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Motion prediction for the sensorimotor control of hand prostheses with a brain-machine interface using EEG

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Abstract—
In this study we present a modified version of the commercially-available myoelectric prosthesis (Myobock©, Ottobock) with the aim of providing a Brain-Machine Interface BMI-based sensorimotor control of this device. The new system uses as input the ElectroEncephaloGraphy (EEG) signals of the user as well as vibrations produced by a bracelet containing vibrating motors whose frequencies are proportional to the forces measured by Force-Sensitive Resistors (FSR) installed on the fingertips of the prosthesis. Four combinations of three different feature extraction methods (CSP, WD, GSO) have been used to construct the feature vectors of the EEG signals collected by two different recording systems with different number of electrodes during the experiments performed with seven able-bodied and four amputee subjects. The classification/prediction performances of three machine learning algorithms (Artificial Neural Network, Support Vector Machine with linear and Radial Basis Function kernels) were then tested. The reported results provide a proof of concept for the use of a wireless BMI to control the main types of movement of myoelectric prostheses using an EEG system with less electrodes rather than a research-grade system.

Keywords—Brain-Machine Interface, Prosthesis, Feature Extraction, Motor Imagery

I. Introduction

Upper-limb amputations account for around 20% of the total number of amputations throughout the world, estimated to be about 65 million people [1]. From those 20%, the World Health Organization (WHO) consider that only 10% have access to prosthetic devices, mainly because of the high cost of the commercially available and certified devices and the lack of personnel and infrastructures [2]. Nevertheless, in a survey conducted by Biddiss & Chau regarding the factors of prosthesis abandonment [3] the team noted that 10 to 50% (depending on the age) of users of upper-limb prostheses have stopped to use their devices as it is considered inconvenient for daily-use, mainly because of the fatigue, the weight, the lack of comfort or because their dexterity is "just as or more functional without it". One can also notice that the absence of sensory feedback in the prosthesis is a significant factor of rejection among users. It is indeed known that myoelectric prostheses - which are based on the use of surface ElectroMyoGraphy (EMG) electrodes to control movements on the device - come with some limitations, for example the stump on the arm of user is subject to constant [illegible] from the prosthesis socket can also make it difficult to properly catch the muscular activity. Those disadvantages offer room for the development of a new system that would go beyond the traditional myoelectric control of the prostheses, in order to improve both the dexterity and the robustness of prostheses for activities of daily living.

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Brain-Machine Interfaces (BMIs) - which allow a user to control various end effectors through the recording and decoding of its brain activity - possess what seems to be an ever growing popularity, evolving both in research and in the general population with great promises. Moreover, an important fraction of the research done on that matter focuses on medical applications of BMIs, particularly for neurorehabilitation in the case of motor impairment following a stroke [4-6] or a spinal cord injury [7,8].

The use of BMIs relies primarily on the good recording of the brain activity of a subject; it is commonly divided in three distinct categories: invasive, semi-invasive and non-invasive [9]. Invasive BMIs use microelectrode arrays implanted directly in the region of interest of the cortex (e.g. the Motor cortex for movement-related applications) that record the activity of a population of neurons [10]. Similarly, semi-invasive recording techniques use a grid of electrodes (also known as ECoG, for ElectroCorticoGraphy) implanted subdurally over the cortex and measure cortical field potentials [11,12]. While offering an excellent signal for BMI applications, those two techniques, as their name suggests, require an important surgical procedure with a decrease of performance over time due to the degradation of the signal coming from the electrodes [13-15]. Despite suffering from its own limitations (mainly a poor signal-to-noise ratio and low spatial resolution of the signal, as well as a long preparation time on a subject), the non-invasive recording of brain activity with ElectroEncephaloGraphy (EEG) is widely common in research, from behavioural research on cognition processes [16] to medical diagnoses [17,18] or neurofeedback treatments [19,20] and even video games [21]. It is also probably the most exploited method for the development of Brain-Machine Interfaces applications thanks to its ease of use and good temporal resolution of the signal, which makes it a promising candidate for the control of prosthesis on a daily basis.

However little has yet been done on that topic, as the current focus concerns the increase of EMG electrodes to recognize muscular patterns of activation when performing different movements [22]. One can also note the use of the Targeted Muscle Reinnervation (TMR) procedure [23,24], which consists in using severed nerves of a patient by relocating them in a new muscular area (e.g. in the chest), giving more possibilities to control a device as well as reducing the pain coming from the injured peripheral nerves [25]. Nonetheless, despite the improvement in the control of prostheses this technique still requires a surgical procedure which reduce the possibilities of a large-scale implementation, leaving some space for the EEG to fill those gaps.

