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The predictive role of pre-cue EEG rhythms on MI-based BCI classification performance

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HIGHLIGHTS

- A novel coefficient computed from pre-cue EEG rhythms over different regions of the brain is proposed.
- The feasibility of predicting the performance of motor imagery-based BCI based on the proposed coefficient is examined.
- Significant positive correlation between the proposed coefficient and accuracies is achieved.
- The results suggest that having higher frontal theta and lower posterior alpha prior to performing motor imagery may result in better BCI performance.

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ABSTRACT

Background: One of the main issues in motor imagery-based (MI-based) brain–computer interface (BCI) systems is a large variation in the classification performance of BCI users. However, the exact reason of low performance of some users is still under investigation. Having some prior knowledge about the performance of users may be helpful in understanding possible reasons of performance variations.
New method: In this study a novel coefficient from pre-cue EEG rhythms is proposed. The proposed coefficient is computed from the spectral power of pre-cue EEG data for specific rhythms over different regions of the brain. The feasibility of predicting the classification performance of the MI-based BCI users from the proposed coefficient is investigated.
Results: Group level analysis on $N = 17$ healthy subjects showed that there is a significant correlation $r = 0.53$ ($p = 0.02$) between the proposed coefficient and the cross-validation accuracies of the subjects in performing MI. The results showed that subjects with higher cross-validation accuracies have yielded significantly higher values of the proposed coefficient and vice versa.
Comparison with existing methods: In comparison with other previous predictors, this coefficient captures spatial information from the brain in addition to spectral information.
Conclusion: The result of using the proposed coefficient suggests that having higher frontal theta and lower posterior alpha prior to performing MI may enhance the BCI classification performance. This finding reveals prospect of designing a novel experiment to prepare the user towards improved motor imagery performance.

1. Introduction

Motor imagery-based (MI-based) brain–computer interface (BCI) systems have been widely used for both therapeutic and non-therapeutic applications (Ang et al., 2011; van Erp et al., 2012). However, one of the current issues in most MI-based BCI systems is that a non-negligible number of users (15–30%) cannot perform motor imagery well (Vidaurre and Blankertz, 2010); hence they cannot properly use BCI systems. This may be known as BCI illiteracy or BCI deficiency. In fact, there is a big variance in the performance of BCI users (Blankertz et al., 2010); however, the reasons of such variation is still under investigation by many researchers.

Performing motor imagery results in event-related desynchronization (ERD) and event-related synchronization (ERS) of electroencephalogram (EEG) rhythms (Pfurtscheller and Lopes da Silva, 1999). In other words, stronger ERD/ERS can indicate how

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well the subject performs MI task. BCI deficiency in subjects using MI-based BCI can be possibly attributed to their inability in modulating EEG rhythms (Vidaurre and Blankertz, 2010). However, this is not the case for all subjects with poor BCI performance. There may be a mismatch between calibration session and evaluation session because of non-stationarity in the EEG (Arvaneh et al., 2013). Machine learning algorithms used in BCI systems may not be capable to deal with such non-stationarity, which may adversely affect the BCI performance in the evaluation session (Vidaurre and Blankertz, 2010). Moreover, the reasons of BCI deficiency may vary among subjects. Thus having some prior knowledge about the performance of the subjects may lead us to investigate other possible reasons of performance variation in different subjects and also yield in designing a novel experiment which aimed to help users with BCI deficiency (Blankertz et al., 2010; Grosse-Wentrup and Schölkopf, 2012). Therefore, it would be valuable to define a performance predictor to predict performance of BCI users. This predictor may estimate the performance of BCI users without performing a long time experiment. Therefore, in therapeutic applications it can quickly help us to investigate whether BCI system is an appropriate assistant device for a patient. The previous studies on prediction of BCI performance can be categorized into two different groups: the first group are those focused on modulation of slow cortical potentials (Daum et al., 1993; Kotchoubey et al., 2000; Neumann and Birbaumer, 2003; kübler et al., 2004), and the second group are those proposed psychological/neurophysiological predictors for sensorimotor rhythm (SMR)-based BCIs (Nijboer et al., 2008; Burde and Blankertz, 2006; Blankertz et al., 2010; Grosse-Wentrup et al., 2011; Grosse-Wentrup and Schölkopf, 2012; Hammer et al., 2012; Maeder et al., 2012). However, so far none of them is widely used in BCI experiments.

