2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)
Bari, Italy. October 6-9, 2019

On-task theta power is correlated to motor imagery performance

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Abstract — **This study aimed to evaluate on-task electroencephalographic spectral measures and its correlation to performance during a motor imagery (MI) task. By investigating this aspect, we hope to understand what makes some individuals MI "illiterates". Eighteen healthy subjects performed an experimental task whereby a cursor was moved to one of two targets (left and right) using only MI of the left and right hands. To evaluate the effect of aptitude, performance was measured as percentage of correct movement to target, and Mahalanobis distances were calculated between whole-scalp spectral patterns during left and right motor imagery. Then the correlation between performance and Mahalanobis distance was investigated for central, and whole-head topographies using Spearman's correlations. In central topographies, distances on alpha band were positively correlated with performance (ρ=0.562, p=0.032), while distances on theta band were negatively correlated to performance (ρ=-0.648, p=0.018) in whole-head maps. The investigation of on-task whole-scalp differences allows a holistic comprehension of the neural basis of motor imagery, as well as how this leads to performance variations.**

I. Introduction

Motor imagery (MI) is defined as the voluntarily mental simulation of a movement without the motor execution [1] and is part of a larger phenomenon, called motor representation, related to the intention and preparation of movement [2]. This simulation can refer to explicit or conscious representations of a movement, like to imagine the opening and closing of the hands, or to implicit or unconscious representations of the movements involved in carrying out a complex action such as the action of taking a glass and pouring its contents [2].

In a recent meta-analysis, Hétu and colleagues [3] compared results from fMRI and PET experiments of MI and found evidences of shared structures also involved on motor execution (ME). The brain regions reported to be consistently activated during MI included the inferior frontal gyri, precentral gyrus, middle frontal gyrus, supplementary motor area (SMA), supramarginal gyrus and primary visual cortex. The primary motor cortex, unexpectedly, did not present a consistent BOLD (blood oxygen-level dependent) signal during MI. In EEG recordings, however, MI can be expressed as a power decrease in the contralateral primary motor cortex within the mu (associated with sensorimotor activity, 8-12Hz) and beta frequency bands [4, 5]. These power variations are commonly used in Brain-Computer Interfaces (BCI) and their applications [6].

Subjects performing MI in a BCI setting require some time to learn to regulate their brain activity and achieve the desired control of the technique required to operate the interface consistently [7]. This learning period may be several minutes up to several weeks. However, even with long periods of training, clear instructions, improvements in experiment protocol and signal processing approaches, it is not possible to accurately distinguish different neuroelectrical patterns in some individuals [7, 8]. This phenomenon is called BCI "illiteracy", and investigation is required into what distinguishes illiterate individuals from the literate ones [8-11].

During the last years, there is an intense debate about possible factors for this lack of ability to perform MI tasks [8, 11]. While some studies reported age, gender and daily routine as influences to MI performance [12, 13], others correlated psychological aspects with performance, such as the self-confidence, frustration and concentration [14-16]. Neuroimaging studies have also found structural and functional differences between literate and illiterate MI performers [17-19]. Resting-state analysis using EEG reveals that greater power in the theta frequency band is indicative of illiteracy [20], and that greater power in alpha and gamma frequency bands is proportional to performance [20-22].

These previous studies looked at differences in frequency power at individual electrodes. This study adds to this literature by looking at global dissimilarities in frequency power across all electrodes using the Mahalanobis distance [23]. In this analysis, spectral topographies are compared in different frequency bands during a simple MI task, with appropriate correction applied. Then this distance is related to performance to reveal global factors that influence BCI literacy.

II. Methods

A. Participants

Eighteen healthy right-handed participants (8 female), aged 23.22±2.98 years and all attending college or graduated. The subjects had no diagnosis of neurological (ICD-10: G00-G99), psychiatric (ICD-10: F00-F99), and/or motor diseases (ICD-10: M00-M99) and had normal or corrected-to-normal vision. Ethical approval was obtained from the local Ethics Committee and participants provided written consent prior to participation.

* The São Paulo Research Foundation (grant number: 13/10952-9).

