# TOWARDS ELABORATED FEEDBACK FOR TRAINING MOTOR IMAGERY BRAIN COMPUTER INTERFACES

M. Mousavi[1], V. R. de Sa[2]

[1]Department of Electrical and Computer Engineering, University of California, San Diego
[2]Department of Cognitive Science, University of California, San Diego, La Jolla, CA, USA

E-mail: mahta@ucsd.edu

ABSTRACT: Motor imagery is one common paradigm in brain computer interface (BCI) systems where the user imagines moving a part of his/her body to control a computer. Motor imagery is endogenous and requires a large amount of training for the user to be able to control the BCI. Therefore, the feedback that is provided to the user is critical to ensure informative insight into improving imagery skills. In this study, we investigate a new protocol for providing motor imagery feedback and compare it to the conventional feedback scheme. The proposed feedback focuses on 'elaborating' how the user can improve imagery as opposed to the conventional training protocols which only provide information on whether the user was 'correct' in performing imagery. Our results show that providing more informative feedback results in more efficient motor imagery training and is preferred by the users.

## INTRODUCTION

Brain computer interface (BCI) systems collect and infer neural signals directly from the brain through bypassing common neuromuscular pathways [1, 2]. One modality to collect brain signals is electroencephalography (EEG) which is popular for being non-invasive and inexpensive. Motor imagery is one common paradigm in EEG-based BCIs in which the user imagines a part of her/his body, such as a hand, foot, tongue, etc. Motor imagery of different body parts results in different spatial patterns of decrease in power across the scalp in mu (8-13 Hz) and beta (14-30 Hz) frequency bands [3, 4, 7, 8]. These features are used to distinguish among the imagined classes.

One of the advantages of motor imagery based BCIs is that they are endogenous [5]; they do not depend on user response to external stimulation. Endogenous BCIs have several benefits: 1) They do not require the user to have good visual or other sensory responses to respond to exogenous stimuli, 2) They do not require the computer presentation of (possibly annoying or fatiguing) stimuli, and 3) They have the potential to be used in natural asynchronous communication. However, because they are endogenous and depend on the user generating the signal, there is wide individual differences in the ability to generate different discriminable motor imagery patterns for different imagined body parts. Therefore, training users to provide classifiable motor imagery signal is critical.

So far, there have been a few training methods proposed in the literature, e.g. [9–13]. Lotte et al. [14] investigated the current state-of-the-art training approaches and identified flaws in their design based on instructional design literature. They looked at the training approaches at the level of feedback provided to the user, instructions provided to her/him and the training task itself. Our current study focuses on the feedback that the user receives. In traditional motor imagery BCI training, the feedback provided to the user is evaluative and corrective, where it only tells the user whether he/she has performed the task correctly and possibly with what confidence [14]. In other words, traditional motor imagery training involves giving the user feedback on the output of the classification. However, this is like training someone to shoot baskets by telling them how close the ball was to going in without giving them information about whether they overshot or undershot. In particular, participants may fail to be successful at right hand vs. left hand motor imagery because they are unable to cause mu-desynchronization or they may fail to be successful because they are causing mu-desynchronization that is bilateral for both right- and left-hand motor imagery. In the first case, they may need to try harder, and in the second, they may need to try less hard and focus on the side of interest to get more lateralized signals.

Motivated by work of [6] we hypothesized that providing richer feedback while users are learning motor imagery would result in faster and better learning. To do so, we decided to provide the users with not just the classification output and its confidence, but a perceivable form of features that are used by the classifier. In other words, our proposed feedback is an example of 'elaborated feedback' as described by [23], where it will provide more information and will let users not only evaluate their performance based on the input to the classifier as opposed to its 1-dimensional output, but also will provide specific information about what could have gone wrong and directions for how the users can improve their motor imagery.

## METHODS

We recorded data from 6 healthy participants recruited from the UC San Diego student population. All participants were naive to BCI and motor imagery skills and before participating in the study, signed a consent form that was approved by UC San Diego Institutional Review Board. The demographic details of the participants (i.e., age, gender and handedness) are specified in Tab. 1.

