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Movement Anticipation and EEG: Implications for BCI-Contingent Robot Therapy

THESIS

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ABSTRACT OF THE THESIS

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Brain-computer interfacing is a technology that could potentially be used to improve patient effort in robot-assisted rehabilitation therapy. For example, movement intention reduces mu (8-13 Hz) oscillation amplitude over the sensorimotor cortex, a phenomenon referred to as event-related desynchronization (ERD). In an ERD-contingent assistance paradigm, initial BCI-enhanced robotic therapy studies have used ERD as a trigger signal for providing robotic assistance to limb movement. Here we investigated how ERD changed as a function of audio-visual stimuli, overt movement from the participant, and robotic assistance. Eight unimpaired subjects played a musical computer game designed for rehabilitation therapy using the FINGER robotic exoskeleton. In the game, the participant and robot matched finger movement timing to audiovisual stimuli in the form of notes approaching a target on the screen set to the consistent beat of popular music. The audiovisual stimulation of the game alone did not cause ERD, before or after training. In contrast, overt movement by the subject caused ERD, whether or not the robot assisted the finger movement. Notably, ERD was also present when the subjects remained passive and the robot imposed movement. This ERD occurred in anticipation of the passive

finger movement with similar onset timing as for the overt movement conditions. These results demonstrate that ERD can be contingent on expectation of robotic assistance; that is, the brain generates an anticipatory ERD in expectation of a robot-imposed but predictable movement. This is a caveat that should be considered in designing BCI interfaces for enhancing patient effort in robotically-assisted therapy.

INTRODUCTION

Robotic devices, such as powered exoskeletons, have been shown to have utility for rehabilitation therapy of the upper extremity for individuals with stroke and other neurologic impairments [1-3]. In the most commonly used paradigm, the robotic therapy device physically assists the patient in completing repetitive desired movements that are pre-specified by a computer game that provides audio-visual cues [1, 4]. Physical assistance is thought to enhance proprioceptive input, which may aid neural reorganization [5]. In past studies, robotic therapy has been shown to match or better the results obtainable with conventional rehabilitation movement therapy [1, 6, 7].

It is thought that an important factor for ensuring the effectiveness of robotic therapy is active effort by the patient [8-13]. In a key study, it was shown that repetitive robotic movement of the upper extremity with a passive stroke patient has little therapeutic effect compared to robotic therapy in which the patient and robot work together [9]. Another study found no improvements in clinical movement scales following continuous passive range of motion therapy of the stroke-impaired arm [14]. It has also been found that physically assisting in movement with a robot can trigger slacking by the motor system, which is an automatic and subconscious reduction in patient effort [1, 5, 15, 16]. Thus it is important in designing robotic therapy systems to develop methods that encourage patient effort during the therapy and prevent slacking, since robotic assistance may in some cases innately encourage slacking.

Electroencephalography (EEG) based Brain Computer Interface (BCI) systems have been proposed for the purpose of enhancing robot-assisted rehabilitation training [17-20]. It is yet unclear how best to harness the strengths of these systems together, but one rationale focuses on promoting engagement. A BCI could be used to detect movement intention, and the robotic therapy system could be programmed to provide assistance contingent on the sensed movement intention. For this purpose, mu and beta frequency bands (8-12, and 13-35 Hz) have been suggested for identifying brain states associated with movement intention [17-27]. Mu and beta sensorimotor rhythm (SMR) oscillatory amplitude is known to attenuate during preparation for an overt movement or motor imagery, a phenomenon referred to as event related desynchronization (ERD) [27].

ERD has been used successfully as a control signal for BCI applications, including, recently, robot-assisted therapy [17, 20, 28-31]. However, use of ERD as a contingent control signal for robotic therapy has not been shown to decisively improve motor outcomes for robotic therapy after stroke. One study that employed a BCI-contingent orthosis movement paradigm found no significant improvement in clinical scales used to rate hand function after the study [17]. Another, larger study found modest improvements in motor outcome measures comparable with previous studies of robotic therapy that did not use BCI-contingent control [20].

