpha\mu + \tfrac{\beta}{2} = \mu \end{aligned} \tag{4}$$

where μ is the mean of $\{P_k\}$ and ρ is the correlation coefficient between P_{k+1} and P_k. Using these coefficients, the posterior probabilities, $\{Y_k\}$, were simulated according to (3) and supplied to the state machine (see Fig. 3) to generate a random sequence of Idle and Walk states. The maximum cross-correlation between this simulated sequence and the computer cue was then calculated. An empirical p-value was defined as a fraction of Monte Carlo trials whose maximum cross-correlation exceeded that achieved by the participant in the suspended walking test. Control was deemed purposeful if the p-value corresponding to the participant's performance was <0.01.

Overground Walking

Similar to suspended walking tests, the subject's performances in the overground walking tests were assessed by performing cross-correlation and ITR analyses between the verbal cues (as recorded by the video data) and the BCI-FES response (estimated based on the gyroscope data). In addition, false alarm and omission rates were calculated. To ascertain whether the subject had purposeful control, 10,000 Monte Carlo simulation runs were generated according to the procedure described above, with verbal cues used as the ground truth. Control was deemed purposeful if the p-value corresponding to the participant's performance was <0.01.

2 Additional Results

2.1 Salient Brain Areas and Frequencies for Classification

The EEG decoding models generated on each visit revealed which spatio-spectral EEG features were salient for distinguishing between idling and walking states. Figures 4 through 9 show the spatial distribution of these features centered at 11 Hz, 15 Hz, 19 Hz, and 25 Hz. The features varied across days, being relatively subtle in the first few visits, and gaining more consistency toward the end of the study. This is especially true for features centered in the low-β (15 Hz) and high-β (25 Hz) bands. In addition, their distribution was mostly confined to the motor and somatosensory brain areas (near electrodes CP3, CPz, and CP4). This is consistent with prior studies [7,8], where in response to motor imagery associated with walking, a bilaterally distributed ERS was observed together with a centrally distributed ERD in both the μ and β-bands. Finally, note that the temporal evolution of the salient feature distribution was concomitant with the improvement of the classification accuracies (Figure 4 in the main text). These may have been caused by reactivation of supraspinal gait control areas [9].

2.2 ERD/ERS and Signal-to-Noise Ratio During BCI Training

The salient spatio-spectral features for classification (Figures 4 through 9) were validated by confirming the presence of EEG power modulation due to attempted walking and idling over the μ (8–12 Hz), low-β (13–20 Hz), and high-β (20–30 Hz) bands (Figure 10). In addition, this figure shows the distribution of the signal-to-noise ratio (SNR) defined as:

$$\mathrm{SNR}(f) = \frac{\left(\mu_I(f) - \mu_W(f)\right)^2}{0.5\left(\sigma_I^2(f) + \sigma_W^2(f)\right)} \qquad f \in [0,\, 30]\,\mathrm{Hz} \tag{5}$$

where $\mu_I(f)$ and $\mu_W(f)$ are the mean power spectra of EEG under idling and walking conditions, respectively, and $\sigma_I^2(f)$ and $\sigma_W^2(f)$ are their respective variances. For each electrode, the PSDs underlying idling and walking were compared across frequencies (0–30 Hz) using a Mann-Whitney U test, in order to identify areas and frequencies with significant SNRs ($p<0.01$). Note that the distribution of significant SNRs (Figure 10) is consistent with the distribution of salient spatio-spectral features in Figure 9.

2.3 BCI-FES Overground Walking Experiments

Figure 11 shows that the number of BCI-FES-mediated overground walking tests performed at each experiment day generally increased over time. The participant started with a single BCI-FES overground walking test (visit 20), and performed as many as six walking tests by the end of the study.