Psychological parameters had shown to have moderate but meaningful role on BCI performance (Burde and Blankertz, 2006; Nijboer et al., 2008; Hammer et al., 2012). Several psychological predictors such as attention, personality or motivation were studied in (Hammer et al., 2012). It had shown by Nijboer et al. (2008) that mood and motivation play roles in learning how to use a BCI system. Hence, psychological predictors could show the feeling of users on BCI systems that could reflect the performance of the BCI users. However, one of the limitations of the psychological predictors is that they are mostly based on self-assessment criteria and not well quantified. Therefore, they are not as effective compared to neurophysiological predictors (Hammer et al., 2012).

A new neurophysiological predictor was proposed by Blankertz et al. (2010) based on the μ- (9–14 Hz) and β- (20–30 Hz) rhythms over sensorimotor area. To derive this predictor, 2 min of EEG data in relax eyes open condition using two Laplacian EEG channels were recorded. They showed that there is a significant correlation $r = 0.53$ between their defined SMR predictor and performance of the 80 healthy users. In a more recent study (Maeder et al., 2012) the effectiveness of this predictor for each single trial was investigated. The results showed that higher SMR amplitude over 1 s prior the cue resulted in significantly better classification performance. Gamma band power was also introduced as another performance predictor for SMR-based BCI (Grosse-Wentrup et al., 2011; Grosse-Wentrup and Schölkopf, 2012). In these studies, they showed that γ oscillation has causal influence on SMR. They also found out that the frontal and occipital γ oscillations positively and centro-parietal γ oscillations negatively correlated to SMR modulation. Finally, their results indicated that through proper training users would be capable of shifting their γ power from centro-parietal to frontal and occipital regions to enhance their performance.

The pre-stimulus alpha band had been previously used for predicting the performance of some other mental tasks rather than motor imagery (van Dijk et al., 2008; Fell et al., 2011; Haig and Gordon, 1998; Tangwiriyasakul et al., 2013; Romei et al., 2010; Rensink et al., 1997) and theta (Guderian et al., 2009; Missonnier et al., 2006). Considering all previously mentioned studies, we can conclude that pre-stimulus EEG data have useful information about the task performance. In other words, the state of brain before providing a stimulus may affect the performance of the subject. Therefore we may assume that by knowing the state of brain over pre-stimulus time segment we can predict the performance of the user over the following task. EEG rhythms can be used to define the state of brain. In fact, there is a correlation between pre-stimulus EEG rhythms and motor imagery performance (Maeder et al., 2012; Grosse-Wentrup et al., 2011). Therefore, the goal of current study is to propose a novel coefficient to predict the classification performance of MI-based BCI. The proposed coefficient is computed from the spectral power of pre-cue EEG rhythms over different regions of the brain. We assume that there is a correlation between our proposed EEG rhythm-based coefficient and the performance of the users. To investigate our hypothesis several statistical analyses has been done.

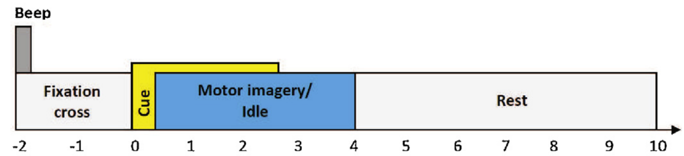

Fig. 1. Timing scheme of each trial in the experiment. A beep sound followed by a fixation cross on the screen notifies the subject about the start of the trial. A cue is shown on the screen at time 0. Subject starts performing either motor imagery or idle right after the cue.

2. Methodology

2.1. Experimental setup

The EEG data was collected from 17 healthy subjects. Two out of 17 subjects were left handed. All the subjects participated in two different sessions: calibration session on a first day and non-feedback session on a separate day. No feedback was provided for the subjects during the experiment.

During the experiment a visual cue was displayed on the computer screen which informed subject to perform either motor imagery or idle. During motor imagery trials, subjects were instructed to perform kinaesthetic hand motor imagery due to their handedness. To define the idle state for subjects during idle trials, they were instructed to perform mental counting. The main reason is to make the idle state more consistent to reduce both inter- and intra-subject inconsistency during the idle state. Prior to the experiments, subjects were instructed to minimize any physical movement and eye blinking throughout the EEG recording process. All subjects were asked for ethics approval and informed consent.