It is possible that the use of ERD as a control signal for robotically assisted therapy is suboptimal because ERD is not tied to movement intention alone. Indeed, previous research has suggested that ERD occurs during passive movements driven by a robotic orthosis or an experimenter, similar to when the subject performs overt movement or motor imagery [18, 20, 22-25] (see). For example, Alegre et al. [25] studied beta band desynchronization in six healthy volunteers during passive wrist extensions performed with the help of a pulley system at random intervals. The passive movements were found to induce ERD after the movement onset. The authors concluded that proprioceptive inputs induce ERD similar to that observed during voluntary movements. Another study analyzed beta ERD during passive and attempted foot movements in unimpaired subjects and subjects with paraplegia after spinal cord injury (SCI) [22]. Passive motions were controlled using a custom foot release mechanism at eight second intervals. The feet were shielded from view. A significant ERD was found to occur ~500ms before movement onset in the unimpaired participants. Thus, in this case, ERD was found to anticipate predictable passive movement of the foot. These findings suggest that ERD is not solely related to the intention to move, but is also influenced by proprioceptive input and/or the expectation of imposed movement. Therefore, these findings have implications for the use of ERD as a control signal for detecting patient engagement during robot-assisted therapy. If the user's expectation and subsequent somatosensory preparation for passive motion is sufficient cause to trigger an ERD, the user might no longer need to actively engage in overt movement to cause the ERD trigger signal and the contingent imposed robotic movement.

The purpose of this study was to determine the effect of passive movement and subject effort on sensorimotor ERD within the context of a robot-assisted therapy paradigm we previously developed for retraining finger individuation after stroke [4]. Robotic assistance and motor activity were treated as binary categorical design factors in a 2^2 factorial experiment, resulting in four primary conditions: 1) active subject/active robot, 2) active subject/passive robot, 3) passive subject/active robot, and 4) passive subject/passive robot. Audio-visual stimulation without subject or robot movement was also tested to identify any changes in ERD that may be elicited by the robotic-therapy computer gaming paradigm itself.

Table 1: Passive Movement Oscillatory Modulation Publications

Study	Limb	Device	Interval	Predictability	ERD/ERS Timing
Alegre '02	wrist	proctor enabled	11-16 sec	n/a - random	post onset ERD
Formaggio '13	arm	robotic	1 sec	metronome 1Hz	-
Formaggio '14	arm	robotic	1 sec	metronome 1Hz	pre onset ERD
Muller-Putz '07	foot	robotic	8 sec	timing -no view	pre onset ERD
Cassim '01	index	proctor enabled	8-12 sec	n/a - random	post offset ERS
Ramos-Murguialday '12	hand	robotic	10 sec	aural cue	-

METHODS

EXPERIMENTAL SETUP

The Finger Individuating Grasp Exercise Robot or "FINGER", described at length in [4], was used as the robotic therapy device in this study (See). This robot facilitates the naturalistic grasping patterns of the index and middle finger together or individuated. Finger movements were mapped to corresponding cues on a screen in front of the participant and set to popular music in the form of a custom video game similar to Guitar Hero© (). The gaming environment and user interface software were developed specifically for this study, but we previously found a therapeutic benefit to playing a similar version of the game after stroke [32].

Figure 1: Experimental Setup: A user is shown using the robot to play the game used in this study. The Finger individuating Grasp Exercise Robot (FINGER) appears in the foreground. FINGER makes use of two stacked, single degree-of-freedom eight-bar mechanisms designed to assist the user in naturalistic grasping trajectories for each, or both of the index and middle fingers. FINGER is backdriveable. Robotic forces were held constant for active robot conditions. FINGER did not provide any assistance during the passive robot cases.

In the game, a note appears for two seconds on screen. The note moves down, reaching a target near the bottom of the screen. An on-screen marker represents the position of the robot. The participant matches the speed and timing of the note to complete the flexion portion of the grasping trajectory just as the note reaches the target. If the participant attains the desired amount of flexion and accurately matches the timing of the note, the game considers this a "hit" and provides visual feedback in the form of fire on the target and a progress bar counter increase (See). In some experimental conditions, we used the robot to assist in completing the movement with the correct finger at the correct time. More details of the assistive control algorithm can be found in [4], but essentially the algorithm guides the subject along an appropriate trajectory to hit the note using a position feedback controller.

