Repetitive execution of a reach-and-lift task causes longitudinal attenuation in movement-related EEG features

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Abstract

Brain Machine Interfaces (BMIs) are systems that can help restore motor function to individuals with paralysis. These systems utilize machine learning algorithms to detect how the user wants to control an assistive device from their brain activity. These algorithms require a training dataset to infer patterns between a user's brain waves and the control signal for the assistive device. These training datasets consist of brain activity recordings while participants perform a very repetitive motor task. We hypothesize that these training datasets can be compromised due to the high number of trials. We anticipate that the movement-related brain waves of interest attenuate over time due to neural efficiency, where the brain becomes more efficient with practice in a motor task. To explore this hypothesis, we used an open-access EEG dataset where participants performed a simple reach-and-lift task. From each trial, time windows associated with resting and movement periods were segmented. Alpha and beta-band spectral power was estimated for each of these epochs and event-related desynchronization (ERD) was estimated as the suppression in spectral power from rest to movement. These ERDs were compared between early and late trials in the dataset. We also used linear discriminant analysis to assess a machine learning algorithm's accuracy in classifying whether the time windows belonged to rest or movement based on the spectral power band. We found that earlier trials had stronger ERDs and larger classification accuracies, suggesting that the repetition in the motor task causes attenuation of movement-related brain wave patterns and reduces efficacy of the dataset. These results call for a reevaluation of BMI performance in datasets that have numerous trials and an exploration of strategies that can compensate for longitudinal changes in movement-related brain activity used for BMIs.

Introduction

Brain machine interfaces (BMIs) are systems that allow users to control external devices through their thoughts [1–3]. These external devices can include assistive devices such as prostheses, powered exoskeletons, or robotic arms, all of which can be used to help restore motor function to an individual with paralysis. The key components in BMIs are the neuroimaging modality used to monitor a user's brain activity and the machine learning algorithms that are used to detect neural patterns of interest to control an external device. These algorithms find a mapping between the variations in brain activity with different commands that would control the assistive device.

While there are a large variety of neuroimaging techniques that can be used for BMIs, scalp electroencephalography (EEG) remains the most popular due to its accessibility and noninvasive nature. A popular brain wave pattern that is used in EEG-based BMIs is event-related desynchronization (ERD)[4–6]. These ERDs manifest as an attenuation in alpha- (8-13 Hz) or beta- (20-30 Hz) band power when the user is engaged in limb movement. The suppression is typically found in sensors that are close to the somatotopic areas associated with the engaged limb.

While it is generally known that sensors close to the sensorimotor cortex are likely to yield suppression in spectral power [5,7–10], machine learning algorithms are routinely used to find the model that works the best for the user [11–13]. This difference can be due to individual variations in the participant's brain activity [13], where it is unknown which sensors will provide the most optimal signal, and what threshold should be used with the spectral power estimates to distinguish when the limb is engaged or idle.

To accommodate each individual's unique brain waves, the algorithms are trained based on the individual's dataset that contains examples of the brain waves with the associated motor commands of interest. This usually calls for the participant to perform a motor task while the participant's neural activity is recorded. To help enhance the movement-related signal of interest, it is common for this dataset to contain numerous trials. It is also typical for the motor task to be very repetitive and for datasets to have a large number of trials that can range from 100 – 600 trials [14–20].

BMI datasets usually contain many trials because of the conventional notion that most machine learning algorithms improve in decoding performance with more data. However, machine learning

algorithms also assume that the relationship between the predictive features and the command of interest are consistent throughout the trials. If the mapping changes throughout the dataset, it could cause the machine learning model to perform poorly[21]. We argue that such nonstationarities could be present in BMI datasets due to neural efficiency, a phenomenon where the brain becomes more efficient in executing well-practiced skills. This phenomenon has been observed in neuroimaging studies where experts displayed less cortical activation than novices when both groups performed the same task[22–24]. While neural efficiency has been mostly studied between novices and experts with years of training, previous studies also have found that the motor cortex can undergo plasticity in 30-minute sessions of repeated movements[25,26]. We hypothesize that when participants in BMI studies perform a repetitive motor task, their movement-related brain waves of interest are likely to attenuate across trials within a dataset.

