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EEG differentiates left and right imagined Lower Limb movement

Adrienne Kline [a,*], Calin Gaina Ghiroaga [b], Daniel Pittman [c], Bradley Goodyear [c], Janet Ronsky [b]

[a] Department of Biomedical Engineering, University of Calgary, Calgary, Alberta Canada
[b] Department of Mechanical and Manufacturing Engineering, University of Calgary, Calgary, Alberta, Canada
[c] Department of Radiology, University of Calgary, Alberta, Canada

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ABSTRACT

Background: Identifying which EEG signals distinguish left from right leg movements in imagined lower limb movement is crucial to building an effective and efficient brain-computer interface (BCI). Past findings on this issue have been mixed, partly due to the difficulty in collecting and isolating the relevant information. The purpose of this study was to contribute to this new and important literature.

Research Question: Can left versus right imagined stepping be differentiated using the alpha, beta, and gamma frequencies of EEG data at four electrodes (C1, C2, PO3, and PO4)?

Methods: An experiment was conducted with a sample of 16 healthy male participants. They imagined left and right lower limb movements across 60 trials at two time periods separated by one week. Participants were fitted with a 64-electrode headcap, lay supine on a specially designed device and then completed the imagined task while observing a customized computer-generated image of a human walking to signify the left and right steps, respectively.

Results: Findings showed that eight of the twelve frequency bands from 4 EEG electrodes were significant in differentiating imagined left from right lower limb movement. Using these data points, a neural network analysis resulted in an overall participant average test classification accuracy of left versus right movements at 63 %.

Significance: Our study provides support for using the alpha, beta and gamma frequency bands at the sensorimotor areas (C1 and C2 electrodes) and incorporating information from the parietal/occipital lobes (PO3 and PO4 electrodes) for focused, real-time EEG signal processing to assist in creating a BCI for those with lower limb compromised mobility.

1. Introduction

The development of brain computer interfaces (BCIs) that assist those with compromised lower limb mobility has been slower to emerge relative to upper limb devices. A lower limb BCI depends on being able to efficiently focus on the most relevant brain activity that differentiates left from right cortical signatures of imagined lower limb movement. The use of EEG signals for such signatures is preferred for BCI development due to the portability and non-invasiveness of EEG devices and the speed with which signals can be fed forward. However, isolating which of the EEG signals is useful in differentiating lower limb left from right movement has been problematic [1–3].

Research on the sensorimotor and cognitive nerological processes associated with such movements has been held back due, in part, to the difficulties associated with acquiring brain signals during locomotion [4]. Limitations in using EEG to study lower limb neural activity include that: 1) EEG data do not possess the spatial resolution necessary to accurately localize or resolve activity to single gyrus or sulcus; and 2) because EEG cannot accurately probe the activity of subcortical brain regions, data are based primarily from activity located near the surface of the skull, within the first centimeter of brain tissue [5]. This is of unique concern for accurate assessment of lower limb motor activity because the leg area of motor cortex is deeply (1−4 cm) and medially located, as well as being vertical in its orientation [6]. It is particularly difficult to distinguish left and right leg movements due to the minor spatial distance between the left and right hemispheres of motor cortex for lower limb areas [5]. The purpose of the present study is to add to the literature that differentiates imagined lower limb left/right movement by using a specially designed device and unique human-like visual stimulus to improve the accuracy of left and right lower limb differentiation via EEG signals.

Imagined movements have a similar cortical signature to that of

* Corresponding author.
E-mail address: akline@ucalgary.ca (A. Kline).

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executed movements [7–12], and is based on the notion of a mirroring motor system. Mirror neurons (visuomotor neurons) discharge not only when an individual performs an action, but also when observing the same behavior in another individual. Thus, executed lower limb movement research that has used EEG signals for left/right differentiation can help to inform those of imagined lower limb movement. Such studies have demonstrated that many cortical areas (e.g., anterior cingulate cortex, dorsal anterior cingulate cortex, posterior parietal lobe, sensorimotor cortex) are involved in the gait cycle [13] and that primary motor, premotor, supplementary motor, cingulate, primary somatosensory and somatosensory association cortices are involved in lower limb movement [5].