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B. Data acquisition

The recording was performed using a 72-channel QuickAmp amplifier system (Brain Products GmbH, Germany), with a sampling frequency of 500 Hz, together with an actiCAP electrodes cap (Brain Products GmbH, Germany) with 32 positioned electrodes according to the 10-20 system arranged in Fp1, Fp2, F7, F3, Fz, F4, F6, FC5, FC3, FC1, FC2, FC4, FC6, T7, C3, Cz, C4, T8, CP5, CP3, CP1, CP2, CP4, CP6, P7, P3, Pz, P4, P8, O1, Oz, O2. The reference was FCz, and the ground was AFz. Horizontal EOG, vertical EOG and two EMG channels (one for each arm on the flexor carpi ulnaris/brachioradialis) were recorded using the same system.

C. Motor-imagery task

Subjects were instructed to imagine kinesthetic movement of opening and closing their left or right hand at a comfortable rate, depending on the stimuli presented on the screen. The session consisted of six blocks (Figure 1A), with each block containing 40 trials (20 for right hand, 20 for left hand) presented in a random order [24].

The intervals between the blocks were as small as possible to avoid any influence on signals. The first two blocks were used to train the classifier, and had no feedback. The next four blocks are the main experiment, and contained visual feedback about performance (basketball paradigm [5]). Visual stimuli were created and presented using the Psychophysics Toolbox extensions [25].

Blocks without feedback: During training blocks, a red target was used to indicate the side of the hand movement to be imagined (Figure 1B). Participants were instructed to keep the imagery while the neutral stimulus (green bar) remained at the screen. For classifier training, we used a well-established protocol of [24], in order to allow comparisons with other studies. For this, the signals from electrodes FC3, FC4, CP3 and CP4 between 4.25-7.25 s after start of trial were chosen as inputs. The signals were initially filtered using a band-pass 5th order Butterworth filter between 0.5 to 30 Hz [24]. After this, the mean spectral power density (mSPD) within the mu (10-12 Hz) and beta (16-24 Hz) bands was calculated for each channel [5].

Classifier training: After two blocks of classifier training, these eight attributes (four electrodes and two frequency bands) were extracted from 80 trials (40 per hand). These data were then used to train a Linear Discriminant Analysis (LDA) classifier to recognize the two classes (left- and right-hand motor imagery).

Main task (blocks with feedback): For each trial, participants were instructed to direct a moving cursor to the rectangle colored red at the bottom of the screen using motor imagery neurofeedback (Figure 1C). For this, real time signal processing of data from electrodes FC3, FC4, CP3 and CP4 was carried out as for the data during classifier training. First, the signals were initially filtered using a band-pass 5th order Butterworth filter between 0.5 to 30 Hz [24]. After this, the mean spectral power density (mSPD) within the mu (10-12 Hz) and beta (16-24 Hz) bands was calculated for each channel [5]. The data were then classified using the LDA model created in the training blocks and the cursor moved proportionally to the output (ranged from -1 for definite left MI classification to +1 for definite right MI classification).

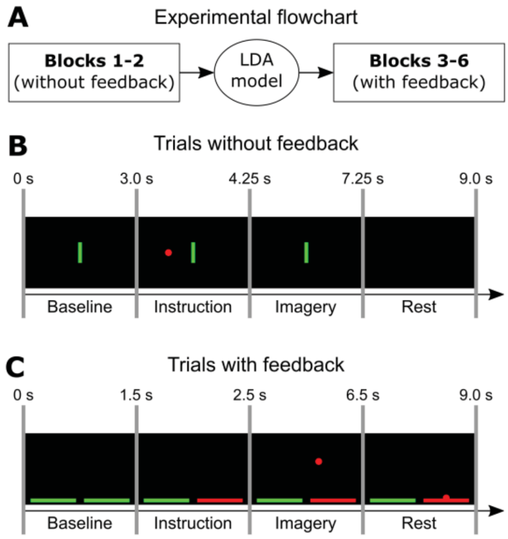

Figure 1- (A) Experimental flowchart. (B) Visual stimuli in classifier training blocks. 0-3.0 s: baseline. 3.0-4.25 s: instruction, 4.25-7.25 s: MI task without feedback, 7.25-9.0 s: rest. (C) Visual stimuli in main BCI task. 0-1.5 s: baseline, 1.5-2.5 s: instruction, 2.5-6.5 s: MI task with feedback, 6.5-9.0 s: rest.