Up until recently, the work from the laboratory was centred around the studies of invasive BMIs for the kinematic and dynamic control of robotic hand & arms [26,27]. The latest study (submitted) reports a performance analysis of mimicking grasp movements by two different robotic hands controlled by BMIs using invasively and non-invasively recorded brain activities as inputs.

In this paper, we will present the preliminary data analysis and development results of our ongoing project conducted in collaboration with the international prosthesis manufacturer Otto Bock (Duderstadt, Germany) and the rehabilitation center Institut Robert Merle d'Aubigné (IRMA, Valenton, France) aiming at the development of an EEG-based BMI for the sensorimotor control of hand prostheses. In parallel to the design & development work seven healthy and four amputee subjects, wearing two different EEG caps, participated to the experiments during which they performed or imagined different types of grasp movements while their motor execution (ME) and motor imagery (MI) signals were respectively recorded. Movements of interest for the control of the prosthesis were then estimated using various combinations of feature extraction and decoding algorithms, and the results of this first analysis phase of the project concerning the movement type estimation performance of the proposed BMI system using EEG signals in MI condition will then be reported.

II. Materials & Methods

The main role of the interface part of a BMI system is to decode what should have been coded in the recorded brain activity, the desired hand motion in our case, and it is composed of two main modules: a) Feature extraction of the recorded EEG signals and b) Estimation of the desired hand motion. On the other hand, a BMI system aiming to be employed for routine use does not only need to be robust, reliable and reproducible in prediction performance of the desired motion but it also needs to be ergonomic and easy to use. Therefore, the work on such systems should also consider an optimisation of the design parameters of the final product among which the number of EEG electrodes (which for example might be installed inside a baseball cap) as well as the training/calibration time of the used machine learning algorithms would be the most important ones.

The critical issues which would affect the performance of a robust daily-life control of the myoelectric prosthesis can be grouped into three sets of problems/questions that need to be answered:

1) Recording of the brain activity: which type of EEG system is suitable for this application? Which brain regions should be recorded to get the highest prediction performance? What is the minimum number of electrodes that we need to use to achieve a satisfying control level?

2) Feature Extraction & decoding of the brain activity: Which feature extraction and decoding algorithms and/or combination of these two can provide the best motion prediction performance? Here we will propose a feature extraction pipeline as well as classification algorithms that are offering promising performances regarding the control of the prosthesis.

3) Sensory Feedback: What is the contribution of the sensory feedback on the performance of the BMI system?

This study focuses particularly on the work on the signal processing, data analysis and training/learning processes in the aim of proposing solutions to the problems of the second group.

A. *Participants*

Seven healthy participants (3 females and 4 males, 5 Right-handed, 2 Left-Handed, 29.8 ± 13.3 years old,) composing the control group and four amputated subjects (4 males, 2 transradial amputations of the left hand and 2 of the right hands, 58.25 ± 3.86 years old) participated in this first phase of experiments. All participants were given information in oral and written forms before giving written informed consent to participate in the study. The protocol was performed in accordance with the Declaration of Helsinki**.** The criteria of inclusion for the amputated subject were the following: person above 18 years old with a transradial amputation and user of a myoelectric prosthesis. All amputees but Amputee #3 declared using their myoelectric prostheses - a polydigital hand (Michelangelo©, Ottobock) – on a daily basis, the third amputee is using his prosthesis (Myobock SensorSpeed©, Ottobock) occasionally.

B. *Experimental Setups*

Two experimental setups (see Fig.1. A & B) were developed to perform experiments and recordings with healthy and amputee subjects using two EEG caps with different number of electrodes and different sampling rates but placed following the 10–20 position system andreferenced to the CPz electrode for each system.

Fig.1. A) Experimental Setup for Healthy subjects: Continuous EEG data were collected from 63 actiCAP EEG electrodes (BrainProducts GmbH) mounted on an elastic cap using the PyCorder system on the recording computer and actiCHamp amplifiers (BrainProducts GmbH, Gilching, Germany) with a sampling rate of 2000 Hz. The second computer was running the experiment on a custom script written with MATLAB 2016b (Mathworks, Navick, MA) using the Psychophysics Toolbox [28]. B) Continuous EEG data were collected from 16 sintered EEG electrodes (OpenBCI, United States) mounted on an elastic cap using the BrainFlow library on the recording laptop and the Cyton+Daisy boards with a sampling rate of 125Hz. The recording laptop was also used to run the experiment via a custom C++ program written and compiled on the QT IDE (QT Creator 4.13.3). C) Modified myoelectric prosthesis controlled by EEG signals and the sensory feedback devices. (from left to right: the vibration bracelet and force-sensing resistors).

