7th Annual International IEEE EMBS Conference on Neural Engineering
Montpellier, France, 22 - 24 April, 2015

Does Feedback Modality Affect Performance of Brain Computer Interfaces?

Sam Darvishi, *Member IEEE*, Michael C. Ridding, Derek Abbott, *Fellow IEEE*, Mathias Baumert, *Senior Member IEEE*.

Abstract— **Brain computer interfaces (BCI) are used for communication and rehabilitation. One of the main categories of BCI techniques is motor imagery based BCI (MI-BCI). A large number of studies have focused on machine learning approaches to optimize MI-BCI performance. However, enhancement of MI-BCI through provision of optimized feedback modalities has not received equal attention. Motor imagery and motor execution activate almost the same area of the brain. During motor skills performance, a combination of proprioceptive and direct visual feedback (PDVF) is provided. Thus, we hypothesized that MI-BCI that receives PDVF outperforms the traditional MI-BCI, which only uses indirect visual feedback (IVF). We studied 8 healthy subjects performing MI through (i) IVF and (ii) PDVF. We used 8 channel electroencephalogram (EEG) signals and extracted features using an autoregressive model and classified MIs using linear regression. On average, PDVF increased the accuracy of MI performance by 11%, and improved information transfer rate (ITR) by more than two times. In conclusion, using PDVF appears to improve MI-BCI performance according to the studied metrics, making this approach potentially more reliable.**

Keywords—EEG; motor learning; brain-computer interfaces; motor imagery; information transfer rate, accuracy

I. INTRODUCTION

Brain-computer interface (BCI) technology has established the foundation for the human brain to communicate with machines directly. Motor imagery (MI) based BCI (MI-BCI) that relies on the rhythm changes occur within the sensorimotor area of the brain during MI [1], is one of the main BCI paradigms. In non-invasive MI-BCI, the brain activity during MI is recorded using EEG [2], functional magnetic resonance imaging [3] (fMRI), or near infrared spectroscopy (NIRS) [4]. Among the aforementioned techniques, EEG is the most practical and affordable technique and thus, the most commonly exploited modality in non-invasive MI-BCI applications.

One of the challenges of MI-BCI is its rather low accuracy and information transfer rate (ITR). This drawback limits the dissemination of MI-BCIs for widespread application. Provision of optimum feedback is believed to improve MI-BCI performance metrics [5]. Proprioceptive feedback, visual feedback, or different combinations thereof are among the most common feedback modalities in MI-BCIs [6]. While visual feedback is mostly supplied via cursor position update on a monitor [7], proprioceptive feedback has been provided using either orthoses [8] or robots [9]. Nijboer et al. [10], investigated suitability of auditory feedback for MI-BCI, and found its performance comparable with indirect visual feedback (IVF). Ramos-Murguialday et al. [11], applied concurrent proprioceptive and direct visual feedback (PDVF) as a feedback modality in MI-BCI restorative applications. PDVF showed increased accuracy of subject response to MI compared to either no feedback or sham feedback. However, they did not compare PDVF with other feedback modalities.

Motor execution and motor imagery of a particular task, activate almost the same area of the brain [12]. Thus, in search for optimization of feedback modality for MI-BCI we surveyed different feedback types in motor learning. Enough repetition of a movement, followed by feedback, results in motor learning in healthy subjects. Intrinsic feedback is realized through proprioceptive and/or visual sensory inputs as a result of the performed motor task. Extrinsic (augmented) feedback, however, is provided artificially by an external agent to enhance the motor learning outcomes; an example of this are athletes who learn new moves via auditory feedback from the coach [13]. When augmented feedback is added to intrinsic feedback, it improves the retention and motor learning outcomes by provision of knowledge of performance and/or knowledge of result [14].

