EEG-based brain-computer interface for alpha speed control of a small robot using the MUSE headband

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***Abstract*— Non-invasive BMI applications are increasingly used in different contexts ranging from industrial, clinical and gaming. After having tested the difference between a classical EEG recorder with electroconductive gel (ANT system) and the MUSE EEG headband, we studied the BCI performances of the later during the control of a small robot. We demonstrated that the participants were able to successfully control the robot using an online brain-computer interface based on the signal power in different frequency bands (delta, theta and alpha) characterizing the eyes-opened and relaxed eyes-closed states. Additionally, we performed a correlation analysis which demonstrated that the BCI commands were more related to a delta or theta power decrease for the determination of the classifier output probability and to the alpha power increase for the speed control of the robot.**

Keywords—BMI, BCI, MUSE, machine learning, dry electrodes

I. Introduction

Non-invasive BCI methods based on EEG signals have been widely applied [1] because of their easy use and the rapid feedback responses allowed by the high temporal precision of the EEG. However, the low signal-to-noise ratio (SNR) and the presence of different types of artifacts due to the movements of the recording cap, the head, the eyes (EOG), the blinks and the muscular activities (EMG) may compromise the identification of real neuronal signals of the brain [2]. In spite of different attempts to develop a hardware solution at the level of the recording montages [3] such as the dual electrode for removing motion artifacts [4] or ICA coupled for the identification of true interconnections, spurious connectivity patterns may have occurred [5]. Despite recent technological advances for classical EEG cap using electroconductive gels, the artifacts problem remains largely unresolved when low-cost consumer-grade dry-EEG cap are used. Indeed, the BCI loop may be disturbed by these artifact recurrences which may be misused as neural features for BCI classification. Other BCI challenges include real but unrelated brain signals dynamics and the interference of such ongoing rhythmic activities related to the maintenance of consciousness [6], to the mind wandering [7] and to the feedback task requirements. This latter aspect is crucial because the brain is mainly oriented to produce actions directly or indirectly on its surrounding environment. The nature, the ecological quality of the feedback signal and the final aim of the BCI approach are the other important elements. Here, we have developed an EEG-BCI paradigm in order to train human participants to pilot a small robot by means of specific frequency targeted brainwaves. The main contribution of this work was to show that real-time and robust robot control with consumer-grade dry-EEG caps is achievable despite their low signal-to-noise ratio. We have presently focused our BCI development for the reinforcement of the frontal alpha oscillation. Similarly to other alpha rhythms recorded in the occipital, parietal and somatosensory regions, the frontal alpha exhibits the 'arrest' reaction initially described by Hans Berger when he discovered the EEG signal in humans. The 'arrest' reaction occurred during the transition from the relaxed eyes-closed state to the eyes-opened state. This state transition is accompanied by a significant decrease (event-related desynchronization, ERD) of the alpha power which reaches its lowest level in about 1 s after the opening of the lids. Conversely, the alpha power increase (event-related synchronization, ERS) occurs at about the same time as the closure of the lids. The frontal alpha is specific because the ERD occurred directly in response to the auditory order to open the eyes and thus before eyes opening [8]. The frontal alpha ERD was also found to be important in social interactions [9]. Because of the high intrinsic variability of the different frequency band powers we have trained a classifier for each participant based on the ERD-ERS difference related to the arrest reaction and taking into account these individual characteristics of the EEG compounds.

II. Materials and Methods

A. Participants

The experiments were collected from 10 right-handed BCI naïve volunteers (6 females and 4 males, mean age: 37.4 ± 16.3 years ranging from 18 to 63 years). They were all in good health and free from neurological disease. They were informed about the testing and have signed a voluntary consent form. The experimental procedures were approved by the local ethics committee of the Brugmann university hospital and conformed with the Declaration of Helsinki.

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B. BCI paradigm

After a short period of adaptation to the experimental environment, the BCI session performed with the MUSE system was initiated by the recording of the eyes-opened versus eyes-closed state (duration of 15 s each). These EEG epochs constituted the training set for a logistic regression classifier. Participants were then asked to move the robot forward during 10 repeated trials of 30 s in the relaxed eyes-closed state. The feedback consisted in the motor drive noise of the moving robot and in the final visual outcome of the accomplished travelled distance.