In this work, we explore if the attenuation exists in an open access dataset where EEG was collected while participants performed a repetitive reach-and-lift task. We also explore if this attenuation can influence the predictive power of machine learning algorithms in classifying when participants are resting vs. moving.

Methods

Open access dataset: WAY-EEG-GAL

We used an open-access dataset named "WAY-EEG-GAL" [14]. In this study, 12 participants performed a reach-and-lift task. Participants were instructed to rest their hand on the starting position and start reaching for the grasped device when the LED on top of it turned on. After grasping the device, they lifted the device above the ground until the LED turned off. This cued the participant to set down the device and return their hand back in the starting position. Each participant performed 10 sessions of experiments, each of which contained 28-32 trials. Each session had experimental variations where the experimenter changed the weight and/or the grip surface, which was hidden to the participant. A 32-channel 500 Hz EEG system (ActiCap electrodes with BrainAmp EEG signal amplifier, Brain Products GmbH, Gilching, Germany) was used to record brain activity, five electromyography (EMG) sensors were used to record muscle around the hand and arm, and kinematic and kinetic sensors associated with the hand and arm were recorded. Further details can be found in [14].

EEG preprocessing

EEG signals were preprocessed to help reduce the artifacts in the data. To remove the drift in the signals, they were high-pass filtered with a 4th order zero phase Butterworth filter at a cutoff of 0.1 Hz. To remove brief deflections in the signals likely caused by head or sensor movements, artifact subspace reconstruction (ASR) was performed [27,28]. Time windows of 0.5 seconds that had a variance beyond 60 standard deviations were corrected with ASR. Lastly, independent component analysis (ICA) was used to find components associated with ocular, muscular, cardiac, and line noise activity [29]. These were automatically detected and removed with the "IClabel" functions, which classifies components based on a pre-made database [30]. ASR, ICA, and IClabel were performed with the EEGLAB toolbox [31] in MATLAB [32].

Comparing ERDs between early and late sessions

From each trial, a 1-second time window was extracted during the rest and movement periods. These periods were extracted based on the movement onset markers that were present in the dataset (labeled "tHandStart") [14]. The rest period was extracted from the trial -2 to -1 seconds with respect to the subsequent movement onset. The movement period was extracted from the trial 0 to 1 seconds with respect to the movement onset.

For each of these windows, spectral power was calculated based on the spectral density calculated using the Welch method. Within the one-second time window, the averaged FFT solution used sample windows with a length of 0.5 seconds and an overlap of 0.25 seconds. The Hamming window was used to reduce spectral leakage. From the power spectral density (PSD), spectral band power was extracted in the alpha band (8-13 Hz) and in the beta band (20-30 Hz).

For each trial, a single value of the alpha and beta-band power was extracted for each rest and movement period. For each participant, the spectral power values were aggregated from the trials that belonged to the early and late sessions. The early sessions contained the 1st, 2nd, and 3rd sessions while the late sessions contained the 7th, 8th, and 9th sessions. The 10th session was omitted since the movement data was omitted in the original dataset to be used in a later BMI competition.

For each participant, the median of the spectral power values was calculated across all trials for the early and late sessions. The ERD was then estimated as the base-10 logarithm of the ratio of the median spectral power in the movement period over the spectral power in the rest period. A

paired sample t-test was then performed to compare the ERD values between the early and late sessions. This process was performed on each EEG channel. To help visualize the spatial distribution of the ERD values, they were also plotted as a scalp map.

Decoding rest vs. movements from EEG

We also wanted to explore if the possible attenuation of the ERDs might influence the ability to predict when participants were moving or resting their hands. To test this, we set up a classification problem where we attempted to classify if participants were moving or resting in the one-second time windows that were segmented from each trial. The predictive features were the alpha and beta-band power values that were extracted as described in the previous section.

