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Reaction Time Predicts Brain–Computer Interface Aptitude

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ABSTRACT There is evidence that 15–30% of the general population cannot effectively operate brain–computer interfaces (BCIs). Thus the BCI performance predictors are critically required to pre-screen participants. Current neurophysiological and psychological tests either require complicated equipment or suffer from subjectivity. Thus, a simple and objective BCI performance predictor is desirable. Neurofeedback (NFB) training involves performing a cognitive task (motor imagery) instructed via sensory stimuli and re-adjusted through ongoing real-time feedback. A simple reaction time (SRT) test reflects the time required for a subject to respond to a defined stimulus. Thus, we postulated that individuals with shorter reaction times operate a BCI with rapidly updated feedback better than individuals with longer reaction times. Furthermore, we investigated how changing the feedback update interval (FUI), i.e., modification of the feedback provision frequency, affects the correlation between the SRT and BCI performance. Ten participants attended four NFB sessions with FUIs of 16, 24, 48, and 96 ms in a randomized order. We found that: 1) SRT is correlated with the BCI performance with FUIs of 16 and 96 ms; 2) good and poor performers elicit stronger ERDs and control BCIs more effectively (i.e., produced larger information transfer rates) with 16 and 96 ms FUIs, respectively. Our findings suggest that SRT may be used as a simple and objective surrogate for BCI aptitude with FUIs of 16 and 96 ms. It also implies that the FUI customization according to participants SRT measure may enhance the BCI performance.

INDEX TERMS Simple reaction time, feedback update interval, brain-computer interface, brain-machine interface, aptitude, information transfer rate.

I. INTRODUCTION

Brain-computer interfaces (BCIs) provide an alternative communication channel for the transfer of the human will to the outside world. However, there is evidence that 15–30% of the general population are not able to effectively operate BCIs [1]. Having access to BCI performance predictors avoids participants that are unable to operate BCIs, thus saving a significant amount of time and resources. To predict BCI performance, a number of neurophysiological [1]–[8] and psychological tests [9], [10] have been proposed. All proposed measures correlate to some degree with motor imagery (MI) performance quality.

However, previously proposed neurophysiological measures [1]–[8] require complicated equipment such as electroencephalography (EEG), magnetoencephalography (MEG), functional near-infrared spectroscopy (fNIRS), or functional magnetic resonance imaging (fMRI) machines. Psychological measures [9], [10] are easily accessible but suffer from subjectivity and low resolution (e.g. questionnaires). Thus, simple (measurable with ubiquitous hardware) and objective (not reliant on subjects' self-assessment) BCI performance predictors remain warranted.

Neurofeedback (NFB) training with real-time feedback involves performing a cognitive task (motor imagery, MI) followed by feedback realisation. The knowledge of performance provided by feedback may be used to adjust the ongoing MI, which in turn will be rewarded by the next round of feedback provision. A simple reaction time (SRT) test is an accurate and simple test [11], which may be implemented in commonly available hardware such as a PC and open source software. The SRT test reflects how quickly a person interacts with the environment while preparing to provide a required action [12]. Thus, we hypothesised that SRT may provide a simple and objective surrogate for BCI performance. Specifically, we hypothesised that those subjects with shorter reaction times will display improved performance during NFB training with more rapidly updated feedback than their counterparts with longer reaction times. Further, following up on our prior studies [17], [45], we investigated whether and to what extent lengthening the feedback update interval (FUI), i.e. decreasing the feedback provision frequency, affects the relationship between reaction time and quality of BCI performance.

We investigated the relationship between BCI performance quality and reaction times, which measures the speed of interaction with the performance environment. Information transfer rate (ITR) is a BCI performance measure that not only reflects the accuracy of performance but also reveals the speed of communication [13]. Therefore, ITR was selected as the measure of quality for BCI performance. Ten participants attended four NFB training sessions with FUIs of 16, 24, 48, and 96 ms in a randomised order. For those FUIs that revealed significant correlations between the ITR and SRT, two follow-up analyses were implemented, investigating: (i) how interaction between BCI aptitude and FUIs affect ITR, and (ii) how interaction between BCI aptitude and FUIs affects event-related de-synchronization (ERD) in alpha (8–13 Hz) and beta (16–30 Hz) frequency bands as neural correlates of quality of MI performance [14], [15].

II. METHODS

A. PARTICIPANTS

Ten healthy participants (six males, four females) aged 18–26 years were recruited in this study. The study was approved by the local human ethics committee of the University of Adelaide, and all participants gave their written informed consent to participate in the study.

B. BCI SYSTEM

A 72 Channel Refa TMSi EXG amplifier, with 64 unipolar and eight bipolar channels and a 64 channel Waveguard EEG cap was used. The EEG data were recorded only from small Laplacian combination of the channels centred on either the C3 or C4 channel. The ground channel was connected to the participants' target hand using a wristband. The impedance between electrodes and the scalp was kept below 20 kΩ. The EMG data of the finger flexor muscles of the target hand were recorded using a bipolar channel of the EXG amplifier. The amplifier uses a built-in common average reference of the recorded channels and thus does not require a reference channel. The amplifier was set to exclude any unipolar channels with impedances larger than 20 kΩ from the common average reference calculation. It also does not consider the bipolar channels used for EMG recording in common average referencing of EEG signals. All EEG and EMG signals were digitised at 1000 Hz and passed through a 50 Hz notch filter (3rd order Chebyshev) followed by a high pass filter (1st order Butterworth) with a corner frequency of 0.1 Hz. To provide the proprioceptive feedback two orthoses were mounted on a platform to serve either the right or left hand. They passively flex fingers of the involved hand according to the motor imagery of four-finger flexion. Each orthosis was driven by a Blue Bird BMS-630 servomotor, using customized software and a Micro Maestro servo controller module.

A customised version of the BCI2000 [16] was used to record the data and run the real-time experiments. The source code was customised to provide auditory commands and to update the position of the servo motors.

C. STUDY DESIGN

The data used in the current study were part of a larger study we conducted to investigate the effect of user-centred strategies on BCI performance. In this crossover study, each of the 10 participants attended one screening session followed by six training BCI sessions under different conditions. The six conditions were (I) proprioceptive feedback with FUI of 16 ms, (II) proprioceptive feedback with FUI of 24 ms, (III) proprioceptive feedback with FUI of 48 ms, (IV) proprioceptive feedback with FUI of 96 ms, (V) visual feedback, and, (VI) No imagery (control condition). The order of conditions was randomised to compensate for a potential training effect during the consecutive sessions of BCI. The data for the current study were derived from conditions I–IV in which participants performed MI-BCI and received proprioceptive feedback that was updated every 16, 24, 48, or 96 ms.

The FUI values were set to be less than 100 ms to allow for frequent repetitions of feedback updates during MI performance for all FUIs. Due to the EEG amplifier's firmware, the FUIs could be increased in 8 ms steps, which in turn dictated the largest FUI of 96 ms within the 0–100 ms range. Also, FUIs were chosen to be logarithmically equidistant that determined their values to be 12, 24, 48, and 96 ms. However, the shortest technically achievable FUI that provided real-time feedback was 16 ms, and thus the FUIs were as follows: 16, 24 (16×1.5), 48 (16×3), and 96 (16×6) ms.