This research leads to the conclusion that electrodes in proximity to the leg area of sensorimotor motor cortex should be important in lower limb movement [5,13,14]. Thus, electrodes C1 and C2 that are located centrally on top of the head (just left (C1) and right (C2) of the major sagittal fissure) were selected for use in this study. Given the extant research into the cortical areas that are activated during motor imagery using EEG and functional magnetic resonance imaging (fMRI), it is likely that a visual stimulus like the one used in this study will result in activation of the occipital and parietal lobes [15–17]. Thus, electrodes PO3 and PO4 that are located on back of the head (just left (PO3) and right (PO4) of the major sagittal fissure) were also selected for use in this study.

Because they are linked to awake, active thinking and fluctuate the most during external stimuli [18], EEG alpha and beta frequency bands have been commonly used in brain computer interface studies due to their importance in sensorimotor activity [19]. Additional studies have suggested that the gamma band may also be involved in robotoc assisted walking [20,21]. Thus, the three EEG frequency bands that are most likely to be associated with lower limb locomotion were used in this study: alpha, beta. and gamma [22,23].

1.1. Research question

The research question posed in this study was: Can left versus right imagined stepping be differentiated using the alpha, beta, and gamma frequencies of EEG data at four electrodes (C1, C2, PO3, and PO4)?

2. Methods

2.1. Participants

Sixteen healthy, right-handed males between the ages of 19 and 31 years of age (mean = 24.7, SD = 3.31), with no history of knee or hip injuries nor reported neurological deficiencies participated in the study.

2.2. Materials and procedure

The protocol for this study was approved by the University of Calgary's Conjoint Health Research Ethics Board (Ethics ID: REB15-1473). All participants were provided written informed consent prior to taking part in the study. Participants took part in two sessions (with a one week interval) conducted at the Clinical Movement Assessment Lab (Foothills, HRIC3C48A). Data were collected at two separate sessions to allow for an assessment of the reliability of the data over time. If the reliability is sufficient, then averaging the data over the two sessions will provide a more robust measure than that collected at a single session [24,25].

Participants were fitted with a 64-electrode EEG headcap (Compumedics Neuroscan, Charlotte, SC) with an additional pair of electrodes integrated for the acquisition of electrooculogram (EOG). The location of electrodes followed the conventional 10–20 electrode international placement system. Prior to data collection electrodes were checked to ensure that impedance levels were appropriate (< 5kΩ) for all 64 electrodes, so no channels warranted being 'dropped'. EEG data were collected continuously during the tasks at a rate of 1 kHz.

Both executed and imagined movement tasks were carried out at each session. Participants first performed executed lower limb movements while on a specially designed device that allowed for controlled lower leg flexion/extension movement (hip, knee and ankle) while the participant was in a supine position. A backboard made of pine was used as the base of the device on which participants lay in a supine position. Several slits on the top half of the board allowed restraint straps to be fed through the backboard. These straps crisscrossed the body and went around the abdomen to limit chest movement, which, in turn, minimized head motion. Handholds allowed participants to brace themselves further against any other torso movement. The force of gravity while stepping was simulated by strapping the participant's feet to pedals that slid in a near frictionless track that were connected to pulleys to which participant-specific weights were attached. Weight was based on leg segment mass (thigh and shank) and was calculated as 17 % of total mass as per anthropometric data for normal individuals [26].

To ensure that participants would be properly practiced with and prepared to imagine the lower limb action, response button pads were incorporated into the design to record the timing of the participant's lower limb executed movement at the distal end of the device (Lumina LS-PAIR, Cedrus Corp., San Pedro, CA). Participants alternated between flexion and extension of the knee joint when completing the executed task. Upon flexion, the foot pedal slid past a spring-loaded depressor, releasing the response button. When the participant extended their leg back down to the neutral position, it pressed the spring-loaded mechanism back into place depressing the response button. This design provided left versus right time stamps in the executed EEG data collected. Fig. 1 shows the apparatus.

