Closing the Sensorimotor Loop: Haptic Feedback Facilitates Decoding of Arm Movement Imagery

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Abstract—**Brain-Computer Interfaces (BCIs) in combination with robot-assisted physical therapy may become a valuable tool for neurorehabilitation of patients with severe hemiparetic syndromes due to cerebrovascular brain damage (stroke) and other neurological conditions. A key aspect of this approach is reestablishing the disrupted sensorimotor feedback loop, i.e., determining the intended movement using a BCI and helping a human with impaired motor function to move the arm using a robot. It has not been studied yet, however, how artificially closing the sensorimotor feedback loop affects the BCI decoding performance. In this article, we investigate this issue in six healthy subjects, and present evidence that haptic feedback facilitates the decoding of arm movement intention. The results provide evidence of the feasibility of future rehabilitative efforts combining robot-assisted physical therapy with BCIs. Moreover, the results suggest that shared-control strategies in Brain-Machine Interfaces (BMIs) may benefit from haptic feedback.**

Index Terms—**Haptic Feedback, Brain-Machine Interfaces, Motor Imagery, EEG.**

I. Introduction

In the past two decades, research on Brain-Computer Interfaces (BCIs) has evolved from basic feasibility studies [1; 2; 3] to a state in which basic communication can be routinely performed after only brief calibration periods with healthy subjects [4; 5] as well as with subjects in early stages of amyotrophic lateral sclerosis (ALS) [6]. Although communication with completely locked-in subjects in late stages of ALS still remains a challenge, this substantial progress has resulted in a growing interest in extending the application domain of BCIs from communication towards restoration of basic motor functions. For example, EEG-based control of an electric wheelchair has been reported in [7], and the feasibility of controlling a mobile robot by means of a non-invasive BCI has been demonstrated in [8].

Interestingly though, most studies in this field only consider replacing dysfunctional body parts by BCI-controlled artificial actuators. Instead, BCIs might may also be applicable to directly facilitate rehabilitation of body parts impaired by neurological conditions such as stroke [9]. While traditional or robot-assisted physical therapy constitutes the key ingredient to rehabilitation after stroke [10; 11], motor imagery has also been shown to have a beneficial effect in stroke rehabilitation [12; 13]. Furthermore, successful MEG-based decoding of motor imagery in chronic stroke has been demonstrated in [14]. The next logical step is to combine these insights into an integrated stroke therapy, in which patients exert control over robot-assisted physical therapy through the decoding of movement intentions using a BCI. Such an integrated therapy can be expected to have a large impact on stroke rehabilitation, as the synchronization of robot-assisted physical therapy with movement intention is likely to result in increased cortical plasticity due to Hebbian-type learning rules [15; 16; 17].

A key aspect of this approach is reestablishing the disrupted sensorimotor feedback loop, i.e., temporarily bypassing the impaired movement execution of stroke patients through robot-assisted physical therapy controlled by means of a BCI. Importantly though, the effect of artificially closing the sensorimotor feedback loop on BCI-decoding has not yet been studied. It is well known that passive movements [18; 19] as well as active arm movements [20] induce patterns in the electromagnetic field of the brain similar to those observed during motor imagery [3]. Moreover, random haptic stimulation has been shown to be beneficial for decoding motor imagery [21]. However, it remains an open question how the electromagnetic field of the brain changes in response to artificially closing the sensorimotor feedback loop, i.e., by providing sensory feedback on the intended movement without actual movement execution, and whether the resulting feedback processes are beneficial or disadvantageous for decoding movement intentions.

In this work, we study the effect of artificially closing the sensorimotor feedback loop on BCI decoding of arm movement intention in six healthy subjects. Specifically, each subject performed motor imagery of arm extension and flexion while being attached to a robot arm. Simultaneously, we performed on-line decoding of movement intention with an EEG-based BCI, and employed the robot arm to move the subject's arm according to the inferred movement intention. By using a block-wise design, we compared subject performance with and without robot-induced movement execution, and provide evidence that artificially closing the sensorimotor loop increases decoding accuracy substantially. Thereby, our results demonstrate that closing the sensorimotor feedback loop is not only feasible, but even facilitates decoding of movement intention. While it remains to be established whether these results can be transferred from healthy subjects to stroke patients, our results provide support for the feasibility of a future integrated stroke therapy, combining robot-assisted physical therapy with decoding of movement intention by means of a BCI. Moreover, including haptic feedback may improve performance in shared-control strategies in Brain-Machine Interfaces (BMIs).