D. SCREENING SESSION

During the screening session, the subjects were asked to perform three runs of left and right hand motor imagery according to the visual and auditory instructions. Each run included 20 trials of right/left and imagery in a randomised order where each trial lasted for 3 s and was followed by 3 s of relaxation. Thereby, for each subject, 60 trials were performed in the screening session, during which the frequency within 8–30 Hz frequency band that maximised the spectral power discrepancy between the motor imagery of right or left hand and relaxation trials was identified. To minimise cognitive load, only right vs. relaxation and left vs. relaxation combinations were considered. Thus, the screening session provided the optimum frequency and the optimum combination of tasks (either right vs. relax or left vs. relax) for each subject. Also, according to the selected imagery task (right or left hand movement), the contralateral channel over the hand representation of the sensorimotor area was chosen (C3 or C4 channels). For all participants but participant P3, right vs. relax was found to provide larger differences compared to left vs. relaxation. For all participants except P3, channel C3 and its closest neighbours (FC3, CP3, C5, and C1) were recorded to provide small Laplacian combinations. For P3 with left vs. relax as their selected tasks, EEG signals were recorded from C4 and its small Laplacian combination (FC4, CP4, C6, and C2). Table 1 summarises participants' selected features. For further details on the schedule of the screening session, refer to Darvishi *et al*. [17], [18].

TABLE 1. Results of screening session to define the optimum tasks, channels and frequency bands for each individual.

Participants	Selected Tasks	Selected Channel	Selected Frequency (Hz)
P1	Right Hand MI vs. Relaxation	C3	20 Hz
P2	Right Hand MI vs. Relaxation	C3	25 Hz
P3	Left Hand MI vs. Relaxation	C4	23 Hz
P4	Right Hand MI vs. Relaxation	C3	15 Hz
P5	Right Hand MI vs. Relaxation	C3	21 Hz
P6	Right Hand MI vs. Relaxation	C3	11 Hz
P7	Right Hand MI vs. Relaxation	C3	17Hz
P8	Right Hand MI vs. Relaxation	C3	11Hz
P9	Right Hand MI vs. Relaxation	C3	15Hz
P10	Right Hand MI vs. Relaxation	C3	15Hz

E. NEUROFEEDBACK TRAINING SESSION

Each training session comprised eight runs of MI of right/left hand finger flexion. Each run included 20 trials with ten motor imagery and ten relaxation trials presented with a randomised order. Each run took almost four minutes and consecutive runs were separated by a 2-minute break. Overall, each session took less than an hour. Sessions were scheduled using BCI2000 operator scripts that determined runs operation and the breaks between consecutive runs.

Every trial was initiated with a ''start'' auditory command that prepared the participant for the following instruction. After 3 s, another auditory command instructed the participant to either relax or perform motor imagery of right hand finger flexion. After another 3 s, the participant was able to receive contingent feedback according to their motor imagery or relaxation as follows. For ''right'' auditory command the right orthosis initialized the right hand's fingers to fully extended position. Within the next 2.5 s, the orthosis was able to flex the right hand's fingers incrementally if the classification result was smaller than a threshold value. However, if the command was ''relax'', the free running left orthosis was initialized to fully extended position. Consequently, it could be flexed again incrementally within the next 2.5 seconds if the classification result was larger than the threshold value. The threshold value was defined as the pooled average spectral power of motor imagery and relaxation trials within the most recent 18 seconds (see below for further details). An auditory 'stop' command cued the end of each trial and after a subsequent 4 s inter-trial interval, the next trial started. Each participant's left hand was placed on the arm rest and not on the left orthosis. As a result, participants received proprioceptive feedback for right hand imagery and visual feedback through observation of the left orthosis flexion on relaxation. For participant P3, however, his left hand was involved with the left orthosis while his right hand was resting on the armrest. Thus, participant P3 was supplied with proprioceptive feedback for left hand imagery and visual feedback of relaxation through the right orthosis. For further details on the design of training session refer to [42]. Fig. 1 illustrates the training session's time course.

F. REAL-TIME SIGNAL PROCESSING

To enhance the spatial resolution of EEG signals a small Laplacian (SLP) transform was used to filter C3 channel (C4 for participant P3). While a large Laplacian slightly outperforms a small Laplacian for spatial filtering, since channel C5 of our EEG cap was disconnected, the small Laplacian was chosen over the large Laplacian in this study. A 20th order autoregressive model of the EEG signal was created using the Burg method [19]. According to each participant's selected frequency and electrode (C3-SLP or C4-SLP), the spectral power of the most recent 500 ms was calculated. The calculated spectral power outputs were z-scored (adaptively normalised to zero mean and unit variance) to compensate for the effect of EEG non-stationarity, by using the content of a buffer that was continuously filled with the most recent 18 seconds of imagery and relax trials (equally represented). More specifically, the adopted classifier was a first order linear regression model made using the spectral power of the EEG signals. The classifier output was considered congruent with motor imagery and relaxation with negative and positive values, respectively. The classifier outputs were used to update the flexion angle of the orthoses at every FUI. For further details on the BCI setup refer to [42], and [44].

To render the comparison between different FUIs unbiased by the amount of movement, it was necessary to provide equal maximum flexion angles during each trial for all FUIs.

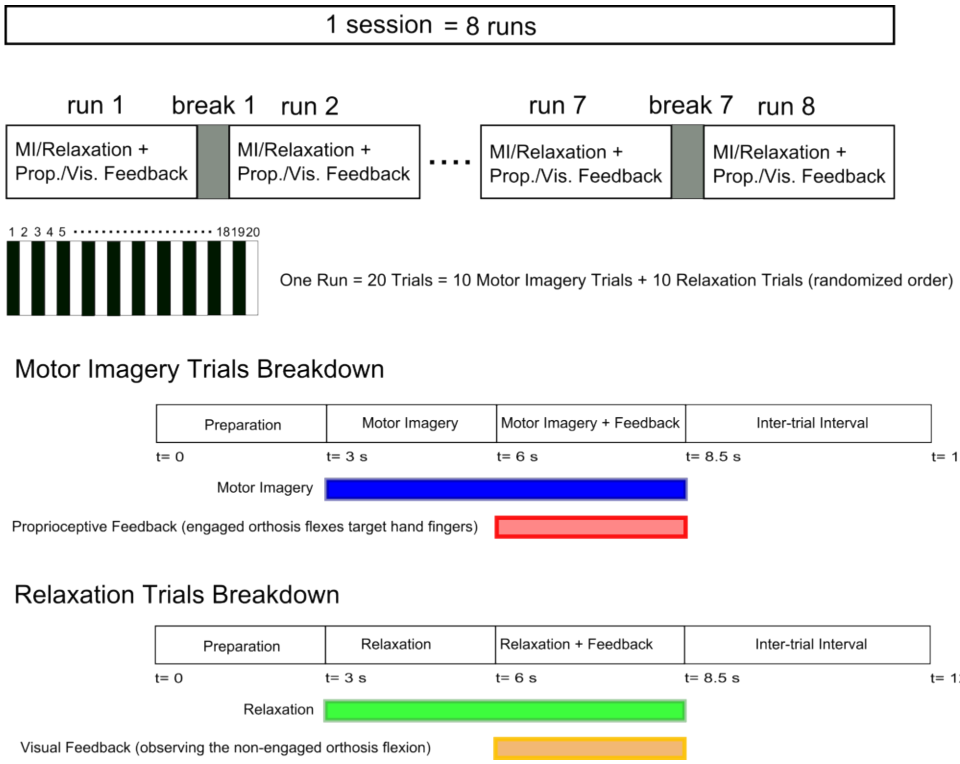

FIGURE 1. Illustration of the time course of each neurofeedback training session. Each session encompasses eight runs, where each run includes 20 trials. Each trial starts with a preparation cue at $t = 0$ s, followed by another command at $t = 3$ s that guides the participant to perform relaxation or finger flexion motor imagery. After 3 s of motor imagery/relaxation performance, feedback provision starts and becomes updated recurrently every 16 or 96 ms according to the session's condition. At $t = 8.5$ s the trial finishes and after a 4 s inter-trial interval the next trial starts.