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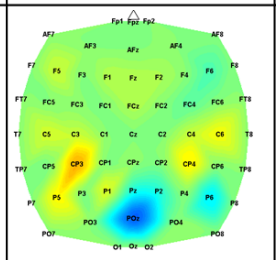
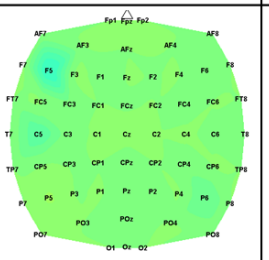
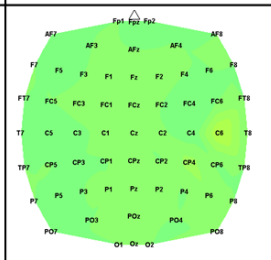
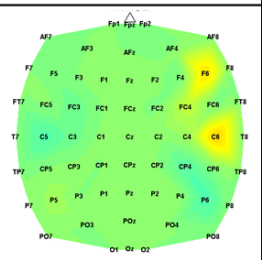
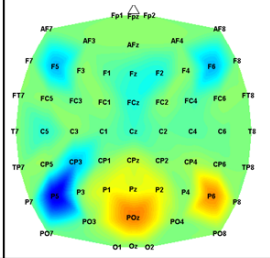
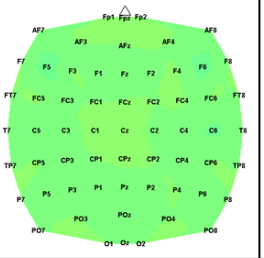
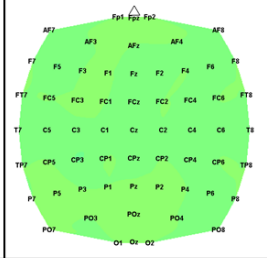
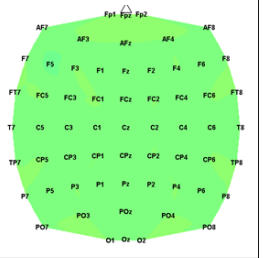
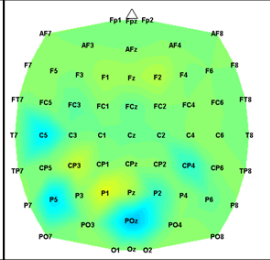
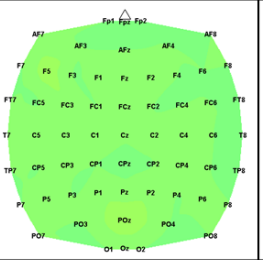
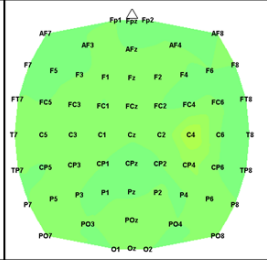
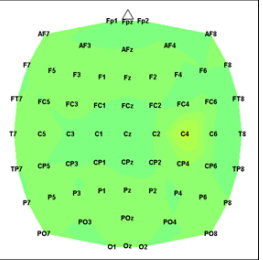
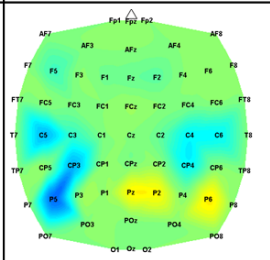
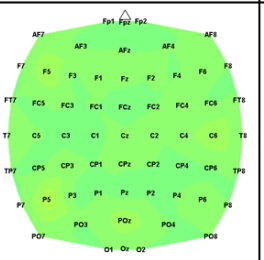
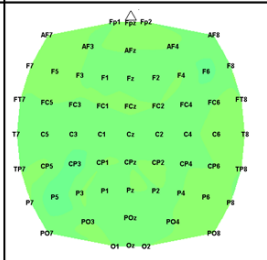
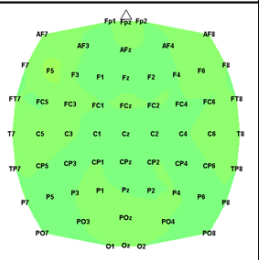
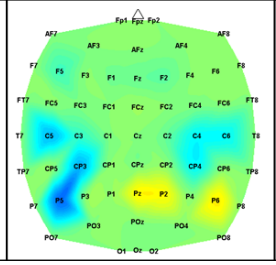
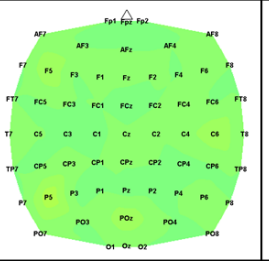
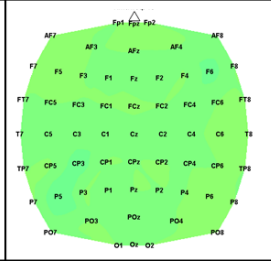
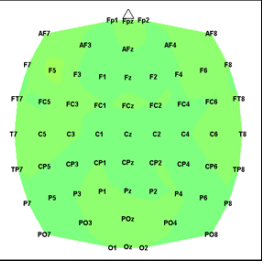
2013-06-25	1				
2013-06-27	2				
2013-07-09	3				
2013-07-11	4				
2013-07-11	5				

Figure 4: Topographic distribution of the feature extraction maps (Eq. 1 in the main text) over the 11 Hz, 15 Hz, 19 Hz, and 25 Hz frequency bins for visits 1–5. The maps were optimized for the classification of the idle and walk states. Dark red and dark blue colors represent the brain areas that were most important for classification over that particular frequency band.