The paper is organized as follows. Section II is devoted to a description of our experimental design, including the necessary equipment and methods from signal processing, on-line decoding and robot arm control. In Section III, experimental results for six healthy subjects are studied. The paper finishes with some discussion and conclusions of our experiments in Section IV.

II. Materials and Methods

A. Human subjects

Six right-handed subjects, four females and two males with ages between 22 and 32 years old, were taking part in this study. None of the subjects had previous experience with motor imagery. All subjects participated in all the conditions of haptic feedback explained in Section II-D. They all gave informed consent prior to the EEG session.

B. Recording

An EEG electrode cap (by Electro-Cap International, Inc.) in combination with a Quickamp (by Brain Products, GmbH) amplifier were used during our experiments. 35 channels of the EEG electrode cap were fed into the amplifier, with a 250Hz sampling rate and a built-in common average reference (CAR) montage. All electrode impedances were kept below 10 kΩ. The electrode array covered parts of the premotor cortex, primary motor cortex and somatosensory cortex as well as several other areas, as shown in Figure 3. EEG signals were acquired from the amplifiers using the general-purpose BCI2000 software [22], and the additional module BCPy2000 [23] was used for on-line signal processing, statistical learning, and transmission of the control signal.

C. Tasks

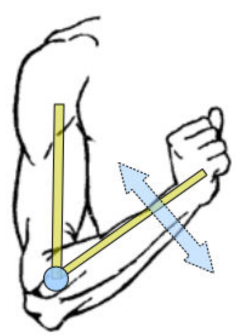

Fig. 1. Subject's imagery task.

The subject's task consisted of motor imagery of the right forearm. The subject was instructed to imagine moving the right forearm forward or backward, using the elbow as the single degree of freedom during the imagined movement, see Figure 1. The forward and backward movements are parts of a pointing movement with the forearm and it is an essential component of a grasping movement. In each block, there were 15 visual and auditory cues ("Move forward", "Move backward") for each movement direction and 30 visual and auditory cues ("Relax") for rest, delivered as a text at a distance of 1.5m from the subject, alternating between 5s movement periods and 3s rest periods. A trial is defined as a rest period followed by a movement period. In each block, on-line visual feedback was provided after an initial training period consisting of 25 seconds for each condition. Two blocks per condition and user were performed. Here, an arrow moved forward, backward or stopped every 300 ms based on the on-line decoding of the EEG signal. The subject's right forearm was attached to a robot arm, which provides haptic feedback as explained in Section II-D. Cues of both types of movement directions were interleaved randomly in a way that the movement direction could not be inferred a priori.

D. Haptic Feedback and Robot Arm

Fig. 2. Robot arm setup.

A Barret WAM robot arm was used to provide haptic feedback during our experiments. A robot arm was attached to the subject's forearm (see Figure 2). The robot was configured in a safe low power mode. It was programmed to only move the joint that mimics the elbow. Hence, we deal with a system with one degree of freedom (DoF). Note that we aim at showing how haptic feedback influence the on-line decoding. A single DoF movement sufficed for this purpose and, hence, it was chosen for simplicity. In order to explore the influence of haptic feedback, we performed four different conditions or experiments (I-IV). During the training periods for Conditions I and II, the robot arm moves the subject's forearm forward or backward in a coherent manner with respect to the text cues. In the test periods for Conditions I and III, the robot arm moves forward, backward or stops based on the classifier output. During the training periods for Conditions III and IV, and test periods for Conditions II and IV, the robot does not move (See Table I). Conditions for each subject were interleaved randomly to have a fair comparison among conditions, avoiding effects caused by training, fatigue or changes in attention over the course of an experiment.