C. Quality control of the EEG signals of ANT and MUSE

In order to estimate the signals quality of the MUSE headband from which the present BCI paradigm was performed, we have compared this low-cost and easily wearable system with a classical EEG recording system with gel electrodes (ANT system). The ANT acquisition system (Advanced Neuro Technology, ANT, Hengelo, The Netherlands) is composed of a high-density WaveGuard cap system connected to a full-band DC amplifier with a sampling rate of 2048 Hz. The WaveGuard cap has 128 Ag/AgCl electrodes with shielded wires reducing the exterior noise.

The MUSE EEG headband (Interaxon Inc, Toronto, Canada) included 4 recording points at AF7, AF8, TP9, and TP10, all referenced to Fpz. AF7, AF8 and Fpz are silver contacts while TP9 and TP10 consist of a conductive silicon material. The headband recorded EEG signals at a sampling rate of 256 Hz. Although EEG signals acquired with MUSE exhibit a substantially lower SNR than research-grade acquisition systems (see Fig. 1), previous works showed that event-related potentials (ERP) and brain rhythms remain well observable [10], [11].

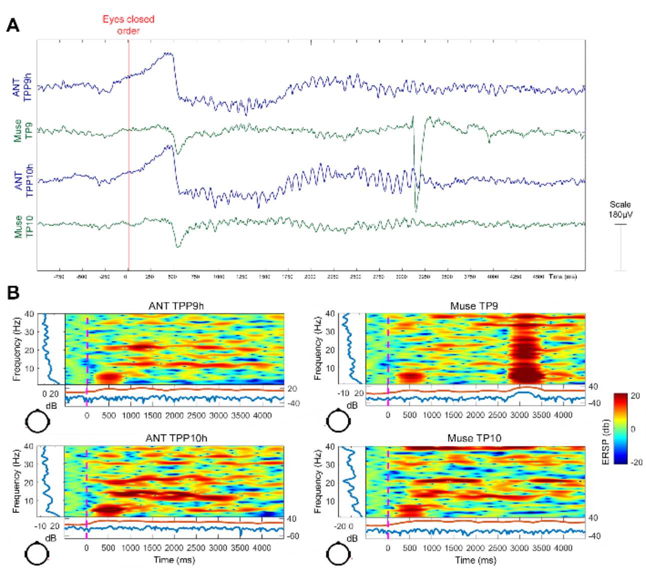

Figure 1. Comparative analysis of the same single EEG trial simultaneously recorded by ANT and MUSE systems during the transition between eye-opened and eye-closed states. In A, raw EEG traces recorded at TP9, TP10 on MUSE and their nearest available electrodes TPP9h, TPP10h on ANT. The blue and green traces correspond respectively to the ANT and MUSE recordings. In B, the ERSP analysis of the same signals presented in A. Note the presence of an artifact in MUSE TP9 clearly visible in the single trace and the ERSP map.

Figure 1 illustrates the major difference of alpha amplitude recorded by the ANT and MUSE systems. After the closure of the lids (which ocular artifact was well identified by both systems), the alpha waves exhibited significantly higher amplitude using the ANT system compared to the MUSE system (Fig. 1A). Even if some spontaneous artifacts emerged with MUSE the ERSP analysis (Fig. 1B) allowed the identification of alpha power increase although to a lesser extent than that obtained with the ANT system. Considering the low-cost, ease of use and portability of the MUSE headband as major advantages, we decided to proceed with the MUSE system for the development of the present BCI.

D. Data treatment

It was previously showed that power ratios in specific frequency bands can be used to infer a participant's mental state and applied for performance enhancement trainings and clinical protocols [12]. Although the alpha brain wave can locally be associated with alert relaxation [13], the alpha power estimated from scalp EEG is substantially contaminated with muscular and ocular artifacts and thus does not constitute by itself a reliable measure of relaxation. In this work, we use the alpha/theta [14]–[16] and alpha/delta [17] ratios to characterize the relaxed eyes-closed mental state. Since physiological artifacts contaminate more prominently the delta and theta frequency bands, dividing the alpha power by either the delta or theta power provides the desirable property to mitigate the spurious effects of artifacts and therefore prevent users from controlling the robot with artifactual activities rather than their mental states. The use of the alpha/theta and alpha/delta ratio for the determination of the activation threshold also avoids to use online complex computation to suppress blinks and eye movements which mainly occurred in the eyes-opened state.