Therefore, normalised outputs were used to flex the target orthosis for 0.4, 0.6, 1.2, and 2.4 degrees with 16, 24, 48, and 96 ms FUIs, respectively at each feedback update. Note that the flexion angle for different FUIs was adjusted to provide a maximum flexion angle of 62.4 degrees for all FUIs. Equation 1 shows the amount of flexion at each update interval for different FUIs

$$\text{Degrees of flexion} = 62.4 \times \frac{2500}{\text{FUI}}. \tag{1}$$

The BCI Performance Measure

We employed information transfer rate (ITR) to compare participants' real-time BCI performance across different FUIs. The ITR was selected to take into account both the accuracy and the speed of data transfer [13]. The ITR calculation was performed according to Wolpow's definition [13] using Equation 2 in which it is expressed in bits per minute (bits/min)

$$\text{ITR} = \left[\log_2 N + P\log_2 P + \frac{(1-P)\log_2(1-P)}{N-1}\right] \times \frac{60}{8.5} \tag{2}$$

where P reflects the average trial-based accuracy, N represents the number of classes (two classes: relaxation and motor imagery), and 8.5 is the total length of each trial in seconds. The ITR has been multiplied by 60, to express it in bits/min. Note that the trial based accuracy (P) was calculated as the percentage of times in the feedback section of each trial that classification outputs conformed to the task and flexed the orthosis. The analysis was performed using custom built Matlab scripts.

It has been argued that the threshold for BCI accuracy to consider one Is controlling a BCI is 70% [7], which is equivalent to an ITR of 0.838 bits/min (Eq. 2). Therefore, in this study participants were dichotomized to good performers if their average ITR with the shortest FUI (16 ms) were more than 0.838, and poor performers if their average ITR with the shortest FUI were less than 0.838. The choice of 16 ms FUI for dichotomization was based on the assumption that any potential effect of SRT on BCI performance may be most pronounced at the shortest FUI.

G. SRT MEASUREMENT

A simple reaction time (SRT) test [11] was carried out to measure the reaction time of participants, using the CANTAB battery test (Cambridge Cognition, UK). Participants sat in a chair and were asked to concentrate on a tablet computer placed on a desk in front of them and to press the button on a press pad as soon as they saw a square on the screen. Each participant repeated the task 30 times to obtain the average latency (reaction time), which was used as their SRT index. Note that our reported values for SRT are measured using CANTAB battery test with subjects aged 18–26 years.

H. OFFLINE ANALYSIS

For offline analysis of the EEG and EMG signals, EEGLAB [20] and custom-built Matlab scripts were used. The EEG signals were spatially transformed using a small Laplacian filter to produce single channel EEG data. Subsequently, the data were band-pass filtered (3–47 Hz) and divided into epochs from −2 to 8.5 s centred around the "start" auditory command. All relaxation trials were rejected. After removing the time averages, data purification was performed as follows: (i) to tag the outlier trials, EEG amplitude, spectral power, skewness, kurtosis and variance were checked; (ii) the trial was labelled as irregular if any of the mentioned indices were beyond the regular values of artefact free EEG signals using the guideline provided elsewhere [21]. The EMG signals of the Flexor Carpi Radialis (FCR) muscles of the target arm, which reflected the actual movement of fingers in the forearm muscle activity, were also band-pass filtered (3–400 Hz). The time averages of motor imagery trials were removed and then divided into epochs using the same time windows as EEG signals. EMG signals recorded during the motor imagery performance were screened and trials with peak-to-peak values larger than 50 mV were tagged. All tagged trials due to irregular EEG or significant EMG signals were discarded (9.2%).

The spectral power of the feedback section of motor imagery trials (6–8 s) and their preceding inter-trial interval (−2 to 0 s) were extracted in three frequency bands: alpha (8–13 Hz), lower beta (16–22 Hz) and higher beta (22–30 Hz). Only the last 2 s of the 4-second-long inter-trial interval were considered as baseline period. This adjustment ensured that the post imagery event-related synchronization (ERS) had elapsed and had has no effect on the baseline spectral power estimation. Only the first 2 s of motor imagery with feedback section (6–8 s) was considered, to equalise the length of imagery and baseline time windows. The Welch method [22] with a frequency resolution of 0.25 Hz was used to estimate the power spectral density (PSD) in decibel (dB). The PSD in the inter-trial interval preceding the imagery trials was also calculated to determine baseline spectral power. The difference between the spectral power during motor imagery and inter-trial intervals were calculated as a measure of task (MI/relaxation) effect on PSD within 3–45 Hz frequency band. The ERD percentage indices were also calculated according to Equation 3 [23]:

$$\mathrm{ERD} = \frac{A - R}{R} \times 100 \tag{3}$$

where A and R stand for the spectral power during motor imagery and the baseline period, respectively. Note that ERD percentage measures in each frequency band were calculated and compared between different FUIs for each group (good and poor performers).

I. STATISTICAL ANALYSIS

To investigate the relationship between the ITR measures obtained with different FUIs and SRT, Pearson correlation coefficients were calculated. To ensure that the small number of samples did not bias the correlation coefficients, 100,000 bootstrapped data samples were used. Using the bootstrapped samples mean values (r', estimated correlation coefficient), standard error and 98.75% confidence intervals (0 and 98.75 centiles of the 100,000 correlation coefficients) were calculated. Note that a 98.75% confidence interval (instead of a 95% confidence interval) has been used to compensate for multiple comparisons (four FUI levels). Furthermore, the left 'tail' was considered for correlation analysis as we hypothesised a negative correlation between SRT and ITR. If the mentioned 98.75% confidence interval did not include zero, the correlation coefficient was considered as significant.

Only those FUI levels that revealed significant correlations between the ITR and SRT values were selected (16, and 96 ms) for a follow-up analysis to study the effect of the FUI and BCI aptitude on the ITR. Accordingly, the ITR indices of the eight runs of each session with different FUI values for each participant were used, to calculate the real-time BCI performance measures. Note that here the ITR was calculated only using the motor imagery trials to appreciate the effect of the frequency of proprioceptive feedback realisation. Since each group (good and poor performers) had five members, each condition (FUI) comprised 40 (five participants × eight runs) measures for comparison. We decided to consider all eight runs of each session for each participant's ITR measures (instead of their average values over each session) to increase the statistical power. A two-way ANOVA with factors BCI aptitude (levels "good" and "poor") and FUI (levels "16 ms" and "96 ms") was used to explore the interplay between the aforementioned factors and ITR.