In the executed practice condition, participants first flexed their left leg upward, then extended it completely, followed by flexing their right leg upward and then lowering it completely before starting the cycle again. This was done to stimulate areas of cortical activity associated only with lower limb movement rather than other motoric tasks involved in the walking task, such as balancing and weight shifting. Practice with executing the task first is consistent with the protocol of other studies of imagined lower limb movement [27,28]. After completing the executed lower limb movement task, they moved on to complete the imagined movement task.

A video stimulus was projected onto the screen using a TV monitor and reflected to an adjustable mirror above the participant's head so that the participant could easily view the stimuli without having to look up or down. The participant was positioned so that the mirrored video display could be viewed with their head comfortably immobilized using compressible foam cushions. The visual stimulus was a custom computer-generated image (CGI) of a human walking generated in *Daz 3D* (Daz Productions Inc., Salt Lake City, Utah, U.S.). The stimulus was presented in a 'block' format, alternating between rest and task blocks. A stationary fixation cross was presented during the rest block and lasted 18 s, during which time participants were instructed to breathe and blink normally while maintaining visual focus on the fixation cross. A task block consisted of an 18-second display of a continuous video of the CGI stepping smoothly left and right, with the step times lasting 1.5 s each. This allowed for 12 steps per block (6 left and 6 right). In total there were 10 blocks each rest (fixation cross alone) and task (CGI presentation). Thus, there were 120 steps in total taken by each participant during the imagined CGI task. The length of visual stimuli presentation remained the same at both sessions.

While executing the lower limb movements, participants were instructed to follow along in time with the visual stimulus. After completing the executed the task, participants completed the imagined task using the same visual stimulus and apparatus. Participants were instructed to observe the stimulus and imagine the feeling of moving their legs (kinesthetic visualization) as they had in the executed task while keeping in time to the motion of the stimulus. Because the figure in the stimulus is shown from the back, the left leg movement corresponds to an imagined left leg movement, and similarly for the right leg