Figure 2: Example of gaming environment: Notes stream down the screen in sync with popular music. The user matches a finger flexion to the timing of the note crossing the target at the bottom of the screen. Fire when a note is hit, and a score bar at the top of the screen give visual performance feedback. Green notes indicate a desired index finger movement, yellow notes a middle finger movement, and blue notes indicate that both fingers should grasp together. Orange and red notes were not used. Red spheres above the three virtual "strings" on the right are mapped to actual robot finger positions in real time, and are intended to be matched to note timing on screen. In this example, the user has just executed a hit with the yellow note/middle finger. A second note has just appeared on screen, and will reach the target 2 seconds later.

256-channel EEG data was collected using the EGI Clinical Geodesic hydrocel EEG System. Impedance values were kept below 100kOhm. Raw EEG data was exported for offline analysis in MATLAB. Marker timing data was captured from the gaming environment. Robot position, velocity, and controller gains were sampled and recorded at 1kHz.

PARTICIPANTS

Twelve unimpaired participants took part in this study (6 male; 6 female). All participants provided written informed consent and the study was approved by the Institutional Review Board of UC Irvine. A prerequisite for study inclusion was naivety to the experiment and gaming environment. All participants were considered healthy, and had no history of neurologic injury.

EXPERIMENTAL DESIGN

We used a two factor, two level (2^2) factorial design (Table 2). The two factors were robot assistance (on or off), and overt motor activity (on or off). We will use the term "overt" to refer to a willed, voluntary, finger movement by the subject. In the factorial part of the experiment, each subject experienced each of the four conditions. We also tested the effect of audiovisual stimulation alone before and after the four conditions.

Table 2: Factor Combinations

		Robot: passive	Robot: active
Participant	active	A	B
	passive	C	D

The subjects' fingers were first fastened to the robot as they sat comfortably in front of the screen. The gaming environment was loaded and the test song ("Blackbird" by The Beatles, 62 notes) played while the participant watched. Participants were instructed to remain as still as possible during this audio-visual only condition. The robot did not provide any assistance. At the conclusion of the experiment, the participant was then asked to complete this same task again.

After the initial audio-visual only session, the participants were allowed to familiarize themselves with the robot and gaming environment during a short training session. Robot assistance was included during the training period, but limited to small forces that could not successfully complete the movement without the overt movement of the subject. Subjects were instructed to actively participate in the motor task to the best of their ability. All participants trained on the same song ("Gold on the Ceiling" by The Black Keys) until both the participant and experimenter felt comfortable in the participant's ability to understand the gaming environment and perform to an acceptable level. All participants exceeded an 80% note "hit" rate in the gaming environment during the training period. All participants gained proficiency within three test songs, and most within two.

The factorial part of the experimental session was divided into eight runs consisting of two runs per each of the four experimental conditions, for each participant. Inter-participant session order was randomized using a Williams Design Latin Square to minimize first order carryover effects. Factor combinations were explained to the participant by the test proctor using standardized scripts. Participants were allowed to ask clarification questions regarding their role during the current factor combinations, but were not privy to why the combination was being tested. During all combinations, participants completed one song, consisting of 62 notes (trials) each. The song, "Blackbird" by The Beatles, was the same for all participants and all conditions.

Data Analysis

Raw EEG data was exported for offline analysis in MATLAB. Trials were manually screened for artifacts such as eye blinks and discarded when necessary. A low pass filter of 50Hz was applied as well as a surface LaPlacian filter to reduce effects of volume conduction. Eighteenth order Legendre polynomials were used with a smoothing factor of $1x10^{-6}$. Mu power topography was averaged across notes (trials) for each condition and all subjects. A combination of electrodes that exhibited time-locked motor behavior were selected for inter-subject analysis. These electrodes encompass the medial area between Cz and Pz and extend laterally. The selected electrodes can be visualized by topography in . For time-frequency decomposition, a Morlet wavelet transformation was chosen. Wavelet cycles varied from 5-12 cycles as a function of frequency. Wavelet analysis was applied from 5-40 Hz at 1Hz steps. The wavelet transformation was performed before any segmentation took place to eliminate any possibility of edge effects. The resulting time-frequency data was segmented into three-second epochs occurring 1.5 seconds before and 1.5 seconds after the note passed the target on each trial.