For statistical analysis of ERD with different FUIs, alpha, lower beta, and higher beta ERDs were compared. The calculations were performed for each of eight runs of each session only with FUIs that revealed a significant correlation with SRT (16 and 96 ms). Selecting all runs for the analysis, resulted in 40 (five participants × eight runs) ERD measures with each FUI in each frequency band for each group. In total, it provided 240 ERD measures (40 runs x two FUIs × three frequency bands) that were analysed using a two-way ANOVA with factors frequency band (levels alpha, lower beta, and higher beta) and FUI (levels "16 ms" and "96 ms") for good and poor BCI performers, separately.

For post-hoc tests in the applied ANOVA for the ITR, planned comparisons between FUI values (16 and 96 ms) were carried out. Therefore, Holm-Sidak's two-sided t-test was adopted for post-hoc analysis to adjust for multiple comparisons. The statistical analyses were implemented using Matlab 2015 and Graphpad Prism 6.

III. RESULTS

A. CORRELATION BETWEEN ITR AND SRT

Table 2 summarises ITR values for all participants at 16, 24, 48, and 96 ms FUIs and their SRT results. Our SRT response times are consistent with those reported using

TABLE 2. **Information transfer rates (ITR) with feedback update intervals of 16, 24, 48, and 96 ms and simple reaction time test measures for each participant.**

Participants	ITR (bits/min)				SRT (ms)
	FUI (16)	FUI (24)	FUI (48)	FUI (96)	
P1	0.09	0.35	0.30	0.17	244
P2	2.10	1.79	0.89	1.71	206
P3	2.22	0.39	0.71	1.31	214
P4	0.24	0.30	0.57	0.50	230
P5	0.50	0.30	0.84	0.23	245
P6	5.16	2.79	2.43	2.25	214
P7	0.18	0.64	0.36	0.15	221
P8	0.41	0.63	0.39	1.43	219
P9	2.83	3.35	3.17	3.10	221
P10	1.75	1.50	1.41	2.48	208

similar age group participants [24]. We observed a linear relation with negative slopes between ITR and SRT (Fig. 2). However, according to the obtained correlation coefficients through 10,000 times bootstrapped samples, only 16 and 96 ms FUIs revealed significant correlations with SRT where their confidence intervals did not include zero. Table 3 summarises the correlation analysis results.

B. PARTICIPANT DICHOTOMISATION

For FUIs that showed significant correlation with SRT the boundary margin for classification of participants according to their ITR is wider at 16 ms (Fig. 2-A) FUI compared to that of 96 ms FUI (Fig. 2-D). Therefore, the ITR with the shortest FUI was employed to dichotomize subjects as good and poor performers. Subjects with ITRs larger than 0.838 (equivalent to accuracies $> 70\%$) at an FUI of 16 ms (P2, P3, P6, P9, P10) were grouped as good performers. The remaining participants (P1, P4, P5, P7, and P8) who achieved ITRs lower than the threshold ITR value (0.838) at the same FUI were grouped as poor performers. The dashed horizontal lines in Fig. 2 represent the threshold ITR.

C. THE EFFECT OF BCI APTITUDE AND FUI ON ITR

Since FUIs of 16 and 96 ms revealed a significant correlation with SRT measure, we further investigated how and to what extent switching FUI between 16 and 96 ms affects real-time BCI performance of good and poor performers. According to

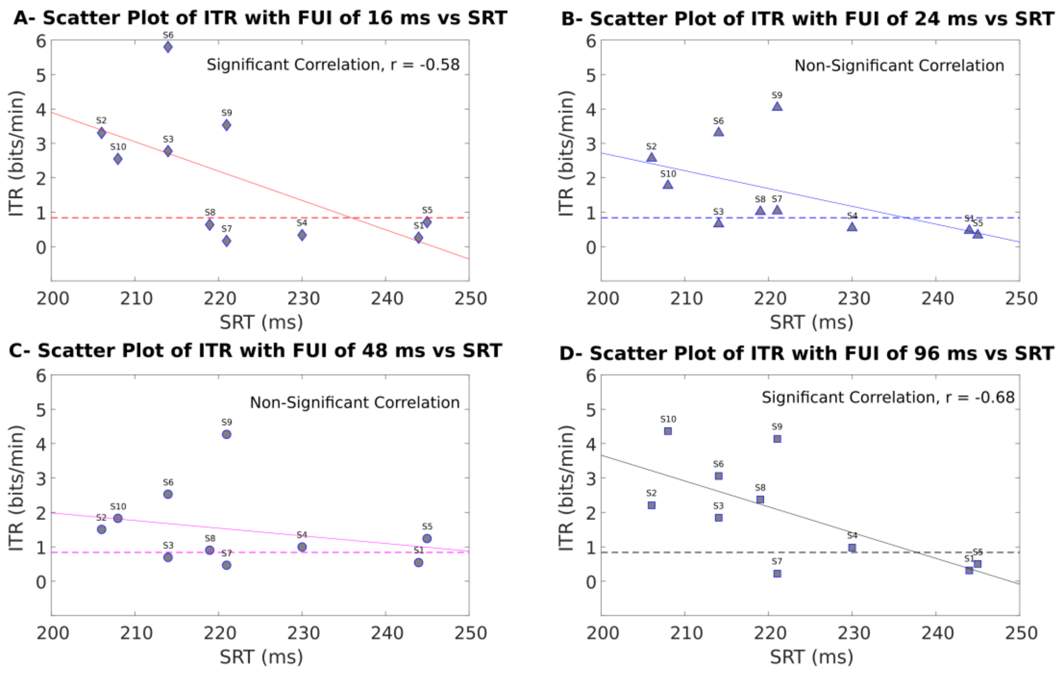

FIGURE 2. **Scatter plots of ITR and SRT at four different FUIs (A: 16 ms, B: 24 ms, C: 48 ms, and D: 96 ms). The horizontal dashed lines represent the ITR of 0.838 which is the threshold for good performance. The FUI of 16 ms (panel A) provides the widest classification margin between good and poor performers.**

TABLE 3. **Results of correlation analysis between simple reaction time (SRT) and information transfer rate (ITR) using 10,000 times bootstrapped samples for ten participants. CI (High) and CI (Low) represent 0 and 98.75 centiles of the 100,000 correlation coefficients, respectively (CI: confidence interval).**

Selected data	CI (High)	CI (Low)	Estimated correlation	Standard Error	Significant
SRT vs. ITR (16 ms)	-0.9993	-0.2009	-0.5789	0.1440	Yes
SRT vs. ITR (24 ms)	-0.9960	+0.0603	-0.5076	0.1959	No
SRT vs. ITR (48 ms)	-0.9984	+0.2335	-0.3231	0.2070	No
SRT vs. ITR (96 ms)	-0.9928	-0.1316	-0.6796	0.1798	Yes

