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Motor imagery based brain-computer interface: a study of the effect of positive and negative feedback

Mar González-Franco, Peng Yuan, Dan Zhang, Bo Hong and Shangkai Gao

***Abstract*— Co-adaptation between the human brain and computers is an important issue in brain-computer interface (BCI) research. However, most of the research has focused on the computer side of BCI, such as developing powerful machine-learning algorithms, while less research has focused on investigating how BCI users may optimally adapt. This paper assesses the influences of positive and negative visual feedback on motor imagery (MI) skills by evaluating the performance. More precisely, a MI based BCI paradigm was employed with fake visual feedback, regardless of subjects' real performance. Subjects were exposed to two experimental conditions –one positive and one negative, in which 80% or 30% of the trials were associated with positive feedback, respectively. The main EEG feature for MI-BCI classification –the asymmetry of mu-rhythm between hemispheres– was more prominent only after the negative feedback session. In addition, the negative feedback condition was accompanied by larger heart rate variability compared to the positive feedback condition. Our results suggest that visual feedback is an important aspect to take into account when designing BCI skill acquisition sessions.**

I. Introduction

Brain computer interfaces (BCIs) are direct communication channels between the neural activity generated by the brain and the outside world [1]. The modulation of mu rhythm (8-12Hz rhythmic brain activity over the sensorimotor areas) by motor imagery (MI) is an important feature exploited in BCI systems [2]. Essentially, MI is based in the mental rehearsal of a kinesthetic movement [3], [4]; when the subject imagines the movement of a certain limb, the imagined movement induces a desynchronization of the mu rhythm over the corresponding sub-regions within the sensorimotor region. In practice, this desynchronization can be detected and used for BCI control. MI-BCIs have been used not only as assistive tools for severely disabled people, but also as a new neural therapy for the restoration of motor functions for stroke patients [2], [5].

It is well recognized that the co-adaptation between the human brain and the computer is an important issue in BCI research [6]. The closed-loop BCI system: the machine-learning algorithms for detecting and recognizing different EEG patterns and their feedback, is built from this co-adaptation between the human brain and the computer. Over the last decade, researchers have developed a variety of powerful EEG-specific algorithms which greatly enhanced the performance of BCI systems [7], [8]. In contrast, little is known about the influence of feedback on BCIs [9], [10], even though it is well accepted that BCI skills require feedback to optimize performance [1]. Feedback design, in the case of the MI-BCI, is particularly critical since MI-BCI requires relatively longer training time than other BCI paradigms such as the SSVEP or P300. Additionally, the experience of MI-BCI is highly subject-specific.

In this paper, we investigate the influence of visual feedback on human response using the classical left/right hand MI-BCI paradigm, the difference is that in this study subjects were exposed to fake feedback –regardless of their real performance. All subjects were exposed to the positive and negative feedback conditions counterbalanced. Their EEG and ECG were recorded for the evaluation of the BCI skill level, mental status and stress level.

II. Materials and Methods

A. Subjects

Eight subjects (4 men and 4 women), aged from 24 to 33 (mean 27), participated in this experiment as paid volunteers (20 RMB / hour). All of them were naïve to BCI experiments.

B. Experimental paradigm

One single trial followed the time line shown in Fig. 1.

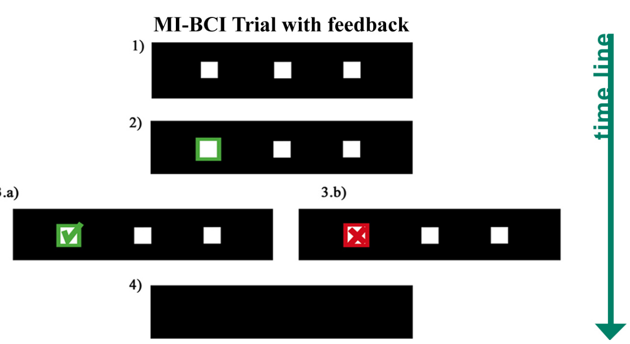

Fig. 1. Graphical interface of one complete trial. 1) preparation cue (1 second); 2) task cue informing the subject to perform left hand MI task (4 seconds); 3) feedback (1 second), can be either positive (3.a) or negative (3.b); 4) inter trial interval (3 seconds)

The subjects first viewed three white squares and were required to fixate on the central square. The MI task instruction of the trial was given by highlighting in green either the

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M. González-Franco was with the Department of Biomedical Engineering, School of Medicine, Tsinghua University, Beijing, China. She is now with the EventLab, Universitat de Barcelona, Spain; holding a FI-DGR fellowship from the Catalan Government (CUR-Gencat) co-founded by the European Social Fund (EC-ESF)

P. Yuan, D. Zhang, B. Hong and S. Gao are with the Department of Biomedical Engineering, School of Medicine, Tsinghua University, Beijing 100084, China

left or the right square. The subjects were asked to imagine their left or right hand moving –e.g. lifting heavy objects– and to sustain their mental status for 4 seconds. After the task execution, visual feedback was presented by a green tick indicating the subject had completed the task correctly or by a red cross informing the subject that his/her mental status during the MI task was not successfully recognized. In this study, the feedback was not associated with the subjects' real performance but predetermined by the trial condition.