A modified Myobock hand prosthesis, allowing the control of the prosthesis via the EEG signals of the user, and a sensory feedback system (Fig.1.C), composed of force-sensing resistors and vibration motors communicating via Bluno microcontrollers, were used during sessions with amputees.

C. *Experimental Protocols*

The experiments with the amputees were realised in three sessions occurring in three different days (with at least ten days between two sessions) while the experiments with healthy subjects were composed only of the second phase experiments with ME and MI conditions of the first session done with amputees, but repeated three times.

1) *Protocol for amputated subjects*

a) First session: Subject dexterity prior to the use of the BMI system

This session is composed of two phases. In the first phase the subjects were asked to do three tests with their own prosthesis in order to evaluate their dexterity prior to the use of the Myobock controlled by our BMI system. The first test is called the *Box and Blocks Test* (BB) and is widely used in rehabilitation to evaluate the object manipulation performance of the subject [29]. The setup is composed of an opened wooden box, divided in the middle with a board. One side of the box contains cubic wooden blocks (2.5 x 2.5 x 2.5cm) and the subject is asked to move as many blocks as he can on the other side of the box in 1 minute. It is reminded that the subject has to move blocks one at a time and that if the subject moves two or more blocks at the same time, only one will be counted for the final result. The total number of blocks moved is used as the outcome score for the test. The second test is derived from [30] and is called the *Cup Relocation Test* (CUP), it consists in 11 plastic cups stacked on each other and placed bottom-up on a plank. The subject is asked to move 10 plastic cups (one cup at a time) from a position ipsilateral to the subject's amputation side to a position located 30 cm towards the contralateral side, as fast as possible. The time needed to move the 10 plastic cups is used as the performance score. The final task is called the *Clothespin Relocation Test* (CS) and is inspired from the work in [31]. The subject is asked to relocate four plastic clothespins from a horizontal position to a vertical position, the plastic clothespins could vary in the force needed to open them. The time needed to relocate the four pins is used as the performance score for the test. Each of the three test were repeated five times in order to have a more accurate measure of the subject's performance.

In the second phase of this first session, we asked the subject wearing the EEG cap (OpenBCI) seating comfortably on a chair and looking at a computer screen to perform a sequence of movements using the same objects used in the first phase but following the visual and audio instructions sent by the computer according to the sequence seen in Figure.2 and in two conditions: *Motor Execution* (ME), where the subject actively performs the movement with his own prosthesis, and *Motor Imagery* (MI), where the subject imagines of performing the movement. Based on the feedback of the first amputated subject we modified the experimental protocol for the MI condition by removing the random time windows (1 second for the **Go** step, and 2 seconds for **Move**) and by reducing the time in the Grip step (2 seconds instead of 3). The experiment consisted in 30 trials with each object and for the two conditions, on which was added the recording of 10 trials of neutral/baseline activity where the subject was asked to simply look at the screen without performing or thinking of any movement. Finally, the subject was instructed to reduce as much as possible the eye blinks during the movement.

