

Control of a Soft Robotic Glove Using a Brain Computer Interface based on Movement Related Cortical Potentials

Giorgio Frego

Department of Electronics and IT, Aalborg University

Abstract- This paper investigates a Brain Computer Interface (BCI) system using the Fast Brain Switch (FBS) paradigm. The endogenous sensory discrimination is implemented through a Graphical User Interface (GUI), while the detection of Movement Related Cortical Potentials (MRCP), using a single channel classifier, is the applied brain switch. The system was employed to control a robotic glove. Classifications results from online tests on six subjects resulted in average precision and recall of 61% and 68%, respectively. Furthermore, the similarity between the movements that generated the MRCP was investigated using a newly defined metric that could be used for feature selection.

Index Terms- Movement Related Cortical Potentials, MRCP, Brain Computer Interface, BCI, Electroencephalography, EEG, Soft Glove Control

I. INTRODUCTION

The idea of controlling things using the mind has always been fascinating. Brain Computer Interfaces (BCIs) are the technology that, although limited, can make it happen. BCIs are a subset of computer interfaces that rely on brain signals as means of control. They have been used for communication [1], control, neurorehabilitation as well as recreational purposes [2] [3]. BCIs have four main components: an acquisition system, a component that interprets the acquired inputs, a component that provides feedback to the user, and finally, an operating environment that supervises how these three components interact with each other and with the end-user [4]. Usually, the fourth component is the computer that runs all the programs.

Most BCIs acquire the initial input from electroencephalography (EEG) or electrocorticography (ECoG), though systems that use other acquisition methods such as functional magnetic resonance imaging (fMRI) [5] or magnetoencephalography (MEG) [6] exist. Systems that use EEG or ECoG can target different kinds of brain signals for the interpretation of user intention. Some target signals are P300 [7], Event Related De/Synchronization (ERD/S) [8], and Movement Related Cortical Potential (MRCP). The targeted signals can be self-generated or generated when the user focuses on an external stimulus.

MRCPs are an endogenous EEG signal generated by movement execution or imagination [9]. The MRCP is a slow cortical potential (<5 Hz) with a very distinctive

shape in the EEG signal. It is characterized by a negative slope that starts up to 2s before the movement onset [10], becomes steeper around 300 to 400ms before the movement, reaches the maximum negative peak close to the movement onset [11], and rebounds to the baseline in 1 to 1.5s [12] [13]. MRCPs are generated both when the movement is self-paced or cued by an external stimulus, furthermore, no training is needed to generate them as they are naturally produced, making them a good choice for the detection of movement intention. Because of that, many movement-related BCIs have used MRCP detection as a control signal [14] [15] [16] [17].

To detect MRCPs, some studies suggest the use of Convolutional Neural Networks (CNN) [18] [19] while using 60 or more EEG electrodes. Others focus on a smaller amount of electrodes and the use of Locality Preserving Projection combined with Linear Discrimination Analysis (LPP-LDA) [20] [21] [15], Independent Component Analysis (ICA) [22] [23] or Support Vector Machine (SVM) [24] [25] [16] [17].

The main drawbacks of the CNN approach are the high number of electrodes required and the necessity of large training sets, furthermore, a recent study suggests that SVMs are the most prominent classifiers for MRCP detection [25].

Even though the MRCP shape contains information on the force and speed of the executed movement [11], and the detection of different speed and force levels is possible [24], increasing the complexity of the detection lowers the True Positive Rate (TPR) [24], consequently more complex classification methods are usually performed offline. To allow for multiple commands, a recent study [12] has introduced the concept of a Fast Brain Switch (FBS). The concept is to remove complexity from the detection and add complexity to the user interface. The user is cyclically offered different sensory stimuli at different times, with each stimulus corresponding to a different command. When the offered command corresponds to the desired command by the user, the user performs the action to generate the MRCP by imaging of performing the movement, activating the desired command [21] [26]. Previous studies have proposed the use of the FBS paradigm to control robotic devices but did not evaluate their systems on actual robotic devices.

The paper proposes an FBS-graphical user interface to control a robotic glove using single-channel MRCP detection as FBS. It also compares the similarities in the

MRCPs generated by two tasks, described in (II.D.1) and (II.D.2), as they both needed to be used as movements for generating the MRCP detection, as explained in (II.D), using the same classifier.

The online classifications results are reported in (III.A) and discussed in (IV.A). The results of the comparison between the MRCP generated while performing the two tasks are presented in (III.B) and discussed in (IV.B).

II. METHODS

A. Subjects

Ten healthy male subjects (mean age 25.30 ± 2.45 years), denoted S0- S9 participated in the experiment. Besides S0, S3, and S4 no subject had any previous experience with BCI systems before the experiment. All subjects but S4 were right-handed. All subjects signed an informed consent form. Due to the difficulty of finding subjects caused by the Coronavirus outbreak, each subject was shared with another experiment.

B. Robotic Glove

The SEMTM Glove from Bioservo Technologies [27], was the robotic glove used in the experiment. The glove, shown in Fig. 1, can support the user providing different levels of additional force to the thumb, middle and ring finger while grasping. The glove is driven via tendons pulled by a motor attached around the waist. However, it does not provide active opening assistance. Nevertheless, in the following section, the glove releasing the tension will be undifferentiated to the opening of the hand.



Fig. 1. Different views of the SEMTM Glove from Bioservo Technologies [27]. Top left, back view of the glove, top right, lateral view of the glove, bottom left frontal view of the glove, bottom right, glove while holding the bottle. The subject is also wearing a blue plastic glove to follow the coronavirus health guidelines. In the background of the bottom right picture the box containing the motor and controller of the glove is present.

C. Data Acquisition

EEG data was collected using a g.USBamp amplifier with a g.GAMMAbox, through ten g.LADYbird passive electrodes, one g.LADYbird ground electrode and one g.GAMMAsys reference electrode, produced by g.tec [28]. Electrodes were placed following the international 10-10 system [29] in positions F3, FC1, FC5, Cz, C3, T7, CP1, CP5, P3, Fp1, and Fpz. Fpz was set as common ground and Fp1 was used to track electro-oculography (EOG) artifacts. The reference electrode for the EEG

acquisition was placed on the left earlobe. All EEG electrodes were set as monopolar.