E. Real-time data processing

The stream of EEG signal measurements was acquired from the Muse headband at a frequency rate of 256 Hz in near real-time access using the Lab Streaming Layer (LSL) collection system. The acquired EEG signal was subsequently processed through the data processing pipeline consisting of the following steps. First, raw signal buffers of size 2560 samples (10 s of EEG signal) were updated with the acquired raw EEG signal and a zero-phase IIR bandpass filter with cut-off frequencies at 1 Hz and 40 Hz was applied for real-time signal visualization. Then, the Power Spectral Density (PSD) was estimated using Welch's method [18] to compute the logarithm with base 10 of the power in the delta (1-4 Hz), theta (4-7 Hz), alpha (7-13 Hz) and beta (13-30 Hz) frequency bands. An average of the bands power over the 5 last seconds was computed and buffered. Averaged bands power allows for a smoother transition between mental states and thus improves the robustness of the system. The alpha/delta (A/D) and alpha/theta (A/T) ratios were then computed in real-time and constituted the inputs vectors for training a logistic regression classification algorithm. Given an input vector x_i, the trained classifier outputs a probability representing its degree of confidence that x_i belongs to the relaxed eyes-closed mental state. More formally, the input vector x_i of instance i is projected to a scalar bounded by a sigmoid function as follows:

$$h(x_i) = \frac{e^{w^T x_i + c}}{1 + e^{w^T x_i + c}}$$

Since the function parameters are penalized by a L2-regularization, training the logistic regression reduces to minimizing the following cost function:

$$\min_w \mathrm{L}(w) = \min_w \frac{1}{2} w^T \mathrm{w} + \sum_{i=1}^{n} log\left(e^{-y_i(x_i^T w + c)} + 1\right)$$

where y_i is the ground-truth label $\in \{-1, 1\}$ associated to instance i and $(w^T \mathrm{w})/2$ is the regularization term.

Two main elements determined the robot moving speed: (1) an activation threshold was arbitrarily set to a classification probability p with $p = 0.75$ for all participants and (2) a dynamically updated linear combination of alpha power (A) and classification probability. More formally, the signal s to the robot wheels actuator was determined as follows:

$$s = \begin{cases} 0 & if\ p < 0.75 \\ 400 * p * A & if\ p >= 0.75 \end{cases}$$

Thus, when the probability threshold was reached, the alpha power had a direct impact on the speed control of the robot. The feedback loop was behaviourally closed by the increased noise due to the increased speed of the robot.

F. Correlation analysis

In order to determine which frequency band (delta, theta or alpha) contributed the most to the alpha/delta (A/D) and alpha/theta (A/T) ratios, we computed Pearson correlation coefficients using each band power with respect to each power ratio. Since the Pearson correlation coefficient assumes a linear relationship between variables, we first applied a logarithmic transformation to the band power and the power ratio. Consequently, as the logarithm is monotonic we can infer the contribution of each band power to the power ratio by using the Pearson correlation coefficient with the logarithmically transformed variables.

III. RESULTS

Most participants have successfully moved the robot for a mean distance of at least 2 meters (Fig. 2A) at the exception of two participants (#1, 2). This was explained by the low alpha power in participant #1 and by a high level of stress reported by participant #2. The short term evolution of performance largely differed among participants. Two main performance trends emerged along the trials: an increase of performance for 7 participants and a decrease of performance for 3 participants (Fig.2 B).

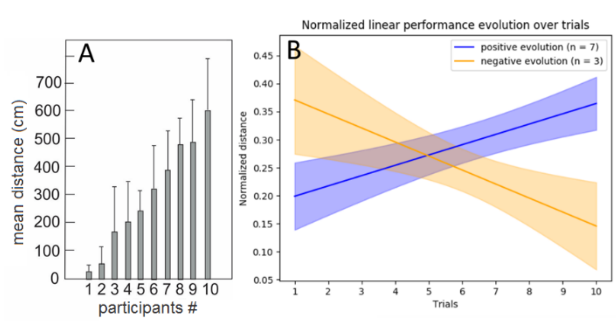

Figure 2.Mean distance of the robot reached by each of the 10 participants (A). Normalized linear performance evolution over the 10 trials period of 30 s (B).