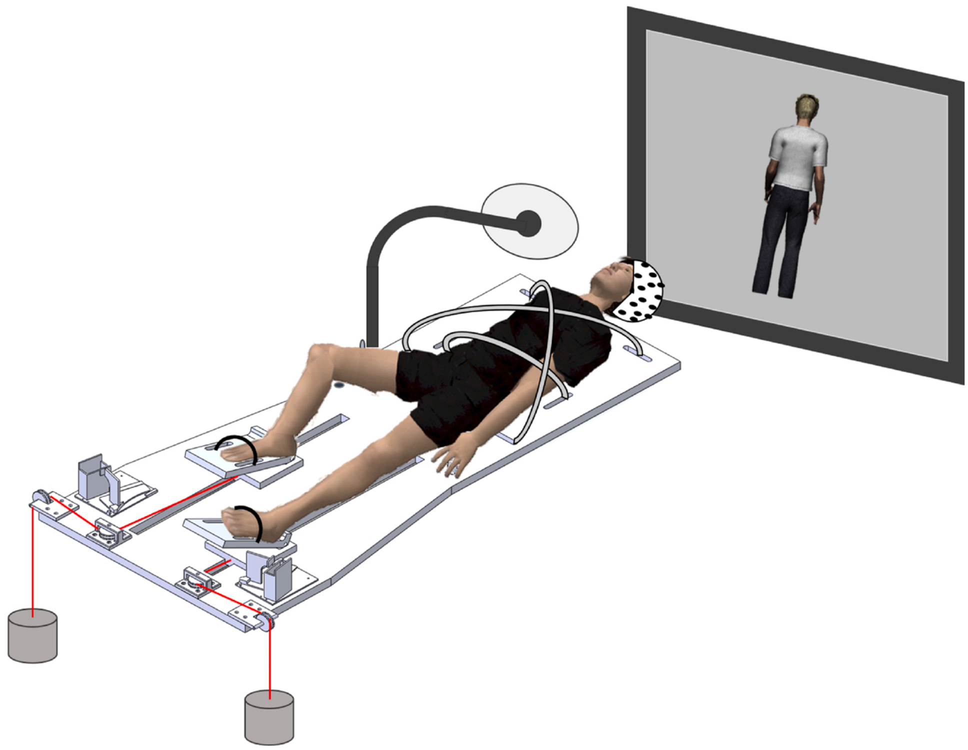

Fig. 1. Apparatus to collect EEG data during supine lower limb executed locomotion. Participants used an adjustable mirror to view the visual stimulus presented behind them on a television screen.

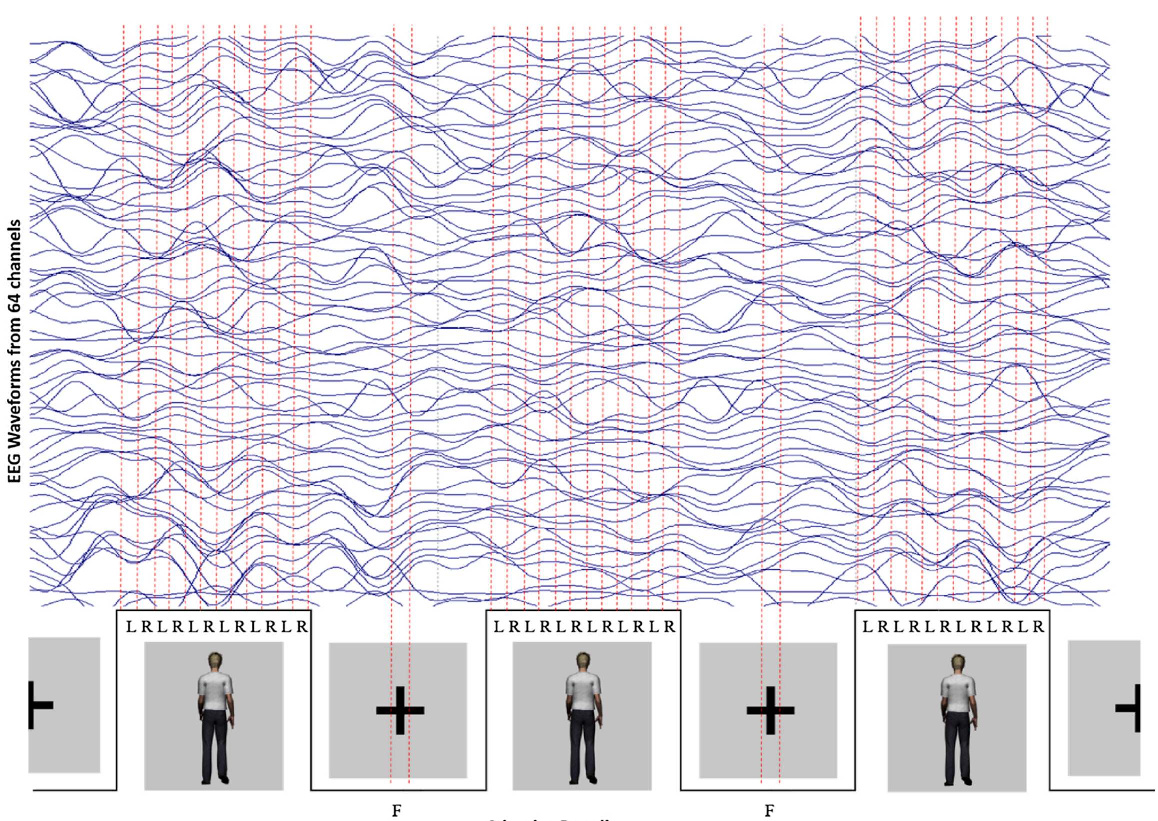

Fig. 2. Visual representation of epoching left (L) and right (R) stepping and the baseline fixation cross (F) condition that occurred within the software on a per channel basis.

movement. A forward facing or side view of the figure would not allow for direct left to left and right to right correspondence in the imaging.