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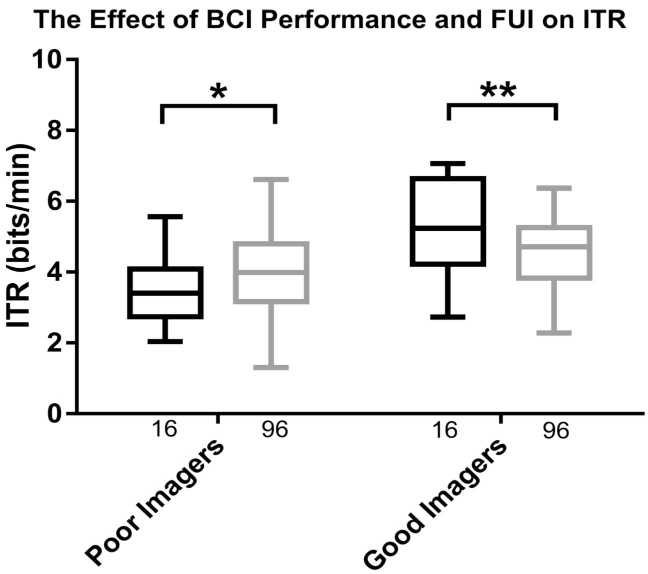

FIGURE 3. **Comparison of the information transfer rate (ITR) for good and poor performers during motor imagery with feedback update intervals (FUIs) of 16 and 96 ms. Good and poor performers produce larger ITRs with 16 and 96 ms FUIs, respectively ($*$: $p < 0.05$, $**$: $p < 0.01$).**

Fig. 3, the direction of ITR change due to FUI modification was dependent on the BCI aptitude. The two-way ANOVA for the ITR showed a significant interaction between BCI aptitude and FUI factors (F (1, 78) = 17.80, $p < 0.0001$) and a significant main effect for BCI aptitude (F (1, 78) = 38.16, $p < 0.0001$). However, FUI factor did not have a significant main effect (F (1, 78) = 0.4037, $p = 0.5270$). The post-hoc analysis showed a significant outperformance of the shorter (16 ms) over the longer (96 ms) FUI for good performers (t (78) = 3.432, $p = 0.0019$). In contrast, the ITR for poor performers was larger with the longer FUI than those of the shorter FUI (t (78) = 2.534, $p = 0.0264$). Overall, poor performers appear to produce larger ITRs with the longer FUI (96 ms), whereas good performers revealed larger ITRs with the short FUI (16 ms). Furthermore, there was a significant main effect of BCI aptitude with ITR across good and poor performers, which implies that good performers produce larger ITRs compared to poor performers regardless of the FUI value.

D. THE EFFECT OF FUI ON EEG POWER SPECTRUM DENSITY

To investigate the underlying neurophysiologic basis for the observed significant correlations between SRT and 16 and 96 ms FUIs, the difference between the spectral power of motor imagery and baseline periods were calculated for each FUI in each group and plotted in Fig. 4-A, and 4-B. Also, ERD percentage measures were calculated according to Equation 3 for both groups and both conditions in alpha, lower beta and higher beta frequency bands and are shown in Fig. 4-C, and 4-D. The statistical analysis was performed on the ERD percentages as the neural signature of kinesthetic motor imagery performance [23]. The ERD indices were analysed using a two-way ANOVA with factors frequency bands (levels alpha, lower beta, and higher beta) and FUI (levels "16 ms" and "96 ms") across good and poor performers, separately. The Two-way ANOVA of

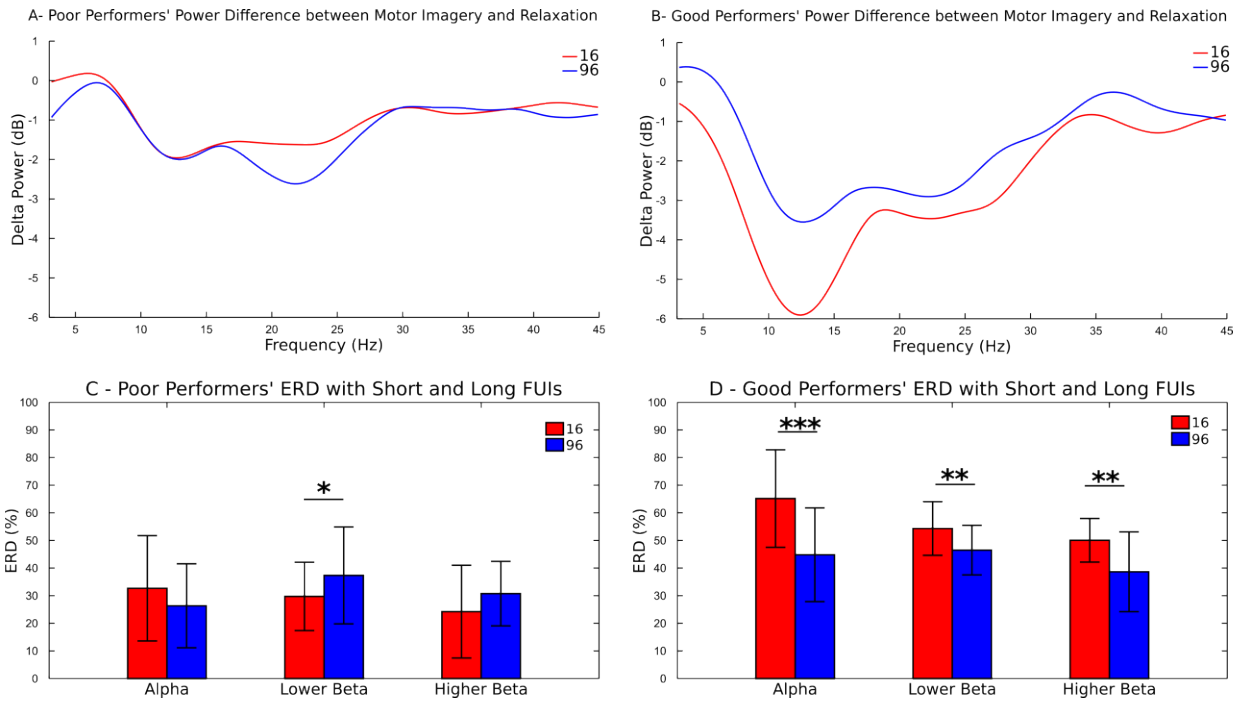

FIGURE 4. **Average power spectral density across 3–45 Hz for different feedback update intervals. Panels A and B depict the difference between spectral power between motor imagery and baseline periods for poor performers and good performers, respectively. ERD percentage measures for both groups (good and poor performers) and both conditions (MI vs. Baseline) in alpha, lower beta and higher beta frequency bands are plotted in panels E, and F (FUI: feedback update interval, ERD: event-related de-synchronization.**

good performers revealed significant main effects for both frequency band (F (2, 234) = 6.178, p = 0.0024) and FUI (F (2, 234) = 32.06, p < 0.0001). The post-hoc analysis showed a significant outperformance for 16 ms FUI over 96 ms in the alpha (t (234) = 4.155, p < 0.0001), lower beta (t (234) = 2.896, p = 0.0041), and higher beta (t (234) = 2.757, p = 0.0063) bands. However, for poor performers, there were no significant main effects neither for frequency band (F (2, 234) = 2.563, p = 0.0792) nor for FUI (F (2, 234) = 1.647, p = 0.2007). However, there was a significant interaction between factors (F (2, 234) = 3.343, p = 0.0370). The post-hoc analysis for poor performers showed that lower beta band supplied significantly stronger ERDs with the longer (96 ms) compared to those of the shorter (16 ms) FUI (t (234) = 2.036, p = 0.0428). Overall, good performers showed significantly stronger ERDs across all studied frequency bands (alpha, lower, and higher beta) with the shorter FUI while poor performers showed significantly larger ERDs only at the lower beta band with the longer FUI.