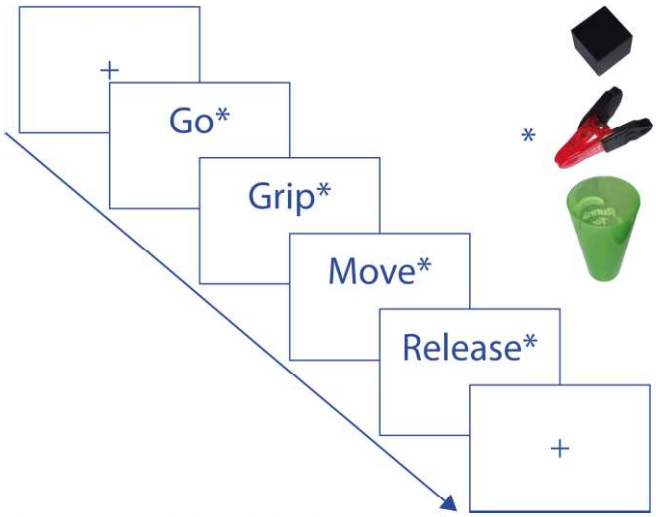

Fig. 2. Sequence of phases during the EEG recording. It is composed of 6 successive steps, the 1st and 6th steps are fixation crosses lasting 1 second each where the subject has no action to perform/imagine. The 2nd step (**Go**) instructs the subject to go to the object represented on the screen, a random time window (1 to 2 seconds following this spacing: 1s, 1.25s, 1.5s, 1.75s, 2s) is used to alleviate the habituation effect coming from the repetition of the sequence. The 3rd step (**Grip**) asks the subject to grasp the object with his prosthesis and lasts 3 seconds. The 4th step (**Move**) asks the subject to move the object to his right or to his left (depending on the previous motion done). Similarly to the **Go** step the **Move** step contains a random time window of 2 to 3 seconds. The 5th step (**Release**) asks the subject to release the object and to go back to his/her initial position. This step lasts for 2 seconds. The asterisk * indicates that one of the three objects presented on the right of the figure was used in the corresponding phases.

b) Second session: ME and MI

The second session consists in experiments with EEG recording identical to the ones presented in the first session but with an important difference in the ME condition; instead of using his original prosthesis the subject uses a modified Myobock prosthesis that is connected to the computer. The PC is controlling the opening and closing of the hand in the **Grip** (Closing) and **Release** (Opening) steps during the experiment. This ME, that we call MEP (for Motor Execution with Prosthesis), recording is thus changing into a hybrid (or

intermediate) condition between the classic ME condition and the MI condition as the subject is now seeing his prosthesis being opened or closed without the motor command coming from the EMG electrodes.

At the end of the recording session, the sensory feedback is tested for a few minutes on the subject to give her/him an idea of the content of the third recording session.

c) Third session: Sensory feedback

The third recording session is identical to the second (MEP and MI) except for the addition of the sensory feedback system in the MEP condition, which adds sensory information to the user during the **Grip**, **Move** and **Release** steps of the sequence.

2) Protocol for control subjects

The sequence of movements and number of trials for control (able-bodied) subjects are identical to the ones defined in the first session of the experimental protocol for amputated subjects (Fig.2.) in ME and MI conditions. At this phase of the study the control subjects did not perform the experiments of the second and third session using the apparatus allowing them to control a prosthesis with their EEG signals and with or without sensory bracelet.

D. EEG Signal Processing

1) Preprocessing

EEGLAB functions were used to segment the trials and retrieve the data from the **Grip** and **Release** steps from the EEG files recorded with the ActiCHamp system [32]. To speed up the computation time, each trial was downsampled from 2000Hz to 250Hz. Similarly, the OpenBCI data were segmented but the sampling rate was kept at 125Hz (internal limitation of the system). We only kept the first second of each trial after the stimulus onset on which an infinite impulse response notch filter set at 50Hz and a 4th order Chebyshev type II bandpass filter between 8 and 30Hz was applied, to minimize noises and artefacts on the trials. In order to increase the size of the dataset and minimize the effect of imbalanced classification, the analogy method from [33] was used so that each class now contains 90 trials. The method consists in computing a ratio between two trials of the same class (using its principal components) and applying this ratio to a third trial of the class to create a new and artificial trial. We considered the movement *Close* (full closure of the hand) as the motion type of the **Grip** step of both the BB and CS objects while the movement *Half* (half closure of the hand) was considered as the motion type only of the **Grip** step of the CUP object. The *Open* movement (full opening of the hand) is a state in common for the **Release** steps of BB, CS and CUP. Finally, the neutral/baseline condition is considered to be *Rest*. Then the z-score of each trial was computed and used as the starting point for the feature extraction pipeline.

2) Feature Extraction

In the following we first present the feature extraction techniques we used in constructing the input vector contents to the classification algorithms. We then study the effect of the use of different combinations of those techniques in the classification performance of the two decoding algorithms used in the current version of the proposed system.

a) Common Spatial Patterns (CSP)

The Common Spatial patterns technique is probably the most commonly used spatial filtering technique in BMIs [34-36]. This method is applied mainly to binary classification; it consists in computing a transformation matrix W that is maximizing the variance of the signal for one class while minimizing it for the other [37]. Finding the optimal transformation matrix W requires to solve:

$$w_c = \max_w w^T \Sigma^{(c)} w \ \ with\ c = 1, 2 \qquad (1)$$

$$with\ w^T (\Sigma^{(1)} + \Sigma^{(2)})\, w = 1 \qquad (2)$$

$\Sigma^{(c)}$ being an estimate of the spatial covariance matrix of class c. Using the Generalized Eigen Value Decomposition (GEVD), the solution to this optimization problem is the transformation matrix composed of the eigenvectors corresponding to the maximal and minimal eigenvalues obtained from $\Sigma^{(1)}$ and $\Sigma^{(2)}$.This technique is applied here to four movements (Open, Close, Half, Rest) using a One-vs-One approach, leading to the computation of six different transformation matrices W ((n*(n-1))/2 = 6, with n = 4, the number of movements to classify). 6 pairs of CSP filters were kept using the setup with healthy subjects while 8 pairs were kept in the setup with amputee subjects, thus giving a matrix size of (m, n, 90) for each of the projection (with m = 248, 124 and n = 12, 16 for the ActiCHamp and OpenBCI EEG systems respectively)[37].