Two experimental conditions were run: one negative feedback condition (NFC) and one positive feedback condition (PFC). Each condition consisted of three stages:

- Stage 1: 10 min. relaxation.
- Stage 2: 10 min. no feedback task with 66 trials.
- Stage 3: 10 minutes of PFC/NFC with 66 trials.

Stage 1 and 2 were the same for PFC and NFC. During Stage 3, in the NFC 30% of the trials were followed by positive feedback (green ticks), while in the PFC 80% of the trials were followed by positive feedback.

C. Procedure

The presentation order of the negative and positive feedback conditions were counterbalanced across subjects.

Subjects were told that the purpose of the study was to evaluate two BCI algorithms and that they would repeat the experiment twice –the two conditions–. Subjects were informed that there may be possible performance differences due to the change of algorithms. Subjects were told that stages 1 and 2 would be used for the calculation of their specific parameters, which would then be used in Stage 3 to generate the trial-by-trial feedback. That is, in Stage 3 subjects expected their real BCI performance as feedback; however, in reality the subjects were receiving predefined feedback. None of the subjects realized that the feedback was fake.

D. EEG and ECG recording

The NeuroScan SynAmp II amplifier with a setup of 32 channels was used for the EEG recording; 1 bipolar electrode pair was placed in both wrists of the subjects for the ECG recording. The sampling rate was 1000Hz.

E. Data Analysis

The mental stress level of subjects was assessed using time domain analysis by analyzing the 10 minutes of ECG data and calculating the heart rate variability (HRV) during each experimental stage [11]. Time-domain analysis was computed from the standard deviation of NN-intervals (SDNN). According to [12], SDNN decreases when subjects are exposed to psychological stress. Inter-subject errors in the statistics were avoided by normalizing the SDNN to the baseline no feedback task (ΔSDNN) as in (1):

$$\Delta SDNN = SDNN_{Feedback} - SDDN_{NoFeedback} \quad (1)$$

In our case a negative ΔSDNN shows a decrease in the SDNN when the feedback was given, and therefore a more stressful situation. On the other hand, when a positive ΔSDNN appears the feedback condition is less stressful than the no feedback condition.

The EEG data were input to an offline classification procedure as described in [13]. Briefly described, a common spatial pattern (CSP) algorithm was employed to find the task-specific EEG features and a Fisher linear classifier was used for classification. The reported classification accuracies were calculated by a 5-fold cross validation. Subject-specific frequency bands were calculated before running the offline classifier.

To further analyze the trial-by-trial change for MI task performance, as a quantitative index we analyzed the asymmetry of mu-rhythm between hemispheres. Since the unbalance between C3 and C4 has been regarded as the most important feature for MI-BCI classification [2], [5], [7], the ratio of 8-12Hz power at electrodes C3 and C4 was employed as a simplified version of the unbalance. The modulation strength can be defined as the asymmetry of the mu-energy absolute values (uV) between hemispheres. The brain activity collected by electrodes C3 and C4 cover the regions of interest for motor imagery paradigms. Therefore, we define (2) as:

$$S = |mu(C3)|/|mu(C4)| \quad (2)$$

When performing a left-hand task, a larger S indicates better execution of the task; whereas when performing a right-hand task, a smaller S corresponds to better execution. The linear correlation between a single-trial S and the trial number was calculated in order to describe the trend of S value changes over time within blocks.

F. Questionnaire

At the end of each condition the participants were asked to answer the following questions on a scale from 1 (disagree strongly) to 5 (agree strongly) concerning their level of agreement with the following sentences:

1) *control*: During the experiment, my performance was mainly good
2) *disappointed*: During the experiment, I felt disappointed with my performance
3) *confident*: During the experiment, I felt confident with my hand motor imagination strategy
4) *stress*: During the experiment, I was stressed
5) *feedback*: During the experiment, I preferred the no feedback stage than the feedback stage

The *control* question was used as a consistency check for each condition since we expected a higher score for the PFC than for the NFC. The *disappointed* and the *confident* questions studied the motivation effects of the PFC and NFC on MI learning. For the PFC we hypothesized that subjects would have lower scores in the second question and higher scores in the third question. For the NFC we hypothesized the opposite. No predictions were made for the *stress* and *feedback* questions.