Two Ambu[®] Neuroline 720 wet gel disposable electrodes for electromyography (EMG) were placed on the muscle belly of the hand extensor muscle located by palpation next to each other in a bipolar setting. The electrodes were connected to the amplifier through two EMG clip leads. The electrode closer to the elbow was used as reference for the EMG, while the EEG electrode in Fpz was used as ground. Sampling rate for all electrodes was set at 1200 Hz. Matlab 2017a was used as software for the acquisition, data elaboration, and the handling of each part of the setup. Fig. 2 shows the setup for the experiment.

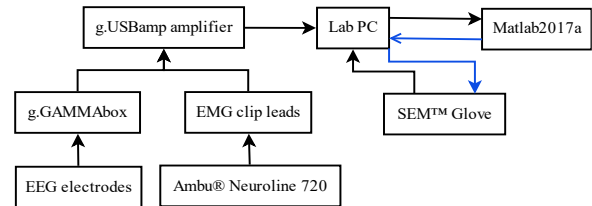


Fig. 2. Configuration of the setup during the experiment. The SEMTM Glove was connected only during the online phase.

D. Experimental Protocol

The experiment consisted of 4 recording sessions and one optional online session performed on the same day. The subjects went through the unrelated study between the last recording and the optional online phase. The first two recordings were executed to compare the MRCP generated by reaching and grasping a bottle with the ones generated by squeezing a bottle. This was done because neither of the two actions could be used on its own to generate commands for the FBS, as you cannot squeeze an object you are not holding, and you cannot reach and grasp an object already within your grasp. The third and fourth recordings were performed to create a training and evaluation dataset for the classifiers.

For all the recording sessions the subjects were asked to sit in a comfortable position in front of a table. Each recording session consisted of repeating a combination of actions a determined number of times, with some resting phases in between actions. All the subjects were instructed to avoid blinking, swallowing, face and general head movements, while performing the instructed actions, and to wait at least 3 seconds before performing an action if one of these events occurred. The subjects were also instructed on focusing on performing the actions and avoiding counting the time between actions or the number of actions performed. All the actions recorded were self-paced, i.e., autonomously initiated. How to perform the action was explained verbally and by example before the start of the recording.

1) First Protocol: Reaching

The subject had to rest his right arm on the table. A bottle was positioned in front of the subject's right hand. The subject had to ballistically reach forward and grasp the bottle, holding it for a short period of time (less than 3s), place it in the same position, and return the arm to the previous resting state. Subjects had to perform these

actions 20 consecutive times. They were also asked to wait for what they felt was around 10s in the resting state.

2) *Second Protocol: Squeezing*

The second recording session was performed shortly after the first. The subject had to rest his arm on the table while having the fingers of the right hand around the bottle. The subjects were instructed to ballistically tighten their grip around the bottle for a short period of time (less than 3 seconds) and then return the hand and arm in the relaxed position while still having the finger around the bottle. Subjects performed this action 20 consecutive times, while resting in the relaxed state for what they felt was around 10 seconds.

3) *Third Protocol: Classification Datasets*

The third and fourth recording sessions consisted of a combination of the previous actions and were recorded a few minutes after the end of the second and shortly after the third recording session, respectively. The subject had to rest his right arm on the table while a bottle was positioned in front of the subject's right hand. The subject had to ballistically reach forward and grasp the bottle, hold it for a short period of time (less than 3 seconds), and then rest his arm and hand on the table while still having the fingers around the bottle. The subject had to rest for what he felt was around 10 seconds and ballistically tighten his grip around the bottle for a short period of time. After tightening the grip, the subject had to rest his hand and finger while still having the fingers around the bottle. After approximately 10s, the subject had to ballistically tighten his grip around the bottle for a short period of time, then place the bottle in the original position and return the arm and hand to the initial resting state. The subjects were asked to perform the placing of the bottle and return to the initial relaxed state as a single movement. The subjects performed this combination of actions 13 times, for a total of 39 recorded movements in each recording.

4) *Online Phase*

If the subject was not too fatigued after the unrelated study, an online phase was attempted. In the online phase, the subject wore the SEM™ Glove. A screen was positioned on the table in front of the subject. On the screen, the visual menu described in (II.G) was shown. A bottle was placed in front of the subject's right hand. The subject was instructed to reach and grasp or squeeze the bottle while trying to perform fifteen arbitrary commands using the menu, i.e., opening, closing the glove, or increase/decrease the force applied. After the fifteenth command, the subject was instructed on trying to give the command to open the glove if the glove was still in the closed state. True, miss, false, and delayed detection were manually annotated. Detections were annotated as true if the system registered the command when the action was performed, as miss detection if an action was performed but the system did not detect it, as false detection if the system detected an action while no action was performed, and as delayed if the system detected the action shortly after it was performed. Subjects were instructed to perform the movement only if they intended to perform

it, to aid in the distinction between true and false detections.

E. *Classification*

To train the classifier, the position of the negative peak (NP) of each MRCP was manually selected from the third recording. To aid in finding the positions of the NPs, locations were suggested based on a thresholding algorithm of the EMG signal. Segments of the EEG signal around the suggested locations ([-4, 2]s interval) were filtered and plotted. The exact location of the NP was then manually selected. An observation window of 2 seconds was then moved along the signals from channels F3, FC1, FC5, Cz, C3, T7, CP1, CP5, P3, as well as a Large Laplacian spatial filter channel centered in C3, obtained as $C3-(F3+FC1+FC5+Cz+T7+CP1+CP5+P3)/8$ [30]. The segments of the signals in the observation window were bandpass filtered from 0.05-3Hz using a second-order zero-phase Butterworth filter. If the NP was in the interval between 0.5s-1.5s of the observation window, the segments were labeled as movement, otherwise, they were labeled as rest. If the segment label was movement, the overlap between the observation window and the next was 98.75%, otherwise, the overlap was 75%. Windows where the maximum absolute amplitude of the EOG channel was above 100 μ V and windows where the maximum absolute amplitude for any of the EEG channels was above 50 μ V were discarded, because those amplitudes were assumed to be artifacts. From each observation window in each channel 29 features were extracted. The first 24 features were every 100th sample of the signal in the observation window. Features 25-27 were respectively the mean, slope, and standard deviation of the amplitude of the signal in the observation window. Features 28 and 29 were the value and position of the minimum amplitude in the observation window. A radial basis kernel with uniform prior SVM was then trained for each channel.