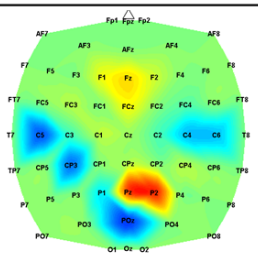
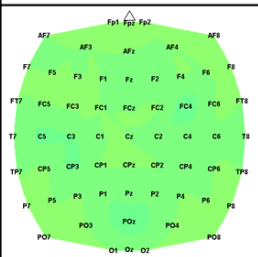
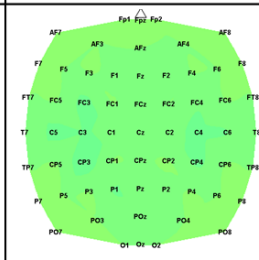
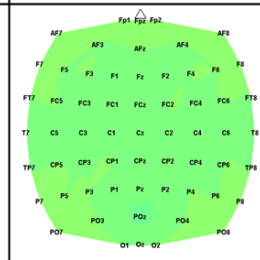
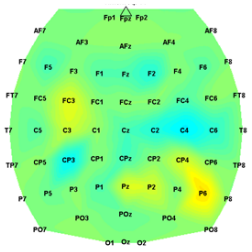
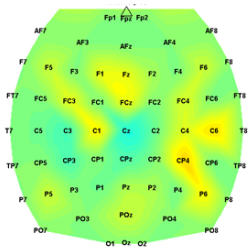
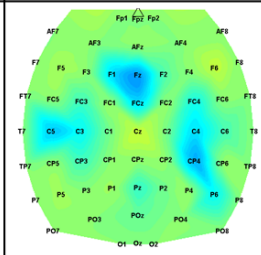
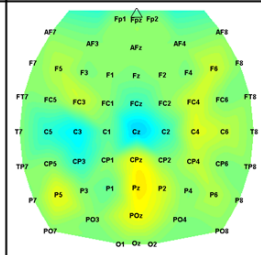
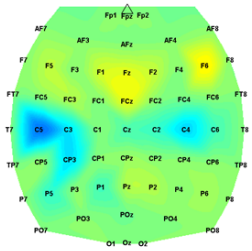
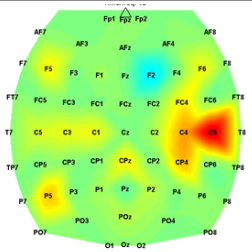
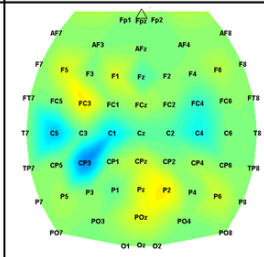
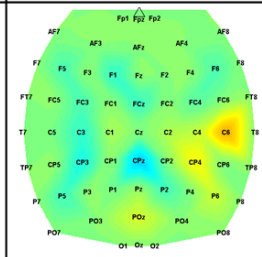
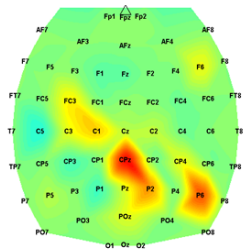
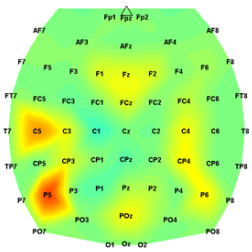
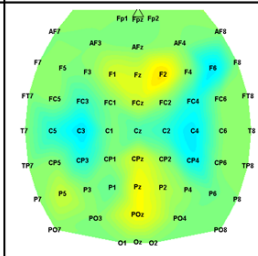
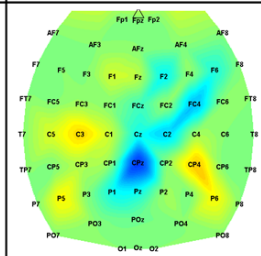
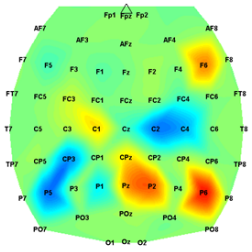
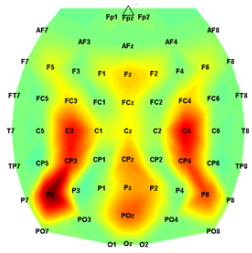
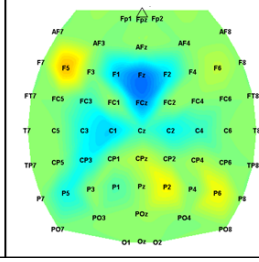
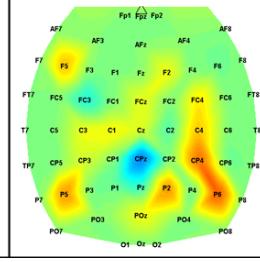
Date	Day	11 Hz	15 Hz	19 Hz	25 Hz
2013-07-18	6				
2013-07-30	8				
2013-08-01	9				
2013-08-06	10				
2013-08-13	11				

Figure 5: An equivalent figure for visits 6–11.