Table 1: The demographics of participants.

| Participant ID | Age | Gender | Handedness |
|---|---|---|---|
| P1 | 18 | Female | Right |
| P2 | 18 | Female | Right |
| P3 | 19 | Female | Right |
| P4 | 21 | Female | Right |
| P5 | 21 | Male | Right |
| P6 | 18 | Female | Right |

Each participant participated in a one-session experiment consisting of 5 blocks, each consisting of 20 motor imagery trials. Each trial began with an arrow on the screen pointing to the right or the left to specify the trial type. After 1.5 seconds, the arrow disappeared and a cross showed up in the center of the monitor and 1 second later, a term "imagery" on top of the cross appeared. Participants were instructed to begin motor imagery of the corresponding hand (depending on the direction of the arrow) for 3 seconds until the cross disappeared. The participants were instructed to imagine their action of choice so long as it involved a hand movement. Fig. 1 shows an example of the frames shown in one trial. At the end of each trial in blocks 1, 3 and 5, no feedback was provided. In blocks 2 and 4, the conventional and proposed elaborated feedback were provided which will be described next. Participants 1, 2, and 6 were shown the elaborated and conventional feedback in blocks 2 and 4 respectively. Participants 3, 4, and 5 on the other hand, were presented with the conventional feedback in block 2 and elaborated feedback in block 4. This is to balance the order of the provided feedback types.

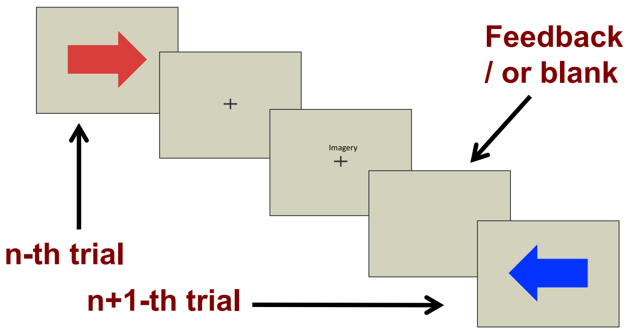


Figure 1: An example of a trial in the experiment.

We designed our experiment in python using the python-based Simulation and Neuroscience Application (SNAP) toolbox [18]. In each trial, data were downsampled to 100 Hz and Laplacian filtered [17] to partially compensate for spatially distributed artifacts by subtracting the mean of the four directly neighboring channels from each channel. Next, an FIR filter of order 225 was used to calculate the average of the normalized power in 3 seconds of motor imagery in 8-13 Hz frequency band for the channels specified over the right and left motor cortices in Fig. 2. The conventional feedback was provided as the difference between the power on the two sides and the proposed feedback protocol showed the power on both sides. Fig. 3 shows an example of the two types of feedback. Since motor imagery results in contra-lateral desynchronization of power [7, 8] the participants were instructed to maximize the bar height on the motor imagery side.

Fig. 4 shows an example of how the same conventional feedback can be mapped to two different elaborated ones; the conventional feedback provides less information to the user similar to the ball and basket example described in the previous section.

As the power over motor cortices may be biased towards one side, we trained a threshold to be the average of the difference in the normalized power on right and left sides of the motor cortex across trials of each block. In blocks 2 and 4, the threshold that was trained with trials in blocks 1 and 3 respectively, was used to adjust for the potential bias. Therefore, the provided feedback to the participant was based on the adjusted bar heights.

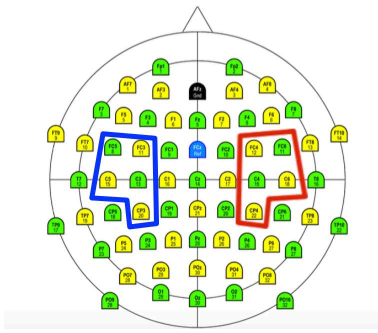

Figure 2: Electrode locations in 10-20 international system EEG cap. The selected electrodes were used to calculate power on each side of the motor cortices.

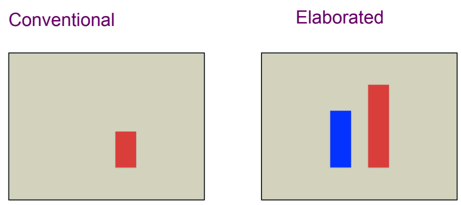


Figure 3: Types of feedback.

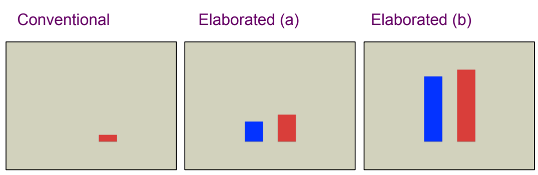


Figure 4: Two different elaborated feedback examples (a and b) lead to the same conventional feedback.