Figure 3 highlights the evolution of the mean classification probability that the participant is in the relaxed eyes-closed state along with the corresponding changes in the power ratios involved in the BCI process. When the probability threshold was reached (yellow strips in Fig. 3A) the speed displacement of the robot was determined using the alpha power.

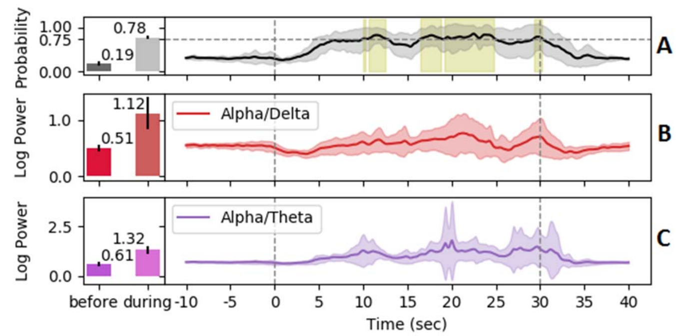

Figure 3. Evolution of the mean classification probability (A) with respect to the alpha/delta (B), alpha/theta (C) ratios recorded in participant 5 during the 10 epochs of 30 s. The respective histograms corresponding to group average values before and during the BCI performance are displayed. The yellow strips correspond to the moments when the classification probability threshold was reached, indicating that the robot wheels actuator is activated and under the speed control related to the alpha power. The differences were statistically significant (one way ANOVA, $p < 0.001$).

For this relatively basic BCI application, only two variables could affect the BCI performances at classification level, i.e. the A/D and A/T ratios. The analysis of the learned coefficients of the logistic regression classifier showed a strong inter-participants variability with regards to the most prevalent ratio. The A/D ratio was the most contributive feature for 6 participants while the A/T ratio was the most contributive for the 4 others.

In order to determine which frequency band (delta, theta or alpha) contributed the most to the prevalent ratio and thus *in fine* to the performances of the BCI system, we first confirmed the non-stationarity of the different frequency bands power and power ratios ($p > 0.05$) using the augmented Dickey-Fuller unit root test [19]. Subsequently, we compared for each participant the sample Pearson correlation coefficient computed using each band power with respect to the participant's most contributive ratio. As a result, the correlation analysis determined that the delta band power was the most contributive to the A/D power ratio for the participants where A/D was the most prevalent feature to the logistic regression classifier. Similarly, the theta band power was the most contributive for the participants for whom A/T was the most prevalent feature.

IV. DISCUSSION

Regardless of their performances, most participants spontaneously reported the feeling that they were in a different mental state when the robot was moving. Although proper causal inference would require more participants and trials, it was paramount to determine which component of the EEG signal contributed the most to the predictions and thus *in fine* to the performances of the BCI system. This step is often overlooked in the literature but is essential in order to better understand how such complex systems work and detect spurious positive results that could negatively impact the reliability of BCI systems in daily use.

The correlation analysis demonstrated that the on-off commands to the robot resulted more from a delta or theta power decrease (ERD) than from an alpha power increase. However, the final movement velocity of the robot and the related increase of the motor noise (which served as auditory feedback signal) uniquely depended on the alpha power measured in the relaxed eyes-closed state. By this way we may infer that the present feedback may specifically influence the speed control of the robot by alpha oscillation. The main advantage of the present method is that our classification methodology avoids the use of online artefacts rejection procedure and preliminary attention of the subject to their default mode in the eyes-opened state.

In this work, we showed that real-time and robust robot control with consumer-grade dry-EEG caps is achievable despite their low signal-to-noise ratio. Moreover, even though the alpha power contributed less than lower frequency bands power to the performances of this particular BCI system, we were able to observe the presence of non-stationary dynamics in the alpha oscillations. Further analysis will be more focused on causal inference as well as on the interest of using such alpha dynamic variations as an alpha trainer related to the moving speed of the robot.

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