IV. DISCUSSION

The main findings of this study are as follows: (i) for FUIs of 16 and 96 ms, SRT and ITR measures are inversely correlated, i.e. a short SRT is a surrogate for possessing a high ITR and vice versa; (ii) the FUI customization affects the ITR and down-regulation of sensorimotor rhythms when operating MI-BCIs with proprioceptive feedback depends on the participants' level of BCI aptitude. Notably, participants with poor and good BCI aptitude produce larger ITRs and stronger ERDs with feedback updated every 96 and 16 ms, respectively.

A. THE SRT AS A BCI APTITUDE PREDICTOR

Recent approaches addressed MI-BCI performance as a dynamic measure on the basis of learning principles. Specifically, a certain degree of challenge for the participant is considered necessary to reinforce continuous effort and improvement of MI-BCI performance [25]. In this context, mathematical simulations [26] and empirical data [27, 28] suggest that dynamic difficulty adaptation in the course of the training relevantly modulates MI-BCI performance. These approaches, therefore, evaluated the impact of different task difficulties [29] and balanced the mental effort involved by adjusting the task demands on the basis of self-ratings by the participants [30]. Therefore, whilst the mentioned approaches provide valuable information for BCI performance enhancement, do not provide objective and simple predictors for BCI aptitude.

Prior work on predicting BCI aptitude of participants has considered a number of methods. Blankertz *et al.* (2010) suggested a neurophysiological measure, which is based on a 2-minute EEG recording during relaxation with open eyes [1]. Their predictor revealed a correlation coefficient of r = 0.53 with MI-BCI performance. Halder *et al.* (2013) reported that myelination quality and the structural integrity of deep white matter of the brain are correlated (r = 0.63) with BCI aptitude [7]. Ahn *et al.* (2013) found that only low aptitude BCI users reveal noticeable spectral powers within low alpha and high theta bands [2] and showed that the spectral power in low alpha and high theta bands were correlated with BCI aptitude (r = 0.59). Bamdadian *et al.* (2014) reported that prior to the MI onset, modulation of the spectral power within the posterior lower alpha as well as frontal higher theta are correlated (r = 0.53) with high BCI aptitude [3]. The study of Fazli *et al.* (2013) also revealed that prior to the MI onset, near-infrared spectroscopy (NIRS) activity is correlated with BCI aptitude in the majority of their studied subjects [5].

Grosse-Wentrup *et al.* (2011) showed that motor imagery-related modulation of the sensorimotor rhythms is positively correlated with the power of frontal and occipital gamma oscillations and negatively correlated with the power of centro-parietal gamma oscillations [6]. Such an extended motor imagery-related cortical motor network that includes frontal and parietal brain areas was also demonstrated by Vukelić *et al.* [31], [32]. These distributed networks were spatially selective and frequency-specific and had effects on cortico-cortical connectivity that lasted beyond the intervention period [8]. Notably, those subjects who were particularly capable of performing sensorimotor brain self-regulation could be predicted by a distributed alpha-band resting state network measured before the intervention [25]. Moreover, functional coupling of coherent theta band oscillations during the BCI task has been shown to be correlated with the skill of sensorimotor modulation [32, 33].

Vuckovic *et al.* (2013) used kinesthetic and visual imagery questionnaires to examine a psychological measure for prediction of BCI aptitude and found it as a useful measure of MI-BCI performance [10]. Another psychological index was suggested by Hammer *et al.* (2012) where they studied the Two-Hand Coordination Test and Attitude Towards Work Test and found a moderate correlation between their adopted tests and MI-BCI performance [9].

Even though the mentioned studies on finding a BCI performance predictor are promising, they either require a lengthy and costly procedure or suffer from subjectivity. The SRT reflects the speed at which a subject can process sensory information i.e. "go" signal and engages behavioural response i.e. movement. Similarly, receiving sensory feedback during BCI performance allows adjustment of the motor imagery. So, we hypothesised that subjects with shorter SRT might be better able to make more use of faster feedback provision of FUI than subjects with longer SRT and more effectively update their behavioural response i.e. MI performance when driving BCI. Therefore, in the present study, we examined the potential for SRT as an objective and simple BCI performance predictor and a biomarker to refine the BCI, e.g. by informing the adaptation of the FUI. The aim was to (i) remove the need for complicated equipment for recording EEG, MEG, fMRI, or fNIRS of the aforementioned neurophysiologic measures; and, (ii) eliminate the subjectivity of psychological predictors that rely on subjects' self-assessment.

At least for one of the investigated FUIs (96 ms), we observed a stronger correlation coefficient (0.68) compared to previous studies, while it was comparable for the FUI of 16 ms (0.58). However, due to the following reason, we cannot claim for the superiority of our proposed novel predictor in terms of the level of correlation: sample sizes, equipment, methodologies, and study protocols were quite diverse both among previous studies as well as compared to our adopted approach. Therefore, we did not find it feasible at this stage to perform a realistic and fair comparison between our proposed predictor and those of the prior studies. Instead, we investigated whether SRT as a *simpl*e and *objective* predictor is *significantly* correlated with BCI performance and our primary results support the hypothesis with correlation values that are at the bottom line comparable with previous results.

The SRT was found to be inversely correlated with ITR only at the shortest and the longest FUIs within the 16–96 ms range (Figs. 2-A, and 2-D). For intermediate FUIs of 24 and 48 ms the correlation between SRT and ITR was not significant (Figs. 2-B, and 2-C). Overall, it suggests that SRT predicts the BCI performance for FUIs on the boundary of 16–96 ms spectrum but does not appear specific for the intermediate values such as 24 and 48 ms. The lack of significant correlation for 24 and 48 ms FUIs suggest that participants may react to intermediate FUIs independent of their SRT index.

We employed Cambridge Cognition equipment due to its highly reliable and dedicated set of hardware and software for reaction time measurement. However, in practice, any PC or tablet may be used to measure participants' reaction time via open source software. Therefore, it appears that SRT provides a predictor for BCI aptitude that is both *simple*, i.e. it can be measured using ubiquitous hardware and software, and*objective* as it does not rely on subject self-reporting.

B. HOW BCI APTITUDE AND SRT AFFECT ITR

In this study, participants were dichotomized according to their BCI performance with the 16 ms FUI. Besides the provision of a wider boundary margin for classification (Fig 2-A), another reason for choosing 16 ms over 96 ms FUI was assuming that using shorter FUIs would make the distinction between good and poor performers more pronounced due to their different speed of information processing.