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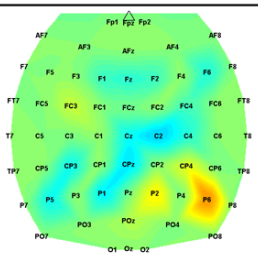
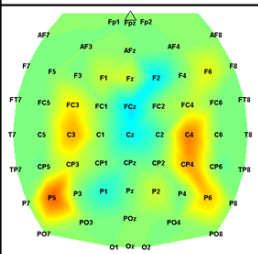
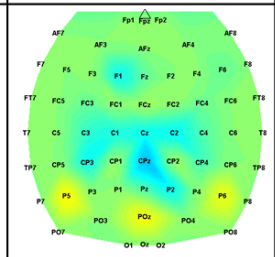
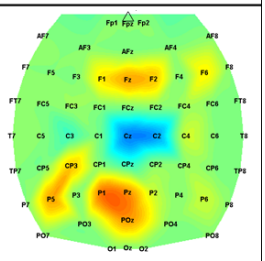
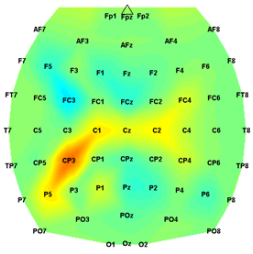
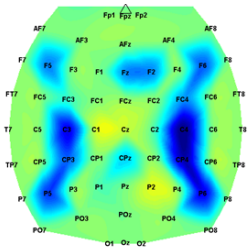
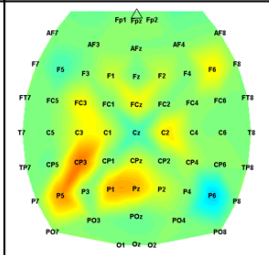
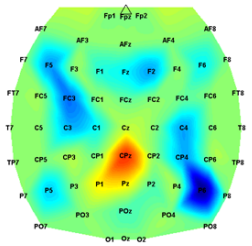
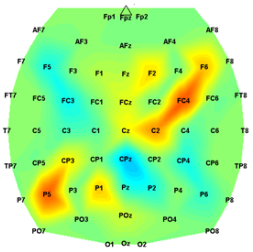
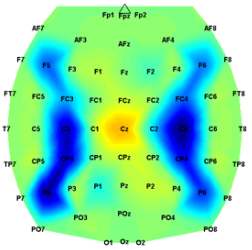
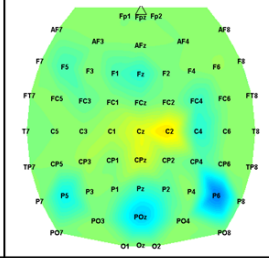
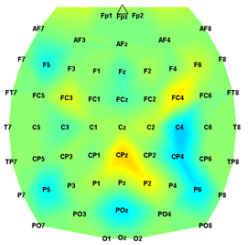
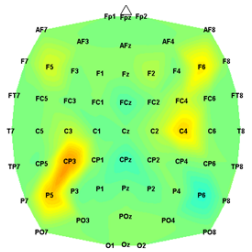
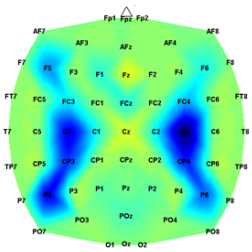
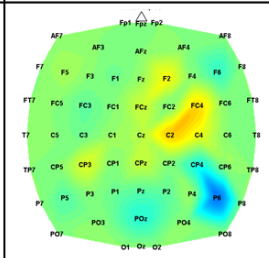
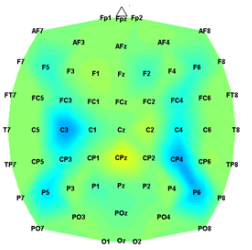
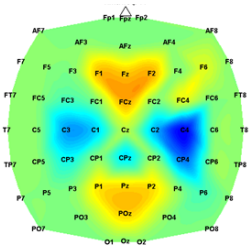
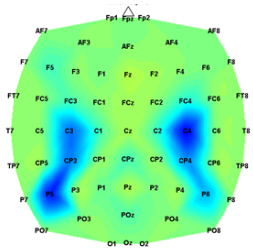
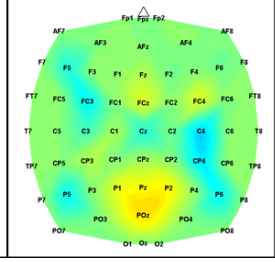
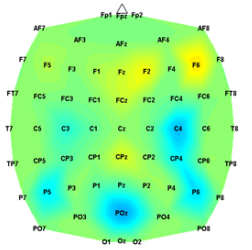
2013-08-15	12				
2013-08-20	13				
2013-08-22	14				
2013-09-07	15				
2013-09-14	16				

Figure 6: An equivalent figure for visits 12–16.

