32nd Annual International Conference of the IEEE EMBS
Buenos Aires, Argentina, August 31 - September 4, 2010

Online Performance Evaluation of Motor Imagery BCI with Augmented-Reality Virtual Hand Feedback

Zheng Yang Chin, Kai Keng Ang, Chuanchu Wang, Cuntai Guan

Abstract—**The online performance of a motor imagery-based Brain-Computer Interface (MI-BCI) influences its effectiveness and usability in real-world clinical applications such as the restoration of motor control. The online performance depends on factors such as the different feedback techniques and motivation of the subject. This paper investigates the online performance of the MI-BCI with an augmented-reality (AR) 3D virtual hand feedback. The subject experiences the interaction with 3D virtual hands, which have been superimposed onto his real hands and displayed on the computer monitor from a first person point-of-view. While performing motor imagery, he receives continuous visual feedback from the MI-BCI in the form of different degrees of reaching and grasping actions of the 3D virtual hands with other virtual objects. The AR feedback is compared with the conventional horizontal bar feedback on 8 subjects, of whom 7 are BCI-naïve. The subjects found the AR feedback to be more engaging and motivating. Despite the higher mental workload involved in the AR feedback, their online MI-BCI performance compared to the conventional horizontal bar feedback was not affected. The results provide motivation to further develop and refine the AR feedback protocol for MI-BCI.**

I. Introduction

Motor imagery involves the imagination of motor movement from the first-person perspective [1], which results in changes in the electroencephalogram (EEG). These changes could be translated into control signals in a non-invasive Motor Imagery-based Brain-Computer Interface (MI-BCI). Potential clinical applications include the restoration of motor control [2], [3] for patients with severe motor disability who could not engage in motor movements without assistance. Motor imagery activates similar brain areas as the motor execution, hence it could form a "backdoor approach" to access the motor system [4] for rehabilitation.

Due to the huge inter-subject variability in the brain signal characteristics [5], [6], an important challenge for practical applications of the MI-BCI lies in the processing of the EEG recordings during motor imagery. New signal processing and machine learning approaches are being developed that discriminate different brain states in different subjects to enable a high classification accuracy of the EEG signals [7]. One such approach to overcome the huge inter-subject variability in MI-BCI is the Filter Bank Common Spatial Pattern (FBCSP) algorithm, which has shown effectiveness in performing an autonomous selection of key temporal-spatial discriminative EEG characteristics, specific to the subject [8].

However, the online performance of the FBCSP algorithm has yet to be evaluated extensively. The performance of the MI-BCI depends on its operation during online sessions, which demonstrates its effectiveness and usability [9] for real-world applications. The MI-BCI depends not only on the EEG processing algorithms but also on other real-time factors, such as the intra-subject variability of the brain signals across sessions [6] and motivation [10].

Thus, feedback is an important component of the MI-BCI during online sessions. The MI-BCI translates the motor imagery action from the EEG data to a certain type of feedback shown to the subject. The subject learns EEG control [11] and adapts his brain activity concurrently [9] based on the information received from the BCI. Typically, visual feedback in the form of a moving horizontal bar [7] or cursor control [5], is employed for BCI during online operations. Existing studies have also proposed the use of virtual reality (VR) environments as a type of feedback for the BCI [10], [12-14] due to its motivational effect when the subject experiences the computer-generated simulation of a real-world environment. In [15], the authors found that 3D virtual hands could induce the feeling of ownership of a virtual limb even in the absence of tactile sensory stimulation. Furthermore, observing hand movements could reinforce the motor imagery process [3]. Recent advances in VR research enable the integration of video and 3D virtual objects in an augmented reality (AR) environment whereby the computer-generated 3D virtual objects are superimposed onto the real world environment in real time [16]. Hence the AR environment could potentially be employed as a type of feedback in MI-BCI.

Based on the findings and motivations discussed above, this paper investigates the online performance of the MI-BCI, implemented using the FBCSP algorithm, with an augmented-reality (AR) 3D virtual hand feedback. The visual feedback is displayed on the computer monitor, which shows a real-time video of the subject's real hands. 3D virtual hands have been superimposed onto his real hands in the display. Hence the subject experiences the interaction with the 3D virtual hands in his real environment from a first

This work was supported by the Science and Engineering Research Council of A*STAR (Agency for Science, Technology and Research), Singapore.

