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Neural correlates of learning in an electrocorticographic motor-imagery brain-computer interface

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Abstract

Human subjects can learn to control a one-dimensional electrocorticographic (ECoG) brain-computer interface (BCI) using modulation of primary motor (M1) high-gamma activity (signal

power in the 75–200 Hz range). However, the stability and dynamics of the signals over the course of new BCI skill acquisition have not been investigated. In this study, we report 3 characteristic periods in evolution of the high-gamma control signal during BCI training: initial, low task accuracy with corresponding low power modulation in the gamma spectrum, followed by a second period of improved task accuracy with increasing average power separation between activity and rest, and a final period of high task accuracy with stable (or decreasing) power separation and decreasing trial-to-trial variance. These findings may have implications in the design and implementation of BCI control algorithms.

Keywords

Brain-Computer Interface (BCI); Brain-Machine Interface (BMI); motor learning; motor imagery; high gamma; electrocorticography (ECoG)

2. Introduction

Brain-computer interfaces (BCIs) provide an alternative way to interface with the external environment and have the potential to ease the burden of neurological disease and disability. BCI systems decode the underlying neural activity directly from the cortical surface and allow a subject to control cursors and prosthetic devices (1). Such systems could be particularly valuable to patients with motor system injury or disease by providing an artificial pathway for patients to perform everyday tasks.

Neural activity can be recorded in many ways, both non-invasively via electroencephalography (EEG), functional magnetic resonance imaging (fMRI) (2,3), magnetoencephalography (MEG) (4), or invasively via microelectrode and electrocorticography (ECoG). All of these recording methods use volitionally modulated areas of cortex as the source signal for BCI control. Primate studies have shown that with training, the animals can successfully gain control of a BCI using neural population firing rates for control (5,6). Further studies in humans have demonstrated volitional modulation of single neuron firing rates (7,8), local field potentials (9,10), and population-level activity in EEG (11–13) and ECoG (14–19) based BCIs. However, translation to clinically useful devices has been hindered in part by low data throughput.

The information carried in a BCI (quantified as information transfer rate or bitrate) can be increased either by degrees of freedom or accuracy (20). Training improves both of these determinants of bitrate, and therefore the bitrate overall. Clinical viability of a BCI may depend in large part on the accuracy of control. The accuracy of a one dimensional BCI can be defined as the proportion of correctly classified commands relative to the total number of commands issued (20,21). Signals classified incorrectly thus negatively affect accuracy. In practice, repeated erroneous classifications that require corrections can be frustrating for the user and can even pose an injury risk in certain applications (e.g. attempting to stop a BCI-driven wheelchair at the top of a stairwell). BCI proficiency can be increased with training, resulting in improved accuracy and higher bitrates over time (16,18,19). Though many studies have demonstrated successful cortical motor imagery BCI systems (16,18,19,22,23), the BCI learning process has not been extensively explored.

In the case of ECoG BCI paradigms that use control signals in the primary motor cortex, the overall pattern of skill acquisition is qualitatively similar to the training of a novel, overt motor task (24). A quantitative measure of the underlying neural activity can be directly correlated to the resulting output. As a subject learns to use a BCI, they exhibit similar learning patterns to other motor tasks, such as learning to use a video game controller: initial low accuracy of BCI movements followed by improving accuracy over the course of training. While the corresponding changes in cortical activity across functional areas have previously been characterized (24), the temporal dynamics of the underlying cortical activity at the control electrode during BCI task learning has not been described.

In this study, we explored in depth what patterns of cortical activity emerge at the control electrode during training on an ECoG-based BCI system. We examine the learning process across multiple subjects doing different tasks at varying levels of precision.

3. Methods

In this study we studied an ECoG BCI that uses characteristic spectral changes in the high-frequency broad-band power changes (25) recorded in a control electrode (15,16,18,19,26). Successful BCI control required volitional modulation of local neural activity. We set a high-gamma trigger threshold at the median high-gamma value during a screening period of overt motor activity compared with rest. (16,18,27).

3.1 Subjects

Eight subjects with intractable epilepsy were implanted with subdural electrocorticography electrodes for the purpose of clinical seizure foci localization at Harborview Medical Center in Seattle, WA. Platinum electrode grids were placed on the cortical surface and positioned according to the clinical epilepsy mapping protocol. Subjects provided written informed consent in accordance with a protocol approved by the University of Washington Institutional Review Board.