Linear discriminant analysis (LDA) was used to classify if the time window belonged to a period of rest or movement. This was trained in a 5-fold cross-validation. The cross-validation was performed under two permutations: by channel groups and by what trials were used. For the channel groups, cross-validations were performed with channels contralateral to the hand (sensors C3, CP5, CP1), ipsilateral to the hand (C4, CP2, CP6), and with both groups of channels. For the trials, cross-validations were performed with trials only in the early sessions, the late sessions, and both the early and late sessions. Figure 1 illustrates the permutations of the cross-validations used. For each participant and the permutation, the average of the classification accuracies was calculated across the folds. A paired t-test was used to compare classification accuracies for the participants between the permutations that involved early vs. late trials. We also compared classifications for each condition between alpha and beta-band power and between channel groups.

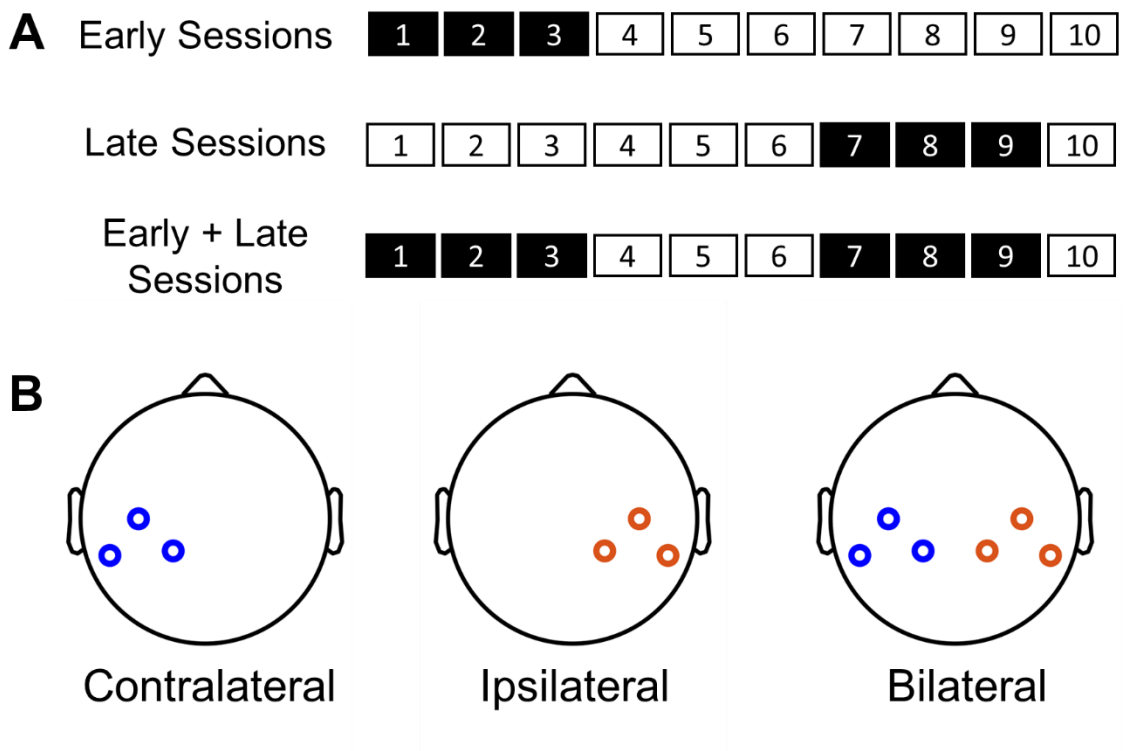

Figure 1) Diagrams indicating groups of experiment sessions and channels used for comparisons. A) The sessions of experiments present in the dataset. The group of sessions that were designated as early and late sessions are shown in black. The last session was not included in the analysis since the kinematic information was omitted in the dataset. B) These scalp maps indicate the group of channels used in the decoding analysis.