F. *Evaluation*

To determine which channel to use in the online phase, the performance of each channel's classifier was evaluated using the fourth recording. To increase the robustness to false positives, a dwell parameter was introduced [12]. The dwell number represents the number of consecutive observation windows classified as movement that needed to be detected before confirming the movement detection. To evaluate the performance of each classifier, the following pseudo-online approach was used. Observation windows of 2s with an overlap of 1.9s were moved along each channel of the signal. The features were extracted from the window and were provided to the classifier of the corresponding channel. To limit the number of detections to one per movement, 3s after a confirmed detection, i.e., respecting the dwell requirement, were skipped. To evaluate the detections, the locations of the movement execution were found using the EMG signal as reference. The detections were marked as follow: true detections were the first detection occurred within a 4s interval centered on the locations of the movement's execution; false detections were the detections occurred a second time, or outside, the 4s

interval around the movement's location; and miss detections were the number of movement's locations that were not detected by the classifier. Different dwell numbers were tested for each classifier and the minimum dwell that reduced the number of false detections by 70% or more was suggested as the dwell to use in the online phase.

G. Graphical User Interface

To control the SEMTM Glove, a graphical user interface (GUI) was developed using the FBS concept [12] [26] [21]. Fig. 3 shows how the FBS concept was integrated into the graphical user interface. The interface offered four possible commands: open the glove, close the glove, increase, and decrease the force applied by the glove. The interface had two possible states. The first state, when the glove was open, presented only the possibility to close the glove. The second state, when the glove was closed, allowed for the possibility to open the glove, increase, or decrease the force applied by the glove. Each one of the three options was offered for 3s, after which the next option in the order was proposed. To select a command, the subject had to execute a movement when the desired command was presented. To avoid multiple detections of the same movement, resulting in the erroneous selection of multiple commands, after a successful detection of the movement the classification was deactivated for 3s. Features for the classifier were extracted from a 2s observation window with an overlap of 1.9s. The initial dwell number and channel to use for the detection were set using the results of the evaluation but were adjusted before recording the online phase based on the live detection.

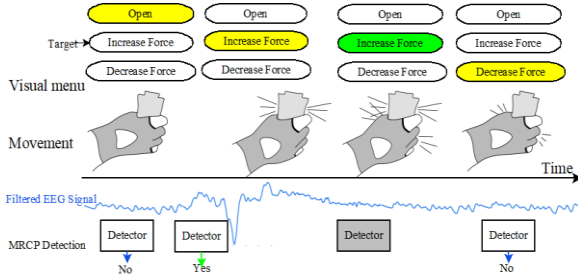


Fig. 3. Implementation of the FBS. While the menu is in the second state (glove closed) different options are offered cyclically. A detection of the movement execution (brain switch) activates the selected option (user differentiated stimulus). In yellow the offered command, green the selected command. After the successful detection, the detector is paused (gray color). When the glove is open, the only available command is to close the glove.

H. Data Analysis

Precision and recall, as well as corrected precision and recall, were calculated to evaluate the performance of the classifiers in the online phase. The corrected precision (Pr^*) and corrected recall (Rec^*) were estimated using (1) and (2) respectively.

$$Pr^* = \frac{TP-D}{TP-D+FP} \quad (1)$$

$$Rec^* = \frac{TP-D}{TP-D+FN} \quad (2)$$

Where TP is the total amount of detections corresponding to a movement, D is the number of detections corresponding to a movement that occurred shortly after the movement was executed, FP is the number of detections not corresponding to a movement execution and FN is the number of movements that were not detected.

To compare the MRCPs generated by the actions performed during the first protocol (reaching action) with the ones generated following the second protocol (squeezing action), the NP locations of each MRCP in the two conditions were manually selected following the procedure of the classification. Each recording for each channel was then filtered using a second-order band-pass Butterworth filter (0.05-3Hz) in the forward direction.

Segments of the so filtered signal in the [-2, 2]s interval surrounding the manually selected NP locations were plotted. If a segment had maximum amplitude of $\pm 110\mu V$ in the interval surrounding the NP location, for more than two channels, the NP was discarded. Using the new subset of NP locations, a new set of segments in the -2s to 2s interval surrounding the NP location were extracted from the unfiltered EEG signal. Each segment was filtered using a second-order band-pass zero-phase Butterworth filter (0.05-3Hz). Seven features were extracted from these segments. The first feature was the amplitude of the NP, the remaining 6 features were the average amplitude and slope of the intervals corresponding to the early Bereitschaftspotential (early BP), the late BP, and Motion Monitoring Potential (MMP), corresponding respectively to the intervals -2s to -0.5s, -0.5s to 0s and 0s to 1s around the NP [13] [9] [10] [12]. The features so extracted were then checked for normality in the two conditions, for each subject and each channel using the Lilliefors test, with alpha level of .05 [31]. If the test did not reject the null hypothesis, the features of the squeezing and reaching action, of the same subject and from the same channel, were confronted using a two-tail Welch's t-test with alpha of .05. If the normality test rejected the null hypothesis, an exact two-tail Mann-Whitney U test with alpha of .05 was conducted instead. The 90% confidence interval for each test was computed to perform equivalence testing [32]. The Hodges-Lehmann estimator [33] was used for the estimation of the confidence level for the Mann-Whitney U tests. The null hypothesis of the equivalence test was rejected if the estimated 90% confidence interval was completely contained in the $-\Delta$ to Δ interval. The pooled standard deviation, s , of the features in the two conditions for each channel and subject was estimated using Cohen's formula [34] (3) and was used as Δ for the equivalence test.

$$s = \sqrt{\frac{\sum(X_A - \bar{X}_A)^2 + \sum(X_B - \bar{X}_B)^2}{n_A + n_B - 2}} \quad (3)$$

Where \bar{X}_A and \bar{X}_B are the two samples means, n_A and n_B are the sample sizes, and X_A, X_B are the samples of the two populations.