Studying the interaction of the SRT and BCI aptitude using a 2-way ANOVA (Fig 3) illustrates that changing FUI from 16 to 96 ms improves the BCI performance for poor performers while decreases those of good performers. Thus, it suggests that within a BCI framework, people with shorter reaction times may be able to perform motor planning and feedback realisation rapidly and thus do well with a short FUI. In contrast, a short FUI might be interfering and distracting for people with longer SRTs (slower people) as the updates occur faster than their information processing speed and therefore, may degrade their BCI performance.

C. NEURAL SUBSTRATES OF FUI ALTERATION

To investigate neural substrates underlying FUI alteration impact on the ITR, the spectral power of the EEG signals over the contralateral hand representation of the primary motor cortex (M1) in alpha and beta bands were analysed. Good performers showed more pronounced ERDs in both frequency bands than their poor counterparts (Fig 4). Besides, good performers showed larger alpha and beta ERDs with the shorter (16 ms) FUI (Figs 4-B, and 4-D). Poor performers, however, showed significantly larger ERDs with the longer FUI (96 ms) only in the lower Beta band (Figs 4-A, and 4-C). Since poor performers showed relatively weaker ERDs compared to good performers with both FUIs, it might explain why they failed to show distinctive ERDs with different FUIs in alpha and higher beta bands. While increasing FUI elicited significantly larger ERDs in the alpha band for good performers, poor performers appeared to be indifferent. However, in the beta band, changing FUI affected ERDs in the lower or both lower and higher beta bands for poor and good performers, respectively. This responsiveness of beta ERDs to FUI change is congruent with prior studies that highlight the role of beta oscillation in motor control [34], corticomuscular coherence [35]–[38] and corticospinal excitability [39]–[41]. Distinctive beta oscillations are also supported by recent studies that highlight the specific relevance of proprioceptive feedback for modulation of beta ERD during NFB training [32], [42].

The opposite effect of FUI change on poor and good performers (Figs. 3–4) may also be explained by the findings of Witham *et al.* (2011), who studied how descending and ascending pathways affect corticomuscular coherence [38]. They demonstrated that both cortical to muscular activity time lag and its re-afferent feedback (muscular to cortical) time delay vary across subjects, implying individual variations in sensorimotor loop duration. Therefore, it implies that specific FUIs may optimise sensorimotor information processing through consideration of intra-subject bidirectional corticomuscular delays manifested in larger ITRs and stronger ERDs.

D. THE APPLICATION OF FUI CUSTOMIZATION

BCIs for communication and rehabilitation require different key performance indices. Notably, in BCIs for communication, accuracy is a critical measure [43], whereas, in therapeutic BCIs, both real-time accuracy and brain facilitation are equally important. For instance, a recent study has demonstrated the significant effect of the FUI value on the efficacy of restorative BCIs for stroke rehabilitation [44]. Overall, our results suggest that FUI customization may benefit both good and poor performers with therapeutic BCIs as well as BCIs for communication.

V. LIMITATIONS OF THE STUDY

In this study, no motor imagery questionnaire such as KVIQ questionnaire was used. If such a measure was administered, it could be used as a validator of SRT test for BCI aptitude.

Even though the statistical analysis of the data showed significant differences between SRT and ERD patterns of two groups, considering the small number of group members, it is recommended to verify the reported results with larger groups.

VI. CONCLUSION

The present study shows that the SRT may be used as a surrogate for BCI performance. People with fast and slow SRT respond differently to FUIs. People with a short SRT produce larger ITRs and stronger alpha and beta ERDs with a short FUI (16 ms), while their slower counterparts reveal larger ITRs and stronger lower beta ERDs with a substantially longer FUI (96 ms).

Follow up studies on the findings of the present study may investigate whether and two what extent the interaction between different feature extraction and classification methods and FUI values affects the BCI performance.

REFERENCES

[1] B. Blankertz *et al.*, "Neurophysiological predictor of SMR-based BCI performance," *NeuroImage*, vol. 51, no. 4, pp. 1303–1309, 2010.

[2] M. Ahn, H. Cho, S. Ahn, and S. C. Jun, "High theta and low alpha powers may be indicative of bci-illiteracy in motor imagery," *PLoS ONE*, vol. 8, no. 11, p. e80886, 2013.

[3] A. Bamdadian, C. Guan, K. K. Ang, and J. Xu, "The predictive role of pre-cue EEG rhythms on MI-based BCI classification performance," *J. Neurosci. Methods*, vol. 235, pp. 138–144, Sep. 2014.

[4] R. Bauer, M. Fels, M. Vukelić, U. Ziemann, and A. Gharabaghi, "Bridging the gap between motor imagery and motor execution with a brain–robot interface," *NeuroImage*, vol. 108, pp. 319–327, Mar. 2015.

[5] S. Fazli, J. Mehnert, J. Steinbrink, and B. Blankertz, "Using NIRS as a predictor for EEG-based BCI performance," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug./Sep. 2012, pp. 4911–4914.

[6] M. Grosse-Wentrup, B. Schölkopf, and J. Hill, "Causal influence of gamma oscillations on the sensorimotor rhythm," *NeuroImage*, vol. 56, no. 2, pp. 837–842, May 2011.

[7] S. Halder *et al.*, "Prediction of brain-computer interface aptitude from individual brain structure," *Frontiers Hum. Neurosci.*, vol. 7, p. 105, Apr. 2013.

[8] M. Vukelić and A. Gharabaghi, "Self-regulation of circumscribed brain activity modulates spatially selective and frequency specific connectivity of distributed resting state networks," *Frontiers Behav. Neurosci.*, vol. 9, p. 181, Jul. 2015.

[9] E. M. Hammer *et al.*, "Psychological predictors of SMR-BCI performance," *Biol Psychol*, vol. 89, no. 1, pp. 80–86, 2012.

[10] A. Vucković and B. A. Osuagwu, "Using a motor imagery questionnaire to estimate the performance of a brain–computer interface based on object oriented motor imagery," *Clin. Neurophysiology*, vol. 124, no. 8, pp. 1586–1595, 2013.

[11] E. T. Klemmer, "Time uncertainty in simple reaction time," *J. Exp. Psychol.*, vol. 51, no. 3, pp. 179–184, 1956.

[12] R. Magill, *Motor Learning and Control: Concepts and Applications*, 10th ed. New York, NY, USA: McGraw-Hill, 2014.

[13] J. Wolpaw *et al.*, "Brain-computer interface technology: A review of the first international meeting," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 2, pp. 164–173, Feb. 2000.

[14] G. Pfurtscheller and A. Aranibar, "Evaluation of event-related desynchronization (ERD) preceding and following voluntary self-paced movement," *Electroencephalogr. Clin. Neurophysiology*, vol. 46, no. 2, pp. 138–146, 1979.

[15] G. Pfurtscheller and F. L. Da Silva, "Event-related EEG/MEG synchronization and desynchronization: Basic principles," *Clin. Neurophysiology*, vol. 110, no. 11, pp. 1842–1857, 1999.

[16] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, "BCI2000: A general-purpose brain-computer interface (BCI) system," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1034–1043, Jun. 2004.