b) Wavelet Decomposition (WD)

The EEG signal is known to be non-stationary meaning that its properties are changing with time, thus by applying traditional techniques such as the *Fast Fourier Transform* (FFT) it is possible that one can miss relevant information regarding the movements. Applying the Wavelet Decomposition method allows to retrieve Time-Frequency information on the original signal [38]. For this operation a function called the Mother Wavelet – which starts at zero, briefly oscillates and comes back to zero – is scaled and translated to create a set of wavelets on which the signal is convoluted with. Here a Daubechies 4 mother wavelet has been used. Two filters are used to convolute the signal: a low-pass filter (LPF) and a high-pass filter (HPF). Following the convolution, a downsampling is done on the two filtered signals and the approximation coefficients a and details coefficient d are obtained. To continue the decomposition to further levels, the approximation coefficients are considered as the base signal for the next decomposition. As the WD technique keeps frequency information of the signal it is possible to choose the decomposition level based on the frequency band of interest of the signal, for this article we chose a 2-level decomposition for the OpenBCI EEG system and 3-level decomposition for the ActiCHamp EEG system to fall approximately in the 0-32Hz frequency band. We decided to use the approximation and detail coefficients from the last level – sufficient for the reconstruction of the original signal with inverse WD – for the next step of the feature extraction process. After the CSP computation, we obtain 12 signals as each of the 6 transformation matrices is used to project the signals of 2 different classes, we thus apply the WD on those 12 signals which gives us a matrix size of (m',

n, 90) (with m' = 62 and n = 12, 16 for the ActiCHamp and OpenBCI system).

c) Gram-Schmidt Orthonormalization (GSO)

From the features vectors composed of the wavelet coefficients, a basis $q_{c,f}$ (with $c = 12$, corresponding to the numbers of comparisons signals and f the number of filters kept after the CSP step) is obtained by orthonormalization following the Gram-Schmidt procedure [39]. For each of the c comparisons and f filters a projection matrix $T_{c,f}$ is computed from the $q_{c,f}$ bases and used to project the feature vectors obtained during the previous step. As we are comparing two different classes, we also use the projection matrix $T_{c,f}$ of the first class to project the feature vector from the other class. Finally, for each projection the logarithm of the variance is calculated and the values obtained are used to build the input vectors for the classification algorithms.

3) Input vectors

With this article we aim at comparing different feature extraction methods by using a combination of the three processing techniques we described. The first method is CSP+WD, the application of CSP then WD in the FE, leading to 6 binary classification model with inputs sizes of 180 x 12 or 180 x 16, for the ActiCHamp or OpenBCI systems respectively (90 trials for the first class and 90 for the second). The second method is CSP+GSO, it gives 12 binary classification models with once again inputs sizes of 180 x 12 or 180 x 16 for the two system. The third method is WD+GSO, for this one we obtain 12 models and the input size is either 180 x 63 or 180 x 16 as we decided to keep all the electrodes during the FE. Finally, the last method is CSP+WD+GSO, the application of the three techniques, it leads to 12 binary models with inputs sizes of 180 x 12 or 180 x 16, similar to the CSP+GSO method.

4) Classification

The training performance has been obtained offline on Matlab 2021a using three different classification algorithms: An Artificial Neural Network (ANN) with a Training/Validation/Test split of 70%-15%-15%, and two Support Vector Machines (SVM) with a Training/Test split of 80%-20% using a Linear and a Radial Basis Function (RBF) kernels. The Accuracy, Precision and F1-score metrics were computed for all the models and for the three classification algorithms.

III. Results

As our BMI control system uses classification algorithms that need to be trained by the user, one of the most important issues concerning the easy use of the final product would be to get the amount of data necessary to train the classification algorithm in a reasonably short time. In machine learning, extending the training dataset by adding to the originally recorded signals an artificial data set is commonly used to increase the amount of data without increasing its collection, especially in image classification [40]. Fig.3. shows the standard deviations of original and artificial data obtained for seven different pairs of electrodes using the data augmentation method described in II.D.1..