In contrast to motor learning, there is no muscle activation during motor imagery and, therefore, no source of feedback. As a consequence, an external actuator is required to supply extrinsic feedback in MI-BCI setups. Provision of IVF through updating the cursor position on a monitor is currently the most ubiquitous feedback modality in BCI applications [11]. This type of feedback provision might be quite effective for some BCI applications, such as in the P300-based Speller [15]. However, considering the outcomes of motor learning studies on feedback modalities [16], IVF may not be as effective in MI-BCI because it lacks intrinsic (direct) feedback to close the sensorimotor loop. By contrast, PDVF, in addition to the augmented feedback of IVF, provides intrinsic visual and proprioceptive feedback.

While, PDVF provides feedback that is closest to motor learning, supplying IVF via updating cursor position on a monitor remains the most prevalent feedback modality in MI-BCI setups. Recently, Lotte et al [17], suggested that current BCI training approaches that use IVF were suboptimal and need to be improved. Thus, to investigate alternative feedback modalities for MI-BCIs we compared two similar BCI designs that used either IVF or PDVF in eight BCI-naive subjects. According to our results, PDVF seems to be superior to the traditional IVF that promotes the application of PDVF to make MI-BCIs more efficient and accurate.

S. Darvishi, M. Baumert, and D. Abbott are with the Centre for Biomedical Engineering, School of Electrical and Electronic Engineering, The University of Adelaide, SA 5000 (phone:+618-8313-4115; e-mail: sam.darvishi@adelaide.edu.au, mathias.baumert@adelaide.edu.au, derek.abbott@adelaide.edu.au).

M.C. Ridding is with the Robinson Institute, School of Pediatrics and Reproductive Health, The University of Adelaide, SA 5005 (michael.ridding@adelaide.edu.au).

II. METHODS

A. Subjects

The study was approved by the human ethics committee of the University of Adelaide and conformed to principles outlined in the Declaration of Helsinki. All subjects provided their written informed consent to take part in the study and all recorded data were de-identified. Ten subjects (6 males) were aged 24–40 years. All subjects were asked to attend an induction session prior to the BCI sessions. During the induction session, they were trained to remain alert, actionless, and concentrate during the experiments. Also, visual and kinesthetic MI were explained to them and then they practiced these techniques.

Only 8 out of 10 subjects (4 females, 4 males) whose right vs. left hand MI performance were distinctive, passed the screening test and were allowed to participate in the study (training sessions).

B. BCI Setup

A 72 Channel Refa TMSi EXG amplifier, containing 64 unipolar and 8 bipolar channels and a 64 channel Waveguard EEG cap, were used for data acquisition. Only 8 out of 64 channels (F3, F4, T7, C3, Cz, C4, T8, Pz) were used to record EEG data. To follow the recommendation of the manufacturer, The AFz channel was used as the ground channel. Due to the very high input impedance (in the order of tera-ohms) of the instrumentation amplifier [18], the impedance between the scalp and recording electrodes were kept below 50 kΩ. As the amplifier uses a built-in common average referencing procedure, there is no need to use an external reference channel to be attached to nose or ears. Any electrode with impedance more than 256 kΩ is considered as disconnected by the amplifier firmware and is excluded from common average reference calculation. The sampling frequency was 1024 Hz and every sample block contained 24 samples. The EEG signals were passed through a 50 Hz notch filter to remove the power line noise. To remove DC offset and non related high frequency elements, a band pass filter with corner frequencies set to 0.1 and 40 Hz was also applied.

After amplification and filtering by the amplifier, EEG signals were transferred through a 10-metre-long fiber optic cable to a FUSBi fiber to USB converter. Then they were conveyed to a PC using a USB cable. The PC contained an Intel Core-2 Duo 3.166 GHz processor, 3 GB of RAM, and used the Windows XP service pack 3 operating system. It was also mobilized with a 23” LCD monitor with a display update rate of 60 Hz to provide the IVF feedback.