EEG data were recorded with a 64-channel BrainAmp system (Brain Products GmbH) located based on the international 10-20 system, as Fig. 2 shows. Data were collected with sampling rate of 5000 Hz but were downsampled to 500 Hz for further processing in offline analysis. We chose 500 Hz instead of 100 Hz — which was the rate of the downsampled signal in the online experiment — to keep information in higher frequencies for the purpose of running independent component analysis (ICA) later.

MATLAB [15] and EEGLAB [16] were used for offline analysis. Data were processed in two cases: 1) without artifact removal to investigate the effect of the feedback that was provided to the participants during the experiment. 2) with artifact removal to investigate the effect of training on brain signals and to verify that the participants are not potentially using muscle movements to control the bar heights.

In the first case, the raw data were filtered in 8 to 13 Hz with a 500-tap FIR filter. Laplacian filter [17] was applied to partially compensate for spatially distributed artifacts by subtracting the mean of directly neighboring channels from each channel. We looked at the 'classifiability' of each trial in blocks 2 and 4 where the feedback was present. 'Classifiability' is estimated as follows: first the power on each channel on motor cortices is calculated — as shown in Fig. 2. Then the power on each channel was normalized to the sum of the powers on the 10 channels and the average of the power on each side of the motor cortex was used as the probability of that side being selected by the classifier.

We also looked at the classification rates in blocks 1, 3 and 5 where no feedback was provided. To do so, we selected three non-overlapping one-second time windows to cover 3 seconds of imagery period in each trial. Since there are 20 trials in each block, each block has a total of 60 one-second windows of imagery. Next we applied common spatial patterns (CSP) [21] to data from all 64 channels and selected the top 3 filters for each class. Linear discriminant analysis (LDA) [22] was chosen as the classifier to classify right/left classes.

For the second case, we first filtered the raw data using a 500-tap FIR filter in 1 to 200 Hz. Next, we removed up to 6 noisy channels with large muscle artifacts mostly from the temporal and one from the occipital cites. Then the cleanline EEGLAB plugin was used to remove the line noise [19]. We removed parts of the EEG data that were suffering from large muscle artifacts; however, no information from the 3 seconds of imagery was removed. We ran independent component analysis (ICA) using the AMICA [20] EEGLAB plugin to isolate eye and muscle artifacts. Eye and muscle artifacts from the top 30 IC components were removed. Similar analysis to the previous case were performed and the results are described next. Significance in what follows is calculated with a two-tailed t-test with 0.05 significance level.

RESULTS

To investigate how the probability of selecting the correct class (left or right motor imagery) changes over time, we looked at it as a function of the trial number in blocks 2 and 4. For each participant in each trial, the probability of selecting the correct class is calculated as the ratio of the power on the corresponding side as described in previous section. A line was fit and the slope of the line was estimated. Fig. 5 shows the slopes calculated in case one (without artifact rejection) as height of the bars in blocks 2 and 4 in separate plots based on whether conventional feedback was provided in block 2 and elaborated in block 4 or vice versa. Fig. 6 shows the same for data from case two (with artifact rejection). Note that P1, P2 and P6 show some improved performance when the elaborated feedback is provided to them — i.e., in block 2. However, they show decreased performance across the trials in block 4 — where conventional feedback was provided subsequently. P3 and P5 who were provided with conventional feedback first in block 2, show decreased performance; however, they both show improved performance during the elaborated feedback in block 4. P4 shows improved performance during both feedback types; however, the improvement is higher in the elaborated feedback block when only brain signals are considered, i.e. in Fig. 6. This shows that the proposed feedback paradigm could potentially be more effective than the conventional feedback.