Participants were provided a 5-minute familiarization period to practice the executed and imagined tasks prior to data collection. Total time for each of the sessions was about 30 min. All data were collected between May and October 2017.

2.3. EEG data preparation

EEG data from the C1, C2, PO3 and PO4 electrodes were analyzed using customized software developed in *Matlab* (Mathworks, Natick, MA). Data were DC offset corrected. To eliminate the effect of eye blinks the EOG channel was used to track blinking. To remove noise associated with blinking this channel underwent thresholding to 'mark' them – creating time stamps in the time series. Sections that were 100 ms on either side of the voltage peak were examined individually, and those that were erroneous were excluded. Using the remaining blink occurrences a waveform filter was developed from the average of the remaining blinks and subsequently applied to the dataset. Following this, a 2nd order, 0 phase bandpass filter was applied between 5 and 55 Hz with a roll off −20 dB/decade. These were subsequently referenced to the global average of all 64 channels. Epochs of data were generated based on the timing of the visual stimuli onset/offset for each individual 'step' (200 ms prior to stimulus and 823 ms after stimulus). Because the CGI visual stimulus of left and right steps altered smoothly every 1.5 s, it was important not to include any overlap in the data resulting from the GCI's body posture in the double support phase of the gait cycle in going from the left to the right conditions. Therefore, we selected a window of the centrally located 1.024 s within the alternating 1.5 s durations. This time frame was also computationally efficient for performing a Fourier transform [29]. Fig. 2 shows the visual stimuli, the timing of left and right stepping, and EEG waveforms captured during the experiment.

Once a discrete Fourier transform (DFT) was performed on these 'left', 'right' and 'baseline – fixation cross' epochs, summations of the spectral power over established EEG bands alpha(8−12 Hz), beta (13−30 Hz) and gamma(31−45 Hz) were performed. The frequency resolution within each of the EEG bands was approximately one (0.9765). This was established by dividing the sampling frequency (1 kHz) by the number of samples in each epoch (1024). Left and right spectral data were normalized with respect to the corresponding spectral data during the baseline fixation cross condition (keeping the epoch time constant), by subtracting the average power during this condition. An overview of data processing is outlined in Fig. 3.

Example averaged time series voltage plots for right imagined lower limb movement data (averaged across sessions 1 and 2) for one participant at the C1 and C2 electrodes are presented in Fig. 4.

These transformations resulted in oscillatory power measurements from each of the 1.024 s windows for each participant for each imagined left and right trial at each session. Left and right lower limb imagined motions are distinguished from each other based on the *a priori* knowledge of the step timing of the visual stimulus.

2.4. EEG reliability analyses

Because we wanted to average the data across the two sessions to obtain more robust measurements it was important to determine the reliability over time of those data. Generalizability analysis was used as it assesses reliability across multiple facets, and we had three: participants (N = 16), trials (N = 60) and sessions (N = 2). The reliabilities of the EEG data were assessed for each of the 12 frequency band/electrode combinations for imagined left and right movements separately using syntax developed specifically to do so [30].

To run the program, characteristics of the data were input (fully crossed and completely balanced), and all effects were set to be random. The absolute G-coefficient (sometimes referred to as an agreement index, index of dependability, or phi-coefficient) was used as the index of reliability as it incorporates agreement in rank order as well as the elevation levels of the measures across facets. The index ranges in value from 0.0 to 1.0, with higher values indicating more reliable data. In addition to producing G-coefficients, generalizability analysis partitions the variability of the data set into that due to each of the facets, their interactions, and error terms.