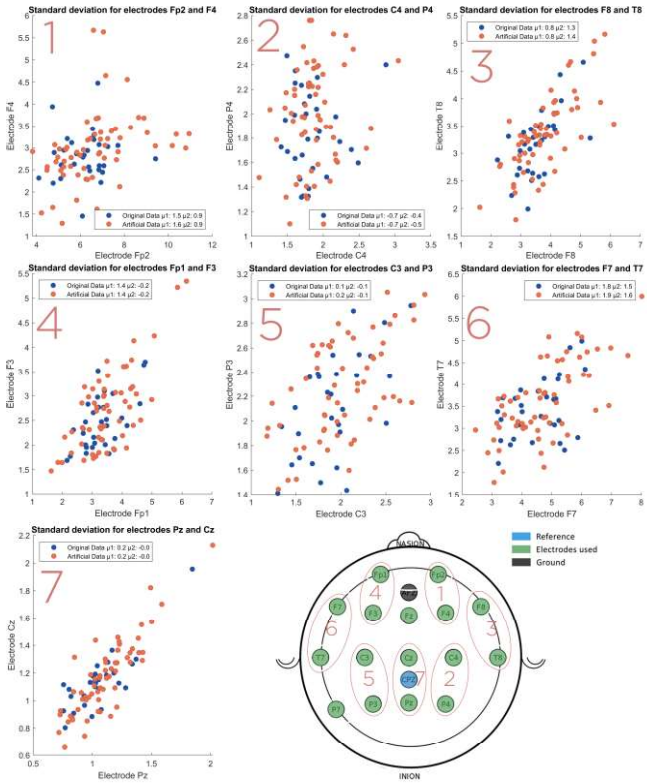

Fig. 3. Distribution of the standard deviation for the trials obtained from the recording using the object noted as CUP (a plastic cup) with the OpenBCI EEG system. The Original (in blue) and Artificial (in red) trials are here represented for several pairs of electrodes. The results are presented here for the first amputee.

Following the order of the critical issues evoked in session II and particularly the second group, we first wanted to explore the training performance of different combinations of the 3 feature extraction techniques (namely CSP, WD and GSO) described respectively in section II.D.2. Four different combinations, namely CSP+WD+GSO, CSP+WD, CSP+GSO and WD+GSO, have been studied. Fig.4. shows the distribution of the log variances corresponding to the first and last variables of the input vector (1st and 12th for CSP+WD+GSO, CSP+WD & CSP+GSO, and 1st and 63rd for WD+GSO for two extreme types of hand movements (Close and Rest), which can be controlled on the Myobock. As it can easily be seen in Fig. 4., results obtained by using CSP+WD are the most promising ones.

We then studied the accuracies of the classification performance of four different types of desired hand positions obtained by different classification algorithms. Table 1, Table 2 and Table 3 represent respectively the accuracies of the ANN and SVMs classification results for several combinations of the Feature Extraction techniques described in II.D.2 obtained from the first session in Motor Imagery with the control and amputee groups.

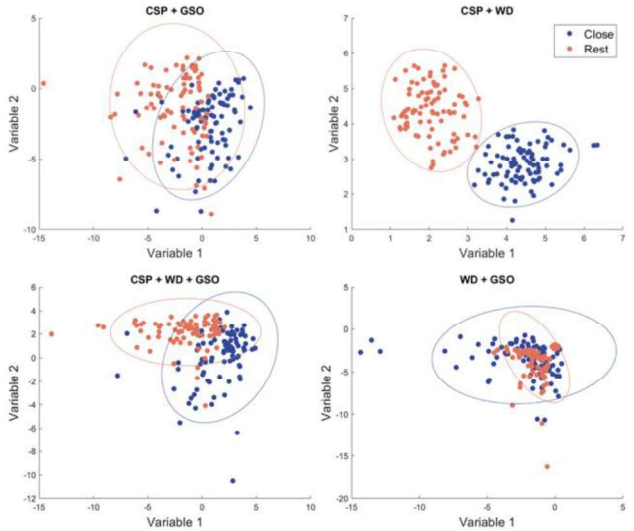

Fig. 4. Distribution of the log variances of the input vectors for the comparison between the movement Close and Rest when using different combination of feature extraction techniques.