The features were then given similarities scores (4) based on the results of the equivalence and unpaired sample tests.

$$Sim = \frac{N_{sim} - N_{dif}}{N_{sim} + N_{dif} + N_{inc}} \quad (4)$$

Where Sim is the similarity score, N_{sim} is the number of equivalence tests that rejected the null hypothesis for the selected parameter (feature, channel, subject, overall), N_{dif} is the number of Welch's t-test or Mann-Whitney U test that rejected the null hypothesis and N_{inc} is the number of features for which both tests did not reject the null hypothesis, in the selected parameter. Similarity scores close to 1 indicate that a majority of the equivalence tests proved statistically significant equivalence, close to -1 that a majority of Welch's t-tests/Mann-Whitney U test proved statistically significant difference. Similarity scores close to 0 indicate that the majority of the tests were inconclusive or that there was an equal number of tests that proved statistically significant differences and statistically significant equivalences.

III. RESULTS

A. Online Evaluation

As the subjects were shared between two studies, only 6 subjects went through the online phase. Table I shows the precision, recall, corrected precision, and corrected recall of the classifiers during the online phase. The number of total movements varies, as some subjects were not motivated and ended the online phase prematurely, while others were a little too eager and continued giving commands even after being informed they could stop. The classifiers that were tried the most were the ones related to Cz and C3. The table shows that the average precision was over 50% even when accounting for delayed detections.

TABLE I. PRECISION AND RECALL OF THE ONLINE PHASE

Sub	Ch	Dw	Pr (%)	Rec (%)	Pr* (%)	Rec* (%)	N
0	T7	1	43	43	33	33	14
3	Cz	2	57	81	50	77	16
4	Cz	8	71	83	60	75	6
6	Cz	5	61	69	59	67	16
7	F3	1	69	61	62	53	18
9	C3	3	65	71	62	68	21
Averages		3 ± 3	61 ± 10	68 ± 15	54 ± 11	62 ± 16	15 ± 5

Sub= subject number; Ch=channel used for the detection; Dw=Dwell used for the detection, Pr=precision; Rec=Recall; Pr*=Corrected Pr; Rec*=Corrected Rec; N=number of executed movements.

B. MRCP Comparison

The results from S8 were not considered in the overall estimation of similarities scores because during the recording of the first experimental protocol an unknown source of low-frequency noise in the MRCP frequency range corrupted the recording for most channels. The low-frequency noise stopped towards the beginning of the second experimental protocol. None of the events of the grasp condition passed the maximum amplitude requirement imposed in the preprocessing of the features. The exact p values, confidence intervals, and effect size for each test-subject-electrode, as well as the summary of the results of the equivalence test and Welch/Mann-Whitney U test for each channel and each patient are in the Appendix.

Table II shows the similarity scores across subjects. The feature that had the highest similarity score was the slope of the late BP ($Sim=0.7$). The most different feature was the slope of the Motion Monitoring Potential ($Sim=0.24$). Channel CP5 and Lap CH had the highest similarity ($Sim=0.56$), while F3 had the lowest ($Sim=0.27$). In the across subjects similarity score, only the average MMP slope of channel CP1 had a negative value (-0.11). The overall similarity score of the two actions was 0.41, this suggests that the signal's features were more likely to result equivalent than having inconclusive results or be significantly different.

Fig. 4 shows the averages of the filtered MRCP, in the two conditions and when combined, from the channel-subject pair with the highest similarity. Fig. 5 shows the filtered MRCP in the channel-subject pair that had the lowest similarity. In both figures, the shape of the signals is consistent with the MRCP morphology. Fig. 6 and Fig. 7 show the compared distribution of each feature in the two conditions for the channel-subject pair with the highest and lowest similarity score, respectively. In the highest similarity case, all the features were statistically equivalent, i.e., $-\Delta < \text{lower bound of the 90\% CI}$ and $\Delta > \text{upper bound of the 90\% CI}$. In the lowest similarity case, the NP value, $t(22.2611) = -3.8722$, $p < .001$, average early BP $t(25.4337) = -3.5587$, $p < .001$, average late BP Mann-Whitney $U = -2.9942$, $n_1 = 15$, $n_2 = 13$ $p < .003$, and average MMP $t(23.4589) = -2.6833$, $p < .013$ were significantly different, while the average early BP slope was statistically equivalent.

TABLE II. SIMILARITY SCORES ACROSS SUBJECTS

	Average NP	Average early BP	Average late BP	Average MMP	Average slope early BP	Average slope late BP	Average slope MMP	Channel
F3	<u>0,00</u>	<u>0,22</u>	<u>0,22</u>	0,44	0,33	0,67	<u>0,00</u>	<u>0,27</u>
FC1	<u>0,11</u>	0,44	<u>0,11</u>	0,33	0,44	0,67	<u>0,00</u>	0,30
FC5	<u>0,11</u>	0,67	<u>0,22</u>	0,67	<u>0,22</u>	0,67	<u>0,00</u>	0,37
Cz	<u>0,00</u>	<u>0,22</u>	<u>0,22</u>	<u>0,22</u>	0,67	0,89	0,44	0,38
C3	0,44	0,67	0,33	<u>0,22</u>	0,33	0,67	<u>0,22</u>	0,41
T7	0,56	0,56	0,33	0,44	<u>0,22</u>	0,56	<u>0,22</u>	0,41
CP1	0,44	0,33	0,44	0,56	0,56	0,78	<u>-0,11</u>	0,43
CP5	0,56	0,56	0,44	0,33	0,56	0,78	0,67	0,56
P3	<u>0,22</u>	0,44	0,33	<u>0,22</u>	0,33	0,67	0,44	0,38
Lap	0,33	0,44	0,56	0,89	0,44	0,67	0,56	0,56
Feature	0,28	0,46	0,32	0,43	0,41	0,70	<u>0,24</u>	0,41

Bold similarities scores are the ten highest. Underlined similarities scores are the ten lowest. Minimum and maximum between total feature and total channel similarity score are respectively underlined and in bold. The similarity score of the two conditions is in the bottom right corner. Similarity scores close to 1 indicate the feature are often statistically equivalent, close to -1 indicate that the features are often statistically different. Results close to 0 suggest an equal amount of statistically significant difference and statistically significant equivalence, or a higher number of inconclusive tests.