Once the cursor reaches one of the targets, the image remains fixed for a short rest interval until the end of the trial.

D. Offline data preprocessing

Performance measure: The performance of each participant was calculated after ocular correction and removal of trials with overt muscle movements. Performance was determined by the number of trials where the cursor finished a trial in the (red) target position (left/right) divided by the total number of trials remaining after artefact correction and removal of trials.

Ocular correction: To eliminate interference from eye movement and blinks, we applied Independent Component Analysis (ICA), using Brain Vision Analyzer 2.0 (Brain Products GMDH, Germany). First the sampling rate was changed to 250 Hz, and then the data were bandpass filtered between 1 and 50 Hz. The signal was then segmented into 9.0s epochs (Figures 1B and C) representing blocks of classifier training and those of the main task. Although only the trials of the main task were used in further analysis, all blocks were segmented for increasing the number of samples used in the ICA correlation. ICA analysis then decomposes the data into 32 components which are visually analyzed for those that resemble eye artefacts. Components with greater than 50% correlation with the EOG electrodes were selected (up to two components, but a maximum of three) to be discarded and the data was reconfigured [26, 27].

Removal of trials with muscle movement: To eliminate those trials where the participants moved their hands, the signal of EMG electrodes of the target hand were segmented into periods of baseline and those of motor imagery (the opposite hand was not considered in the calculations). These segments were then filtered with a high pass 7th order Butterworth filter at 10 Hz and subsequently rectified (extraction module). The baseline epochs were then examined using windows of 0.3 s, moving along the data with steps of

0.15 s. From these windows a root mean square (RMS) baseline EMG was calculated. Each trial was examined in the same way, and a mean and standard deviation of baseline EMG RMS was calculated for each participant. The motor imagery periods were pre-processed in the same way as the baseline to create RMS values. Trials where the RMS exceeded the baseline mean + 1.96 of the standard deviation were excluded as having muscle movement. The average number of rejections 24.56±31.26 of 160 trials.

E. *Spectral Analysis and Statistical analysis*

Central channels analysis: First, we evaluated the spectral pattern over the central channels to validate the experimental procedure. For this, the main MI task trials which were retained after ocular correction and after discarding those with muscle movement were segmented into baseline (0-1500 ms, see Figure 1C) and motor imagery (2500-6500 ms, see Figure 1C). The mSPD was calculated in central electrodes (FC5, FC3, FC1, FC2, FC4, FC6, C3, Cz, C4, CP5, CP3, CP1, CP2, CP4, CP6) for the two frequency bands used by the LDA classifier during the MI task: mu (10.0-12.0 Hz) and beta (16.0-24.0 Hz). For each trial, the mSPD from the baseline was subtracted from the mSPD for MI segment to create a value corresponding to the variation in power in these frequency bands above baseline [24]. The use of a baseline period allows the assessment of relative variations compared to a "neutral" non-imagery period [28]. This relative variation can present indirect information regarding the event-related desynchronization (ERD) and/or synchronization (ERS). For example, a power decrease indicates ERD and a power increase indicates ERS [4, 29].

To reduce the number of multiple comparisons, the first analysis consisted of the evaluation of the conditions of motor imagination by Mahalanobis distance [23, 30]. Mahalanobis distance uses the data from the topography of each condition as a multidimensional dataset and compares it to another multidimensional dataset. Its output is the number of standard deviations one dataset is from the other [23]. First, for each subject we take the topographies of each band for each trial of left and right MI. Then we get the Mahalanobis distance between the average topography of each imagery condition. Now we randomly shuffle the labels of the trials and calculate the Mahalanobis distance between permuted left-right trials. We repeat this step 10^5 times to generate a permutation distribution. After that we calculated the z-scores of the real distance between left and right MI relative to the distribution of the permutations (we did this by assigning a p-value to the real distance relative to the permutation distribution, and then using the inverse normal distribution to transform the p-value into a z-score).