Results

Alpha band ERDs are larger in early sessions compared to late sessions

In the comparisons of ERDs between the early and late sessions, we largely found differences in alpha-band ERDs, with few differences in beta-band ERDs. In the alpha band, there was bilateral attenuation in the central-parietal areas due to movement. These ERDs were found to be weaker in the later sessions, where significant differences were found in the parietal and ipsilateral central sensors (C4 p=.0059, T8 p=.0085, CP1 p = .024, CP2 p = .0023, CP6 p=.0061, Pz p=.011). Beta-band ERDs were more pronounced in the contralateral central-parietal areas, but the difference was not significant. Other than the Cz sensor (p =.011) and peripheral sensors (T7 p=.044, PO9

p=.035, PO10 p=.0021), significant differences were not found in beta-band ERDs between early and late sessions.

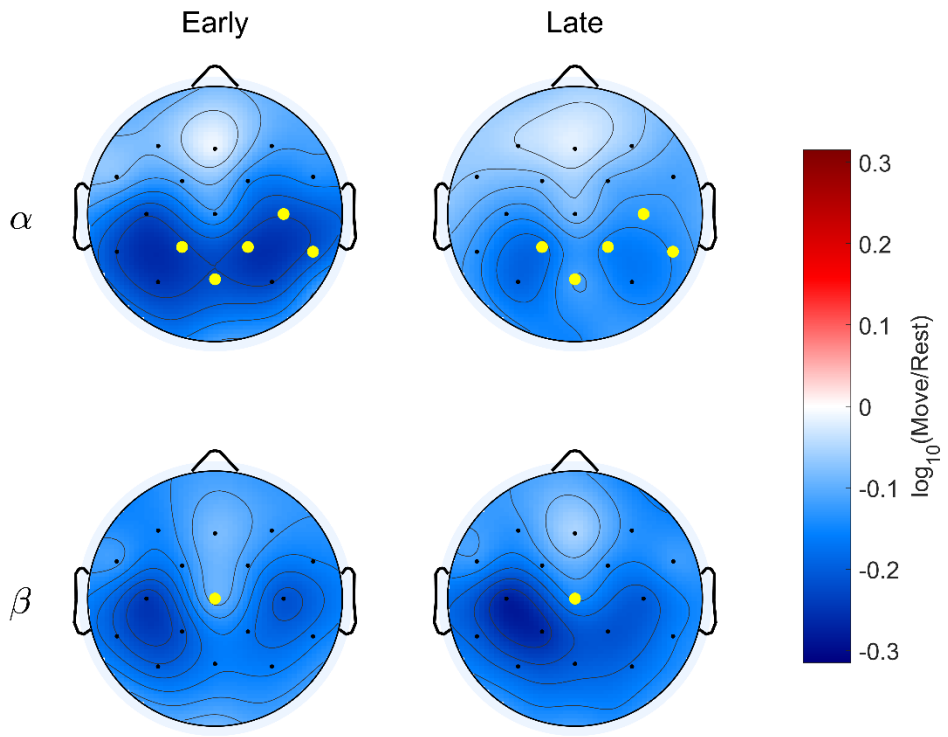

Figure 2. Scalp map of spectral power ERDs due to movement. Top and bottom rows correspond to alpha (8-13 Hz) and beta band (20-30 Hz) ERDs, respectively. The left and right columns correspond to ERDs from early and late sessions. Darker blue colors indicate stronger ERDs. Yellow circles indicate sensors that had significantly different ERDs between the early and late sessions (p<0.05, N=12 participants).

Neural decoding with early trials reveals high accuracies in predicting rest vs. movement

Figure 3 contains boxplots of the classification accuracies for predicting if the time windows belonged to movement or rest from the spectral power features. For all channel and session conditions, beta-band power yielded significantly higher accuracies than alpha-band power (p <.05; see appendix for all p-values). For both alpha-band and beta-band power as predictive features, we also found that decoding with groups of channels on both sides performed better than the ipsilateral side (alpha: p=.0043, beta: p=.0018) and the contralateral side (alpha: p=.0028, beta: p=.024). Tables of the statistics in the classification accuracies as well as the p-values for all comparisons can be found in the Appendix.