E. Signal Analysis

Initially, a centre-surround spatial sharpening filter or *surface Laplacian* [24], band pass filtering (2-115 Hz), and notch filtering (50 Hz power line) were applied on the raw signals. Normalized average power spectral densities in 2 Hz frequency bins for each electrode were used as on-line features, as previously used in motor imagery and for real movement decoding [25; 26]. Burg's and Welch's methods were used to compute an estimation of the power spectral density (PSD). During the experiment, the estimation was computed on-line using Welch's method over incrementally overlapping bigger time segments during each 5s movement or 3s resting periods. Larger segments provided less noise and more reliable estimates while smaller time segments were necessary to enable on-line classification already at the beginning

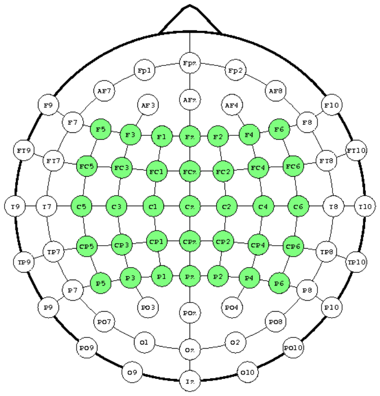

Fig. 3. EEG electrode grid configuration used in our experiments. Recorded electrodes are shown in green.

of every trial. In further off-line analysis using MATLAB (by The MathWorks, Inc.), Burg's maximum entropy estimation was used to estimate the PSD over incrementally overlapping bigger time segments during each 5s movement or 3s resting periods, given its greater performance over the dataset.

F. On-line decoding

On-line classification was carried out to discriminate movement and resting, providing on-line visual feedback and haptic feedback, as explained in Section II-D. For each run, a linear support vector machine (SVM) classifier [27] was generated on-line after a short initial training period in which spectral estimates for 25 seconds of each condition (both movement directions and rest) are computed. Given the number of recorded channels (35) and frequency bins (20), we have a vector of 700 features per data point. In addition, the parameters of a sigmoid function are estimated by crossvalidation over the training set in order to map the SVM outputs into probabilities [28]. To be able to analyze the classifiers outputs in rest and movement periods together, we redefine the probabilistic output to mean always probability of success, i.e. probability of rest for periods of rest and probability of movement for period of movement. Such probabilities will help us to study the differences among different schemes of haptic feedback in Section III. We decided to use a linear kernel in the SVM in order to limit the number of hyper-parameters. Off-line analysis indicated that the use of non-linear kernels did not improve the classification performance significatively.

Condition	Training	Test (Visual feedback is always given)
I	Robot moves	Robot moves (following classifier)
II	Robot moves	Robot does not move
III	Robot does not move	Robot moves (following classifier)
IV	Robot does not move	Robot does not move

TABLE I
CONDITIONS TO EXPLORE HAPTIC FEEDBACK.

III. RESULTS

A. Performance

In our experiments, we generated a linear support vector machine (SVM) classifier [27] on-line after a short initial training period in which spectral estimates for 25 seconds of each condition (both movement directions and rest) are computed. Moreover, we estimate the parameters of a sigmoid function to map the SVM outputs into probabilities. Two binary classifiers are generated: one that distinguishes between moving forward vs resting and another one that classifies between backwards vs rest, but we provide results not making a distinction between moving backward and forward, i.e. movement vs rest is shown.

First, we study the probabilitic outputs in the on-line classification in order to see wether there is a significant difference among conditions of brain-signal based haptic reinforcement (see Table I for a definition of the conditions). Afterwards, we show the present average accuracy and the area under the receiver operating characteristic (AUC) [29] of all classifiers for every condition as well as every subject to illustrate our initial findings.

We perform a two-way analysis of variance (ANOVA) with a Bonferroni adjustment to compensate for multiple comparisons [30] over the probabilistic outputs of all trials (sessions) and subjects. This step lets us discover if there are differences in the classification accuracy among all four conditions of haptic feedback. Figure 4(a) shows the confidence intervals and the average probabilistic output per condition of haptic feedback. ANOVA rejected the null-hypothesis that the classifier decision values means are equal for all pair of conditions except Condition II vs Condition III at significance level $\alpha = 0.05$. The results suggest that a better classification performance when comparing arm movement intention vs rest if the robot provides robot-based haptic reinforcement during the training and the test periods, i.e. condition I outperforms the rest. Note that during test, the robot arm is programmed to move or stop according to the output of the classifier in an on-line manner. Moreover, the classification performance is substantially higher when the robot was guiding the subject during the classifiers' training than if only the visual stimulus was supplied, i.e., condition II outperforms condition IV. This last finding may be caused by an improved representation of the arm movement intention of the subject due to the robot-induced passive movement.