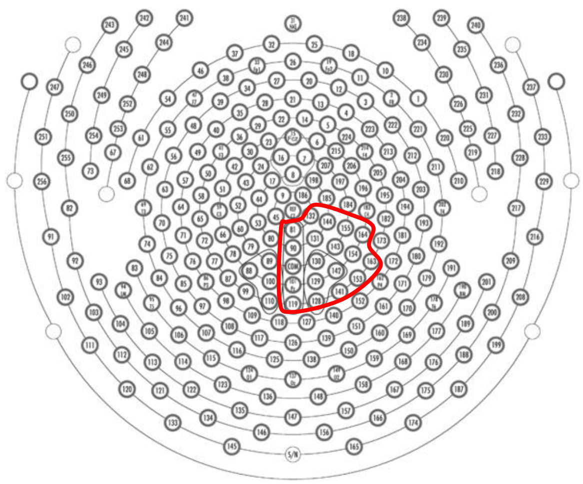

Figure 3: Topography of sensorimotor channels: Channels selected for inclusion in processing. Topographical activity of sensorimotor rhythms was analyzed for each subject. Channels exhibiting time-locked modulation were selected for further analysis. Channels were found to stem from the medial area between Cz and Pz, extending laterally towards C6/P6.

Power within a frequency bin was calculated as the magnitude of the complex coefficient result of the wavelet transformation. Power was then normalized using the decibel normalization method outlined in [33], and described by Equation 1.

$$dB_{tf} = 10\, log_{10}\left(\frac{activity_{tf}}{\overline{baseline}_f}\right) \qquad (1)$$

$\overline{baseline_f}$ is the scalar mean power taken across the baseline time period, the initial 250ms of each note (trial). t and f are time and frequency points, respectively. The baseline period began 500ms after the note initially appears on screen. The baseline period ended approximately 800ms before movement, and 1250ms before the note reaches the target (end of flexion).

A 2x2 ANOVA was conducted on the max pre-movement decibel normalized desynchronization value and max post-movement offset decibel normalized synchronization value. Robot assistance and overt movement (i.e. active movement by the subject) were treated as binary categorical design factors.

RESULTS

None of the 12 subjects exhibited ERD during the audio-visual only condition presented at the beginning and end of the experiment (). Consistent with this, no ERD was seen in the audio-visual only condition in the factorial part of the experiment (passive subject/passive robot,).

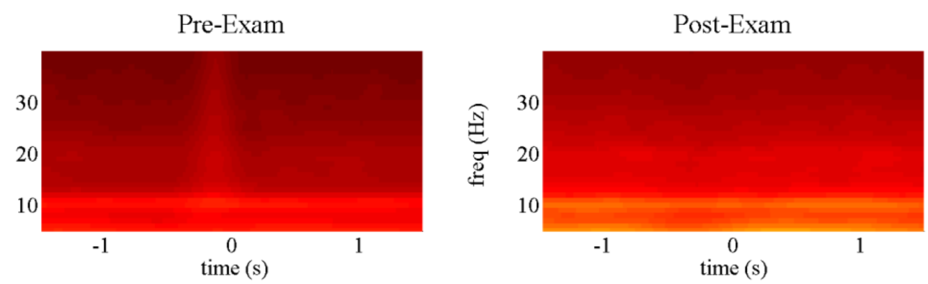

Figure 4: Audio-visual only condition: Group-level mean power amplitude time-frequency map. Results are shown at pre-exam and post-exam tests. No significant power modulation was recorded in either test. Time = 0 corresponds to the moment when the moving note crossed the target location.

In contrast, ERD was observed in the three conditions that involved physical movement of the fingers, including the condition in which the subject remained passive and the robot moved the subjects' fingers (Figure 4). In all, 10 out of 12 subjects exhibited ERD during active subject/passive robot movements. 11 out of 12 exhibited ERD during active subject/active robot movements. 10 out of 12 exhibited ERD during the passive subject/active robot movements. All 12 subjects exhibited ERD within at least one of the physical movement conditions. There was also evidence of event-related synchronization (ERS) in these three conditions, as seen by a rebound in power occurring at the end of the initial finger flexion, approximately 200 ms after movement offset ().

