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TOWARDS ELABORATED FEEDBACK FOR TRAINING MOTOR IMAGERY BRAIN COMPUTER INTERFACES

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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 easily interpretable feedback results in more efficient motor imagery training and is preferred by the users.

INTRODUCTION

Brain computer interface (BCI) systems attempt to infer certain cognitive or affective states based on neural signals collected from the brain while 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 moving 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 are large 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 signals is critical.

So far, there have been a few training methods proposed in the literature, e.g. [9–14]. Lotte et al. [15] 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 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 [15]. In other words, traditional motor imagery training involves giving the user feedback on the output of the classification. When classification is unsuccessful, however, this feedback does not provide any information about why it failed. For example, participants may fail to be successful at right hand vs. left hand motor imagery because they do not induce sufficient mu-desynchronization or the induced desynchronization is bilateral for both right- and left-hand motor imagery.

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 [25], where it will provide more easily interpretable feedback and will let users evaluate their performance based on the input to the classifier.

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.

Each participant participated in a one-session experiment consisting of 5 blocks, each consisting of 20 motor im-

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agery 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.

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

We designed our experiment in python using the python-based Simulation and Neuroscience Application Platform (SNAP) toolbox [20]. In each trial, data were downsampled to 100 Hz and Laplacian filtered [19] 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 power in 3 seconds of motor imagery in the 8-13 Hz frequency band for the channels specified over the right and left motor cortices in Fig. 2. The average power in each channel was then normalized with respect to the sum of power in all channels specified 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. In each trial, the feedback was provided as a single (static) image after the imagery period was over. Fig. 3 shows an example of the two types of feedback. Since motor imagery results in contra-lateral de-synchronization of power [7, 8] the participants were instructed to maximize the bar height on the motor imagery side.
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.

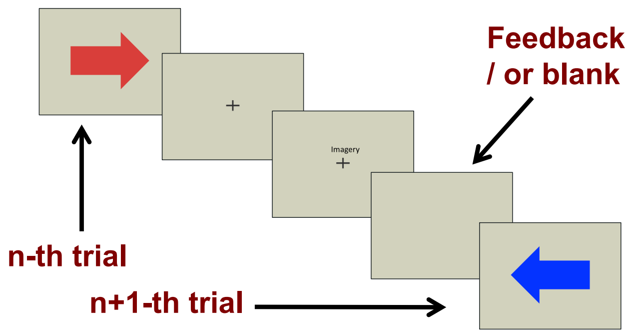

Figure 1: An example of a trial in the experiment.

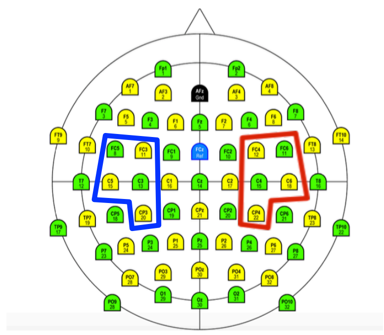

Figure 2: Electrode locations in 10-20 international system EEG cap. The selected electrodes were used to calculate power on each side of the motor cortices.

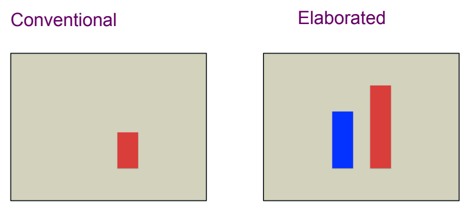

Figure 3: Types of feedback.

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. EMG data were also recorded with the same system through two sets of bipolar electrodes on each arm and wrist — for more details on the set-up please refer to [16]. 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 [17] and EEGLAB [18] were used for offline analysis. Data were processed in two cases: 1) without

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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 facial muscle movements to control the bar heights.

In the first case, the raw data were filtered from 8 to 13 Hz with a 500-tap FIR filter. Laplacian filter [19] was applied to partially compensate for spatially distributed artifacts by subtracting the mean of directly neighboring channels from each channel. We looked at the classifier score of each trial in blocks 2 and 4 where the feedback was present. This score is estimated as follows: first the power on each channel over 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 specified 10 channels and the average of the power on each side of the motor cortex was used as the classifier score.

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) [23] to data from all 64 channels and selected the top 3 filters for each class. Linear discriminant analysis (LDA) [24] was chosen as the classifier to classify right/left imagery 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 sites. Then the Cleanline EEGLAB plug-in was used to remove the line noise [21]. 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 [22] EEGLAB plug-in 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 paired-sample two-tailed t-test with 0.05 significance level.

EMG data (4 channels, two on each hand and arm) were bandpass filtered in 10 to 200 Hz using a 500 tap FIR filter, and the line noise was removed with the Cleanline plug-in [21]. EMG data during the three seconds time interval of motor imagery were epoched into non-overlapping one second intervals and used for classification. Results are presented in the next section.

RESULTS

To investigate how the right/left classifier score 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 right/left classifier score is calculated as the ratio of the power on the corresponding side as described in the previous section. A line was fit and the slope of the line was estimated. Fig. 4 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. 5 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. 5. This shows that the proposed feedback paradigm could potentially be more effective than the conventional feedback.