In the calibration session two runs of EEG data were collected. Each run comprised of 40 trials of motor imagery and 40 trials of idle state and lasted about 16 min. Fig. 1 represents the timing scheme of each trial. As shown, each trial comprised a preparatory segment of 2s, the presentation of the visual cue for 4s, and a rest segment of at least 6s. Each trial lasted approximately 10s, and a break period of at least 2 min was given after each run of EEG recording. The EEG data collected during calibration session was used to calibrate the subject-specific model from motor imagery. During the non-feedback session three runs of EEG data were collected while subjects performing motor imagery of the chosen hand versus idle state. These three runs were almost similar to that of the calibration session, each lasted approximately 16 min and comprised of 40 trials of motor imagery and 40 trials of idle state.

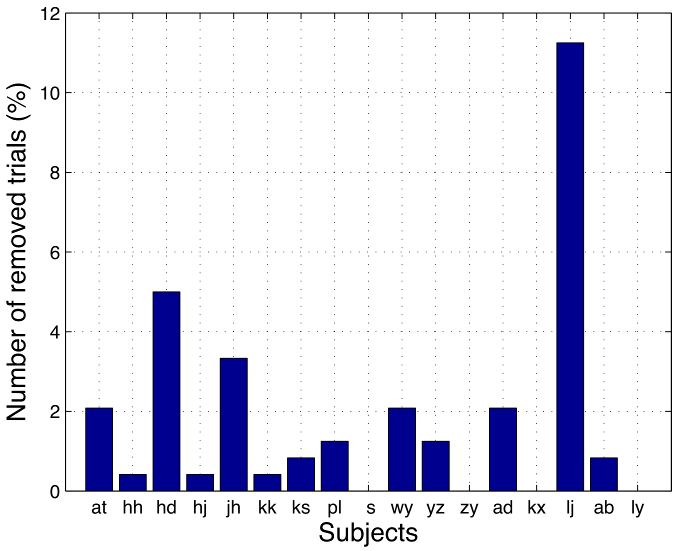

Fig. 2. Number of trials (%) with excessive eye-blinks which removed from our study.

The Nuamps EEG acquisition hardware (http://www.nueroscan.com) with unipolar Ag/AgCl electrodes channels was used to collect EEG data. The recorded signal was digitally sampled at 250 Hz with a resolution of 22 bits for voltage ranges of ±130 mV. EEG recordings from all 27 channels were band pass filtered from 0.05 to 40 Hz by the acquisition hardware.

2.2. *Proposed coefficient for performance prediction*

In this current work, we aim to propose a novel coefficient to predict the classification performance of MI-based BCI from pre-cue EEG data. As stated earlier, the state of subject's brain before providing a cue contains some information about the performance of the following task, and can be defined based on EEG rhythms.

The ratio of θ/β had been used as an attention score in some attention deficit hyperactivity disorder (ADHD) studies (Massar et al., 2012; Barry et al., 2009). Moreover, the role of α and θ band power on attention had been previously studied (Missonnier et al., 2006; Lou et al., 2014; Wyart and Tallon-Baudry, 2009). It had shown that higher pre-stimulus α power represents low attention state. However, higher θ power represents higher attention state. On the other hand, it had shown (Klimesch, 1999) that the effect of alpha and theta band are related in an opposite way, which means that better performance is achieved by increasing theta band power and decreasing alpha band power. Hence, we seek to define a new coefficient which is computed from power of pre-cue EEG data over three frequency bands of theta, beta, and alpha.

The recorded EEG signals are visually inspected and those trials with excessive eye-blinks, which have amplitude bigger than 220 µV are rejected. This is mainly done to avoid theta band power being obscured by eye-blinks components in our proposed coefficient. Fig. 2 summarizes the number of the removed trials for each individual subject. As shown, less than 5% of trials are removed for all except one of the subjects.

Before calculating spectral powers, the cleaned EEG data from all the channels are filtered over θ (3–8 Hz), α (8–13 Hz), and β (16–24 Hz) frequency bands. Then, the filtered data are spatially filtered by means of local average reference (LAR). The average activity of the closest neighboring electrodes is subtracted from each individual electrode.

On the next step, the EEG band power over each of the three specified frequency bands is calculated and normalized over all trials (Eq. (1)):

$$\bar{\mathbf{E}}_i^2 = \frac{\mathbf{E}_i^2}{\sum_{j=1}^{N_T} \mathbf{E}_j^2} \tag{1}$$

where $\mathbf{E}_i \in \mathbb{R}^{c\times t}$ denotes the filtered single trial EEG measurement of the ith trial; $\bar{\mathbf{E}}_i \in \mathbb{R}^{c\times t}$ is the normalized spectral power of the ith trial over all trials; and N_T shows the number of trials; t is the number of EEG samples per channel; and c is the number of channels.