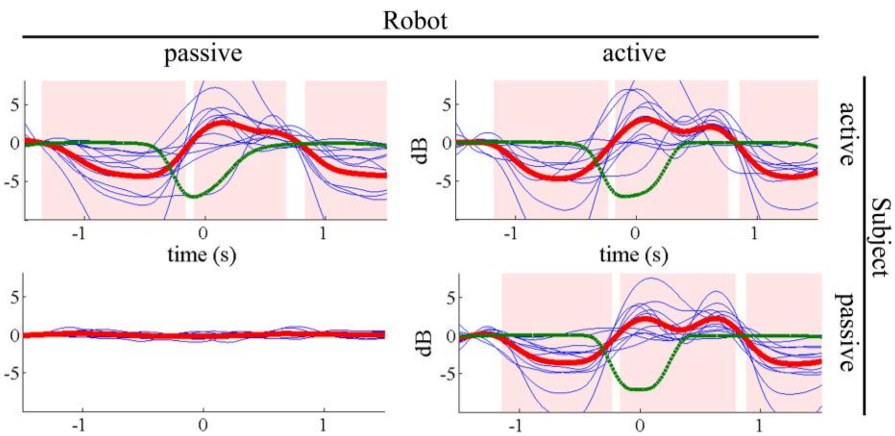

Figure 5: Mean mu band (8-13 Hz) power across subjects: Time = 0 corresponds to the moment when the moving note crossed the target location. Thin blue traces represent individual participant means. Thick red trace represents group-level mean. Red shading indicates amplitude significance (t-test) for each condition compared to the Audio-Visual only (passive subject/passive robot) condition. Significant ERD and ERS were seen in all three conditions in which a movement occurred. ERD preceded movement in all cases. Peak ERS values occurred just after finger flexion. A second ERS following finger extension appears during the active robot conditions. Green traces show mean robot trajectory, with flexion being defined downward. A smooth grasping movement consisting of a flexion followed immediately by an extension with no pause between is seen in the active subject/passive robot condition. The robot is seen to discretize the flexion/extension portions of the grasping trajectory, with a no-movement interval occurring at the target time (t=0), as illustrated by the passive subject/active robot condition. There was no movement in the passive subject/passive robot condition.

The timing of the ERD and ERS were similar in the three experimental conditions in which they occurred (Figure 4,

Table 3) with some minor differences. ERD began approximately 600-900 msec before the start of movement in all three conditions, including when the subject remained passive but the robot moved. ERD in the active subject/passive robot condition preceded that of the remaining two movement conditions. Secondary ERS can be seen following the finger extension period in in the active robot conditions. These secondary ERS signals were not statistically significant from the active subject/passive robot condition. However, the mean secondary ERS value was largest in the passive subject/active robot condition (2.19 dB), followed by the active subject/active robot condition (1.96 dB). No secondary local maxima were seen in the active subject/passive robot condition. ERS was also seen to last longest in the active robot conditions, likely due to the secondary ERS feature. In these conditions, ERS extends to approximately 1000 ms after finger-extension was complete.

Table 3: Significant Modulation Timing: Periods in which event related desynchronization and synchronization achieved statistical significance relative to baseline, via pointwise t-test ($p < 0.05$). All times are in milliseconds relative to mean movement onset.

	ERD		ERS	
Condition	**start**	**end**	**start**	**end**
robot+motor (active)	-682	263	323	1258
motor only (active)	-854	333	405	1169
AV only (passive)	N/A	N/A	N/A	N/A
robot only (passive)	-642	266	333	1287

Robotic assistance increased ERD magnitude for the pre-movement onset ERD, but it only approached significance (ANOVA, p = 0.07). It also increased the magnitude of the post-movement, but again it only approached significance ERS (p = 0.06). Overt movement did not significantly alter ERD amplitude (p = 0.66) or ERS amplitude (p = 0.88). Interaction effects between robotic assistance and overt movement were not significant for ERD (p = 0.59) or ERS (p = 0.99). A comparison of each time point revealed no significant differences in the passive subject/active robot condition compared to the active subject conditions as well (t-test, p > 0.05). The maximum across-subject ERD value seen in the passive subject/active robot condition was found to reach 3.68 (+/- 2.96) dB. The maximum across-subject ERD value seen in the active subject/passive robot condition was larger at 4.35 (+/- 3.71) dB, but the difference was not significant (t-test, p = 0.63).