After this single-subject analysis, the next step for group analysis is to simply calculate one sample t-tests for each band to test which frequencies that significantly distinguish between left and right MI. To investigate whether the distinguishing power of spectral patterns for each frequency is related to performance in the task, or BCI literacy, Mahalanobis distances were correlated with performance using the Spearman's correlation. A new permutation test was applied with 10^5 permutations for each frequency band, to compare the obtained correlation values with the randomly by chance obtained correlations. Then, p-values were adjusted by using the Bonferroni correction for two comparisons.

Whole-head analysis: Finally, we investigated the relation between whole-head frequency patterns with MI performance. The mSPD was calculated in all 32 electrodes for four classical EEG frequency bands: theta (4.5-8.0 Hz), alpha (8.5-12 Hz), beta (12.5-30.0 Hz) and gamma (30.5-50 Hz). Here we did not include the delta band (1.0-4.0 Hz) due to the influence of the ICA correction in this band. For each trial, the mSPD from the baseline was subtracted from the mSPD for MI segment to create a value corresponding to the variation in power in these frequency bands above baseline.

Following the same permutation method previously described, we obtained the Mahalanobis distances from left to right MI in each band, for each subject. Then, for each frequency band, Mahalanobis distances were correlated with performance using the Spearman's correlation, and this coefficient was compared with a random distribution of correlation coefficients obtained after 10^5 permutations. P-values were adjusted by using the Bonferroni correction for multiple comparisons (four EEG bands).

III. Results

A. *Task performance*

In this study we adopted the task performance as an indicative of literacy. The average performance of our sample was 54.39±13.42%, ranging from 38.75% to 90.14%, with 10 subjects above and eight subjects bellow the chance (50.0%). The idea of such heterogeneous sample was exploring different levels of literacy.

B. *Spectral patterns over the central channels*

The topographical maps with spectral patterns during the MI for the left and right hands, and the respective differences (left minus right MI), are illustrated in Figure 2A. The topographical differences in alpha present a cluster of higher values mainly over channels FC1 and C3, but extended to FC3 and CP3, and a lower peak over channel FC4. However, the peak of positive differences in beta is centralized, mainly over FC1, FC2, Cz and CP1, while a negative peak is found over CP5 and CP3. When evaluating the Mahalanobis distances of the central spectral patterns during the imagery of both hands, a significant difference was found in the alpha band ($p=0.004$), but not in the beta band ($p=0.166$), when compared to zero (Figure 2B). Also, the Mahalanobis distance in the alpha band was positively correlated with performance ($\rho=0.562$, $p=0.032$ – Figure 2C), but no significance was found in beta ($\rho=0.027$, $p=1.00$).

C. *Whole-head Mahalanobis distance and performance*

No significant correlation was found for alpha ($\rho=0.183$, $p=1.00$), beta ($\rho=0.235$, $p=1.00$), or gamma ($\rho=-0.381$, $p=0.594$) bands. However, a negative correlation negative correlation was found between theta band and performances ($\rho=-0.648$, $p=0.018$). The Figure 3A shows the distribution of subjects according to their performances and distances in theta band. The topographical map of the differences in mSPD between MI for the left and right hands in theta band is shown in Figure 3B.