Z. Y. Chin, K. K. Ang, C. Wang and C. Guan are with Institute for Infocomm Research, Agency for Science, Technology and Research (A*STAR), 1 Fusionopolis Way #21-01 Connexis (South Tower) Singapore 138632 (email: {zychin, kkang, ccwang, ctguan}@i2r.a-star.edu.sg).

person point-of-view. While performing single-trial motor imagery of the left hand or right hand, he receives continuous visual feedback from the MI-BCI. The MI-BCI translates his motor imagery action into different degrees of reaching and grasping actions of the 3D virtual hands with other virtual objects. The online performance of the MI-BCI will also be investigated with the conventional horizontal bar feedback.

II. Filter Bank Common Spatial Pattern (FBCSP)

The FBCSP algorithm [8] achieved relatively the best offline classification performance amongst the other submissions on the single-trial EEG motor imagery data from 9 subjects in Dataset IIa and Dataset IIb during the International BCI Competition IV [17], [18]. The FBCSP algorithm, comprises 4 stages that perform an autonomous selection of subject-specific temporal-spatial discriminative EEG characteristics for two-class MI-BCI, shown in Fig. 1.

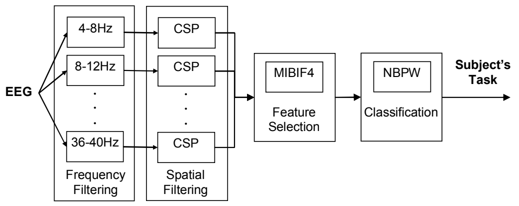


Fig. 1: Architecture of the Filter Bank Common Spatial Pattern (FBCSP) algorithm for two-class motor imagery EEG data to extract subject-specific spatial-temporal features. MIBIF4 and NBPW represent the Mutual Information Best Individual Feature and the Naïve Bayes Parzen Window classifier respectively.

The first stage of FBCSP performs frequency filtering and artifact removal using a filter bank that decomposes the EEG measurements into 9 pass-bands from 4-8Hz, 8-12Hz … 36-40Hz. The second stage performs spatial filtering by linearly transforming the EEG data using the CSP algorithm [19]to the following feature vector for the i^{th} trial,

$$\mathbf{x}_i = \left[\mathbf{cf}_1, \mathbf{cf}_2, \ldots, \mathbf{cf}_9\right], \tag{1}$$

where $\mathbf{cf}_b \in \mathbb{R}^{2m}$ denotes the m pairs of CSP features for the b^{th} band-pass filtered EEG measurements, $\mathbf{x}_i \in \mathbb{R}^{1\times(9*2m)}$.

The third stage performs feature selection of the extracted features using the Mutual Information Best Individual Features (MIBIF) algorithm. This algorithm selects the best k=4 features sorted by mutual information with the class label in descending order. Since CSP features are paired, the corresponding CSP features which come in pairs with the selected k features are also selected.

The fourth stage performs classification using the Naïve Bayes Parzen Window (NBPW) Classifier is used and the classification rule is given as

$$\omega = \underset{\omega=1,2}{\arg\max}\; p\left(\omega \mid \mathbf{x}\right), \tag{2}$$

where $p(\omega|\mathbf{x})$ denotes posterior probability of the class being ω=1,2, given the random trial $\mathbf{x} = \left[x_1, x_2, \ldots x_d\right]$ and d denotes the number of selected features from the third stage.

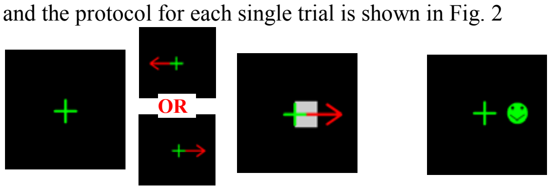
The choice of these algorithms is based on a previous study conducted on the BCI Competition III Dataset IVa [8]. For further details on the FBCSP algorithm, the reader is referred to.

III. Continuous Cue-Based Online Visual Feedback

In this study, subjects are instructed to either perform left hand or right hand motor imagery, while continuous visual feedback is displayed during each trial. The posterior probability output $p(\omega|\mathbf{x})$ computed from the NBPW classifier varies the degree of visual feedback.

A. Horizontal Bar Feedback

The setup for the horizontal bar feedback is similar to [7] and the protocol for each single trial is shown in Fig. 2



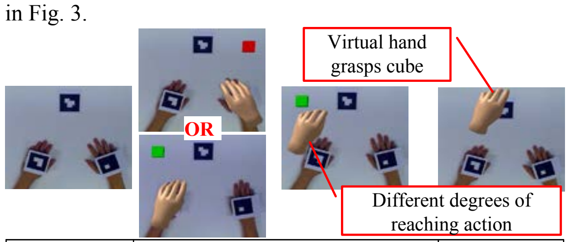
Start of Trial	Visual cue; continuous visual feedback with bar feedback		Visual Reward ; break
-1s	0s	0.5s	4s

Fig. 2: Timing Sequence of the Horizontal Bar Feedback Protocol for single-trial EEG in MI-BCI.