Both average accuracy and area under the ROC curve for every condition of haptic feedback as well as every subject are shown in Figure 4(c). Please note that the differences among conditions are consistent with the findings discussed during the analysis of variance. In Condition I, the classification performance appears to be the highest but Condition II also exhibits a higher performance than Condition IV. AUC is independent of the threshold applied to the probabilistic output of the classifiers, and thus might be a fairer comparison between the conditions than the average accuracy.

These observations provides empirical evidence of a greater spectral power decrease (or event-related desynchronization) when comparing movement intention vs rest in cases in which the robot arm guides the subject's arm. Classification of real (overt) active arm movements vs rest has been shown to achieve performance superior to classification of imagined arm movements vs rest [31]. Our results indicates that this statement can be extended to the case of classification of real passive arm movements guided by a robot arm vs rest.

B. Spatial and Spectral Features

Figure 5(a) shows a comparison of the classifier weights per electrode averaged over the (8, 40) Hz frequency band and across the subjects between training periods in which the robot arm guided the subject's arm and training periods in which it did not. We focus on this frequency range because it contains the μ (9-13 Hz) and β (18-24 Hz) rhythms, reported as highly discriminative in motor imagery experiments [32]. We can see how more electrodes over the motor area representing the right arm, i.e., C3, CP3, FC3, FC1, ..., get larger weights (i.e., have a higher discriminative power) when the robot arm guides the subject's arm during the training period. The spatial distribution of the weights in the classifiers indicates that the classifiers employ neural activity, as the weights in the peripheral locations are low. Hence, electromyographic (EMG) activity is not likely to play a major role.

The average weights per frequency bins of 2 Hz for the most discriminative electrodes, C3 and CP3, are shown in Figure 5(b). A shift towards higher frequencies can be observed, i.e., from μ rythm desynchronization to β rythm desynchronization. At the same time, a narrower frequency band accumulates most of the weights when the robot arm guides the subject's arm during the training period.

IV. Discussion

In this article, we have demonstrated that artificially closing the sensorimotor feedback loop facilitates decoding of movement intention in healthy subjects. This result indicates the feasibility of a future integrated stroke therapy that combines robot-assisted physical therapy with decoding of movement intention by means of a BCI. Specifically, we provided evidence that the strength of the sensorimotor rhythm (SMR), as measured by the class probability estimates of the SVM, is modulated by the haptic robot-based feedback. Furthermore, our results suggest that this modulation of the SMR is actually beneficial for decoding of arm movement intention. An increased classification accuracy is exhibited by comparing performance with haptic feedback to no haptic feedback (cf. Conditions I and IV in Figure 4).

The spatial and spectral structure of the classifier weights in Figures 5 indicate that haptic feedback activates the somatosensory cortex and increases ERD/ERS modulation in the β-frequency range. Interestingly, this observation is in agreement with previous reports on the effect of passive haptic stimulation [18; 19; 21], even though in these studies haptic stimulation was performed independently of the actual (or decoded) movement intention.

Besides the most prominent difference between decoding performance with no haptic feedback (Condition IV) and haptic feedback during training and testing (Condition I), it is noteworthy that our results also suggest an effect on the decoding performance when haptic feedback is provided only during training. Haptic feedback during the training session increased performance during testing relative to the condition with no haptic feedback during training, even though the haptic feedback was not applied during the test session (cf. conditions II and IV in Figure 4). Potential explanations for this observation include a positive after-effect of passive arm movement during training on a subject's capability to perform motor imagery during the test session, as well as the possibility that providing haptic feedback during training provides features that enable learning a classification procedure with a better generalization error than without haptic feedback.

Regarding the positive effect of closing the sensorimotor loop on the decoding of movement intention, we speculate that haptic feedback supports subjects in initiating a voluntary modulation of their SMR. However, further investigations into the neuronal correlates of this effect are required.

It should be pointed out, however, that the support provided by this study for a future stroke rehabilitation, combining robot-assisted physical therapy with BCI-based decoding of movement intention, hinges on the assumption that the results presented here with healthy subjects can be transfered to stroke patients. While this issue has to be addressed in future studies, there is no a-priori reason why the beneficial effect reported here should require an intact motor execution system - particularly as the design of this study deliberately avoided active movement execution.