We found that only classifications with alpha-band power yielded differences in accuracies depending on what sessions were used for decoding. On all channel group conditions, there were significantly larger classification accuracies when only early session trials were used compared to using early and late session trials (contralateral: p=.045, bilateral: p=.018, ipsilateral: p=.00036). For the bilateral and ipsilateral channel conditions, classifications with only early trials were significantly higher than only using late trials (bilateral: p=.013, ipsilateral: p=.0077). When beta-band power was used to classify rest vs. movement, we found that none of the conditions had significant differences between the session group conditions.

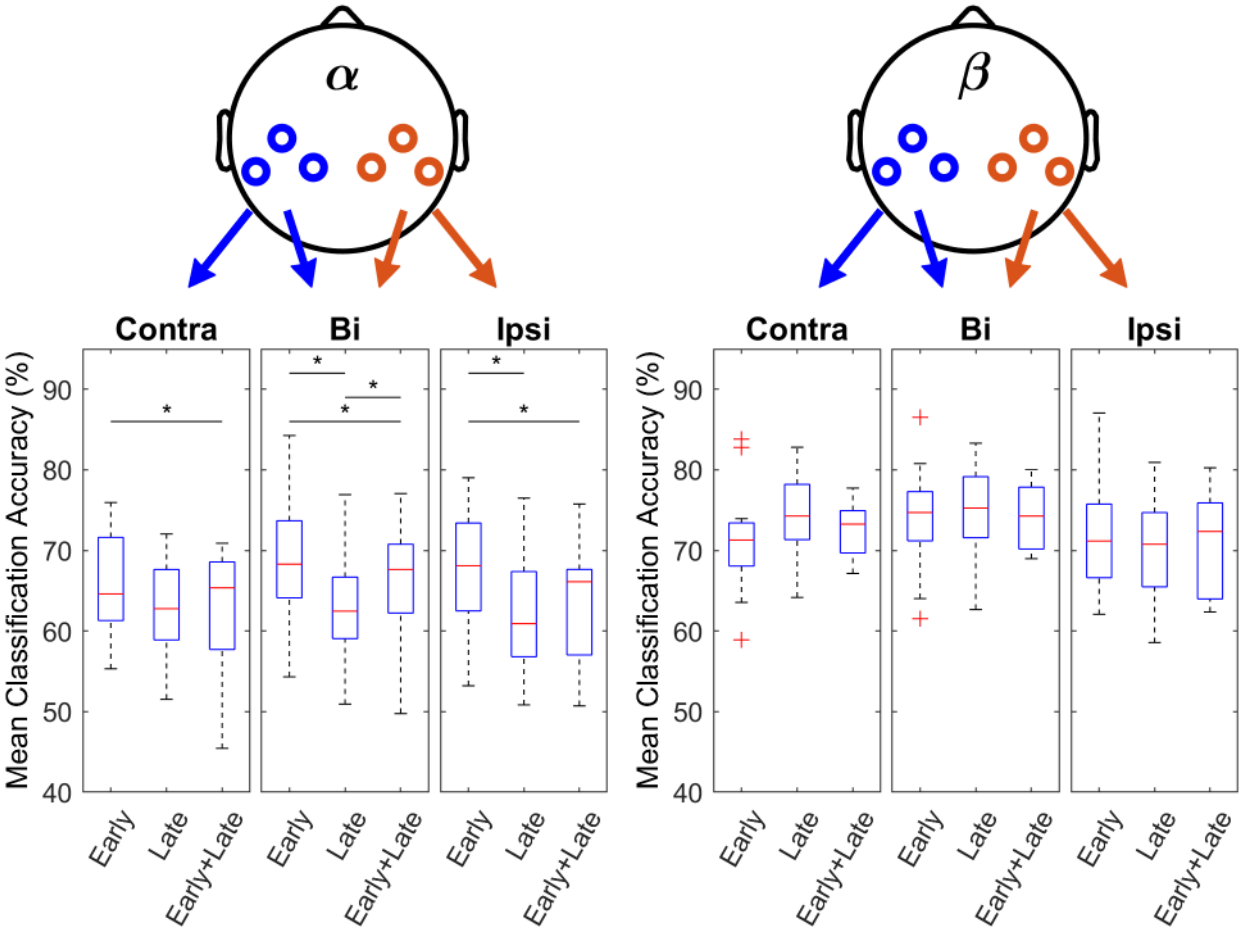

Figure 3) Boxplots of the classification accuracies for predicting rest vs movement with spectral band features. The left and right panels correspond to accuracies when alpha and beta-band power were used, respectively. Within each panel, the left, center, and right boxplots pertain to classifications were the group of contralateral (Contra), bilateral (Bi), and ipsilateral (Ipsi) channels were used. Each group of boxplots contains classifications that used trials from only the early sessions (Early), only the late sessions (Late), and from both the early and late sessions (Early + Late). Each boxplot corresponds to the spread of classification accuracies averaged across all

cross-validation folds for each participant (N=12). Asterisks indicate significant differences in classification accuracies between each condition based on the paired sample t-test ($p<0.05$).

Discussion

In this work we examined whether movement-related EEG features used to drive BMIs can attenuate over repetitive executions of a task. We also assessed if these changes result in changes in BMI performance over time. We found that spectral power modulations associated with movements attenuated over time in a repetitive reach-and-lift task. When directly comparing the spectral-power ERDs between early and late sessions, we found that alpha-band power modulations significantly attenuated whereas beta-band power modulations did not significantly change. In the alpha band, the attenuation of movement-related ERDs were focused on the central-parietal areas, especially on the side ipsilateral to the engaged hand. While the presence of ERDs in the central area corroborates with other EEG studies focused on hand movements[7–10], we highlight the finding in this work that alpha-band movement ERDs can attenuate over time with repeated execution of the motor task.