During each trial, the visual cue is represented by an arrow, which specifies the class of motor imagery to perform. The horizontal bar appears 0.5s after the onset of the visual cue. The direction and length of the horizontal bar is proportional to $p(\omega|\mathbf{x})$. The MI-BCI translates the motor imagery of the subject into the position of the horizontal bar, which is updated every 0.5s till the end of the motor imagery period at 4s. If the subject could position the bar correctly for at least 1.5s, a visual 'reward' in the form of a smiley face is shown at the end of each trial. This is followed by a break period where the system does not process any input from the subject before the next trial begins.

B. Augmented Reality 3D Virtual Hand Feedback

The setup for the AR 3D virtual hand feedback is shown in Fig. 3.



Start of Trial	Visual cue; continuous visual feedback with reaching virtual hand		Visual reward;break
-1s	0s	0.5s	4s

Fig. 3: Timing sequence of the Augmented-Reality-based Hand Feedback Protocol for single-trial EEG in MI-BCI.

The visual feedback is displayed on the monitor, which shows a real-time video of the subject's real environment captured by a webcam. 3D virtual hands are superimposed onto special markers which have been positioned onto the subject's real hands. During each trial, the visual cue that specifies the class of motor imagery to perform is indicated by the appearance of the specific virtual hand. A 3D virtual cube is also displayed on the same side as the virtual hand.

The subject receives visual feedback in the form of different degrees of the reaching action by the virtual hand towards the cube, since the distance from the virtual hand to the cube is proportional to 1-$p(\omega|\mathbf{x})$. In the event of a misclassification, the virtual hand stays at its original marker position. In addition, the subject does not observe the movement of the other virtual hand as it may cause interference in facilitating the required motor imagery [7]. The MI-BCI translates the motor imagery action continuously and updates the position of the virtual hand every 0.5s till the end of the motor imagery at 4s. If the subject could perform the correct reaching action for at least 1.5s, the visual 'reward' is presented, whereby the virtual hand finally grasps the virtual cube and places it onto the top marker shown in Fig. 3. This is also followed by a break period where the system does not receive any input from the user before the next trial begins.

IV. EXPERIMENTAL STUDY

8 male healthy subjects, denoted S1 to S8, were recruited to evaluate the online performance of the MI-BCI using these two types of visual feedback. S1 had prior experience using the MI-BCI, while S2 to S7 were BCI-naïve. EEG data was recorded using 25 electrodes placed around the sensorimotor cortex area using the Neuroscan Quikcap with a sampling rate of 250Hz. There were 3 experiment sessions: 1 screening and 2 online feedback sessions. In each session, each subject performed 80 trials of left hand and 80 trials of right hand motor imagery. EEG data from the screening session was used to train the FBCSP algorithm for the online feedback sessions.

During the screening session, a fixation cross is displayed on the computer screen for 1s at the start of each trial. Subsequently, a visual cue instructs the subject to perform left-hand or right-hand motor imagery without feedback for 4s, followed by an inter-trial break period.160 trials of left hand and right hand motor imagery EEG data (equally distributed among the two classes) were collected from each subject in the screening session. The segment of 0.5s to 2.5s of EEG data after the onset of the visual cue was extracted to train the FBCSP algorithm. The choice of m for the CSP algorithm in equation (1) was set to 2, based on the selection parameters in previous studies [8], [18].

For the two online feedback sessions, the subjects were randomly split into two groups. The first group performed the horizontal bar feedback first, followed by the AR feedback. The second group performed the AR feedback first, followed by the horizontal bar feedback.

A. Classification Results

The FBCSP algorithm was evaluated on the screening data using 10×10-fold cross-validation and using session-to-session transfer from the screening data onto each of the feedback session. The performance measure used is the classification accuracy in percentage; classification was performed on the same segment of EEG data used to train the FBCSP algorithm: 0.5s to 2.5s after the onset of the visual cue. The classification results are shown in Table 1.