2.5. EEG predictive analyses across participants

Analyses were undertaken to identify the EEG data, from the different frequency band/electrode combinations, that significantly predicted when the visual stimulus was left versus right stepping during the imagined condition across all 16 participants. Given that: 1) the

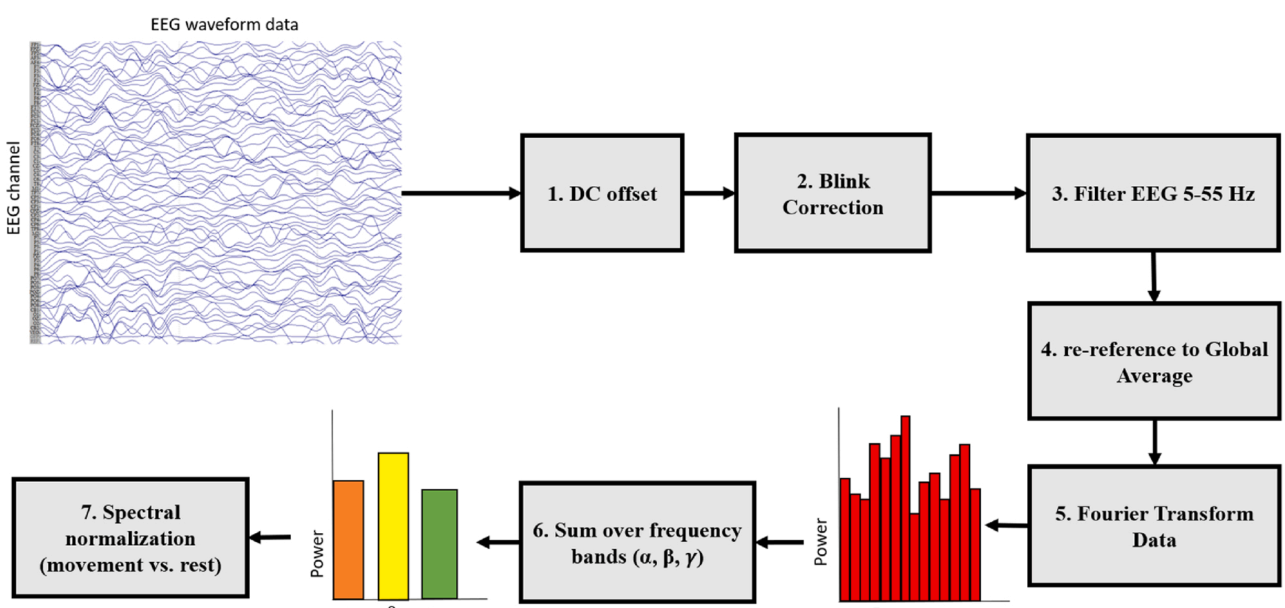

Fig. 3. EEG Processing Pipeline; EEG data is imported, band pass filtered between 5 and 55 Hz, re-referenced to a global average of all 64 electrode channels, converted to spectral data via Fourier transform and summed over alpha, beta and gamma bands respectively.

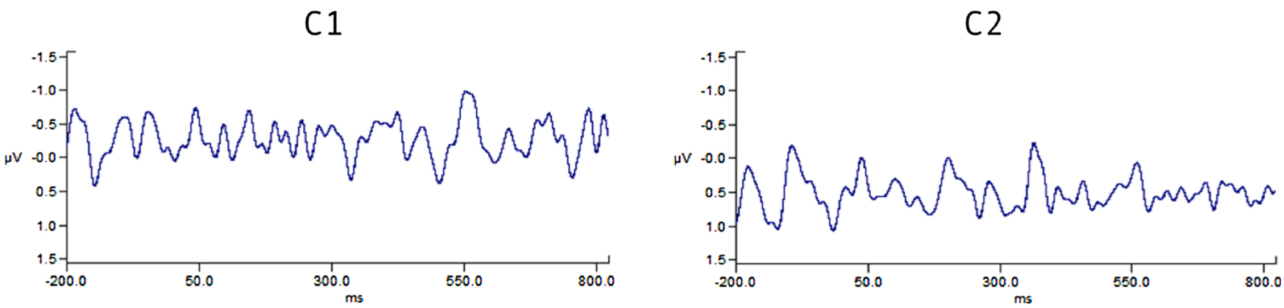

Fig. 4. Traces during a right lower limb movement for electrodes C1 and C2, averaged over 120 epochs (averaged across sessions 1 and 2), over an interval of 200 ms before the stimulus and 823 ms after the stimulus during the imagined task for a single participant.