The comparisons in ERDs corroborate with the performance in using machine learning algorithms to classify rest vs. movement. When we compare the performance of using alpha-band power and beta-band power, we find that beta-band power performed consistently over time, yielding no significant differences between the groups of trials that were used (i.e., early, late, or both early and late). When alpha-band power was used, we found significant attenuation depending on the trials that were used in the cross-validation schemes. Specifically, we found that only using trials from the early session performed better than using trials from both early and late sessions.

Based on the current study, it is uncertain if the attenuation in ERDs is associated with either skill acquisition or task fatigue. While our hypothesis is based on previous neuroimaging studies that observed neural efficiency between experts and novices[22–24,33], a task with repetitive movements could also cause the participant to experience boredom or muscular fatigue. Neuroimaging studies have found neural correlates associated with task boredom or sensory habituation, but they mainly found changes in frontal cortical activity associated with later trials [34,35]. Muscular fatigue was also associated with changes in coherence between muscular and cortical activity [36–38]. Tracking the

task performance during the trials could help distinguish these two types of factors, but this was absent in the present dataset as well as most datasets used in BMI studies. This is typically the case since most tasks used in BMI studies involve tasks of daily living, which are usually well-practiced among most participants. Future work that correlates task performance with the strength of ERDs across trials in a repetitive task could help distinguish these two factors, where a slow increase in task performance is likely to be associated with gradual skill acquisition and neural efficiency.

While we observed attenuation in ERDs in the central parietal area for the alpha band, we found that it was more pronounced on the ipsilateral side. This also coincided with the classification performance, where the differences in classification between early and late trials were more pronounced in both the bilateral and ipsilateral group of channels. This could suggest that while ERDs may attenuate over time, the sensors contralateral to movement may be more robust to this attenuation. This could suggest that decoding schemes that use bilateral central channels for decoding limb movements may be more susceptible to ERD attenuation related to repetitive task execution. Previous studies that decode unimanual movements or control a robotic arm have used this strategy to maximize the number of predictive features [39–44].