TABLE 1
CLASSIFICATION PERFORMANCE OF SCREENING AND ONLINE FEEDBACK SESSIONS. CV STANDS FOR CROSS-VALIDATION, S2S STANDS FOR SESSION-TO-SESSION TRANSFER FROM SCREENING SESSION TO ONLINE FEDBACK SESSIONS

	Mean classificiation accuracies								
	S1	S2	S3	S4	S5	S6	S7	S8	AVG
10x10 CV Screening	88.1	78.1	79.6	43.4	88.0	81.3	66.2	58.5	72.9
S2S Bar Feedback	91.3	75.0	80.0	57.5	87.5	75.0	57.5	60.0	73.0
S2S AR Feedback	92.5	80.0	71.3	51.3	91.3	73.8	63.8	65.0	73.6

Statistical analysis using one-way ANOVA revealed no significant difference between the screening session and the feedback sessions (p-value = 0.99). Hence, the 10×10-fold cross-validation classification performance on the screening session is similar to the session-to-session transfer classification results on the online feedback sessions. 7 of the 8 subjects performed better than chance accuracy in the screening session. Although S4 achieved <50% classification accuracy in the screening session, he was not excluded from the subsequent feedback sessions.

The mean classification accuracy of the AR feedback session is slightly higher than that of the bar feedback session, but not statistically different (p-value = 0.76). Among the 3 subjects who performed >80% classification accuracies in the screening sessions, S1 and S5 performed slightly better for the AR feedback. However, S6 and S7 performed poorer in both online feedback sessions compared to the screening session.

Some subjects (S6 and S7) performed relatively poorer during the online feedback sessions compared to the screening session. The results are similar to the findings in another study [20], where some subjects performed slightly poorer for online feedback sessions because they got excited at the prospect of controlling the BCI in real-time and were thus overwhelmed by the new experience. The subjects in this study were mostly BCI-naïve and reported that the AR feedback seemed relatively more difficult to obtain the visual reward compared to the bar feedback. Some subjects felt that the protocol for the horizontal bar feedback was similar to that for the screening session, which represented a relatively more familiar task compared to the AR feedback.

B. Classification time course

Fig. 4 shows the time course of the classification accuracy averaged over all trials in the respective feedback sessions and over 7 subjects. S4 was omitted due to poor MI-BCI performance. Similar MI-BCI performance was observed for both types of visual feedback. Maximum classification accuracies were around 2s to 3s after the onset of the visual cue. This is consistent with the training time segment, 0.5s to 2.5s from the visual cue, used to train the FBCSP algorithm.

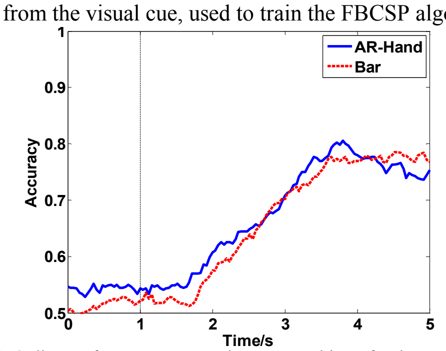


Fig. 4: Online performance averaged across 7 subjects for the two feedback sessions on the single trial EEG starting from the start of trial to the visual cue to the end of motor imagery period denoted as 0s, 1s and 5s respectively. A shifting time window of 2s is used to calculate the time course classification accuracies.

C. Subject Opinions

The subjects found the AR feedback more interesting and engaging as they could interact with virtual objects in their real environment. Some subjects were motivated by the perceived higher level of difficulty of the AR feedback, and were thus motivated to overcome the challenge and achieve a higher degree of control as exhibited in the higher classification accuracies for the AR feedback. Finally, these subjects reported having a greater level of satisfaction when they could receive the visual reward during the AR feedback.

V. CONCLUSION

This paper investigated the online performance of the MI-BCI using the Filter Bank Common Spatial Pattern (FBCSP) algorithm with an augmented-reality (AR) 3D virtual hand feedback, while performing left or right hand motor imagery. 8 subjects (7 BCI-naïve) were recruited for this study, which found the AR feedback to be more challenging compared to the horizontal bar feedback. However, session-to-session transfer results from the training session without feedback to the online sessions with feedback showed that the subjects' online MI-BCI performance using the AR feedback were not affected, compared to the bar feedback (p-value = 0.76). They felt more motivated to achieve the correct movement of the 3D virtual hands and the reward condition of grasping other virtual objects. The importance of motivation has been mentioned in a study [10], where motivated subjects had a better BCI performance. In the restoration of motor control, rehabilitation professionals believe that patient motivation plays an important role in determining rehabilitation outcome [21]. Evaluating the AR feedback forms another study to evaluate more portable and affordable types of feedback for a MI-BCI system that studies its clinical application in stroke rehabilitation [22]. Thus, findings from this study motivate future work on the development of more engaging forms of virtual feedback for the MI-BCI.

REFERENCES

[1] H. H. Ehrsson, S. Geyer, and E. Naito, "Imagery of Voluntary Movement of Fingers, Toes, and Tongue Activates Corresponding Body-Part-Specific Motor Representations," *J. Neurophysiol.,* vol. 90, pp. 3304-3316, 2003.