9 out of 12 subjects showed ERD primarily within the mu band (8-13 Hz). The remaining exhibited primarily beta-focused desynchronization (13-30 Hz). Two of the these subjects exhibited ERD from 17-22 Hz, and the remaining subject showed ERD from 12-18 Hz. An example of broadband power amplitude can be seen for one subject in . Again, no significant modulation was seen in the passive subject/passive robot, audio-visual stimulation only condition. Mu-rhythm specific ERD was seen prior to movement onset with a peak at approximately -500ms and 10 Hz. This subject also exhibited prominent beta rebound at the end of finger flexion. These were especially noticeable in the active subject/active robot condition where beta ERS can be seen after flexion at approximately 12-28 Hz.

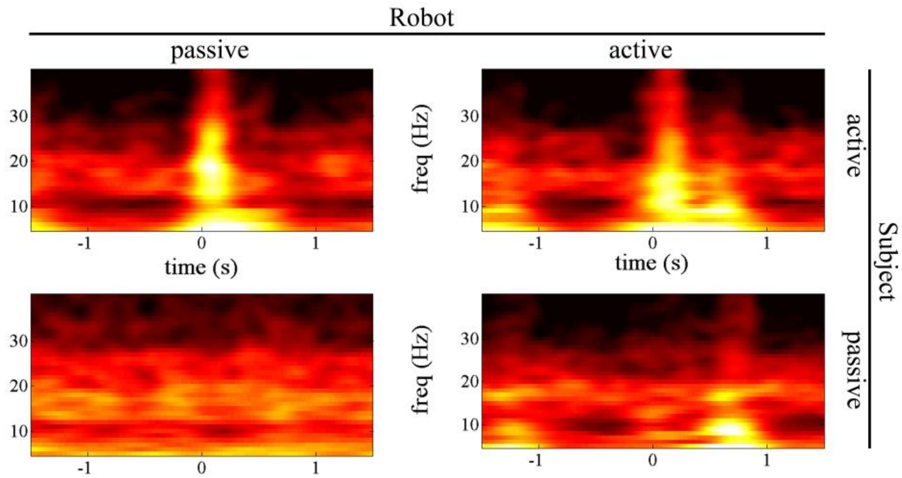

Figure 6: Single subject example of power: Time-frequency maps during the four conditions. Time = 0 corresponds to the moment when the moving note crossed the target location. This subject showed mu band (8-12 Hz) ERD and beta band (13-30 Hz) ERS in the three movement cases. Mu ERD preceded movement in all conditions. Beta ERS followed the completion of finger flexion, occurring at t=0 in the subject active conditions. A second, smaller ERS was seen in the robot active conditions. ERS appeared only after finger extension in the passive subject/active robot condition.

Discussion

In a robotic neurorehabilitation setting, the patient is often faced with the task of mixing overt movement, robotic assistance, and external audio-visual stimuli associated with a computer game. The effects of these stimuli and interaction with one-another on ERD have not yet been well defined. The aims of this study were to identify the effects of these factors on ERD using a prototypical robotic therapy paradigm. ERD was found to precede movement during all three movement conditions, and notably even in the passive subject/active robot condition. No significant power modulation was seen in the audio-visual only condition before or after the factorial conditions were completed. ERS was identified during post-movement periods, with a tendency toward a secondary ERS in the robotically assisted conditions. Next we discuss the effects of robotic assistance on ERD and ERS. We will highlight the implications of these effects with regard to patient engagement in therapy and future BCI-robot therapy paradigms.