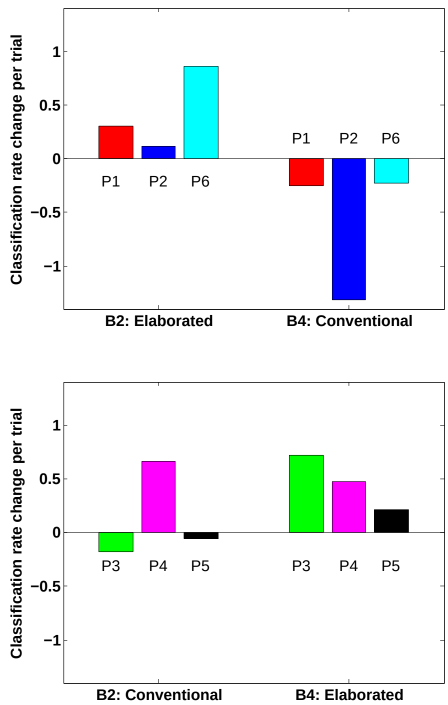


Figure 5: Percent change of classification rate per trial in data during feedback blocks, **without** artifact rejection.

Classification results in no-feedback blocks — 1, 3, and 5 — are provided in tables 2a, 2b, 3a, and 3b. The training and testing were performed within each block separately and we made sure that both train and test sets were balanced and the test set was absolutely separate from the training. We ran 10-fold cross-validation while making sure that the three one second time windows from one trial will appear all in either train or test sets and the results are presented in Tab. 2a and Tab. 2b. For ease of comparison, we have included the type of feedback in blocks 2 and 4 in these tables: EF and CF stand for elaborated feedback and conventional feedback respectively.

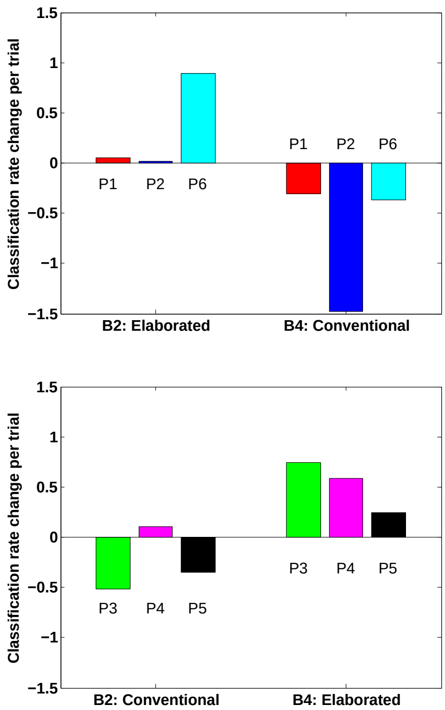


Figure 6: Percent change of classification rate per trial in data during feedback blocks, **with** artifact rejection .

Table 2a: P1, P2, P6 performances **without** artifact rejection

| ID | B1 | B2 | B3 | B4 | B5 |
|---|---|---|---|---|---|
| P1 | 0.58 / 0.048 | EF | 0.60 / 0.051 | CF | 0.37 / 0.074 |
| P2 | 0.73 / 0.051 | EF | 0.85 / 0.058 | CF | 0.80 / 0.065 |
| P6 | 0.75 / 0.057 | EF | 0.85 / 0.058 | CF | 0.78 / 0.043 |

Table 2b: P3, P4, P5 performances **without** artifact rejection.

| ID | B1 | B2 | B3 | B4 | B5 |
|---|---|---|---|---|---|
| P3 | 0.52 / 0.080 | CF | 0.57 / 0.037 | EF | 0.65 / 0.063 |
| P4 | 0.82 / 0.072 | CF | 0.87 / 0.048 | EF | 1.00 / 0.000 |
| P5 | 0.42 / 0.057 | CF | 0.57 / 0.057 | EF | 0.52 / 0.052 |

P1, P2 and P6 were provided with the elaborated feedback in block 2. P2 and P6 show clear improvement in block 3 compared to block 1 which can be associated with the training they received in block 2. These two participants also show decreased performance in block 5 which is right after block 4 where they were provided with the conventional feedback but the decreased performance is not significant. Performance of P1 in all three blocks is below chance level which is calculated as described in [24] to be $0.62\%$ with significance level of $0.05$.

P3, P4 and P5 were provided with conventional feedback in block 2 and elaborated feedback in block 4. P3 and P4 show improvement after being exposed to the proposed elaborated feedback in block 4. Especially, P3 shows chance level performance in blocks 1 and 3 but above chance performance in block 5. However, P5 shows chance level performance in all blocks.