outcome was binary (left/right), 2) the predictors were continuous (EEG signals), and 3) multiple steps were processed (60 steps each left and right) and nested within the 16 subjects, general estimating equations (GEE) analyses using the IBM SPSS program was used [31,32]. GEE accounts for the correlation within these nested data. The working correlation matrix was specified as unstructured and robust estimation was specified as it provides consistent estimators of the covariance matrix of the predictor estimates, even if the working correlation matrix is unspecified [33]. The Wald test determines the statistical significance of each predictor above and beyond the others in the model, and is based on the change in log-odds when there is a 1-unit change in the predictor variable with all other variables in the model held constant. It has a similar distribution to the chi-square, and so larger values are associated with higher significance. Twelve GEE analyses were run; one at each electrode with the three frequency bands (alpha, beta and gamma).

2.6. *Participant-level classification accuracy analyses*

Supervised classification analyses, using the Multiplayer Perceptron neural network IBM SPSS program, were run to classify left versus right leg movement for each participant using the electrode/band combinations that were significant for the group as a whole. The neural network approach allows the researcher to specify the predictors, size of the training group on which the network is trained and size of the testing group, as well as the number of hidden layers. A 75 % training/25 % testing split was set for each participant and one hidden layer specified to allow for interaction and quadratic terms to be formed. A 5-fold (5 repetitions) of the analyses were run for each participant to provide more stable results.

3. Results

3.1. *EEG generalizability results*

The G-coefficients of the EEG data, averaged across imagined left and right leg movements, at each frequency band/electrode combination was moderate at 0.62 [34]. On average, only 0.3 % of the variance in the data set was due to the facet of session. Therefore it was justifiable to average the EEG data for each participant across sessions (i.e., Session 1, trial 1, C1 alpha, left and Session 2, trial 1, C1 alpha, left were averaged). This provided a more robust measurement of the EEG data than if measured at only one point in time. The average percent variance accounted for in the data set by the other facets and interactions were: participants = 13.5 %, trials = 1.5 %, participantsX sessions = 10.3 %, participantsXtrials = 2.6 %, sessionsXtrials = 0.4 %, and the 3-way interaction/error term = 71.3 %.

3.2. *EEG predictive results across participants*

The results of the analysis to determine which frequencies at which electrodes distinguished between left and right stepping movements are presented in Table 1. The table shows the electrode and frequency band being assessed, Wald value of each coefficient, and its significance. Using a cutoff of 0.01 to determine significance to protect against Type I error, several electrode/frequency band combinations were able to successfully distinguish between imagined left and right lower limb movements: C1 and PO4 alpha and beta, C2 alpha, and PO3 alpha, beta and gamma.

Table 1
Results of Alpha, Beta and Gamma Frequency Bands at C1, C2, PO3 and PO4 Electrodes in Predicting Left and Right Imagined Lower Limb Movement.

Electrode and Frequency Band	Wald and Significance
C1 Alpha	14.2, $p<.001$
C1 Beta	8.6, $p = .003$
C1 Gamma	6.2, $p = .013$
C2 Alpha	12.7, $p<.001$
C2 Beta	4.6, $p = .033$
C2 Gamma	1.5, $p = .217$
PO3 Alpha	17.6, $p <.001$
PO3 Beta	24.3, $p<.001$
PO3 Gamma	7.4, $p = .007$
PO4 Alpha	16.7, $p<.001$
PO4 Beta	7.1, $p = .008$
PO4 Gamma	0.7, $p = .388$

3.3. *Participant-level classification accuracy results*

Table 2 presents the 5-fold accuracy results for the test samples for each participant. The mean right leg, left leg, and overall classification accuracies collapsed across the individual participant values were all 63 %.