3.2 Electrode Positioning

Preoperative thin-slice (1 mm) T1 MRI scans were used in combination with the Freesurfer software suite to produce cortical ribbon brain hulls (28). Two subjects had low-resolution MRI scans (1cm slices) that only allow a rough estimation of anatomic location. Postoperative CT scans were co-registered and aligned to MRI voxel space and subsequent electrode positions were identified using the software suite BioImage Suite (29). Final electrode positions were determined by projection using the algorithm described by Hermes et al. (30).

3.3 Recordings

Experimental recordings were performed at the patient's bedside by splitting clinical leads into a bank of Synamps2 (Neuroscan, El Paso, TX, USA) or g.USBamps (GugerTec, Graz, Austria) sampled at 1000Hz and 1200Hz, respectively. Research recordings did not interfere with clinical care. Recorded cortical potentials were then digitized and processed using the BCI2000 software suite (31), allowing for the simultaneous recording of behavioral and

neural activity while providing visual feedback to the subject on a screen located comfortably within their field of view. Implanted arrays contained 3mm diameter platinum electrode pads with 2.4mm diameter exposed, spaced at 1cm center-to-center arranged in $8 \times 2, 4, 8$ grids or $1 \times 4, 6, 8$ arrays embedded in silicone elastomer.

3.4 Control Feature Selection

We first performed overt motor screening to identify volitionally modulated areas of motor cortex. At a visual prompt, the subject performed a gross motor movement of the hand (open/close) or tongue (protrude/retract) for 3 seconds, followed by a period of 3s of rest (16,18). Though all subjects performed both tongue and hand motions, the locations of the grids was dictated by clinical protocol and only covered one of the two primary motor areas in each subject. The subject repeated this protocol 10–30 times per stimulus. Offline spectral analysis identified electrodes that showed robust increases in high frequency, broad-band (75–200Hz) power during periods of motor imagery or movement as compared to rest. An electrode that showed a statistically significant increase in spectral power (R^2 correlation of ≥ 0.25 , $p < 0.01$) would be a candidate for BCI control as per previous studies (16,18,22,31). Seven of eight subjects had electrodes that recorded power increases in the signals recorded during tongue movement, with the last subject able to generate an increase in power during hand motor movement. Active areas of motor cortex were in the expected locations based on the primary motor cortex homunculus (30).

3.5 Online Control Task

The subjects achieved online control with one of two tasks programmed in the BCI2000 software suite: the standard Right Justified Box (RJB) task (12) and vertical 1-dimensional (1D) control (15,16,18,22) (Figure 1A) as demonstrated in previous studies. For each subject, we selected a 5–30 Hz frequency band centered near 80–100 Hz in the control electrode because it both captured the broad-band power increase associated with local cortical activity, and excluded 60 Hz line noise and harmonics. Using the motor activity identified during feature selection and quantified by an autoregressive spectral estimation with a 15th order auto-regressive filter with a 500 millisecond window (32), subjects modulated brain activity at the control electrode by either overtly moving or imagining the movement. The cursor moved upward when the sum of the power over the preceding 500 ms was above the linear threshold in the power spectra (see Figure 1B) that was identified during model creation and adaptation. We organized testing in a series of “trials” (individual RJB or vertical 1-D tasks) grouped into sets of “runs” (multiple consecutive trials). We initially performed threshold selection with adaptation enabled in the form of an inter-trial gain normalizer. We then froze adaptation for subsequent trials and runs, keeping parameters constant. The cursor fell when the subject was at rest and the power spectra remained below the threshold. A normalized autoregressive filter quantified the spectra, with adaptation of the linear threshold disabled after successfully demonstrating control of the BCI system (31) (e.g. hitting 70% or more of targets in a single 18-trial run).

In the RJB task, the cursor moved at a constant pace from the left side of the screen to the target on the right, over 3 seconds. In the 1D vertical control task, we locked horizontal movement and the subject attempted to move the cursor to one of two targets at the top and

bottom of the screen. Because the 1D vertical control task constrained the motion of the cursor in the x-direction, the feedback duration was of variable length lasting until either the subject successfully guided the cursor to the target or a 3 second time limit expired. The subject performed multiple trials, limited by fatigue. Subjects performed trials each day until explant.