[2] J. J. Daly and J. R. Wolpaw, "Brain-computer interfaces in neurological rehabilitation," *The Lancet Neurology,* vol. 7, pp. 1032-1043, 2008.

[3] G. Pfurtscheller, G. R. Muller-Putz, R. Scherer, et al., "Rehabilitation with Brain-Computer Interface Systems," *Computer,* vol. 41, pp. 58-65, 2008.

[4] N. Sharma, V. M. Pomeroy, and J.-C. Baron, "Motor Imagery: A Backdoor to the Motor System After Stroke?," *Stroke,* vol. 37, pp. 1941-1952, July 1, 2006 2006.

[5] B. Blankertz, G. Dornhege, M. Krauledat, et al., "The non-invasive Berlin Brain-Computer Interface: Fast acquisition of effective performance in untrained subjects," *NeuroImage,* vol. 37, pp. 539-550, 2007.

[6] G. Pfurtscheller, C. Brunner, A. Schlögl, et al., "Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks," *NeuroImage,* vol. 31, pp. 153-159, 2006.

[7] C. Neuper, R. Scherer, S. Wriessnegger, et al., "Motor imagery and action observation: Modulation of sensorimotor brain rhythms during mental control of a brain-computer interface," *Clin Neurophysiol.,* vol. 120, pp. 239-247, 2009.

[8] K. K. Ang, Z. Y. Chin, H. Zhang, et al., "Filter Bank Common Spatial Pattern (FBCSP) in Brain-Computer Interface," in *Proc. IJCNN'08*, 2008, pp. 2390-2397.

[9] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, et al., "Brain Computer interfaces for communication and control," *Clin Neurophysiol.,* vol. 113, 2002.

[10] R. Leeb, F. Lee, C. Keinrath, et al., "Brain-Computer Communication: Motivation, Aim, and Impact of Exploring a Virtual Apartment," *IEEE Trans. Neural Syst. Rehabil. Eng.,* vol. 15, pp. 473-482, 2007.

[11] D. J. McFarland, L. M. McCane, and J. R. Wolpaw, "EEG-based communication and control: short-term role of feedback," *IEEE Transactions on Rehabilitation Engineering,* vol. 6, pp. 7-11, 1998.

[12] J. D. Bayliss and D. H. Ballard, "A virtual reality testbed for brain-computer interface research," *IEEE Transactions on Rehabilitation Engineering,* vol. 8, pp. 188-190, 2000.

[13] J. A. Pineda, D. S. Silverman, A. Vankov, et al., "Learning to control brain rhythms: making a brain-computer interface possible," *IEEE Trans. Neural Syst. Rehabil. Eng.,* vol. 11, pp. 181-184, 2003.

[14] R. Scherer, F. Lee, A. Schlögl, et al., "Toward Self-Paced Brain-Computer Communication: Navigation Through Virtual Worlds," *IEEE Trans. Biomed. Eng.,* vol. 55, pp. 675-682, 2008.

[15] D. Perez-Marcos, M. Slater, and M. V. Sanchez-Vives, "Inducing a virtual hand ownership illusion through a brain-computer interface," *NeuroReport,* vol. 20, pp. 589-594, 2009.

[16] R. Azuma, Y. Baillot, R. Behringer, et al., "Recent Advances in Augmented Reality," *IEEE Computer Graphics and Applications,* vol. 21, pp. 34-47, 2001.

[17] B. Blankertz, BCI Competition IV, 2008, http://www.bbci.de/competition/iv/

[18] Z. Y. Chin, K. K. Ang, C. Wang, et al., "Multi-class filter bank common spatial pattern for four-class motor imagery BCI," in *Proc. EMBC '09*, 2009, pp. 571-574.

[19] H. Ramoser, J. Muller-Gerking, and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Trans Rehabil Eng,* vol. 8, pp. 441 - 446, 2000.

[20] C. Guger, G. Edlinger, W. Harkam, et al., "How many people are able to operate an EEG-based brain-computer interface (BCI)?," *IEEE Trans. Neural Syst. Rehabil. Eng.,* vol. 11, pp. 145-147, 2003.

[21] N. Maclean, P. Pound, C. Wolfe, et al., "Qualitative analysis of stroke patients' motivation for rehabilitation," *BMJ,* vol. 321, pp. 1051-1054, Oct 2000.

[22] K. K. Ang, C. Guan, K. S. G. Chua, et al., "A clinical evaluation of non-invasive motor imagery-based brain-computer interface in stroke," in *Proc. EMBC '08*, 2008, pp. 4178-4181.