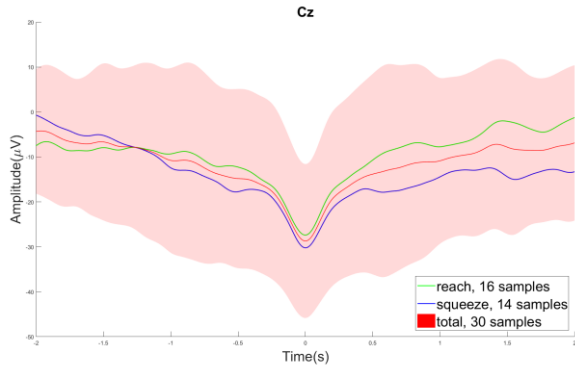


Fig. 4. Averages of the MRCP signal in the two conditions, compared with the combined average, for the channel-subject combination with highest similarity. In green the average MRCP of the reach action, in blue the average MRCP of the squeeze action, in red the combined average. The red shade is the standard error of the combined average. Data from channel Cz of S0. The number of samples in each condition is summarized in the legend. Both MRCPs averages are very close to the common average line in the interval of interest [-2, 1]s.

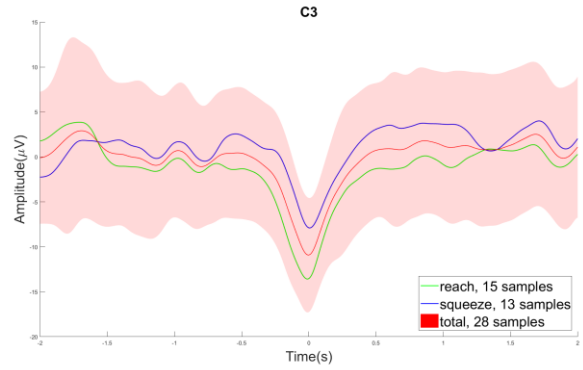


Fig. 5. Averages of the MRCP signal in the two conditions, compared with the combined average, for the channel-subject combination with lowest similarity. In green the average MRCP of the reach action, in blue the average MRCP of the squeeze action, in red the combined average. The red shade is the standard error of the combined average. Data from channel C3 of S3. The number of samples in each condition is summarized in the legend. The MRCPs averages of the two condition are far apart from the common average line in the interval of interest [-2, 1]s. The average slope of the early BP [-2, -0.5]s is statistically equivalent.

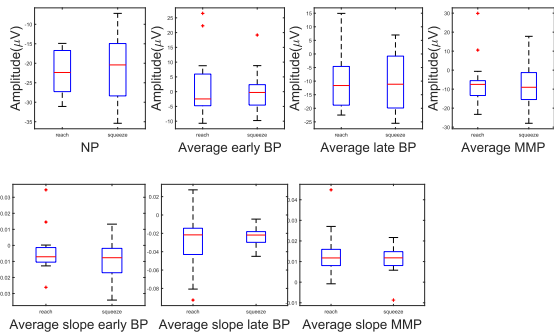


Fig. 6. Distribution of the features in the two conditions for the channel-subject combination with highest similarity. The left side of the pair corresponds to the reach action, right to the squeeze action.

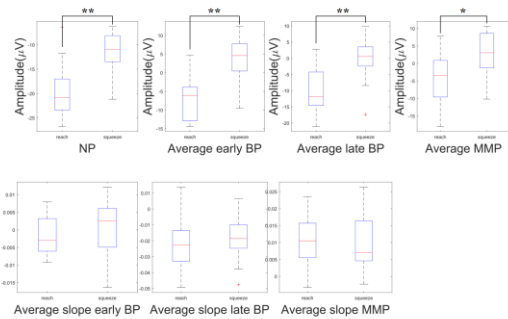


Fig. 7. Distribution of the features in the two conditions for the channel-subject combination with lowest similarity. The left side of the pair corresponds to the reach action, right to the squeeze action.

IV. DISCUSSION

A. Online Detection

This study investigated the FBS paradigm using a visual GUI and a single channel classifier for MRCP detection. The system has been tested online in six different subjects while controlling a robotic glove. The classification was performed using a single channel as it has been suggested that limiting the number of electrodes used for the implementation of BCI systems could aid the transition of the BCI usage from the lab to the clinic and public [30]. Precision and recall were above chance level in almost all the cases, confirming the feasibility of the approach. Classifiers trained on channel Cz were the most frequently used in the online phase, suggesting that exploring electrode's configuration centered around Cz, as performed in [21] [24] [35], might be worthwhile.

Using the FBS paradigm the system was not only able to open or close the glove, but also modulating the force. The system could also be implemented providing the option choice using vibrotactile stimulation, that could be a more practical solution outside the lab environment.

The term MRCP is used to describe both self-paced and cued movements, however, it has been proven that there is difference between the Bereitschaftspotential (BP) and the Contingent Negative Variation (CNV) [36]. The training and evaluation datasets for the classifier were performed using a self-paced paradigm, and although the movements were not directly cued during the online phase, the subjects were preparing to execute the movement analogously to a cued paradigm. Further studies investigating whether using self-paced or cued movements for the training of classifiers when using the FBS paradigm should be pursued.