3.6 Offline Analysis

Recorded signals were notch filtered for line noise at 60 Hz and its harmonics at 120 and 180 Hz. To capture the subject-specific changes in real-time, the voltage from each control electrode was band passed within the same control range used during online control (ranging by subject from 67.5–102.5Hz). We then applied the Hilbert transformation to this band passed signal and computed the absolute value of the resulting complex signal to get the signal's amplitude. We approximated the final signal power by squaring the signal's amplitude. A moving window sum of 500 ms was applied to match the control signal used during online recording. The continuous signal power was segmented based on epochs of active feedback. We calculated the mean signal power and z-score for each target based on the mean and standard deviation of power during rest periods for the current run (set of consecutive trials). Z-scoring the data to each run's resting baseline period between target normalizes the results and allows a comparison to be drawn between runs performed on different days.

4. Results

4.1 Control Modalities

Ten subjects participated in the experiments, although two subjects did not gain control over the BCI system and were omitted from the analysis, as they would not be expected to show any common patterns of learning. In the clinical environment, reasons that subjects do not achieve BCI control can be multifactorial including clinical status change, grid migration, medication effects, subject motivation, and electrode/ lead failure. Seven subjects performed overt or imagined tongue movements (absence of movement based on observation of the subject and subject self-report); one subject performed overt hand movement (see Table 1). By the end of the BCI training period, all subjects included in this study had gained volitional control over the BCI, as defined by an accuracy of 70% or greater.

4.2 Power Changes During Learning

All 8 subjects were able to modulate the power in the band chosen for control. Over the course of BCI training, three distinct periods of learning were observed in all subjects: *identification*, *amplification* and *refinement*. *Identification periods* were defined from the start of BCI training until the first major positive-to-negative inflection point in the smoothed difference between up and down targets, where the difference was positive. *Refinement periods* were defined from inflection point preceding the last negative slope in the derivative to the end of the training. *Amplification periods* occurred between the end of the identification period and the beginning of the refinement period. Each stage of the learning pattern was marked by the first inflection point (first moment) of the smoothed difference between up and down targets (see Figure 2), calculated by subtracting a moving

average window of the last 5 up trials from a window of the moving average window of the last 5 down trials.

Identification periods represented the time when subjects were unfamiliar with the task, and there was initially no major difference between the measured mean broad-band power during active (up) targets and inactive (down) targets. Late in the identification period, there occurred a separation between the two about the set linear threshold, and a commensurate increase in the number of successfully reached targets. Following identification, an amplification period occurred as the subject acclimated to the BCI system and began to show improvements in accuracy. Subjects showed increased cortical power for active targets during amplification, as compared to the identification period. Both of these periods exhibited an increase in the mean power for each active target along with an increase in the variance of the means. There was also a constant or increased target hit rate. Figure 3 demonstrates the typical three-stage learning process as seen in subject 7.

During refinement, the subject continued to improve the hit accuracy, but the variance between runs decreased. The overall signal power did not continue to increase during refinement, and in some cases actually decreased while accuracy was unchanged. Figure 4 demonstrates the increased power separation during amplification and constant (or decreasing) power separation during refinement. It is crucial to note that since the subjects produced less cortical activity while retaining the same or better accuracy, any increase in separability of the BCI control feature did not stem from absolute increases in power. Rather, it is likely that the gain in accuracy developed from the subject learning the imposed classification threshold and a subsequent refinement of the cortical activity modulation around it.

Table 2 summarizes the metrics of the power for targets that required modulation of cortical activity (“up” targets). All eight subjects showed similar patterns during their training on the BCI (see Figure 5). A consistent decrease across the inter-trial standard deviation could be seen between the amplification and refinement stages across all subjects. This decrease in power variability was not accompanied by a change in accuracy, suggesting the subjects were refining the level of cortical activity that was required to successfully hit the required target.

In all but two subjects, the mean raw power increased from the identification to the amplification stage. In subjects 6 and 7, while the mean power may have decreased the difference between active and rest targets showed an increasing trend. In addition, the standard deviation of the inter-trial power decreased from the amplification stage to refinement across all subjects (see Table 2). This was indicative of finer and more precise control over the power, as the accompanying accuracy did not drop in proportion.

4.3 Fine-grained Control – Multitarget BCI from a single channel

One subject achieved continuous runs of the 1D RJB task with accuracies above 93%. To better understand the BCI refinement capabilities, we asked this subject to use the same control signal to perform a modified RJB task. The subject guided the cursor to an increased number of targets (3 or 5) occupying a smaller area of the screen (33 and 20%, respectively).