According to the timing scheme of the experiment (see Fig. 1), the time between hearing the beep sound and providing a cue on the screen is 2 s. Hence, the normalized band power is averaged over this pre-cue time segment ($t \in [-2, 0]$):

$$\mathbf{P}^b = \sum_{i=1}^{N_T} \sum_{t\in[-2,0]} (\bar{\mathbf{E}}_{i,t}^b)^2 \tag{2}$$

where $\bar{\mathbf{E}}_i^b \in \mathbb{R}^{c\times t}$ denotes the filtered single trial EEG measurement of the ith trial over frequency band of $b \in \{\theta, \alpha, \beta\}$; $\mathbf{P}^b \in \mathbb{R}^c$ denotes the average pre-cue frequency band-power over all trials; t is the number of EEG samples per channel.

The proposed coefficient is defined based on the averaged frequency band powers as follows:

$$F = \frac{\sum_{c\in C_\theta} P_c^\theta}{\sum_{c\in C_\alpha} P_c^\alpha + \sum_{c\in C_\beta} P_c^\beta} \tag{3}$$

where P_c^b denotes the average of pre-cue frequency band-power for cth channel; b is frequency band of $\in\{\theta, \alpha, \beta\}$; and C_θ, C_α, and C_β are selected channels from frontal, parietal and central area.

The activation patterns of different regions of the brain over specific frequency bands are not similar, this leads us to consider topographical information in our proposed coefficient. We assumed that a coefficient based on EEG rhythms from different brain regions might be more informative in predicting the performance of the users. It had shown previously in some studies that theta band power over frontal area and alpha band power over parietal area can somehow represent the attention of the users (Missonnier et al., 2006; Sauseng et al., 2005). Therefore, to have a more meaningful neurophysiological predictor, we calculate the pre-cue EEG band powers over different regions of the brain. In Eq. (3), the theta, alpha and beta band powers are averaged over frontal area C_θ = {F3, Fz, F4}, parietal area C_α = {P7, P3, Pz, P4, P8} and central midline area C_β = {Cz, Cpz}.

We hypothesize that there is a positive correlation between our proposed EEG rhythm-based coefficient (Eq. (3)) and the performance of user. To investigate our hypothesis we perform a group level analysis, Pearson's correlation coefficient between the proposed coefficient of all users and their accuracies is computed. The significance level of the test can prove the validity of our initial assumption and show how well this novel coefficient can predict the performance of users.

2.3. *Classification performance evaluation of subjects*

In this paper the performance of subjects are evaluated based on the classification accuracy of the non-feedback session. As mentioned earlier in Section 2.1, a model is trained based on the EEG data collected during calibration session to detect motor imagery during the non-feedback session. For estimating the performance of the users, filter bank common spatial pattern (FBCSP) algorithm proposed by Ang et al. (2012) is used. Comparing to common