B. MRCP Comparison

The similarity between the movements used for the generation of the MRCP has also been examined. A new metric based on the combination of results of Welch/Mann-Whitney U tests and equivalence tests for scoring the similarity was proposed. The advantages of this new metric are that it does not require normality in the distribution of the samples or an equal number of samples to be computed.

The slope of the late BP was consistently the most similar feature, with a total similarity score across subjects and channels of 0.70, suggesting that it could be a valuable feature for the detection of general hand movements. The slope of the MMP of channel CP1 was the only feature-channel combination that had a negative similarity score. That means that the statistical test proved statistically significant differences more often than statistical equivalence, suggesting they could be potentially investigated for the development of systems that try to distinguish between similar grasping movements. The channels that had the highest similarity across features and subjects were the CP5 and the spatially filtered Laplacian channel centered on C3 (sim=0.56), which was unexpected, as their correspondent classifier were not used for the online tests. Due to the small sample size, almost a third of the test were inconclusive both when

considering the noisy results of subject 8 (30.3%) and when they were removed from the total count (31.1%). This is particularly surprising as the Δ chosen for the similarity test was very big compared to usual equivalence tests. Nevertheless, the study presents a new methodology to compare the MRCP signal while performing similar tasks. This new approach could be used to pursue new research questions and the analysis of the features to select while creating MRCP-based BCIs.

ACKNOWLEDGMENT

I would like to thank Pr. Dosen for always providing insightful feedback and aiding the decisions related to the direction of the project. I also like to express my appreciation to Susan and, especially, Jacob for assisting me in the lab, as well as to the Aalborg University institution for providing the lab and equipment. Special thanks are reserved for my sister Cecilia, for always helping me in every crisis, even from the other side of Europe, my parents, Livia and Enrico, and grandparents, Marta and Gino, for always supporting me both emotionally and financially, and my "extended" siblings, Lorenz, Tangui, James, Odette, and Alessandro.

I also want to thank Emanuele, Macca and Miriam for accompanying me at the beginning of my higher education journey, as well as Maria, Alessandro, Francesco, Olena, and Elena. I am also compelled to thank Ander and Iñigo for helping me through the beginning of the master's education, as well as Karolina, Vivian, Adrian, Daniela, Jesper, Sarvesh, Guilherme, Beda, Rahul, Rasmus, Guille, Gala, Carolina, Eduardo, and Andrej.

Special thanks are also reserved for Dario, Emil, Simon, Kasper, Jonas, Peter, Mathias, and Tobias for accepting to be subjects in the experiment or pilot tests. I want to thank all the friends that supported me here in Aalborg and have not been mentioned yet, Sara, Karen, Tim, Mikkel, Daniela, Coco, Casper, Asger, and Jonas as well as my expatriated compatriots' group, Giovanni, Davide, Daniele, Silvia, Veronica, Riccardo, Andrea, Samuele, Lorenzo, Costanza, Cristina, Laura, Federico, Alessia, Carlos, Patricia and Kenia. Finally, I want to thank my teammates in the Tuzki team, and all the friends I could not mention, but that shaped me into the person I am today.

REFERENCES

- [1] H. Christian and S. Tanja, "Automatic Speech Recognition from Neural Signals: A Focused Review," *Frontiers in Neuroscience*, vol. 10, p. 429, September 2016.
- [2] J. s. R. Millán, R. Rupp, G. R. Müller-Putz, R. Murray-Smith, C. Giugliemmo, M. Tangermann, C. Vidaurr, F. C. A. Kübler, R. Leeb, C. Neuper, K.-R. Müller and D. Mattia, "Combining Brain-Computer Interfaces and Assistive Technologies: State-of-the-Art and Challenges," *Frontiers in Neuroscience*, vol. 4, p. 161, September 2010.
- [3] L. Tonin and J. d. R. Millán, "Noninvasive Brain-Machine Interfaces for Robotic Devices," *Annual*

Review of Control, Robotics, and Autonomous Systems, vol. 4, no. 1, pp. 191-214, 2021.