The same electrode and frequency band power were used for control. The increased number of targets required finer grain control of neural activity, both above and below the linear threshold. The subject was able to control the destination of the cursor with accuracies well above chance level for multiple targets.

The three periods identified during learning of the 2-target task were also present in the multi-target task. The subject was not only able to modulate the mean cortical power above or below a single threshold (a binary signal), but also control activity between one of many arbitrarily set thresholds. Periods of identification were followed by separation of the means over each run (amplification) and a refinement in the standard deviation of cortical power.

In the case of this single subject, the first run (R1) showed characteristics of identification, with tightly clustered means and overlapping standard deviations. During the second and third runs (R2/3), the means began to separate, consistent with the amplification pattern observed in the standard RJB task (see Figure 6, top row). During the fourth run (R4), the means converged again, consistent with the refinement phase. However, in this run there was an accompanying loss in accuracy, and subsequent negative feedback. In the following run (R5), the signal underwent amplification again, separating the means further and increasing both the variance and accuracy, as well. The means of runs R6 and R7 then converged while maintaining and increasing the accuracy. Similar patterns were found when the subject was asked to control the 5-target task (see Figure 6, bottom row). Runs R1 and R2 showed tightly clustered means, runs R3 and R4 demonstrated increased accuracy over the initial runs and a separation of the means, and R5 showed a narrowing of the standard deviations without a large loss in accuracy.

5. Discussion

ECoG may provide a robust BCI control signal, but BCI usability depends on user control. We need to understand how people achieve control, and why some people never do. ECoG can provide a stable control signal for BCI over multiple days (22), but how this stability develops has not been investigated until now. Common, robust changes were observed in the neural activity between early and late trials over a training period lasting anywhere from minutes to days - analogous to how one would learn any new activity such as throwing a ball or driving a car. The advantage of using a BCI to explore the learning process is that the task itself is straightforward, tightly controlled, and provides a metric for the efficacy of learning in the form of target accuracy.

5.1 Robust Patterns of Learning Across Patients & Modalities

Born out of the sports and physical performance domains, Fitts and Posner described the general pattern of implicit motor learning through *cognitive*, *associative*, and *autonomous* stages of processing, describing the transition of task learning that begins with explicit understanding of the task and ending with the implicit motor skill (33). Subsequent functional imaging studies demonstrated changes to neural network activation patterns over the course of task learning (*non-declarative*, or *implicit* learning), generally indicating increased metabolic activity in the contralateral primary motor area, and decreases in activity in related premotor and association areas (34–36).

The pattern of neural activity we observed was robust for both overt motor movement and motor imagery, suggesting that these changes were not a product of the BCI modality, but rather reflective of how the brain adapted to feedback. In addition, this pattern was present in each of vertical, RJB, and multi-target 1D BCI task design subtypes. Taking into account the similarity of the pattern across subjects, control modalities, and experiments, these observations suggest that this observed pattern is independent of the experiment and most likely a product of the underlying neurophysiological changes that occur during BCI learning. This pattern could also be indicative of physiological learning processes in a broader sense.

Our findings are qualitatively similar to prior findings in single-neuron BCI learning tasks in which monkeys exhibited increasing single-neuron depth of modulation over the course of early task acquisition, followed by a period of decreasing depth of modulation and concurrent decrease in variance of the depth of modulation, all during a period of increasing BCI task performance (37). These findings may suggest a common underlying neural mechanism.

5.2 Engineering and BCI Design Considerations

It is vital to note that while the subjects were able to modulate the underlying population of neurons, it should not be assumed that the trend of power separation would continue with additional training. In fact, the power separation plateaued during refinement (the third observed phase). One could surmise that the subjects learned the optimal degree of cortical activity required to operate the BCI without sacrificing accuracy. Such a strategy might optimize the metabolic energy expenditure, or effort, required to complete the task because of down-regulation of local neural activity.

Though the spectral power leveled off with training, and in some cases even dropped, the inter-trial variance in power decreased, indicating an improvement in control. The decreased variance suggests that the subject achieved a finer level of control over neural activity based on the feedback provided by training on the BCI. Hence, the subject achieved a more reliable BCI control signal. These findings also imply that the cortex can and does adapt around an artificial constraint imposed on neural activity levels, opening up the possibility that the cortex may also adapt to more complex methods of online BCI decoding.