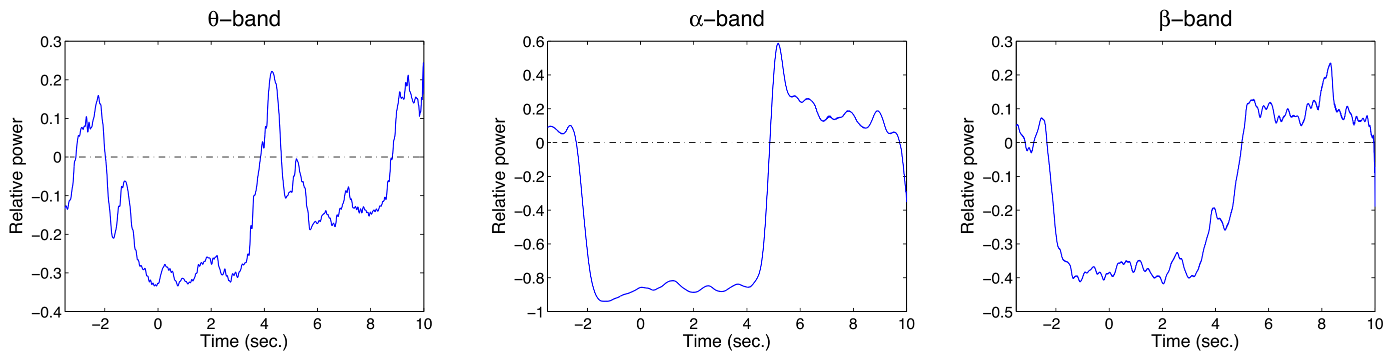

Fig. 3. ERD/ERS time courses of healthy subject *kk*. Plots show θ, α, and β bands ERD/ERS averaged over selected channels from frontal (F3, Fz, F4), central (Cz, Cpz) and parietal (P7, P3, Pz, P4, P8) area, respectively. The graphs are smoothed by means of moving average.

spatial pattern (CSP), FBCSP can select subject-specific frequency bands and results in better performance.

FBCSP has four progressive stages, on the first stage it band pass filters the EEG signal in 9 different bands, namely, 4–8, 8–12, ..., 36–40 Hz. Then second stage employs the CSP to spatially filter the signal. For each band 2 pairs of features are selected. Therefore, the total number of features is 36. On the third stage a feature selection algorithm is applied to select the discriminative CSP features. The best 4 pairs are selected by means of mutual information. On the last stage the selected features are fed into a support vector machine (SVM) classifier. The final accuracy shows how well the subjects can discriminate motor imagery versus idle state.

3. Results

As stated earlier the proposed coefficient (Eq. (3)) was computed from 2 s of pre-cue EEG data. In order to show the changes of EEG power over each studied frequency bands, the ERD/ERS time courses for each single channel were calculated based on the method described by Pfurtscheller and Lopes da Silva (1999). Fig. 3 shows ERD/ERS time courses of subject *kk* who had high performance. In this figure the average relative power of each θ, α, and β frequency bands over selected channels from frontal, parietal and central area are plotted. As can be seen in this figure, EEG band powers start to decrease before a cue is provided for the subject at time 0. Hence, we may infer that pre-cue time segment contains information about the task that subject is instructed to perform after cue timing.

Here in this paper, the accuracy of subjects is used as a measure of performance in MI task. To have a better estimate of users' performance, 10×10-fold cross-validation (CV) accuracies of users for non-feedback session was calculated and used for future analysis. Fig. 4 shows box plot of 10×10-fold cross validation (CV) accuracies for 17 healthy subjects during the non-feedback session. As shown, the median accuracies of the subjects vary from 50% to 95.8%. Subjects with accuracies less than 70% can be considered as low performance subjects (kübler et al., 2004). In other words, subjects with accuracy less than 70% are not successful in using BCI system and they can be considered as BCI deficient (Blankertz et al., 2008). Hence, the subjects can be divided into two groups: subjects with low performance (median = 58.33%) and subjects with high performance (median = 85.42%).

A Pearson correlation coefficient was computed to assess the relationship between the proposed predictor and the classification performance of the subjects. The higher correlation value r and lower corresponding significant level p demonstrate the strength of their relationship. There was a significant positive correlation between the proposed predictor and CV accuracies (r = 0.53, p = 0.02). This means that the proposed predictor explained as much as r^2 = 29% of the variance in classification performance of the subjects. Therefore, the correlation result indicates that subjects with higher classification accuracy have higher value of the predictor and vice versa. Fig. 5 represents the values of the proposed predictor versus CV accuracies for each individual subject. As can be seen in this figure, high performance subjects (*pl*, *s*, *ks*, *lj*, *kk*, *hj*, *ab*, *zy*) have higher values of the predictor in comparison with low performance subjects (*hh*, *hd*, *wy*, *kx*, *ly*, *at*).

A Mann–Whitney *U*-test (Fig. 6) was conducted to compare the value of the proposed predictor for low (Group 1) and high performance subjects (Group 2). The subjects in Group 1 and Group 2 were chosen based on their classification performance. Group 1 contains subjects with accuracy less than 35th percentile, while Group 2 contains subjects with accuracy above 65th percentile. The results of the test showed that the value of the predictor for subjects with high performance (F_{median} = 0.54) was significantly (p = 0.008) higher than the value of the predictor for subjects with low performance (F_{median} = 0.33). Therefore, it can be concluded that subjects with higher classification accuracy have significantly higher value of the proposed predictor or higher attention level. By the way, the significance level of the result may change by grouping the subjects in other ways.