Table 2
5-Fold Testing Sample Percent Correct for Imagined Left Leg, Right Leg and Overall.

Participant	Correct Left	Correct Right	Overall Correct
1	71.7	63.3	67.1
2	63.5	64.2	63.7
3	51.4	62.2	56.9
4	62.6	55.5	60.3
5	54.6	68.8	62.8
6	56.5	59.6	57.4
7	52.3	70.6	63.1
8	71.4	55.3	62.8
9	61.7	66.7	67.1
10	72.6	54.9	63.3
11	72.8	68.2	70.9
12	78.6	49.4	63.6
13	62.9	76.4	70.4
14	63.3	54.9	59.6
15	66.6	65.2	66.0
16	48.1	75.9	61.0

4. Discussion

The hypothesis of this study that it would be possible to differentiate imagined left and right lower limb movement using EEG alpha, beta, and gamma frequency data collected from the C1, C2, PO3, and PO4 electrodes was generally supported. The results of the across participants analyses showed significant results at the C1 and C2 electrodes, suggesting areas associated with sensorimotor cortex are important sources of information for isolating left from right lower limb movement [4,35,36]. Significant results were also found at the PO3 and PO4 electrodes. This supports prior research that has found activity in the occipital and parietal lobes, and the potential influence of mirror neurons associated with the stimulus, is an important consideration for imagined lower limb movement [37–39]. The significant results were obtained at the alpha, beta, and gamma frequencies. Alpha and beta are the two EEG bands most closely linked to executed walking [38,39] and the results of the current study are in contrast to other studies unable to find significance in the beta band [27]. The one significant result we found with the gamma band is consistent with recent assisted robotic walking findings [20,21].

Using the eight significant frequency band/electrode combinations found in the across participants analyses to test classification accuracies for left and right movements within each participant resulted in significantly greater than chance classification for most of them. Future research into why individuals have varied classification accuracies is warranted.

The overall correct classification value of 63 % highlights the difficulty of using EEG signals to separate left and right lower limb movement [4–6]. This accuracy rate is comparable with studies using more complex combinatorial strategies, far more features to classify left versus right lower limb movements, and more liberal classification processes [28,40] A parsimonious model that uses as few EEG features as possible will facilitate lower limb BCI development.

To evaluate the ecological validity of these results, further work will need to be done testing other demographic groups (e.g., women, older adults). Young males were selected for this study as this is the demographic group most likely to suffer from traumatic spinal cord injury [41], and thus most likely to benefit from BCI research. Another important group on which to collect similar data are those with compromised lower limb mobility. A review of animal and human cerebral plasticity, the potential of the brain to re-organize after damage (such as that from a spinal cord injury), shows promise primarily in animal models, and to some degree for upper limb function in humans [42], particularly those with incomplete spinal cord injury [43]. This reorganization is likely due to synaptic plasticity in pre-existing circuits and the formation of new circuits. The EEG signatures of these new circuits could be compared to those from normal subjects such as those in the current study. Future research into why some individuals have such varied classification accuracies and why the left leg accuracies were generally lower than right leg classification accuracies is warranted.

5. Conclusions

Our study moves the literature on EEG signals in imagined lower limb motion forward. Specifically, it was demonstrated that it is possible to differentiate imagined left from right lower limb movements using information from primarily the alpha and beta bands at electrodes C1, C2, PO3 and PO4. These results should be useful in future studies and in the design of lower limb BCI development to assist those with lower limb compromised mobility.

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CRediT authorship contribution statement

Adrienne Kline: Conceptualization, Data curation, Formal analysis, Writing - original draft. **Calin Gaina Ghiroaga:** Data curation, Writing - review & editing. **Daniel Pittman:** . **Bradley Goodyear:** Supervision, Writing - review & editing. **Janet Ronsky:** Supervision, Writing - review & editing.

Declaration of Conflicting Interest

The Authors declare that there are no conflicts of interest.

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