Effects of robot assistance on ERD

This study identified pre-movement ERD during passively imposed movement, suggesting that ERD during passive movement is not tied solely to proprioceptive feedback, but is likely the result of cortical preparation for the impending somatosensory input the movement will produce. In many past studies, ERD has been found to follow imposed movement onset, and has been attributed to proprioceptive feedback [24, 25, 29]. During self-paced movements however, ERD has been observed to precede movement onset [27, 34-36]. Pre-movement ERD has also been observed previously before cued predictable movements [21, 26], including passive movements imposed on the subject [22, 23]. This study verified these findings, showing that ERD appeared in advance of a predictable imposed movement from a robotic orthosis operating within a robotic therapy paradigm, when the subject was instructed to remain passive. Because proprioceptive feedback is not yet affected by the imposed movement during the pre-movement interval, these findings suggest there is a cortical preparation of the somatosensory system in advance of an imposed movement. The existence of ERD before movement onset, comparable to that found preceding overt movement, suggests that ERD can become contingent on the expectation of robotically-imposed movement. That is, ERD is not uniquely tied to active movement but can reflect preparation for movement, whether active or passive.

ERD preceding both active and passive movements may be explained by two physiological mechanisms: the efference copy and anticipatory attention. Unlike other studies, which used random movement intervals [24, 25], participants in the present experiment were aware of the existence and timing of oncoming notes. Participants had sufficient time to prepare for the movement, whether active or imposed by the robot. Past studies have found that the brain predicts oncoming sensory information related to an intended movement so that the system can learn and adapt to changes [37-39]. When a command is sent to the motor system to generate movement, an internal copy of the command is created to predict sensory consequences of the movement. This phenomenon is referred to as an efference copy. The efference copy is collated with sensory inputs produced by the movement, allowing a comparison of the expected movement (forward model) and the actual movement. In one study, subjects performed a self-paced finger-tapping task that alternated hands [40]. ERD was observed to occur up to two seconds before movement over the contralateral hemisphere during dominant hand movements, and bilaterally during non-dominant hand movements. The authors suggest that while ERD of the contralateral sensorimotor cortex is an excitatory process, ERD of the ipsilateral hemisphere may be the result of an efference copy reflecting inhibition of movement. During the passive subject/active robot condition of the current experiment, participants expected movement but suppressed overt intention of that movement. Although the descending motor command was inhibited, the internal network requires the efference copy to predict the sensory input of the imposed movement [41]. Therefore, in the current experiment, ERD preceding movement may be the EEG correlate of the efference copy sent in preparation for predictable imposed movement. Others have suggested that contralateral beta ERD may be a corollary of anticipatory attention to a future motor stimulus [42]. It may be the case that ERD measured here is the result of maintained attention to the oncoming note stimulus. Examination of the effects of predictable and unpredictable cueing would be necessary to further explore the roles of the efference copy and movement inhibition on the magnitude and temporal features of ERD.

IMPLICATIONS FOR PATIENT ENGAGEMENT IN BCI-ROBOT THERAPY

Although ERD has been shown to be a reliable control signal for BCI applications, the use of BCI-contingency in robot therapy has not yet been proven superior to traditional or robotic therapy. One important rationale for using BCIs in robotic therapy is ensuring the active effort of the patient in the movement task [5, 9]. This study shows that ERD can be contingent on the expectation of passive, imposed robotic movement. Therefore, in a predictable task therapy environment, the use of ERD as an orthosis control signal does not necessarily require the patient's active engagement in the motor task, but simply the expectation of robotic movement. As such, ERD may be suboptimal in the context of patient engagement in BCI-contingent robot therapy.

ABSENCE OF EFFECTS OF AUDIO-VISUAL STIMULI

Power modulation did not appear in any of the audio-visual only condition exams. The final audio-visual only condition is of particular interest, as it occurred after repetitive conditioning of motor activity to the audio-visual stimuli. The gaming environment in this study utilized very engaging visual and aural cueing matched to overt movement and haptic feedback. Popular music with a consistent beat was chosen for maximum influence on the participant; and indeed the game paradigm used here is similar to the third most popular game in video game history. By repeatedly matching hundreds of individuated finger movements to the audio-visual cues on screen, the participant was placed in a scenario that one might expect would lead to classical conditioning. However, the lack of activity in the final audio-visual condition suggests an insusceptibility of EEG power modulation to conditioning based on audio-visual cueing or gaming environments commonly seen in robot therapy. This finding also rules out the possibility that the gaming environment affected ERD in the remaining conditions. This is an important null result for ERD-based BCIs relying on aural and/or visual cues, as it suggests that the cueing environment alone is unlikely to falsely trigger a BCI contingent robot; rather the imposed movement by the robot plays a key role.