III. RESULTS

A. Questionnaire

We performed an ANOVA test for differences on the questionnaire data; the results are shown in Fig. 2 and confirm our expectations. The *control* had a higher score for the PFC than for the NFC (p=0.001). For the PFC a low score in the *disappointed* (p=0.01) and a high score in the *confident* (p=0.04) were found. For the NFC the scores were the opposite, as expected. The *stress* result of 2.5 in both PFC and NFC conditions indicated that the participants were not stressed while performing MI-BCI. The *feedback* results suggested that participants preferred the feedback condition to the no feedback, even in the NFC (p=0.08).

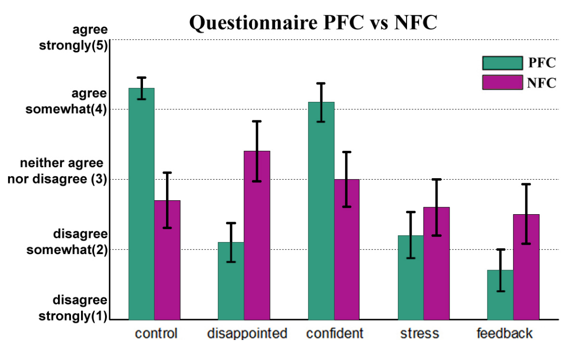

Fig. 2. The questionnaire responses: 1(disagree strongly); 2(disagree somewhat); 3(neither agree nor disagree); 4(agree somewhat); 5(agree strongly)

B. EEG Analysis

1) BCI Performance: The BCI performance for all subjects in the feedback and no feedback stages for both the PFC and NFC conditions is shown in Table I.

TABLE I

BCI PERFORMANCE

ID	C	O	No Feedback Performance	Feedback Performance	Performance Difference
11	PFC	1	98.33%	92.00%	-6.33
	NFC	2	97.00%	92.00%	-5.00
12	PFC	2	72.00%	66.00%	-6.00
	NFC	1	61.00%	62.67%	1.67
13	PFC	1	81.33%	72.33%	-9
	NFC	2	71.33%	78.67%	13.66
14	PFC	2	78.00%	79.00%	1.00
	NFC	1	72.33%	74.00%	1.67
21	PFC	1	85.67%	74.00%	-11.67
	NFC	2	93.33%	85.33%	-8.00
22	PFC	2	91.00%	92.67%	1.67
	NFC	1	88.67%	89.00%	0.33
23	PFC	1	90.00%	79.67%	-10.33
	NFC	2	79.67%	93.33%	7.34
24	PFC	2	79.67%	83.67%	4.00
	NFC	1	83.00%	78.00%	-5.00

ID: subject number; C: condition PFC (positive feedback condition) NFC (negative feedback condition); O: order of the repetition

To calculate each condition's learning effects, each subject's performance was normalized to his/her no feedback performance. The normalized results suggest that, after completing the first condition (either PFC or NFC), subjects who were exposed to the PFC first, performed significantly worse -suggesting that there was a negative learning effect- than subjects exposed to the NFC (ANOVA, p=0.003). When comparing the normalized average performance of subjects during the PFC to the NFC, regardless of trial order, we find a slight trend showing that participants performed better when given NFC (ANOVA, p=0.122). We found no order effects when comparing the overall performance of subjects who were first exposed to the NFC and then to the PFC compared to subjects performing PFC first and then NFC (ANOVA, p=0.318).

2) Mu-rhythm Tendency: In Fig. 3 we can observe the increasing trend of the S value –the mu-Rhythm modulation strength– for Subject 11 while performing the NFC with the left hand (correlation r =0.14).

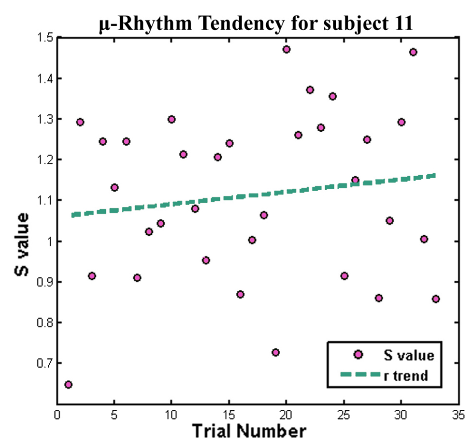

Fig. 3. Mu-rhythm improvement for subject 11 while performing NFC with the left hand.