We note that the results of this work are limited to the dataset used in this study. Some EEG-based BMIs utilize strategies that engage both hands as well as the legs and tongue to construct multiple commands for a BMI [45–49]. Given that this dataset involved a task with the participant's right hand, it is uncertain if the attenuation in ERDs and their effect on classifying rest vs. movement observed here confer to classification schemes that involve classifying left vs. right hand movements. We also note that the task was not identical throughout all the trials; some trials involved switching the grasped object weight and surface texture without the participant's knowledge. Neuroimaging studies also suggest that parietal areas of the brain might be involved in generating internal models about the grasped object [50–53], which may have been more engaged when the experimenter actively changes the object's weight and grip surface. This may explain the ERDs observed in the parietal areas and influence our principal result where we found attenuation of the ERDs between early and late sessions.

Overall, we found that alpha-band activity can attenuate over time throughout a repetitive motor task that's typically used in BMI studies. We also found that this attenuation can affect classification performance in predicting when a participant is moving or resting. The results from

the study raise questions on whether an excessive number of trials in a motor task can reduce a BMI's performance, especially given the prevailing thought that generating more data will improve predictive models from machine learning algorithms. Future work should explore if modifying the context of the task throughout different trials (such as reaching for different objects) may help reduce the attenuation alpha band ERDs found here. We also note that in this case, beta-band activity generally seemed to yield higher accuracies than alpha-band activity and seems to be robust throughout the trials. This could promote the use of beta-band power as a predictive feature for BMIs, in contrast to the current convention of using alpha-band power for BMIs.

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Appendix

Table A1) Classification Accuracies for each of the cross-validation conditions. The mean across participants is shown for each cell, while the standard deviation across participants is shown in parenthesis.

	Early + Late	Early	Late
α Bilateral	66.0% (8.1%)	68.4% (8.2%)	63.1% (7.5%)
α Contralateral	62.6% (7.4%)	65.7% (6.5%)	62.8% (6.3%)
α Ipsilateral	63.5% (8.1%)	67.7% (7.6%)	62.0% (7.0%)
β Bilateral	74.3% (4.1%)	74.0% (6.8%)	74.6% (6.4%)
β Contralateral	72.5% (3.4%)	71.5% (7.0%)	74.1% (5.8%)
β Ipsilateral	70.7% (6.4%)	71.9% (7.4%)	70.2% (6.9%)

Table A2) P-values of the t-test pair wise comparisons in classification accuracies between groups of trials from different sessions. Underlined p-values indicate significant differences (p < .05).

Alpha	Bilateral	Contralateral	Ipsilateral
(Early + late) vs. Early	1.78E-02	4.47E-02	3.59E-04
(Early + late) vs. Late	3.75E-02	9.14E-01	2.81E-01
Early vs. Late	1.30E-02	1.76E-01	7.66E-03

Beta	Bilateral	Con	Ips
(Early + late) vs. Early	8.39E-01	5.33E-01	3.83E-01
(Early + late) vs. Late	8.47E-01	3.05E-01	7.31E-01
Early vs. Late	8.32E-01	3.98E-01	4.68E-01

Table A3) P-values of the t-test pair wise comparisons in classification accuracies between groups of channels. Underlined p-values indicate significant differences (p < .05).

Alpha	Bilateral vs. Contralateral	Bilateral vs. Ipsilateral	Contralateral vs. Ipsilateral
Early + Late	2.85E-03	4.26E-03	5.05E-01
Early	6.01E-02	3.75E-01	1.45E-01
Late	6.48E-01	4.03E-01	6.16E-01

Beta	Bilateral vs. Contralateral	Bilateral vs. Ipsilateral	Contralateral vs. Ipsilateral
Early + Late	2.38E-02	1.81E-03	1.62E-01
Early	1.91E-02	3.56E-02	7.29E-01
Late	4.10E-01	2.53E-05	2.15E-03

Table A4) P-values of the t-test pair wise comparisons in classification accuracies between using alpha or beta band as the predictive feature. Underlined p-values indicate significant differences (p < .05).

	Bilateral	Contralateral	Ipsilateral
Early + Late	5.91E-04	1.18E-04	2.05E-04
Early	2.64E-02	4.66E-03	3.89E-02
Late	5.58E-06	6.65E-07	1.91E-04