BCI2000 [19] was adopted as the software platform of the study because of its real time characteristic. We customized the source code of the software to supply auditory commands. We also altered the application module of the software to progressively update servomotors position throughout the feedback section of each trial.

To provide PDVF, we fabricated a platform with two orthoses (one for each hand) to passively flex four fingers incrementally, according to the attributes of the MI of the target hand. Each orthosis included a servomotor (Blue Bird BMS-630) and a mechanical structure made of PVC. BCI2000 supplied the control commands for servomotors operation that were transformed via a Micro Maestro servo controller module to a format readable by the servomotors.

C. Study design

Each participant took part in one screening session followed by an online training session. The goal of the screening sessions was to identify the extent to which subjects could produce distinctive EEG signals out of right/left hand MI. Next, the most discriminative features of each subject’s EEG signals were extracted and used to calibrate their following training sessions. Finally, the extracted features of EEG signals produced during online sessions were classified in real time to generate control signals that were used to provide either PDVF or IVF.

1. Screening session setup

During the screening session, each participant went through 3 runs of MI of right/left hand. In each run subjects were instructed to perform ten right and ten left hand MI in a randomized order. At the onset of each trial, an auditory command of “left” or “right” was supplied concurrently with an equivalent visual stimulus. To present the visual cue, a monitor was placed 1 metre away from the subject at which an arrow pointing to either the left or right was shown. The sound levels of the auditory commands were kept constant throughout the study. Subjects were instructed to perform MI of their target hands involving four finger flexion within the 3-second-long period in which the arrow was shown. The subjects were cued to stop the MI and concentrate on their breathing (relaxation) when the arrow disappeared. After 3 seconds of relaxation, they were given new stimuli to perform MI for the next trial.

To appreciate the specificity of MI attributes of each subject, the combination (left vs. relax or right vs. relax) that resulted in the highest value of the coefficient of determination (r^2) was selected for each individual, where r^2 represents the proportion of the single-trial variance that is due to the task. While for the majority of subjects right vs. left hand MI generated the highest discrimination in sensorimotor rhythms; only right vs. rest and left vs. rest were considered in this study to minimize the cognition load and fatigue level.

2. Subjects’ optimum features

According to the findings of Pfurtscheller et al. [1] MI of hand movement results in a decrement followed by an increment in the spectral power of sensorimotor rhythms. The former is known as event related desynchronization (ERD) whereas the latter is called event related synchronization (ERS). According to the results of same study, for the majority of cases these phenomena takes place in the contralateral rolandic area within the μ (8–13 Hz) and β (18–25 Hz) frequency bands. However, in some occasions ERD and ERS may occur bilaterally. To extract the relevant features of MI as early as possible during the online sessions, only ERDs were considered. Among the eight subjects that proceeded to the online session, six subjects generated only contralateral ERDs, whereas the other two exhibited simultaneous ERDs in both, C3 and C4 channels.