The use of a fast and efficient Feature Extraction method in constructing the inputs to the classification/prediction algorithm is also critical for such applications with real-time processing needs. For the first part, we showed in Table 1 that the combination of CSP & WD gives the most promising results both for the two groups of subjects (above 90% of accuracy for the Control group, and above 70% for the amputees). While the Feature Extraction could probably have given similar results if it stopped after the application of the CSP technique, the addition of WD allows a reduction of the size of the signal, as only the coefficients from the last level of the decomposition were kept. This is of course not so important for a research work (offline study) aiming at searching for the best feature extraction method but it will reveal of extreme importance when we will tackle a real-time control of the prosthesis, as we need to continuously process data and thus need that processing to be done as fast as possible. Even though the addition of the GSO was found to be interesting we selected the CSP+WD as the feature extraction method to be used for the remaining part of the study by taking into account those aspects. Figure 4 also confirms those results by representing how the partitioning of the features space by the two classes is more clear/distinct for the combination of CSP+WD comparing to the other possible combinations.

Table 1. Mean accuracies across participants for the two groups of subjects with four feature extraction techniques using an ANN.

	Groups	Close /Half	Close /Open	Close /Rest	Half /Close	Half /Open	Half /Rest	Open /Close	Open /Half	Open /Rest	Rest /Close	Rest /Half	Rest /Open
CSP+ WD+ GSO	Control	0,776	0,635	0,883	0,710	0,699	0,901	0,631	0,660	0,876	0,873	0,918	0,855
	Amputees	0,656	0,586	0,948	0,634	0,697	0,946	0,557	0,573	0,926	0,944	0,947	0,943
CSP+ GSO	Control	0,767	0,676	0,904	0,749	0,731	0,899	0,663	0,717	0,894	0,907	0,911	0,889
	Amputees	0,658	0,589	0,944	0,627	0,694	0,941	0,571	0,583	0,921	0,937	0,950	0,949
WD+ GSO	Control	0,638	0,514	0,839	0,641	0,632	0,884	0,529	0,601	0,828	0,862	0,901	0,844
	Amputees	0,612	0,553	0,776	0,651	0,603	0,862	0,534	0,577	0,824	0,853	0,868	0,854
CSP+ WD	Control	0,987	0,954	1		0,974	1			1			
	Amputees	0,902	0,752	0,993		0,839	0,997			0,994			

Table 2. Mean accuracies across participants for the two groups of subjects with four feature extraction techniques using a linear SVM.

	Groups	Close /Half	Close /Open	Close /Rest	Half /Close	Half /Open	Half /Rest	Open /Close	Open /Half	Open /Rest	Rest /Close	Rest /Half	Rest /Open
CSP+ WD+ GSO	Control	0,793	0,662	0,906	0,725	0,731	0,922	0,666	0,689	0,903	0,869	0,927	0,872
	Amputee	0,693	0,617	0,946	0,680	0,730	0,950	0,592	0,614	0,932	0,911	0,908	0,917
CSP+ GSO	Control	0,764	0,644	0,875	0,701	0,716	0,901	0,660	0,689	0,887	0,863	0,914	0,861
	Amputee	0,690	0,614	0,943	0,665	0,726	0,954	0,591	0,607	0,933	0,906	0,912	0,916
WD+ GSO	Control	0,676	0,549	0,852	0,688	0,655	0,886	0,570	0,672	0,842	0,862	0,897	0,848
	Amputee	0,693	0,617	0,946	0,680	0,730	0,950	0,592	0,614	0,932	0,911	0,908	0,917
CSP+ WD	Control	0,989	0,964	1		0,978	1			0,999			
	Amputee	0,908	0,781	0,998		0,842	0,997			0,996			

Table 3. Mean accuracies across participants for the two groups of subjects with four feature extraction techniques using a RBF SVM.

	Groups	Close /Half	Close /Open	Close /Rest	Half /Close	Half /Open	Half /Rest	Open /Close	Open /Half	Open /Rest	Rest /Close	Rest /Half	Rest /Open
CSP+ WD+ GSO	Control	0,839	0,683	0,947	0,793	0,760	0,955	0,675	0,728	0,932	0,947	0,970	0,938
	Amputee	0,800	0,655	0,957	0,800	0,793	0,954	0,582	0,688	0,940	0,954	0,949	0,957
CSP+ GSO	Control	0,825	0,672	0,934	0,787	0,769	0,949	0,675	0,716	0,917	0,947	0,962	0,922
	Amputee	0,787	0,647	0,954	0,802	0,788	0,953	0,600	0,690	0,948	0,953	0,946	0,959
WD+ GSO	Control	0,810	0,596	0,959	0,799	0,763	0,974	0,609	0,760	0,949	0,965	0,980	0,958
	Amputee	0,781	0,608	0,906	0,794	0,762	0,937	0,588	0,713	0,922	0,944	0,952	0,944
CSP+ WD	Control	0,989	0,958	1		0,978	1			1			
	Amputee	0,935	0,774	0,995		0,873	0,998			0,997			

Finally, the three different classifiers we used in this work to decode the desired motions provided very close prediction performances without any statistically significant difference, confirming the results we reported in our previously published [26] and submitted work. Moreover, among these three classifiers, the two SVMs were the fastest to train (around 2 minutes) while the ANN (around 10 minutes) presented significantly longer training time. This allowed us to designate the SVM with a linear kernel as the potential decoding algorithm in the future work, being the fastest classifier to train and the simplest one to use in a real-time application.