5.3 BCI As A Neuroscience Tool

These results have fundamental implications for BCI training. We observed all three periods of learning within a relatively short amount of training on the BCI system. These findings suggest that continued training would result in refinement of neural activity control rather than continual power increases; an observation supported by the fact that the standard deviation of the inter-trial power decreases with continued training. As further training on such BCI systems would likely not elicit any additional power increases, a shift in focus from studying cortical activity modulation to optimizing the endogenous learning mechanisms of the brain may prove fruitful.

The results also support the use of BCI as a platform for investigating deep, complex neural interactions (38) during learning. Further studies investigating the relationship between the

high gamma changes observed in this study and high frequency activity previously observed in remote areas (23) are warranted. In a reciprocating fashion, understanding the neuroscience and behavior of such learning mechanisms would seem to be critical for ideal implementation of BCI systems.

We have defined a common pattern of behavior associated with BCI learning, though we do not define the extensive neuronal network changes that underlie other learned tasks. The pattern of three phases – identification, amplification and refinement – seems particularly well-suited when applied to tasks that require increasingly continuous output, (e.g. the multichannel BCI task). Continuous output signals could be used to control a dexterous prosthetic device (39). It is pertinent to note that the improvement in overall bitrate extraction from the target signal resulted entirely from learning by the end user.

5.4 A target for future studies

The experimental circumstances surrounding each patient varied, and therefore the experimental paradigm was not designed to isolate the period of motor learning. Furthermore, the BCI task was relatively simple and task performance reached a maximum early in the study. However in spite of the varying experimental parameters and conditions, the observed pattern is repeatable across a large subject population and is present in every subject studied that gained control of the BCI, and warrants further study. The implications are particularly important in the realm of BCI. When designing a BCI system around increases in high gamma activity, it should not be assumed that any trends indicating increases in high gamma would continue. Rather, high gamma amplitude may be finite and possibly decrease with time as the user becomes more fluent in control.

It is unknown if similar patterns of cortical activity are present during overt motor task learning. In this instance, we used the brain-computer-interface to study human neurophysiology during a tightly controlled BCI training exercise. Further studies could elucidate the patterns of cortical activity during generic motor learning activities.

6. Conclusions

Accuracy of task performance with an ECoG 1-D motor imagery BCI improves with time; however, the increase in accuracy is not directly correlated with an increase in high-gamma power at the control electrode. These findings suggest that there are other underlying mechanisms to BCI skill acquisition than maximal modulation of local high-gamma activity, and improved BCI accuracy could be achieved by incorporating other metrics high-gamma signal classification, such as signal variance, especially in the later stages of task learning.

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Figure 1.

Two experimental designs were implemented: the Right Justified Box Task and the 1D Vertical Box Task. The subject observed a computer screen placed comfortably in front of them. A) For both tasks, there were four periods for each trial: a 1 second rest period where the screen was blank, a 1 second target presentation, a period of feedback where the subject had control over the direction of the cursor's trajectory, and a 1 second reward period after the trial. The RJB task's feedback period remained constant at 3 seconds, whereas the Vertical Box task's x-position was fixed, leading to a variable period of feedback. Both tests required the user to perform motor movement or imagery to drive the cursor upwards, and for the user to remain at rest to allow the cursor to fall. B) Time-frequency plots of the control electrode activity for two individual runs relative to the preceding rest period, showing typical active (up direction) trial (top plot) vs. a typical passive (down direction) trial (bottom plot). Increases in high frequency power are shown in red, with decreases illustrated at blue. For up trials where the subjects performed motor movement or imagery, a broad, high frequency (70 Hz+) increase in power can be seen in the control frequency range (dotted box), which drives the cursor upwards. For down targets, there is no increase in the control range and the cursor falls.

Figure 2.

Periods of identification, amplification and refinement were marked according to inflection points of the power difference between up and down targets. The first inflection point (first local maximum of the derivative) denoted the end of the identification period while the last inflection point (local minima of the derivative) of the difference defined the refinement period.

Figure 3.

Subjects learned to use the BCI system over a period of many trials. A) The control electrode for this subject is highlighted in the green circle and was driven by overt tongue movement. Note that the poor resolution of sulci/gyri was due to a low resolution MRI. B) Mean powers for each trial were calculated in the control range (80–98Hz for Subject 7) and plotted as red points for active/up targets, and blue points for down, with a smoothed mean trace through each type. Three distinct periods of learning can be seen: a period of identification where the mean powers begin to separate between up and down targets (red, top of graph), a period of amplification where the power steadily increases (green), followed by a period of refinement where the difference between the two cases diminishes without a corresponding loss in accuracy (blue). Squares indicate missed targets. C) Taking the difference between the up and down targets illustrates the three stages well. There was a maximal difference of 6 standard deviations, ending the training at a difference of 3 standard deviations.