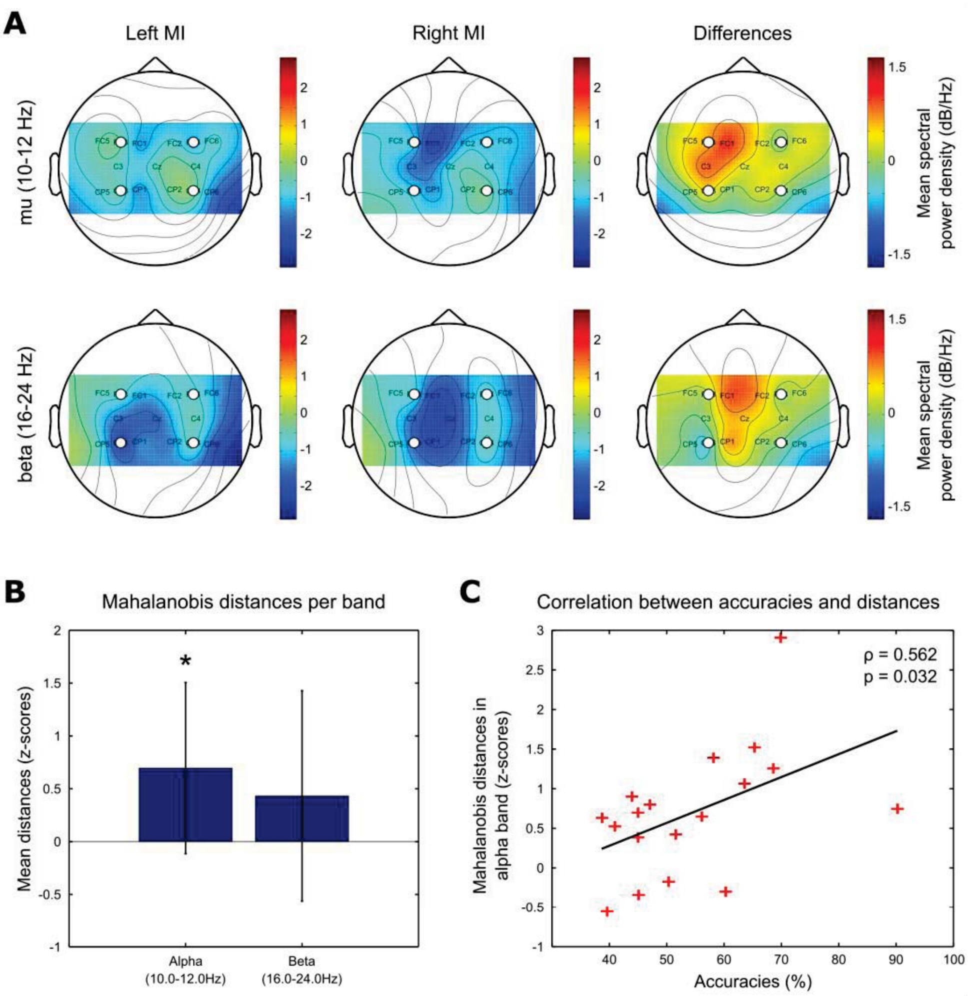

Figure 2- (A) Topographic maps with the mean spectral power density (mSPD) during left- and right-hand motor imagery for bands used by the LDA classifier during the MI task. White dots represent the four electrodes used for classifying imagery. (B) Bar graph with mean and standard-error for z-scored Mahalanobis distances between MI for the left and right hands. Asterisk represents significant difference from zero ($p<0.05$). (C) Scatter plot with distribution of subjects according to their performance accuracies and Mahalanobis distances in mu band. The black line represents the tendency.

IV. Discussion

The objective of this study was to investigate possible on-task whole-head spectral characteristics correlated with MI aptitude (literacy), not only specific channels as in conventional statistical comparisons.

A. Alpha band in central channels

Considering that central mu and beta rhythms are the basis of the feedback algorithm [5, 24], Mahalanobis distances in mu band significantly differing from zero work as a validation of our experiment setup. However, although significance in beta was also expected, this result might be related to the inclusion of subjects with poor performance in this analysis. Indeed, poor imagery performances lead to reduced differences between topographical distributions in left and right MI.

The mu rhythm also presented positive correlation with performance. In fact, spectral topographies indirectly reflect the ERD/ERS intensity [4, 29], and is an indicative of how well the subject performs the MI task [31]. For example, the clearer the ERD/ERS patterns are the higher is the distance between spectral topographies and consequently, the higher is the LDA classifier accuracy and the participant performance.

B. Whole-scalp theta band and performance

The large differences in the Mahalanobis distance between left and right MI were not seen in the whole head analysis. However, the presence of theta rhythms during a resting block before task [20], as well as during the baseline pre-cue period [31], was described as correlated to performance. Considering the on-task periods, different studies already showed increased theta frequencies [20, 32], but did not investigated any level of correlation with performance. The current data extends these findings to reveal that theta during task also correlates to performance.