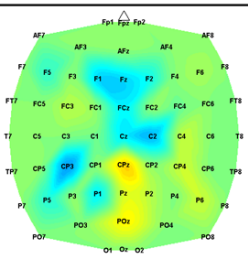
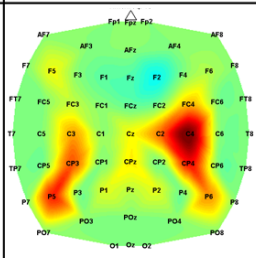
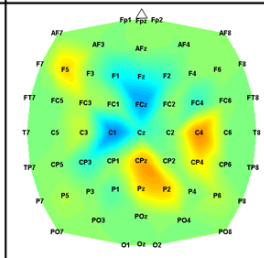
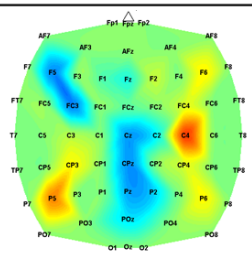
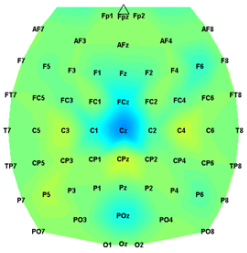
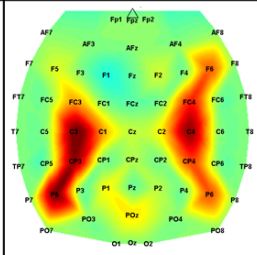
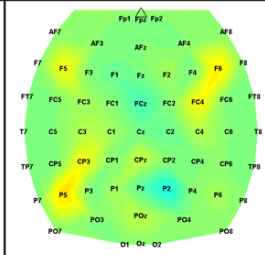
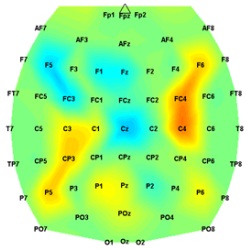
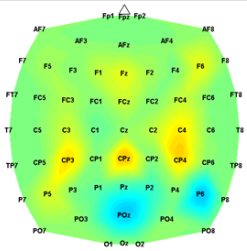
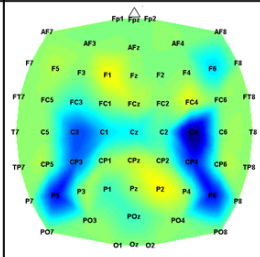
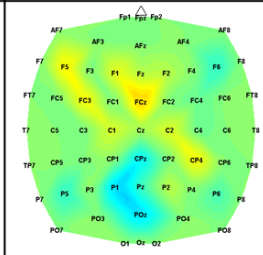
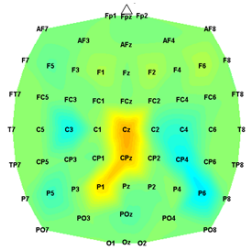
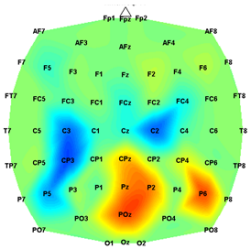
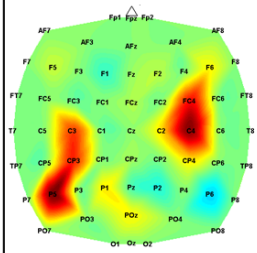
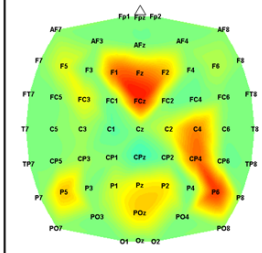
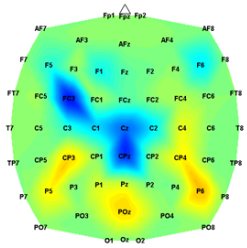
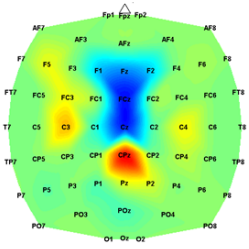
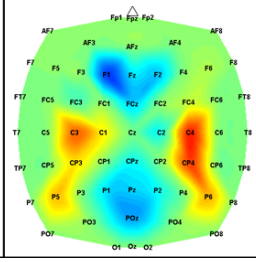
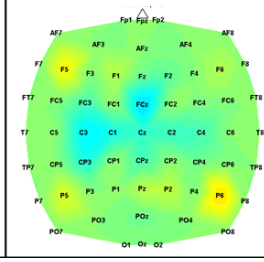
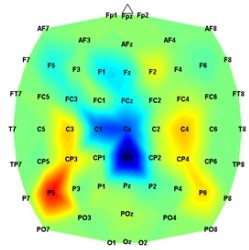
Date	Day	11 Hz	15 Hz	19 Hz	25 Hz
2013-09-28	17				
2013-10-19	19				
2013-10-26	20				
2014-01-10	23				
2013-01-18	24				

Figure 7: An equivalent figure for visits 17–24.