EFFECTS OF ROBOTIC ASSISTANCE ON SYNCHRONIZATION AFTER MOVEMENT

Event related synchronization or "rebound" occurred following finger flexion offset in all three movement conditions. These findings agree with Pfurtscheller et al. , who characterized the temporal traits of ERS, finding that a burst of beta power appeared within a one second interval following movement offset [35]. Post movement beta ERS has since been shown to follow voluntary hand movements [36, 43-45], as well as passive movements [24, 43]. ERS following movement matches previous findings, with the exception of a second, smaller synchronization that was more prominent in the robot active conditions.

The presence of a secondary synchronization in the two active robot conditions may be a result of the discrete flexion/extension forces applied by the robot. Secondary synchronizations seen in the active robot conditions were not statistically significant from the active subject/passive robot case. However, the group-level mean ERS was larger in the active robot conditions and ERS significance periods ended later. The mean secondary synchronization was greatest in the passive subject/active robot condition, followed by the active subject/active robot condition. ERD and ERS in relation to kinematic and kinetic hand movements were recently characterized by use of a 3x4 factorial design experiment in which the subjects repeated hand grasping movements at different speeds and forces [21]. The authors found that although grasping force did not affect the magnitude or time course of ERD/ERS, repeating grasping motions caused repeated up-modulation of the signal power. This supports our findings, because in the present experiment the robot assistance for flexion and extension were separated by approximately a ~200ms interval in which no movement occurred, thereby creating two distinct motions (flexion, pause, extension), and therefore two distinct synchronization features. In contrast, in the active subject/passive robot condition the finger extension occurred immediately after the finger flexion without a pause, and therefore did not show a secondary ERS.

LIMITATIONS AND FUTURE RESEARCH

One caveat of the current study is that we studied unimpaired subjects. Our rationale for this selection was exclusion of the confounding influence of a brain lesion on EEG activity, allowing us to gain insight into the normative interaction between robotic assistance and brain activity. In a study of event-related beta EEG modulation during passive and attempted foot movements, Müller-Putz et al. found that individuals with paraplegia after SCI did not exhibit a significant ERD or ERS during the passive movement condition [22]. Another study found that peak ERD during attempted shoulder-elbow movements was significantly smaller in individuals with a stroke compared to unimpaired subjects [19]. Neither study tested passive movements in people with a stroke. However, their findings suggest that robot-contingent triggering of ERD during passive movements may be diminished in people with neurological impairment. A future aim of this research is the replication the experiment utilizing participants with a stroke.

This study used a factorial combination of overt movement and robot assistance, rather than online BCI contingent control of the robot to study the potential effects of robotic therapy on event related EEG features. The observation that the pre-movement ERD was contingent on the robotic assistance has implications for using contingent-BCI to improve patient engagement. However, it will be important to verify the results presented here in an online BCI-contingent robot therapy paradigm in future work.

Fine motor tasks such as finger individuation are important for daily function. Furthermore, it has been suggested that isolated, individualized movement deficit also affects impairment in gross movements, such as elbow extension [46]. A recent study employed an EEG based BCI in decoding individuated finger movements, and achieved accuracy significantly above chance level [47]. It may therefore be possible to decode EEG-based signals in real time for the online BCI-contingent control of individual fingers in the FINGER robotic orthosis, which may improve outcome after therapy.

A logical progression of this work would be the identification of an event-related brain state robust to the effects of robot-contingent triggering. Functional connectivity has been shown to vary between active and passive movements during motor tasks [23], and therefore may be useful as an indicator for active engagement in the context of BCI-robot therapy. A second approach might forego a-priori feature selection altogether, using machine learning algorithms to decode movement intention. Past studies have used similar approaches to classify resting state versus active or imagined movements [28, 48]. To our knowledge, no such approach has been applied to the classification of passive versus active movements. Such an approach may be able to isolate the spatio-spectral EEG features associated with active engagement in the motor task. This would circumvent the robot-contingency observed in ERD preceding passive movements. If patients are indeed slacking in the current BCI-contingent robotic therapy paradigms, a passive/active classification BCI paradigm might encourage patient engagement in the motor task, improving motor outcomes after therapy.

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