From the results summarized above, we can say that the use of a wireless EEG system, with less electrodes rather than a research-grade system, can give satisfying results when looking at the classification performances of the four movements, which are the movements that can be performed by this type of prosthesis. Indeed, the results reported on the fig. 5 show how the classification performance in the Control and Amputee groups evolves in the same range for the different binary classification models, a range that is much higher than the chance level in the case of binary classification (50%) when we match the electrodes on the two recording systems.

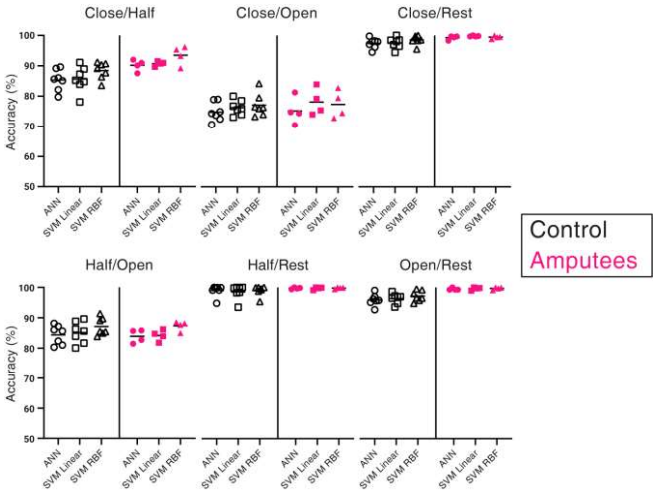

Fig. 5. Comparisons of the performance between the Control group (in black) and the Amputees (in pink) using three different classification algorithms (ANN, SVM Linear & SVM RBF, respectively the circle, square and triangle symbols) after feature extraction with CSP+WD, using the same locations of electrodes for the two EEG systems.

IV. Discussion

This study investigates the use of a Brain-Machine Interface to control a commercially-available myoelectric prosthesis (Myobock©, Ottobock). Even though the current research project is being conducted on the three groups of problems evoked in II, due to difficulties concerning the recruitment of both able-bodied and amputee subjects for the experiments with the Covid-19 pandemic conditions, the results reported in this article are the ones obtained by processing the EEG signals recorded during the first session of the experimental protocol for both groups.

One of the first aim of this work is to propose to the potential users of the BMI system a reduced calibration time, comprising both the recording of the EEG signals and their processing. The data augmentation technique we used [33], is a promising solution to answer to such needs. The results presented in Fig. 3. confirm that the original and artificial data sets occupy the same feature space, which supports the use of this technique. Therefore we always used the augmented dataset in the remaining steps of this study.

The final evaluation step of the project will be the comparison of the scores obtained during the three tests (BB, CUP, CS, described in the first session of the experimental protocol for the amputee subjects) with the scores of these subjects obtained while they use the modified prosthesis. Only one amputee among four could finish the three sessions and realized a first trial of using the modified prosthesis together with the vibrating bracelet to perform a CUP test. Therefore, the ongoing development and research phase of our project focuses particularly on performing the experiments with more amputee subjects for all three sessions. Secondly we aim to be able to perform the experiments of the three sessions also with the control subjects, by allowing them to use a copy of the modified prosthesis and control it with their own EEG signals and use the vibrating bracelet.

Nonetheless, we are well aware that the results presented here are only preliminary ones and that we require more subjects in both the control and amputee groups to bring answers to the various issues we raised in this article. In particular, there is a need to analyze the potential changes on the control performances which, would occur with the amputees all along the three sessions: would the training of the task give higher performance? or does it stay the same over time for the two groups? Can we see distinct activation patterns on the EEG recordings? Does the addition of the sensory feedback change anything on the decoding and control performances?

We will be obtaining more clear and concrete answers to those questions as the experiments go by, but the presented results show a promising proof of concept for the efficiency of the use of BMIs for the control of myoelectric prostheses for amputees.

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