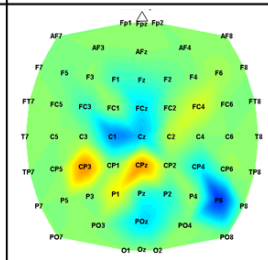
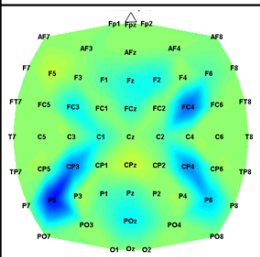
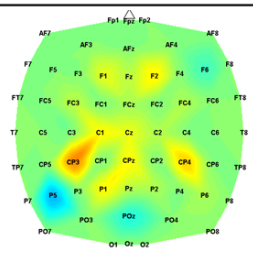
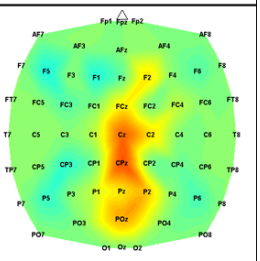
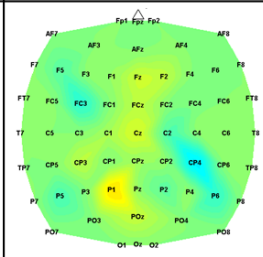
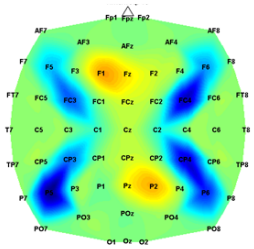
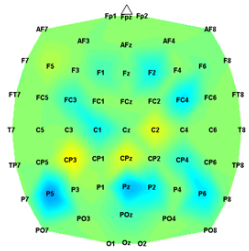
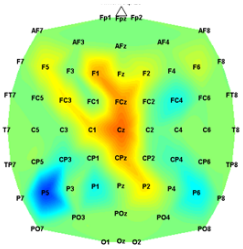
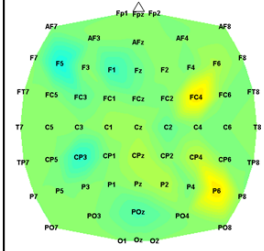
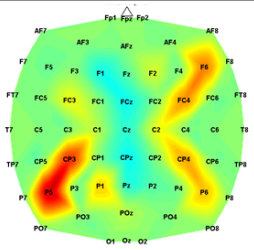
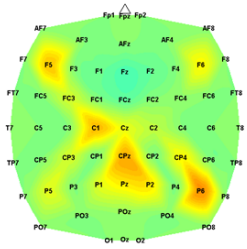
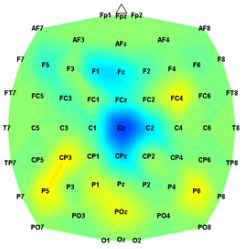
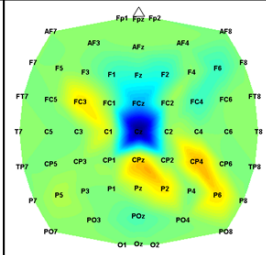
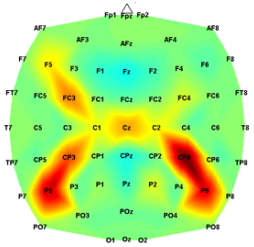
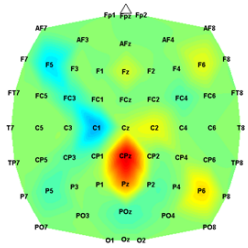
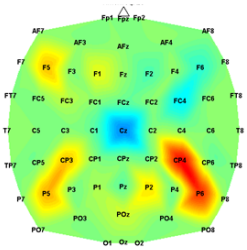
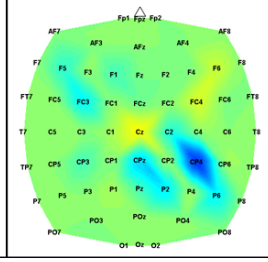
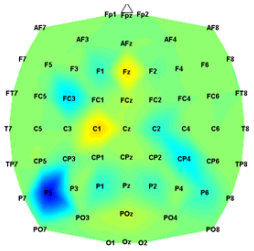
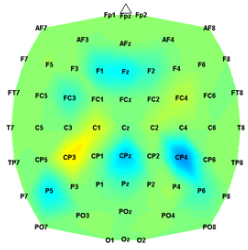
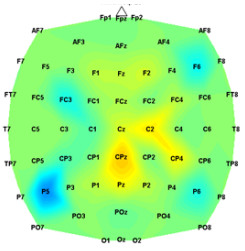
Date	Day	11 Hz	15 Hz	19 Hz	25 Hz
2014-01-24	25				
2014-02-01	26				
2014-02-07	27				
2014-02-15	28				
2014-02-21	29				