Besides the relevance of our results for a potential stroke therapy, it is furthermore noteworthy that the positive influence of haptic feedback on decoding accuracy might also prove to be beneficial for other scenarios and subject groups. For example, subjects in late stages of ALS appear not to be capable of sufficiently modulating their SMR, as indicated by fact that so far no communication with a completely locked-in subject has been established by means of a BCI. While the extent of sensory feedback in late stages of ALS remains unclear, haptic feedback might also support these subjects in initiating volitional modulation of their SMR. In a shared-control scenario in BMIs, we may improve performance by means of haptic feedback.

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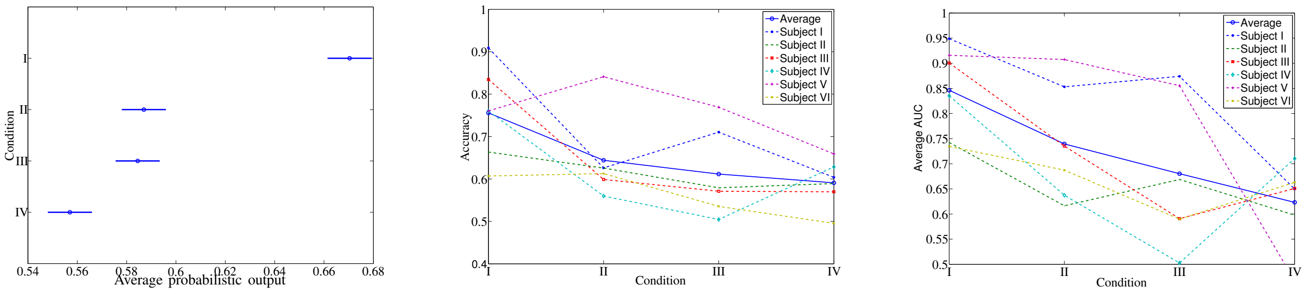
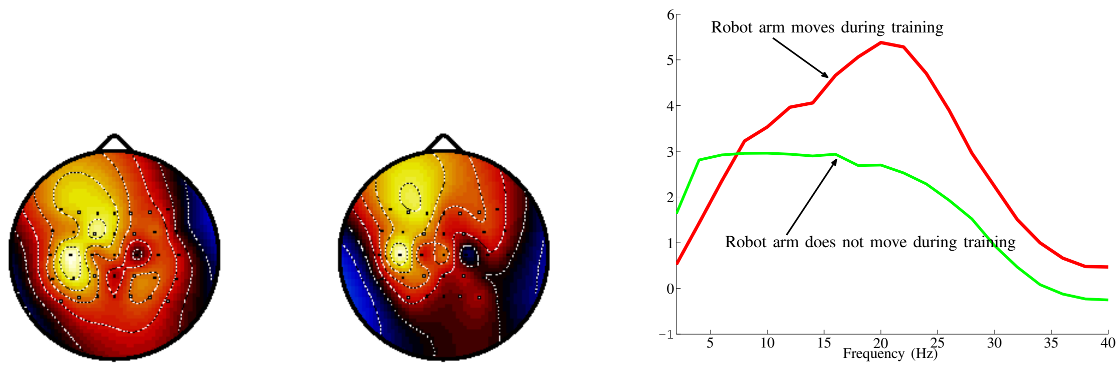


(a) ANOVA (b) Accuracy (c) AUC

Fig. 4. **Comparison of classification accuracy among Conditions I-IV:** (a) average probabilistic outputs with confidence intervals given by ANOVA using a Bonferroni adjustment to compensate for multiple comparisons, (b) average accuracy and (c) average AUC values of the on-line classifiers over all trials (sessions) and subjects for all four conditions, i.e., 60 trials per condition and user. See Table I for a description of the conditions.



(a) Classifier weights per electrode averaged over the (8, 40) Hz frequency band. On the left, the robot moved during training and on the right, the robot did not move

(b) Classifier weights of the average over C3 and CP3 for the (2, 40) Hz frequency band

Fig. 5. **Discriminative power of the electrodes**: Comparison of the classifier weights between the classifiers generated when the robot arm guides the subjects' arm and when the robot arm is not moving during training. (a) shows the average weights over the (8, 40) Hz frequency band for all the electrodes and (b) shows all the weights in the band (2, 40) Hz for the electrodes C3 and CP3. 60 trials per condition and user were recorded. Refer to Fig. 3 for electrode grid spatial configuration.

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