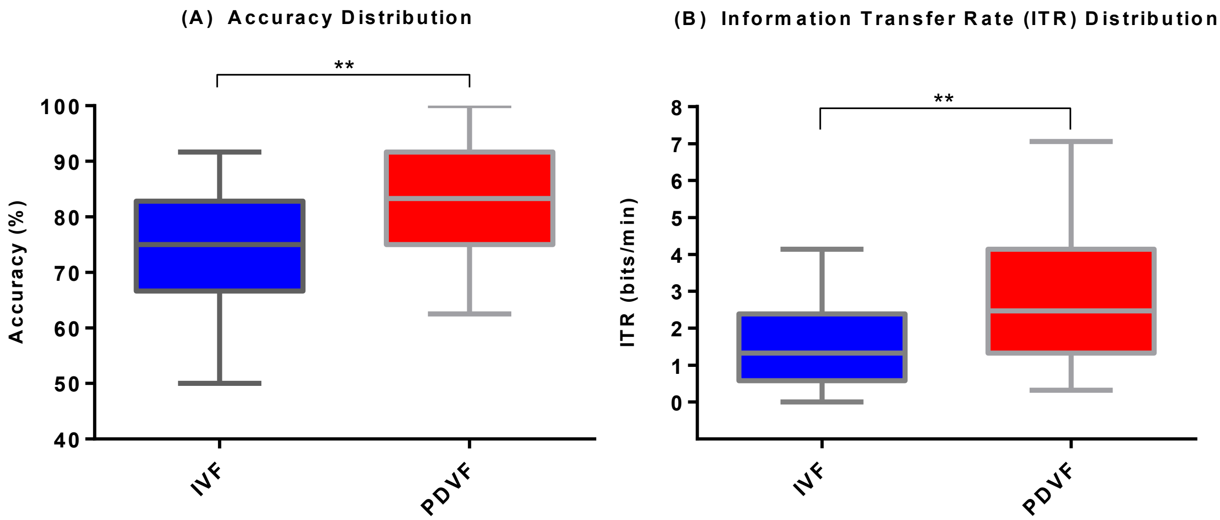

Figure 1: Comparing the accuracy and ITR between two equal MI-BCI setups where either PDVF or IVF feedback provided. The edges of the boxes are the 25th and 75th percentiles, the horizontal line in each box is the median, and the whiskers extend to the minima and maxima.

3. Feedback provision

Every 24 ms either the position of the cursor on the monitor (IVF feedback) or the angle of the orthosis (PDVF feedback) was updated according to the classifier outputs. Feedback modality of the first run was randomly selected and then was alternated for the following runs. To ensure availability of a sufficient amount of data for comparison, the minimum number of runs set to be four. If subjects were not exhausted, the number of runs could rise up to eight.

4. Online training session

All participants took part in an online training session no later than 2 weeks after their screening sessions. The online session included 4–8 runs of MI of right/left hand four-finger flexion. Each run comprised 15 randomly presented trials with 8/7 left/right hand MIs and 7/8 relaxations. Trials started with auditory commands of "left /right" or "relax" that cued participants to start MI or relaxation according to the command. Then, feedback provision section started after two seconds of trial onset and became updated every 24 ms for 2.5 seconds. Finally, a "beep" signal, cued the end of trial. The following trial was initiated after a four-second-long break.

D. Signal Processing

1. Power spectrum estimation

EEG signals become blurred because of the heterogeneity in the tissues of the cortex and the scalp. To deblur the EEG signals a large Laplacian spatial filter as an effective method for reduction of data blurring [20] was applied. To define an autoregressive (AR) model of the EEG data, the maximum entropy method [21] (MEM) was adopted. It was chosen over fast Fourier transform (FFT) due to its capability of robust power spectrum estimation of short time series [21]. The spectral power of the most recent 500 ms was progressively estimated every 24 ms at the predefined frequencies and electrode positions.

2. Classification

A linear regression algorithm was used to classify the extracted feature of the EEG data every 24 ms (the duration of each sample block) due to its simple procedure and fast processing time. The classification results showed whether the subject's performance during the most recent 500 ms conforms to the requested task (either left/right hand MI or relaxation). Finally, the classification result was transferred to the application module to provide either IVF or PDVF.

E. Measures & Statistics

1. Performance measures

To compare the effects of different feedback modalities on BCI performance two measures were used. First, the conventional measure of the percentage of the trials that ended with hit in each run as an index of accuracy was applied. As a second metric, information transfer rate (ITR) that simultaneously considers accuracy and speed of data transfer [22] was used. To calculate ITR in bits per minute (bits/min) the following formula was applied [22]:

$$\mathrm{ITR} = \left(\log_2 N + P\log_2 P + (1-P)\log_2 \frac{1-P}{N-1}\right) 60/8.5 \quad (1)$$

Where, N is the number of classes (which is two in this study), and P is the accuracy of each run, and 8.5 is the duration of each trial in seconds.