To make sure that the classification rates are not affected by non-brain sources including eye and muscle movements, we performed the same analysis described above with the ICA-cleaned data. In this case, we filtered each trial in 8 to 30 Hz frequency band to include both mu (8-13 Hz) and bet (14-30 Hz) frequency bands. The reason we did not include the beta band when we were classifying the non-ICA-cleaned data is that beta band is usually more contaminated with muscle artifacts. After filtering the data, non-overlapping one second time windows were selected and 10-fold cross-validation was performed — while making sure that the three one second time windows from one trial will appear all in either the train or test set — to classify right/left motor imagery in blocks 1, 3, and 5 separately.

Table 3a: P1, P2, P6 performances **with** artifact rejection

| ID | B1 | B2 | B3 | B4 | B5 |
|---|---|---|---|---|---|
| P1 | 0.55 / 0.043 | EF | 0.55 / 0.056 | CF | 0.47 / 0.060 |
| P2 | 0.82 / 0.084 | EF | 0.85 / 0.046 | CF | 0.85 / 0.052 |
| P6 | 0.77 / 0.079 | EF | 0.85 / 0.058 | CF | 0.83 / 0.043 |

Table 3b: P3, P4, P5 performances **with** artifact rejection.

| ID | B1 | B2 | B3 | B4 | B5 |
|---|---|---|---|---|---|
| P3 | 0.68 / 0.052 | CF | 0.52 / 0.052 | EF | 0.78 / 0.071 |
| P4 | 0.80 / 0.074 | CF | 0.82 / 0.063 | EF | 1.00 / 0.000 |
| P5 | 0.43 / 0.051 | CF | 0.55 / 0.043 | EF | 0.55 / 0.086 |

Tab. 3a and Tab. 3b show the classification results. For ease of comparison, we have included the type of feedback in blocks 2 and 4 in these tables: EF and CF stand for elaborated feedback and conventional feedback respectively. P3 and P4 who were provided with the conventional feedback first and proposed feedback next, both show significantly improved classification rates in block 5 compared to blocks 1 and 3. On the other hand, P1 and P5 do not show improved performance in either of the blocks similar to results in Tab. 3 which is classification in the same blocks before artifact rejection. Performance between blocks 3 and 5 in P2 and P6 is not significant after artifact rejection. It is possible that the participant has been controlling the bars with muscle movements and that is why before artifact rejection the performance in block 3 was higher than chance level whereas after artifact rejection, performance in blocks 3 and 5 are similar. Nevertheless, this shows that the elaborated feedback was more effective for the participant to somehow (either through brain signals or muscle) control the bars. Note that since the number of samples in each class is 30, chance level calculated as described in [24] is $0.62\%$ with significance level of $0.05$.

DISCUSSION AND CONCLUSION

In this pilot study, we have explored the capability of a richer elaborated feedback in training motor imagery BCI and proposed a training protocol that suggests providing the participant the input to the classifier, i.e. an interpretable version of the features that are available to the classification algorithm as opposed to the classifier output. Since any classifier needs motor imagery data from the user and our participants were all naive to motor imagery BCI, we chose to use a very simple classifier, i.e. a threshold, to minimize the effect of instability in a classifier trained with motor imagery data that is changing as the user learns how to control his/her event-related desynchronization signal. All our participants (6/6) chose the elaborated feedback in an answer to a question on the post-study questionnaire: "Which type of feedback did you like better and found more useful?". This shows that the elaborated feedback has the potential to replace the standard conventional feedback paradigm for motor imagery training.

Our results from offline analysis show that the elaborated feedback protocol is potentially more powerful in training motor imagery which is expected as described in [23]. In fact, our participants found the proposed feedback more 'informative' which again emphasizes this point.

One downside of the conventional feedback strategies that our proposed protocol could overcome is the need to have the first block of training with no-feedback or sham feedback as there is no data yet to train a classifier on — the conventional feedback is the output of a classifier. The issue occurs if the participant does not provide proper imagery during this time period, then the classifier is trained on 'incorrect' data. Our method provides the features to the user that later could be used to train a classifier on. We propose to use the power on the motor imagery cortices and train a threshold to compensate for biases towards either side. Even if the bias is not compensated for, the participant could still be provided with the power on two sides of motor cortices and be instructed to control the bars towards the ideal bar heights, i.e. suppressed power on left side in right motor imagery and suppressed power on right side in left motor imagery trials. Hence, our proposed elaborated feedback can function without training data.

To evaluate the elaborated feedback further, we are interested in comparing it with the conventional feedback across multiple sessions and to see whether there is more significant difference between the two schemes when more time elapses between training sessions.

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