Figure 8: An equivalent figure for visits 25–29.

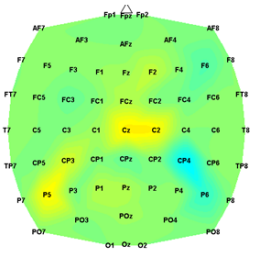
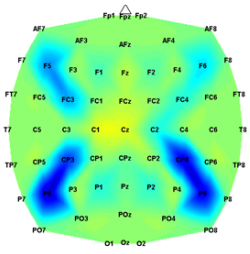
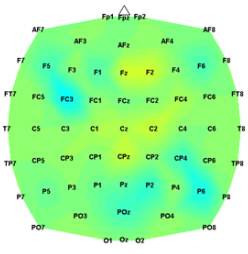
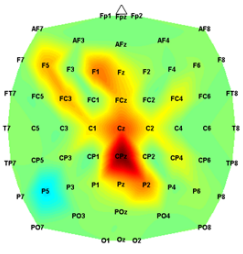
Date	Day	11 Hz	15 Hz	19 Hz	25 Hz
2014-03-07	30				

Figure 9: An equivalent figure for visit 30 (last visit).

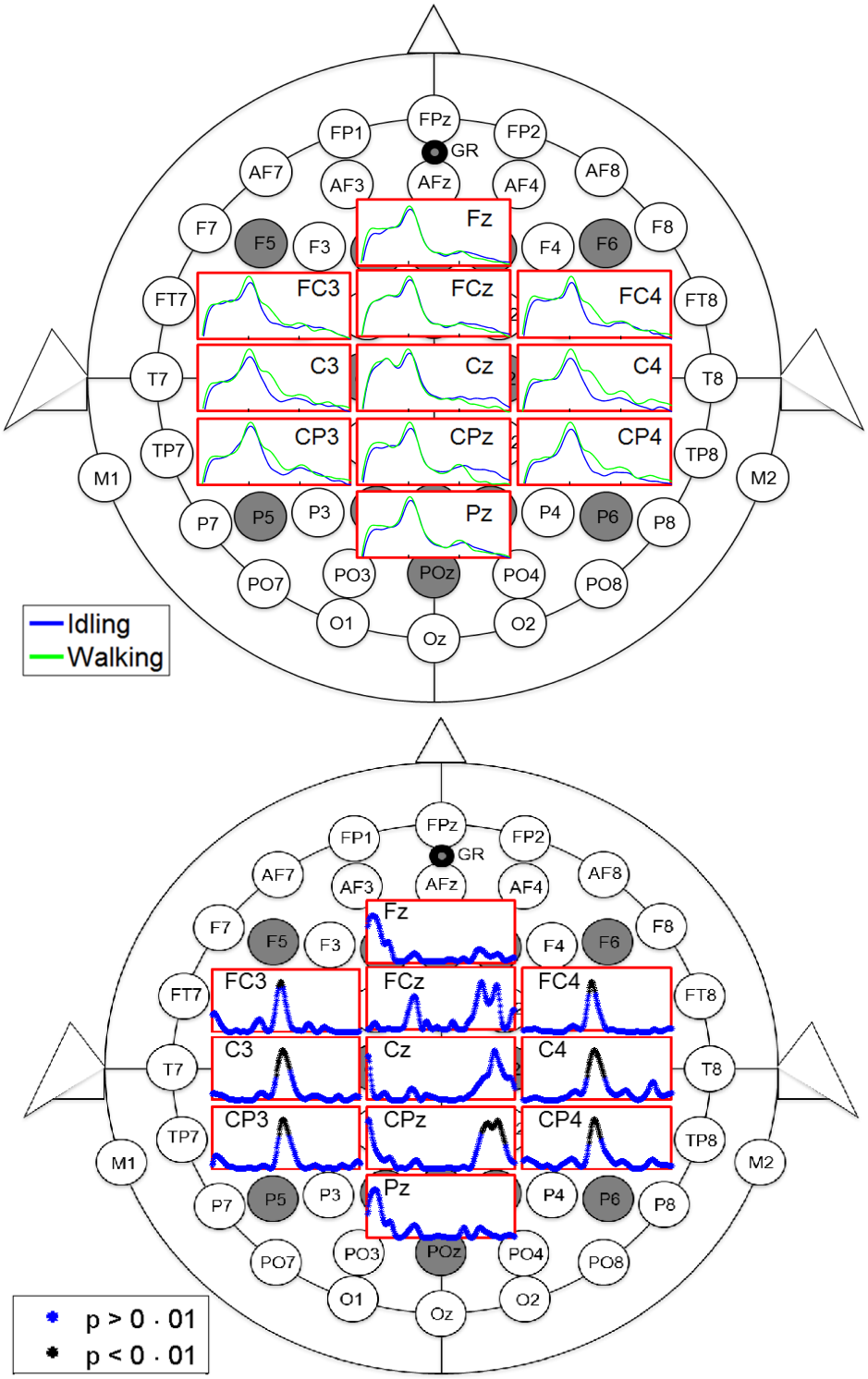


Figure 10: Top: The logarithm of PSDs across frequencies (0–30 Hz, tick marks 10 Hz apart) and electrodes (Fz, FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4, Pz) during BCI