2. Statistical analysis

Since the resultant values of the aforementioned metrics did not have a normal distribution, the two-sided unpaired Wilcoxon rank-sum test [23] was used. Due to application of two comparison measures, Bonferroni correction [24] for multiple comparisons was applied and therefore, the significance level set to 0.05/2 = 0.025.

III. Results and Discussion

Task performance was quantified using accuracy (hit rate percentage) and ITR. Fig. 1−A compares hit rate percentage distribution between PDVF and IVF. It shows that PDVF with average accuracy of 83% outperforms that of IVF by 11% ($p = 0.0015$). Fig. 1−B shows the comparison between the ITR distribution out of PDVF and IVF setups. This figure depict that using PDVF results in the average ITR of 2.81 bits/min which is greater than two times of the average ITR of IVF (1.32 bits/min) ($p = 0.001$).

The main finding of our study is that the adoption of PDVF in MI-BCI systems significantly improves the accuracy and ITR of the BCI setup. While PDVF only improves the average accuracy by almost 10%, it resulted in enhancing the ITR by more than two times due to the logarithmic relationship of ITR and accuracy. In other words, application of PDVF enables subjects to communicate more than two times faster than IVF.

Our results are also in accordance with the findings of Gomez-Rodriguez et al (2011), who showed that supplying proprioceptive feedback in parallel with IVF enhances the accuracy of MI performance compared to that with only IVF [25]. However, they only studied the effect of adding proprioceptive feedback to the IVF. Thus, prior to our study, it remained unclear whether and to what extent PDVF (the natural feedback for motor learning) outperforms IVF (the most used feedback with MI-BCIs).

According to the Kahneman's attention theory [16] attention resources of the human brain are limited. In other words, it is difficult for human agents to focus on a number of different tasks concurrently. Thus, it makes it cumbersome to fully concentrate on both MI task and realizing IVF, simultaneously. In contrast, when PDVF is received during MI performance, the intrinsic visual and proprioceptive sensory feedback mechanisms are perceived quite similar to feedback perception in motor learning. Therefore, it may be concluded that receiving PDVF improves performance and does not distract subjects during MI.

Since we did not record electromyogram (EMG) of the hand muscles in this study, we cannot exclude the possibility that active movement has affected our results.

IV. Conclusion

In the current study, the feature extraction and classification procedure used for both PDVF and IVF feedback were entirely equivalent. Thus, the improvement of the adopted metrics is expected to be due to more discriminant features elicited from PDVF. Specifically, receiving PDVF enables subjects to produce MIs that are easier to differentiate from relaxation compared to those with IVF. These high quality MIs in turn, lead to improved control over the BCI task and results in higher accuracy and faster communication. Thus, provision of PDVF feedback in MI-BCI may be used to render MI-BCI communication faster and more accurate.

References

[1] G. Pfurtscheller, *et al.*, "EEG-based discrimination between imagination of right and left hand movement," *Electroencephalogr Clin Neurophysiol,* vol. 103, pp. 642–651, Dec 1997.

[2] N. Birbaumer, *et al.*, "A spelling device for the paralysed," *Nature,* vol. 398, pp. 297–298, Mar 25 1999.

[3] N. Weiskopf, *et al.*, "Principles of a brain-computer interface (BCI) based on real-time functional magnetic resonance imaging (fMRI)," *IEEE Trans Biomed Eng,* vol. 51, pp. 966–970, Jun 2004.

[4] S. M. Coyle, *et al.*, "Brain-computer interface using a simplified functional near-infrared spectroscopy system," *J Neural Eng,* vol. 4, pp. 219–226, Sep 2007.

[5] J. E. Huggins, *et al.*, "Workshops of the fifth international brain-computer interface meeting: defining the future," *Brain-Computer Interfaces,* vol. 1, pp. 27–49, 2014.