The theta rhythm plays an important role in MI tasks due to this relation with different cognitive processes, such as information processing [33], working memory [34, 35] and sensorimotor integration [36, 37], with the frontal theta reflecting mental activity, attention and arousal [38, 39]. If theta in this task it indexing attention or working memory load, then an interpretation of the data in Figure 3 would be that higher bilateral theta activity (so greater attention or load)

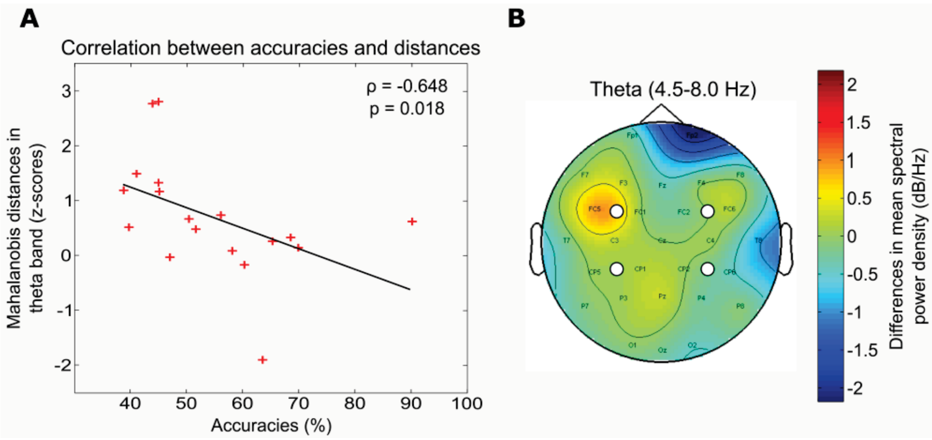

Figure 3- (A) Scatter plot with distribution of subjects according to their performance accuracies and Mahalanobis distances in theta band. The black line represents the tendency. (B) Topographic map of differences on mean spectral power density (mSPD) between left- and right-hand motor imagery for theta band (4.5-8.0 Hz). White dots represent the four electrodes used for classifying imagery.

leads to lower Mahalanobis distance and this greater attention may underlie the greater performance seen in these individuals.

On the other hand, theta activity is also seen during learning where feedback is given. This is observed when individuals compare the expected result of their response with the feedback given, and is related to behavioral adaptation for the next trial [40, 41]. Higher learners in these tasks have greater mid-frontal theta power in response to incorrect feedback [41]. Therefore, an alternative explanation for our data is that more literate participants (those with better feedback) are more engaged in feedback and learning than those who perform less well. In this case, they may have a large midline theta across hand conditions, so a small Mahalanobis distance.

C. Limitations and future perspectives

One limitation of this study is the use of FCz as the reference channel. Although not interfering in performance estimation, the reference channel may lead to different topographical distributions [42-44]. Thus, future studies should validate our findings using other referential setups. One possibility is to replicate this analysis using the publicly available databases with nasion [45] or common average references [46].

The correlation found between the theta band and performance results allows some future research approaches. Using task performance as a measure of MI ability has some issues, and another type of measurement, such as motor imagery questionnaires might be useful to validate this effect. For instance, the Movement Imagery Questionnaire (MIQ) [47], the Vividness of Motor Imagery Questionnaire (VMIQ) [48] and Kinesthetic and Visual Imagery Questionnaire (KVIQ-20) [49] are widely used to investigate motor imagery in healthy and/or pathological subjects. Then, the near step would be to evaluate possible correlations of the topographic maps and the measured scores.

Another possible follow-up would be the long-term monitoring of these participants in the MI training. Wander and colleagues [50] followed seven epilepsy patients with implanted electrocorticography electrodes during 4-10 days of training of a one-dimensional MI-BCI, finding growth performance of almost all participants during the sessions. It could be that "literacy" of participants just indicates different learning styles, which would be interesting to follow up in a longitudinal study.

Finally, this study suggests that theta power might index ability in BCI, and therefore be used to stratify those who would most benefit from MI-BCI neurorehabilitation [6, 51]. For example, the evaluation of the on-task theta distances during a few sessions might guide physicians about the maintenance of the MI-based technique, or the choice for another physiotherapeutic approach.

V. Conclusion

Our results showed that MI of hand movements causes significant distances between the on-task left and right whole-head spectral maps. Moreover, the same distances measured on the theta band are negatively correlated to the task performance, opening doors for different applications in BCI experiments.

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