The values of the proposed predictor for two of the subjects *yz* and *ad* with low performance (accuracy less than 70%) are quite comparable to that of the subjects with high performance such as *kk*. On the other hand, subject *jh* with CV accuracy = 74.7% has the

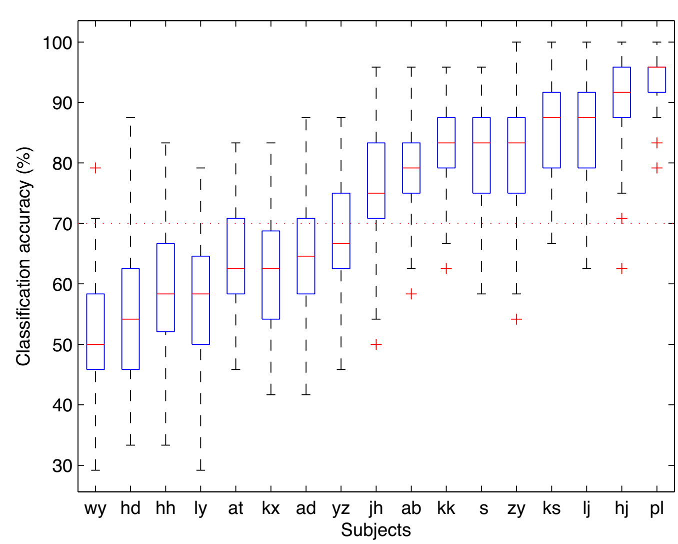

Fig. 4. Box-plot of 10×10-fold cross-validation accuracies of 17 healthy subjects during non-feedback session.

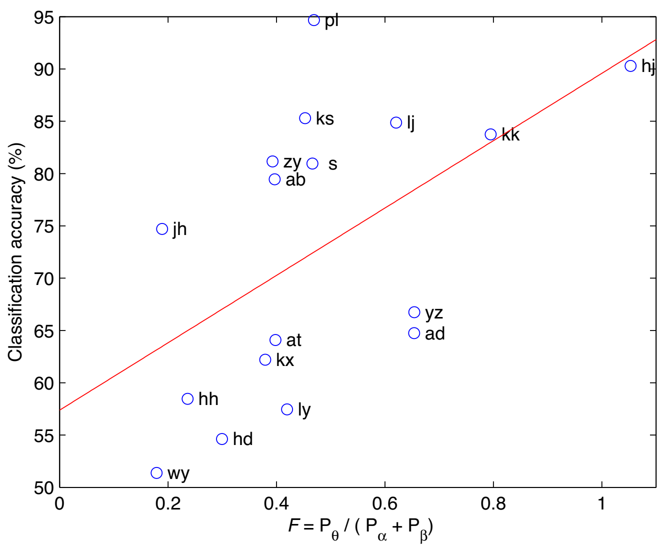

Fig. 5. Correlation of the proposed EEG rhythm-based coefficient F with BCI classification accuracy. The accuracies are 10×10-fold CV accuracies of the users over non-feedback session. Each circle represents a healthy subject. The solid (slope = 0.32) line is linear regression result.

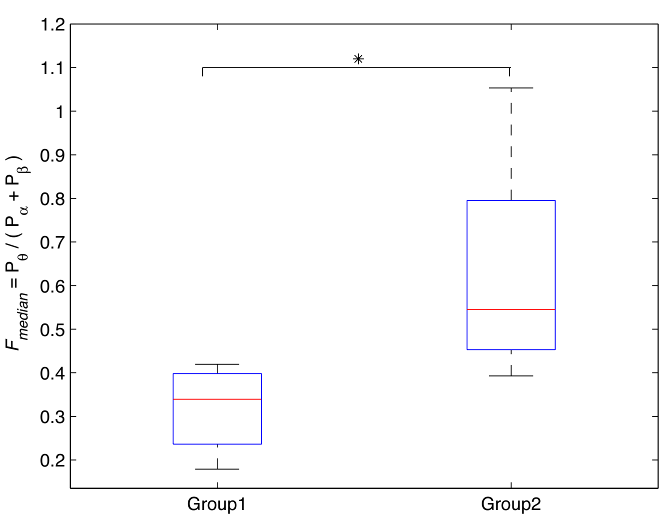

Fig. 6. Comparing the proposed EEG rhythm-based coefficient F for two groups of subjects. Group 1 are six subjects with accuracy less than 35th percentile and Group 2 are the six subjects with accuracy above 65th percentile. (Mann–Whitney U-test $^*p < 0.05$).

lowest predictor value. As shown in Fig. 4, these three subjects have moderate accuracies, they are placed somehow in the middle of the graph between two groups of subjects.