[6] K. K. Ang and C. Guan, "Brain-computer interface in stroke rehabilitation," *Journal of Computing Science and Engineering,* vol. 7, pp. 139–146, 2013.

[7] G. Prasad, *et al.*, "Applying a brain-computer interface to support motor imagery practice in people with stroke for upper limb recovery: a feasibility study," *Journal of NeuroEngineering and Rehabilitation,* vol. 7, pp. 1–17, 2010.

[8] A. Caria, *et al.*, "Chronic stroke recovery after combined BCI training and physiotherapy: a case report," *Psychophysiology,* vol. 48, pp. 578–582, Apr 2011.

[9] K. K. Ang, *et al.*, "A large clinical study on the ability of stroke patients to use an EEG-based motor imagery brain-computer interface," *Clin EEG Neurosci,* vol. 42, pp. 253–258, Oct 2011.

[10] F. Nijboer, *et al.*, "An auditory brain-computer interface (BCI)," *J Neurosci Methods,* vol. 167, pp. 43–50, Jan 2008.

[11] A. Ramos-Murguialday, *et al.*, "Proprioceptive feedback and brain computer interface (BCI) based neuroprostheses," *PLoS One,* vol. 7, p. e47048, 2012.

[12] S. de Vries and T. Mulder, "Motor imagery and stroke rehabilitation: a critical discussion," *J Rehabil Med,* vol. 39, pp. 5–13, Jan 2007.

[13] P. M. van Vliet and G. Wulf, "Extrinsic feedback for motor learning after stroke: what is the evidence?," *Disabil Rehabil,* vol. 28, pp. 831–840, Jul 2006.

[14] D. E. Thorpe and J. Valvano, "The effects of knowledge of performance and cognitive strategies on motor skill learning in children with cerebral palsy," *Pediatr Phys Ther,* vol. 14, pp. 2–15, Spring 2002.

[15] E. Donchin, *et al.*, "The mental prosthesis: assessing the speed of a P300-based brain-computer interface," *IEEE Trans Rehabil Eng,* vol. 8, pp. 174–179, Jun 2000.

[16] D. A. Richard Magill, *Motor Learning and Control: Concepts and Applications*, Tenth ed.: McGraw-Hill Education, 2014.

[17] C. Jeunet, *et al.*, "How well can we learn with standard BCI training approaches? A pilot study," in *6th International Brain-Computer Interface Conference*, Graz, Austria, 2014.

[18] I. Volosyak, *et al.*, "Brain-computer interface using water-based electrodes," *J Neural Eng,* vol. 7, 066007, Dec 2010.

[19] G. Schalk, *et al.*, "BCI2000: a general-purpose brain-computer interface (BCI) system," *IEEE Trans Biomed Eng,* vol. 51, pp. 1034–1043, Jun 2004.

[20] B. Hjorth, "Principles for transformation of scalp EEG from potential field into source distribution," *J Clin Neurophysiol,* vol. 8, pp. 391–396, Oct 1991.

[21] S. L. Marple, *Digital Spectral Analysis with Applications*: Englewood Cliffs, NJ, Prentice-Hall, Inc., 1987.

[22] D. J. McFarland and D. J. Krusienski, "BCI Signal Processing: Feature Translation," in *Brain-Computer Interfaces: Principles and Practice*, J. R. Wolpaw and E. W. Wolpaw, Eds., ed Oxford; New York: Oxford University Press, 2012, pp. 147–163.

[23] F. Wilcoxon, "Individual comparisons by ranking methods," *Biometrics Bulletin,* vol. 1, pp. 80–83, 1945.

[24] O. J. Dunn, "Multiple comparisons among means," *Journal of the American Statistical Association,* vol. 56, pp. 52–64, 1961.

[25] M. Gomez-Rodriguez, *et al.*, "Closing the sensorimotor loop: haptic feedback facilitates decoding of motor imagery," *J Neural Eng,* vol. 8, 036005, Jun 2011.