[17] S. Darvishi, D. Abbott, and M. Baumert, "Prediction of motor imagery based brain computer interface performance using a reaction time test," in *Proc. 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Aug. 2015, pp. 2880–2883.

[18] S. Darvishi, M. C. Ridding, D. Abbott, and M. Baumert, "Does feedback modality affect performance of brain computer interfaces?" in *Proc. 7th Int. IEEE/EMBS Conf. Neural Eng.*, Apr. 2015, pp. 232–235.

[19] S. L. Marple, Jr., *Digital Spectral Analysis With Applications*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1987.

[20] A. Delorme and S. Makeig, "EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," *J. Neurosci. Methods*, vol. 134, no. 1, pp. 9–21, Mar. 2004.

[21] I. Daly, F. Pichiorri, J. Faller, and V. Kaiser, "What does clean EEG look like?" in *Proc. 34th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Aug. 2012, pp. 3963–3966.

[22] P. D. Welch, "The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms," *IEEE Trans. Audio Electroacoust.*, vol. AU-15, no. 2, pp. 70–73, Jun. 1967.

[23] G. Pfurtscheller, "Functional brain imaging based on ERD/ERS," *Vis. Res.*, vol. 41, nos. 10–11, pp. 1257–1260, 2001.

[24] P. Philip, J. Taillard, M. Quera-Salva, B. Bioulac, and T. Åkerstedt, "Simple reaction time, duration of driving and sleep deprivation in young versus old automobile drivers," *J. Sleep Res.*, vol. 8, no. 1, pp. 9–14, 1999.

[25] R. Bauer and A. Gharabaghi, "Estimating cognitive load during self-regulation of brain activity and neurofeedback with therapeutic brain-computer interfaces," *Frontiers Behav. Neurosci.*, vol. 9, p. 21, Feb. 2015, doi: 10.3389/fnbeh.2015.00021.

[26] R. Bauer and A. Gharabaghi, "Reinforcement learning for adaptive threshold control of restorative brain-computer interfaces: A Bayesian simulation," *Frontiers Neurosci.*, vol. 9, p. 36, Feb. 2015, doi: 10.3389/fnins.2015.00036.

[27] G. Naros and A. Gharabaghi, "Reinforcement learning of self-regulated β-oscillations for motor restoration in chronic stroke," *Frontiers Hum. Neurosci.*, vol. 9, p. 391, Jul. 2015, doi: 0.3389/fnhum.2015.00391.

[28] G. Naros, I. Naros, F. Grimm, U. Ziemann, and A. Gharabaghi, "Reinforcement learning of self-regulated sensorimotor β-oscillations improves motor performance," *NeuroImage*, vol. 134, pp. 142–152, Jul. 2016.

[29] R. Bauer, M. Vukelić, and A. Gharabaghi, "What is the optimal task difficulty for reinforcement learning of brain self-regulation?" *Clin. Neurophysiology*, vol. 127, no. 9, pp. 3033–3041, 2016.

[30] R. Bauer, M. Fels, V. Royter, V. Raco, and A. Gharabaghi, "Closed-loop adaptation of neurofeedback based on mental effort facilitates reinforcement learning of brain self-regulation," *Clin. Neurophysiology*, vol. 127, no. 9, pp. 3156–3164, 2016.

[31] M. Vukelić, R. Bauer, G. Naros, I. Naros, C. Braun, and A. Gharabaghi, "Lateralized alpha-band cortical networks regulate volitional modulation of beta-band sensorimotor oscillations," *NeuroImage*, vol. 87, pp. 147–153, Feb. 2014.

[32] M. Vukelić and A. Gharabaghi, "Oscillatory entrainment of the motor cortical network during motor imagery is modulated by the feedback modality," *NeuroImage*, vol. 111, pp. 1–11, May 2015.

[33] A. Gharabaghi, "What turns assistive into restorative brain-machine interfaces?" *Frontiers Neurosci.*, vol. 10, p. 456, Oct. 2016.

[34] M. Feurra, G. Bianco, E. Santarnecchi, M. Del Testa, A. Rossi, and S. Rossi, "Frequency-dependent tuning of the human motor system induced by transcranial oscillatory potentials," *J. Neurosci.*, vol. 31, no. 34, pp. 12165–12170, 2011.

[35] D. M. Halliday, B. A. Conway, S. F. Farmer, and J. R. Rosenberg, ''Using electroencephalography to study functional coupling between cortical activity and electromyograms during voluntary contractions in humans,'' *Neurosci. Lett.*, vol. 241, no. 1, pp. 5–8, 1998.

[36] T. Mima, T. Matsuoka, and M. Hallett, ''Information flow from the sensorimotor cortex to muscle in humans,'' *Clin. Neurophysiology*, vol. 112, no. 1, pp. 122–126, 2001.

[37] T. Mima, K. Toma, B. Koshy, and M. Hallett, ''Coherence between cortical and muscular activities after subcortical stroke,'' *Stroke*, vol. 32, no. 11, pp. 2597–2601, 2001.

[38] C. L. Witham, C. N. Riddle, M. R. Baker, and S. N. Baker, ''Contributions of descending and ascending pathways to corticomuscular coherence in humans,'' *J. Physiol.*, vol. 589, no. 15, pp. 3789–3800, 2011.

[39] D. Kraus *et al.*, ''Brain state-dependent transcranial magnetic closed-loop stimulation controlled by sensorimotor desynchronization induces robust increase of corticospinal excitability,'' *Brain Stimulation*, vol. 9, no. 3, pp. 415–424, 2016.

[40] D. Kraus *et al.*, ''Brain–robot interface driven plasticity: Distributed modulation of corticospinal excitability,'' *NeuroImage*, vol. 125, pp. 522–532, Jan. 2016.

[41] V. Royter and A. Gharabaghi, ''Brain state-dependent closed-loop modulation of paired associative stimulation controlled by sensorimotor desynchronization,'' *Frontiers Cellular Neurosci.*, vol. 10, p. 115, May 2016.

[42] S. Darvishi, A. Gharabaghi, C. B. Boulay, M. C. Ridding, D. Abbott, and M. Baumert, ''Proprioceptive feedback facilitates motor imagery-related operant learning of sensorimotor β-band modulation,'' *Frontiers Neurosci.*, vol. 11, p. 60, Feb. 2017.

[43] J. R. Wolpaw and E. W. Wolpaw, ''The future of BCIs: meeting the expectations,'' in *Brain-Computer Interfaces: Principles and Practice*, J. R. Wolpaw and E. W. Wolpaw, Eds., New York, NY, USA: Oxford Univ. Press, vol. 2012, pp. 387–392.

[44] S. Darvishi, M. C. Ridding, B. Hordacre, D. Abbott, and M. Baumert, ''Investigating the impact of feedback update interval on the efficacy of restorative brain–computer interfaces,'' *Roy. Soc. Open Sci.*, vol. 4, no. 8, p. 170660, 2017, doi: 10.1098/rsos.170660.

[45] S. Darvishi, M. C. Ridding, D. Abbott, and M. Baumert, ''Investigation of the trade-off between time window length, classifier update rate and classification accuracy for restorative brain-computer interfaces,'' in *Proc. 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2013, pp. 1567–1570.