In order to improve the proposed predictor in Eq. (3), it had been modified by normalizing theta band power over weighted sum of alpha and beta band powers as follows:

$$F_{new} = \frac{\sum_{c \in C_\theta} P_c^\theta}{\lambda \sum_{c \in C_\alpha} P_c^\alpha + (1-\lambda) \sum_{c \in C_\beta} P_c^\beta} \tag{4}$$

where $\lambda \in [0, 1]$ is a weighting factor. Fig. 7a summarizes the results of group level correlation analysis for different values of λ in Eq. (4). As can be seen, for $\lambda \leq 0.67$ we have a significant correlation between F_{new} and performance. Highest correlation ($r = 0.62$, $p = 0.007$) is achieved by $\lambda = 0.16$. Fig. 7b shows group level correlation analysis for some of the selected λ values. However, for different values of weighting factor λ, the six lowest performance subjects had always significantly lower values of F_{new} in comparison with the six highest performance subjects.

4. Discussion

In this study, we hypothesize that current state of brain which is defined based on pre-cue EEG data is informative for performance prediction. According to our experimental design, the subject was instructed to stop any movement and be ready for the following task after hearing a beep sound. Before this beep sound there was a rest time during which the subject was allowed to be relaxed without any special instruction. Hence, the recorded signal contained several artifacts and it was not reliable to be used for our analysis. The time between hearing the beep sound and the cue timing was around 2 s. As stated earlier the power of EEG signal over this time segment was computed for α, β, and θ frequency bands and used to quantify the current state of brain. ERD/ERS time course shown in Fig. 3 reveals that the relative powers start to decrease two seconds before cue timing. Therefore, this time segment was used in calculating the attention level of user prior the start of trial at time 0.

Although brain's functionality during different tasks is not the same, it is common in all tasks that state of brain can affect the subject's performance. To define the brain's state we tried to capture spatial and spectral information in our new predictor. There are several studies in performance prediction which reviewed in Section 1; however, pre-cue information of different frequency bands over different regions of the brain has not been used for prediction so far.

As stated earlier, in the proposed coefficient theta band power is calculated over frontal area. Frontal theta activity had previously shown to be related to attention (Missonnier et al., 2006). It had shown that attentional processes and working memory are closely related, which means that increase in frontal theta activity is due to increase of working memory load. In other words, higher attention level is expected when there is higher frontal theta activity. This may justify the reason of focusing on frontal theta as a part of the coefficient proposed for attention level quantification. According to our electrode setup the frontal channels F3, Fz, and F4 are selected to calculate theta activity. Several studies had shown the role of pre-stimulus alpha over parietal and occipital area (Haig and Gordon, 1998; Romei et al., 2010; Rensink et al., 1997). They concluded that lower alpha results in higher accuracy (Romei et al., 2010; Rensink et al., 1997) and faster reaction time (Haig and Gordon, 1998). Therefore, in our proposed coefficient alpha band power is calculated over parietal area (P7, P3, Pz, P4, P8).

As we define brain's state by attention level, we assume that subjects with higher accuracies have higher attention level, which means that we do expect to see higher values of the coefficient for users with high performance. Due to the definition of our proposed coefficient (Eq. (3)), higher attention level is achieved by having higher frontal theta and lower parietal alpha. Our results showed significant positive correlation between our proposed coefficient and accuracies of the users, which implies our initial assumption was correct. Moreover, group level analysis demonstrated that by giving different weights to alpha and beta band power in Eq. (4), higher correlation was achieved. This may suggest that EEG rhythms should have different weights in quantifying attention level of subjects.