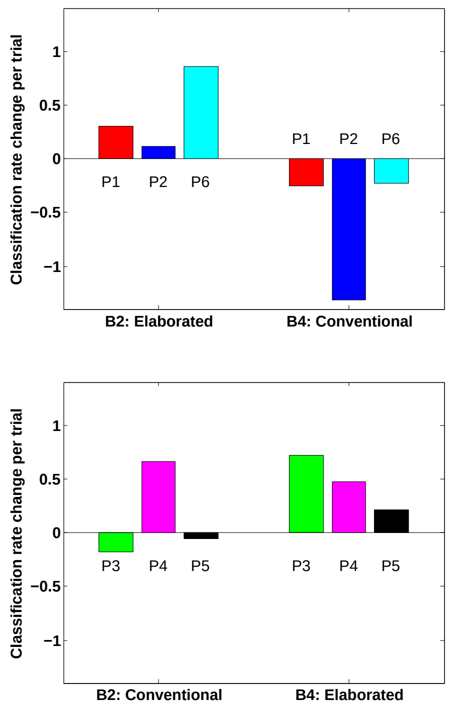

Figure 4: Percent change of classification rate per trial in data during feedback blocks, **without** artifact rejection.

To verify how the percent change in classification rates per trial (i.e. the height of the bars in Fig. 4 and Fig. 5) are different in the two elaborated and conventional feedback conditions among the 6 participants, we ran a paired-sample two-tailed t-test between the bar heights across participants. We found significant difference in both cases with p-values 0.036 and 0.006 for cases one and two respectively — i.e., with and 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. The first number in each table specifies the mean and the second number is the standard error.

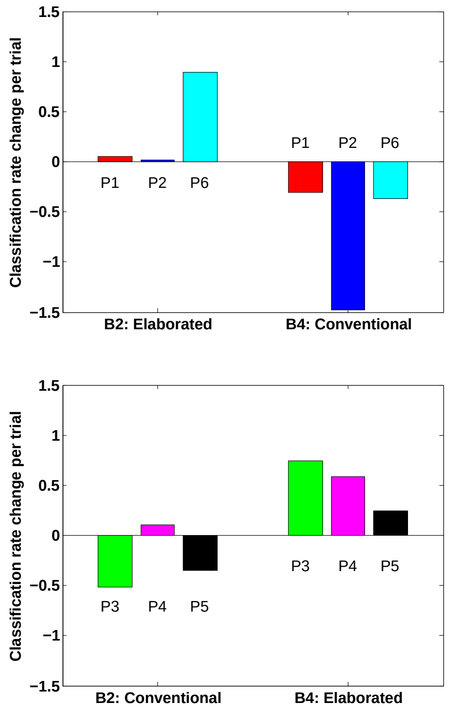

Figure 5: Percent change of classification rate per trial in data during feedback blocks, **with** artifact rejection .

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 improvement in block 3 compared to block 1 which can be associated with the training they received in block 2; however, this improvement is not significant. 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 [26] to be 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. P4 shows significant improvement after being exposed to the proposed elaborated feedback in block 4; however, P3 and P5 show 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 beta (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. Tab. 3a and Tab. 3b show the classification results. The first number in each table specifies the mean and the second number is the standard error. 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. Moreover, P3 shows significantly disimproved performance after being exposed to conventional feedback in block 2. On the other hand, P1 and P5 show chance level performance in all of the blocks before and after artifact rejection. P2 and P6 do not show much difference in performance between blocks 3 and 5 after artifact rejection, which was not the case before artifact rejection. It is possible that these participants have been controlling the bars with muscle movements after elaborated feedback not brain signals. 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 [26] is 62% with significance level of 0.05.

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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

Aside from EEG data, we looked at classification rate of a right/left classifier trained on EMG data in each block. 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. As Tab. 4 shows, all classification rates are chance level or very close to chance level which is 62% with significance level of 0.05 except for participant 4 in block 3. However, this participant shows improved EEG classification after the elaborated feedback block in which the classification rate on EMG rate is chance level.

Table 4: EMG classification results per block.

ID	B1	B2	B3	B4	B5
P1	0.58	0.57	0.52	0.43	0.68
P2	0.32	0.60	0.57	0.55	0.40
P3	0.55	0.47	0.48	0.47	0.48
P4	0.50	0.43	0.82	0.48	0.48
P5	0.58	0.48	0.53	0.62	0.38
P6	0.52	0.33	0.63	0.68	0.57

DISCUSSION AND CONCLUSION

In this pilot study, we have explored the capability of a visually 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 data to be trained on 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 approach 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 [25]. 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 hand motor imagery and suppressed power on right side in left hand motor imagery trials. Hence, our proposed elaborated feedback can function without training data.

To evaluate the elaborated feedback further, we are interested in investigating providing participants with the power on both sides of motor cortices normalized with respect to a 'baseline' time period where the participant is relaxed and not performing motor imagery. Another aspect worth investigating further is how the two approaches differ 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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