operation on the final experimental day. Note the prominent bilateral ERS in the low-β band ($\sim$15 Hz) and central ERD in the high-β band ($\sim$25 Hz) during attempted walking. Bottom: The corresponding distribution of SNR across the same frequencies and electrodes during BCI operation. Note the significant SNR ($p<0.01$) in the low-β band (15 Hz) over electrodes FC3, FC4, C3, C4, CP3, and CP4, and high-β band (25 Hz) over electrode CPz.

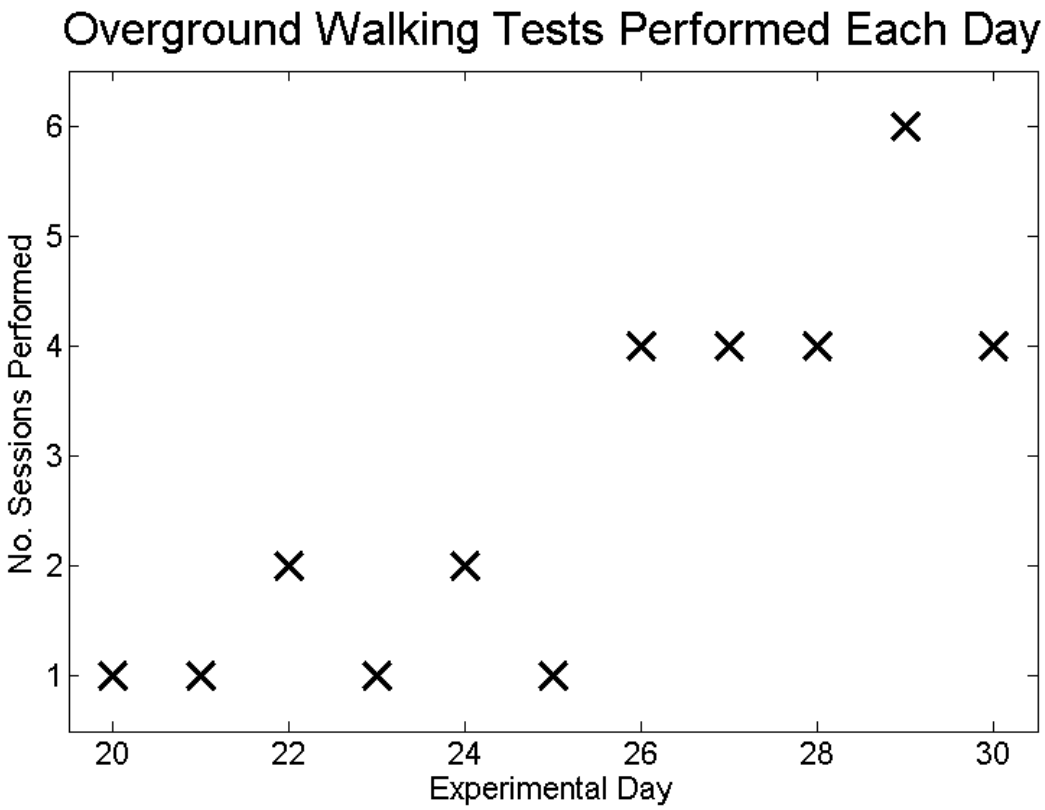


Figure 11: Number of overground walking tests performed on each visit.