The global tendencies of the left hand linear correlations can be observed in Fig. 4. A strong trend between linear correlations for the left hand between PFC and NFC indicate that the S values -the modulation strengths- went more positive when the subjects were in the NFC, and thus, that the NFC had greater learning effects (ANOVA, p=0.06). No significant trends were found for the right hand. No significant learning effects were found for the no feedback stage.

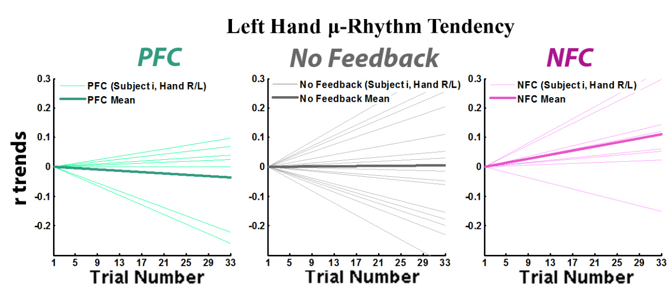

Fig. 4. Linear correlations of the S values for the left hand when in the PFC, the No feedback and the NFC. Each thin line represents the mu-tendency for one subject while performing left hand motor imagery. The mean tendency for each condition is represented as a thicker line.

C. HRV

In the PFC the ΔSDNN was of $-2.2 \pm 16.3ms$, i.e. the HRV decreased compared to the no feedback task; in the NFC the task ΔSDNN was of $15.4 \pm 18.49ms$, i.e. the HRV increased compared to the no feedback task. The NFC had a larger HRV compared to the PFC with a significant difference (ANOVA, p=0.006). That is, the PFC generated a more stressful situation than the NFC [11].

IV. Discussion

The length of time required to train subjects in MI-BCI is a major concern of many researchers [14]. Thus, it is important to focus research efforts on one key aspect of the learning process: the feedback. In [15], authors investigated how instantaneous, delayed or nonexistent feedback affected EEG control; reporting that feedback can have different effects on EEG control, and that it varies across subjects. Our experiment goes one step further and studies the effects of positive versus negative visual feedback for naïve subjects.

Results indicate greater learning effects when performing the MI-BCI with negative feedback than with positive feedback, both for the mu-rhythm tendency (ANOVA, p=0.06) and BCI performance (ANOVA, p=0.003). We suspect that the visual feedback encouraged subject to try harder in the NFC, thus participants improved their performance when the feedback informed them that they were not performing well. One interesting finding is that the learning effect of the NFC for the mu-rhythm was only found significant on the left hand. We speculate that this may be related to the handedness of the subjects since all but one were right handed.

HRV results show a higher level of stress during the PFC compared to the NFC. Nevertheless in the experience questionnaires all subjects reported low levels of stress while performing MI-BCI.

Overall, the results are promising even though the study was limited to only 8 subjects. Moreover, the learning period consisted only of two MI-BCI experiences per subject. Further studies with larger populations and longer learning periods may clarify these trends.

V. Conclusions

We have investigated feedback and mental stress of the participants aiming to improve the MI-BCI learning methodology. Negative feedback was found to have greater learning effects for MI-BCI than positive feedback. We believe that these results may only apply for non-experience subjects in their first MI-BCI sessions, since longer periods of negative feedback training may lead to frustration. Previous experiments with biased feedback [9], have shown that non-naïve subjects who are already capable of modulating their sensorimotor rhythm, drop their performance when exposed to inaccurate feedback. However our experiment evaluated non-experienced subjects and our results suggest that the sham feedback may shorten learning periods when beginning to train MI-BCI.

HRV –our measure of mental stress of participants– was found lower in the PFC. We speculate that this effect may be caused by the initial euphoria of the non-experienced subjects when seeing that they are doing well. It would be interesting to see if through a larger number of sessions if this HRV effect would vary in favor of the PFC; while the NFC, although it produces better results in the beginning, may lead to higher disappointment and stress.

There are several applications of these results. First of all we speculate that these findings may serve to improve current MI-BCI learning methodology and help systems to adapt in better ways to a subject's needs. The second application is in the general area of BCI medical treatments: the fact that only non-experienced subjects participated in our experiment confers that this research has a greater interest with positive benefits for MI-BCI during rehabilitation or medical treatment, where most of the patients are naïve to these therapies and have not yet developed MI skills.

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