- [4] C. Guger, N. Mrachacz-Kersting and B. Z. Allison, *Brain-Computer Interface Research: A State-of-the-Art Summary 7*, Springer, Cham, 2019.
- [5] N. Weiskopf, R. Veit, M. Erb, K. Mathiak, W. Grodd, R. Goebel and N. Birbaumer, "Physiological self-regulation of regional brain activity using real-time functional magnetic resonance imaging (fMRI): methodology and exemplary data," *Neuroimage*, pp. 19(3):577-86., July 2003.
- [6] J. Mellinger, S. G. B. C. H. Preissl, W. Rosenstiel, N. Birbaumer and A. Kübler, "An MEG-based brain-computer interface (BCI)," *Neuroimage*, pp. 36(3):581-593, December 2007.
- [7] F. LA and D. E., "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials.," *Electroencephalogr Clin Neurophysiol*, pp. 510-523, December 1988.
- [8] G. Pfurtscheller and F. L. d. Silva, "Event-related EEG/MEG synchronization and desynchronization: basic principles," *Clinical Neurophysiology*, vol. 110, no. 11, pp. 1842-1857, May 1999.
- [9] A. Shakeel, M. S. Navid, M. N. Anwar, S. Mazhar, M. Jochumsen and I. K. Niazi, "A Review of Techniques for Detection of Movement Intention Using Movement-Related Cortical Potentials," *Computational and Mathematical Methods in Medicine*, December 2015.
- [10] M. Jochumsen, K. N. Imran, R. Helene, C. Rovsing, A. N. Gebbie, K. A. Tina, P. D. Nhung, E. S. Marina, N. Mrachacz-Kersting, J. Ning, D. Farina and K. Dremstrup, "Detection of Movement Intentions through a Single Channel of Electroencephalography," *Replace, Repair, Restore, Relieve – Bridging Clinical and Engineering Solutions in Neurorehabilitation*, pp. 465-472, 2014.
- [11] O. F. d. Nascimento, K. D. Nielsen and M. Voigt, "Movement-related parameters modulate cortical activity during imaginary isometric plantar-flexions," *Experimental Brain Research*, vol. 171, no. 1, pp. 78-90, November 2005.
- [12] N. Jiang, N. Mrachacz-Kersting, R. Xu, K. Dremstrup and D. Farina, "An Accurate, Versatile, and Robust Brain Switch for Neurorehabilitation," *Brain-Computer Interface Research*, vol. 3, pp. 47-61, November 2014.
- [13] M. Jahanshahi and M. Hallett, *The Bereitschaftspotential: Movement-Related Cortical Potentials*, New York: Springer US, 2003.
- [14] N. Mrachacz-Kersting, S. R. Kristensen, I. K. Niazi and D. Farina, "Precise temporal association between cortical potentials evoked by motor imagination and afference induces cortical plasticity," *The Journal of Physiology*, vol. 590, pp. 1669-1682, 2012.
- [15] R. Xu, N. Jiang, N. Mrachacz-Kersting, C. Lin, G. Asín Prieto, J. C. Moreno, J. L. Pons, K. Dremstrup and D. Farina, "A Closed-Loop Brain-Computer Interface Triggering an Active Ankle-Foot Orthosis for Inducing Cortical Neural Plasticity," *IEEE Transactions on Biomedical Engineering*, vol. 61, pp. 2092-2101, 2014.
- [16] A. B. Nikunj, A. Venkatakrishnan, B. Abibullaev, J. A. Edward, N. Yozbatiran, A. B. Amy, J. French, C. Karmonik, G. G. Robert, K. O. Marcia, E. F. Gerard and L. C.-V. Jose, "Design and Optimization of an EEG-Based Brain Machine Interface (BMI) to an Upper-Limb Exoskeleton for Stroke Survivors," *Frontiers in Neuroscience*, p. 122, 2016.
- [17] N. Mrachacz-Kersting and S. Aliakbaryhosseinabadi, "Comparison of the Efficacy of a Real-Time and Offline Associative Brain-Computer-Interface," *Frontiers in Neuroscience*, vol. 12, p. 455, 2018.
- [18] N. Mammone, C. Ieracitano and F. C. Morabito, "A deep CNN approach to decode motor preparation of upper limbs from time-frequency maps of EEG signals at source level," *Neural Networks*, vol. 124, pp. 357-372, 2020.
- [19] K. Roots, Y. Muhammad and N. Muhammad, "Fusion Convolutional Neural Network for Cross-Subject EEG Motor Imagery Classification," *Computers*, vol. 9, no. 3, p. 72, September 2020.
- [20] R. Xu, N. Jiang, C. Lin, N. Mrachacz-Kersting, K. Dremstrup and D. Farina, "Enhanced Low-Latency Detection of Motor Intention From EEG for Closed-Loop Brain-Computer Interface Applications," *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 2, pp. 288-296, February 2014.
- [21] R. Xu, S. Dosen, N. Jiang, L. Yao, A. Farooq, M. Jochumsen, N. Mrachacz-Kersting, K. Dremstrup and D. Farina, "Continuous 2-D control via state-machine triggered by endogenous sensory discrimination and a fast brain switch," *Journal of Neural Engineering*, vol. 16, no. 5, p. 056001, July 2019.
- [22] N. Jiang, L. Gizzi, N. Mrachacz-Kersting, K. Dremstrup and D. Farina, "A brain-computer interface for single-trial detection of gait initiation from movement related cortical potentials," *Clinical Neurophysiology*, vol. 126, no. 1, pp. 154-159, January 2015.
- [23] K. Fatemeh, K. Jonathan, M.-K. Natalie, F. Dario and J. Ning, "Detection of Movement Related Cortical Potentials from EEG Using Constrained ICA for Brain-Computer Interface Applications," *Frontiers in Neuroscience*, vol. 11, p. 356, June 2017.
- [24] M. Jochumsen, I. K. Niazi, N. Mrachacz-Kersting, D. Farina and K. Dremstrup, "Detection and classification of movement-related cortical potentials associated with task force and speed," *Journal of Neural Engineering*, vol. 10, no. 5, p. 056015, August 2013.
- [25] S. Rodpongpun, T. Janyalikit and C. A. Ratanamahatana, "Influential Factors of an

- Asynchronous BCI for Movement Intention Detection," *Computational and Mathematical Methods in Medicine*, March 2020.
- [26] R. Xu, N. Jiang, S. Dosen, C. Lin, N. Mrachacz-Kersting, K. Dremstrup and D. Farina, "Endogenous sensory discrimination and selection by a fast brain switch for a high transfer rate brain-computer interface," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 8, pp. 901-910, January 2016.
- [27] Bioservo Technologies AB, "Bioservo: Strength for Life," Bioservo Technologies AB, [Online]. Available: <https://www.bioservo.com/customer-support/carbonhand/support-documents>.
- [28] C. Edlinger and G. Guger, "g.tec," g.tec, [Online]. Available: <https://www.gtec.at/>.
- [29] G. E. C. Nelson, E. Lettich and P. L., "Ten Percent Electrode System for Topographic Studies of Spontaneous and Evoked EEG Activities," *American Journal of EEG Technology*, vol. 25, no. 2, pp. 83-92, February 1985.
- [30] M. Jochumsen, I. K. Niazi, D. Taylor, D. Farina and K. Dremstrup, "Detecting and classifying movement-related cortical potentials associated with hand movements in healthy subjects and stroke patients from single-electrode, single-trial EEG," *Journal of Neural Engineering*, vol. 12, no. 5, p. 056013, August 2015.
- [31] Wilkinson, G. E. Dallal and Leland, "An Analytic Approximation to the Distribution of Lilliefors's Test Statistic for Normality," *The American Statistician*, vol. 40, no. 4, pp. 294-296, April 1986.
- [32] L. Barker, H. Rolka, D. Rolka and C. Brown, "Equivalence Testing for Binomial Random Variables," *The American Statistician*, vol. 55, no. 4, pp. 279-287, 2001.
- [33] J. L. H. Jr. and E. L. Lehmann, "Estimates of Location Based on Rank Tests," *The Annals of Mathematical Statistics*, vol. 34, no. 2, pp. 598-611, June 1963.
- [34] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed., New York: Lawrence Erlbaum Associates Inc, 1988.
- [35] I. K. Niazi, N. Jiang, O. Tiberghien, J. F. Nielsen, K. Dremstrup and D. Farina, "Detection of movement intention from single-trial movement-related cortical potentials," *Journal of Neural Engineering*, vol. 8, no. 6, p. 066009, October 2011.
- [36] M.-K. Lu, N. Arai, C.-H. Tsai and U. Ziemann, "Movement related cortical potentials of cued versus self-initiated movements: Double dissociated modulation by dorsal premotor cortex versus supplementary motor area rTMS," *Human Brain Mapping*, vol. 33, no. 4, pp. 824-839, March 2011.