Although significant positive correlation was achieved in group level analysis, as shown in Fig. 5 and stated in Section 3, the values of the proposed coefficient is totally different for subject *yz*, *ad*, *jh*. These three subjects have moderate accuracies with different values of the predictor. Hence, it may be assumed that the predicted accuracies for some of the subjects are not precise. Currently our

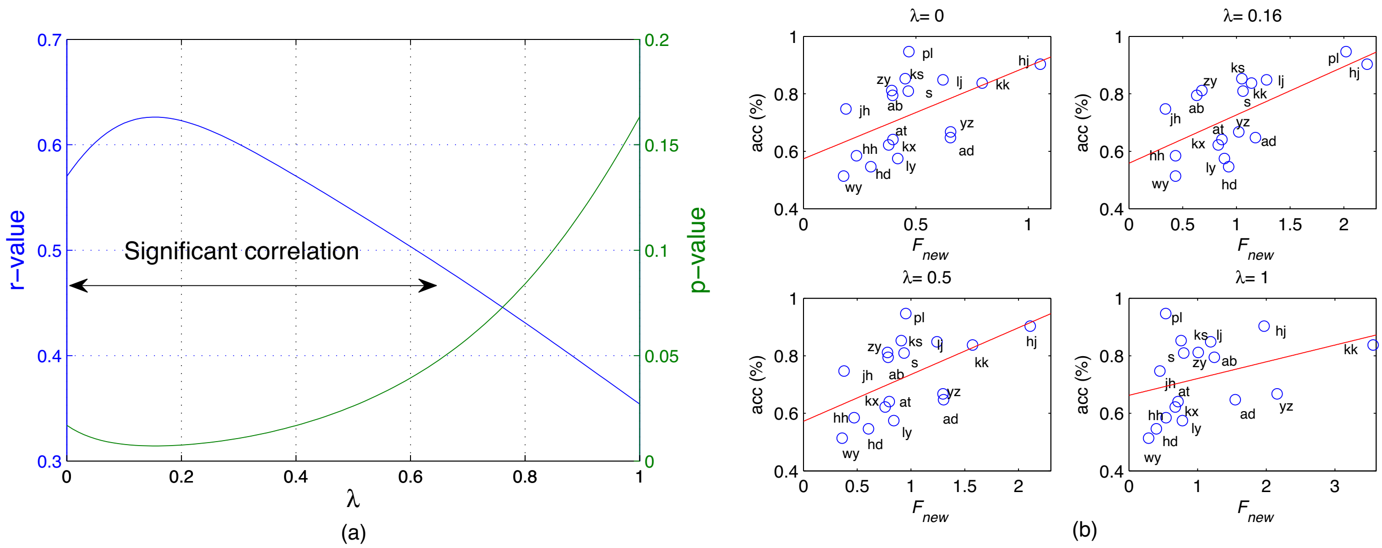

Fig. 7. Analysis the effect of weighting factor $\lambda = [0\ 1]$ on the proposed coefficient. (a) Corresponding r- and p-values for different values of λ. (b) Correlation between accuracy and proposed coefficient (F_{new}) for selected values of $\lambda = 0$, 0.16, 0.5, and 1.

findings were tested on a group of 17 subjects with various range of performance. This can be considered as a limitation of our study. It would be appreciated to test the proposed coefficient on a bigger data set with more number of subjects, which is one of our future goals.

5. Conclusion

In this work we demonstrated that pre-cue EEG rhythms contain useful information about the following motor imagery task. It had shown in several previous studies that pre-stimulus EEG data can be used for predicting the performance of the users for the following task regardless of the type of the task (i.e., memory task, mental workload, engagement, oddball). In fact, pre-cue EEG data can somehow show the current state of brain. Defining the current state of brain is not straightforward, since it may be affected by different factors such as changes in subject's attention, concentration, engagement, mood and some other factors.

Therefore, it can be concluded that by defining the current state of brain, we can predict the performance of user. Here, we assumed that the attention level of user is a good indicator of brain's state. Hence, we tried to quantify the attention level. The proposed coefficient may be considered as one of the possible quantification of attention level. In order to include topographic information in the proposed coefficient, power of EEG signal over different regions of the brain was computed. In this way we can capture spatial and spectral information and better represent the current state of brain.

The group level correlation analysis represents that the new proposed coefficient was positively correlated to the accuracies of users during motor imagery versus idle task. The results suggested that subjects with higher (lower) accuracies have higher (lower) values of the proposed coefficient. However, from this study we cannot infer that this is a causal correlation. In conclusion, the results of this paper are based on group level analysis. In future, we plan to validate the effectiveness of our proposed coefficient in single trial analysis, and the parameters of the proposed coefficient may adapt according to attention level of subject. This can also leads us to have a new design of experiment to specifically help subjects with BCI deficiency. As an example, in the new design whenever the subject is not ready to perform motor imagery task we may ask user to perform a small test to reach an appropriate attention level. This new experimental design can make MI-based BCI systems to be applicable for all users.

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