Figure 4.

Cumulative Distribution Function (CDF) generation for Subject 2. A) Log of high gamma in the control range (varied per-subject, but generally 80–100Hz) for a single active trial in red, and rest trial in blue. B) Cumulative histogram of the high gamma power for one active and one rest trial. C) CDF for a single active (red) and rest (blue) trial. A rightward shift in the CDF indicates a higher mean log power for the active target. D) CDF for each of six 18-trial runs. The initial run shows low separation in the CDFs for each trial. Runs 2–4 show increasing separation, with runs 5 and 6 showing constant or decreasing separation without a corresponding loss in accuracy, suggested by the decreasing variability in CDF for runs 5 and 6.

Figure 5.

Eight subjects underwent on-line BCI training using either hand or tongue control signals with overt (boxed) or imagined (bubble) movement. The type of task is shown underneath the modality. Control electrodes are highlighted in green. All subjects show all three periods, denoted along the top of each graph: identification (red), amplification (green), and refinement (blue). Squares denote missed trials.

Figure 6.

Subject 4 performed exceptionally well at the RJB task and performed the same task with additional targets. The subject modulated the control signal in order to reach targets that were not at the extreme top or bottom of the screen. For three targets (top graph), the same pattern of learning can be observed. The mean power and one standard deviation of all trials are shown for the top target (red), middle target (green) and bottom target (blue). Run accuracies are indicated as a percentage underneath each run.

Table 1

Subject characteristics and control parameters

Subject	Control Modality	Imagery/Overt	Control Freq Range	Task Type	No. of Trials
Subject 1	Hand	Overt	80 – 86Hz	1D Vertical	128
Subject 2	Tongue	Imagery	77.5 – 102.5Hz	RJB	198
Subject 3	Tongue	Imagery	77.5 – 92.5Hz	RJB	90
Subject 4	Tongue	Overt	77.5 – 97.5Hz	RJB	108
Subject 5	Tongue	Imagery	67.5 – 92.5Hz	RJB	108
Subject 6	Tongue	Overt	77.5 – 97.5Hz	RJB	108
Subject 7	Tongue	Overt	80 – 98Hz	1D Vertical	271
Subject 8	Tongue	Overt	80 – 98Hz	1D Vertical	177

Table 2

Summary of metrics of cortical power for the control electrode across subjects and stages. Identification (I), Amplification (A), and Refinement (R), in the Stage column correspond to each stage of learning. Mean (μ) accuracy for all subjects increases between stages I and A, and increases or remains constant in most cases between A and R. The standard deviation (σ) of power during each stage – a measure of how consistent the subject can control the power in the control electrode – decreases between stages A and R across all subjects, indicating a tighter control over the control feature without an accompanying drop in accuracy.

Subject	Stage	Accuracy (%)	Average Power	Std Dev Power	Avg	SD
Subject 1	I	54	0.53	1.20	-	-
	A	77	0.66	1.07	0.12	-0.13
	R	71	0.64	0.64	-0.02	-0.43
Subject 2	I	66	0.845	0.86	-	-
	A	72	2.31	1.34	1.47	0.47
	R	86	2.05	0.89	-0.26	-0.44
Subject 3	I	70	1.63	0.98	-	-
	A	78	2.96	1.48	1.33	0.49
	R	76	1.61	0.77	-1.35	-0.70
Subject 4	I	80	1.48	0.75	-	-
	A	86	3.73	0.70	2.25	-0.04
	R	91	1.71	0.61	-2.02	-0.09
Subject 5	I	80	1.48	0.99	-	-
	A	98	3.73	1.44	2.25	0.45
	R	100	1.71	0.60	-2.02	-0.84
Subject 6	I	86	2.01	1.00	-	-
	A	95	1.74	0.93	-0.267	-0.07
	R	96	2.62	0.77	0.88	-0.16
Subject 7	I	100	3.71	1.17	-	-
	A	100	2.25	1.19	-1.46	0.01
	R	99	1.42	0.99	-0.83	-0.20

Subject	Stage	Accuracy (%)	Average Power	Std Dev Power	Avg	SD
Subject 8	I	68	1.01	1.52	-	-
	A	86	2.63	1.56	1.62	0.04
	R	87	0.29	0.86	-2.33	-0.71