APPENDIX

Tables containing the types of tests performed (t-test= Welch's t-test; U-test=Mann-Whitney U test), p value of the test, delta used for the equivalence test, 90% confidence intervals and Cohen's d. Bold p values <.05; underlined p <.01

S0		peak negativity		90% c.i.		effect		U-test		p		Delta		90% c.i.		effect		U-test		p		Delta		90% c.i.		effect																													
		A	Low	Up	Low	Up	Low	Up	Low	Up	Low	Up	Low	Up	Low	Up	Low	Up	Low	Up	Low	Up	Low	Up	Low	Up	Low	Up																											
U-test	0.08	8.4	-10.7	-0.3	-0.7	U-test	0.61	8.8	-8.7	7.0	0.2	U-test	0.55	11.7	-9.6	5.6	-0.38	U-test	0.85	12.1	-8.2	6.5	-0.27	U-test	0.39	8.0	-11.9	-0.4	-0.3	U-test	0.50	10.12	-0.003	0.010	0.38	U-test	0.62	0.75	-0.20	0.07	-0.15	U-test	0.58	0.62	0.75	-0.20	0.07	-0.15	U-test	0.58	0.62	0.75	-0.20	0.07	-0.15
U-test	0.08	8.4	-10.7	-0.3	-0.7	U-test	0.61	8.8	-8.7	7.0	0.2	U-test	0.55	11.7	-9.6	5.6	-0.38	U-test	0.85	12.1	-8.2	6.5	-0.27	U-test	0.39	8.0	-11.9	-0.4	-0.3	U-test	0.50	10.12	-0.003	0.010	0.38	U-test	0.62	0.75	-0.20	0.07	-0.15	U-test	0.58	0.62	0.75	-0.20	0.07	-0.15							
U-test	0.08	8.4	-10.7	-0.3	-0.7	U-test	0.61	8.8	-8.7	7.0	0.2	U-test	0.55	11.7	-9.6	5.6	-0.38	U-test	0.85	12.1	-8.2	6.5	-0.27	U-test	0.39	8.0	-11.9	-0.4	-0.3	U-test	0.50	10.12	-0.003	0.010	0.38	U-test	0.62	0.75	-0.20	0.07	-0.15	U-test	0.58	0.62	0.75	-0.20	0.07	-0.15							

	peak negativity		Effect						Endp BR average						Lack BR average						MDP average						Early BR slope						Lack BR slope						MDP slope													
									p		A		p		A		p		A		p		A		p		A		p		A		p		A		p		A		p		A		p		A		p		A	
									Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est	Test	Est
S5	R1	Test	0.02	1.63	-25.9	-5.9	-1.0	Test	0.30	1.45	-3.4	1.42	0.4	Test	0.07	15.3	-26.8	-5.2	-1.09	Test	0.19	15.4	-16.7	2.0	-0.47	Test	0.02	0.013	-0.018	-0.004	-0.83	Test	0.95	0.64	-0.015	0.018	0.18	Test	0.13	0.025	-0.001	0.028	0.59	Test	0.42	0.014	0.004	0.028	0.69			
		S6	R1	Test	0.02	1.63	-25.9	-5.9	-1.0	Test	0.30	1.45	-3.4	1.42	0.4	Test	0.07	15.3	-26.8	-5.2	-1.09	Test	0.19	15.4	-16.7	2.0	-0.47	Test	0.02	0.013	-0.018	-0.004	-0.83	Test	0.95	0.64	-0.015	0.018	0.18	Test	0.13	0.025	-0.001	0.028	0.59	Test	0.42	0.014	0.004	0.028	0.69	
				S7	R1	Test	0.81	10.7	-6.1	7.2	0.2	Test	0.38	10.4	-0.8	1.1	0.2	Test	0.72	11.9	-2.8	6.8	0.5	Test	0.70	10.2	1.0	-4.7	7.6	Test	0.23	0.002	-0.008	0.002	-0.55	Test	0.12	0.021	-0.001	0.028	0.45	Test	0.13	0.008	-0.009	0.004	-0.55					
						S8	R1	Test	0.77	8.1	-4.3	6.1	0.1	Test	0.02	29.4	9.4	50.5	1.0	Test	0.03	63.6	1.5	99.3	1.3	Test	0.02	100.2	3.6	150.0	1.17	Test	0.05	0.028	0.006	0.034	1.12	Test	0.02	0.042	-0.006	0.049	1.13	Test	0.05	0.049	0.006	0.065	1.09			
								S9	R1	Test	0.18	14.6	-15.1	1.6	-0.5	Test	0.012	1.8	-28.5	-5.3	-0.9	Test	0.14	-16.5	10.1	-11.1	0.6	-0.52	Test	0.17	0.0085	-0.001	0.006	-0.13	Test	0.33	0.020	-0.005	0.019	0.24	Test	0.18	0.013	-0.001	0.028	0.44	Test	0.18	0.012	-0.001	0.028	0.44

TABLE III RESULT SUMMARY OF THE STATISTICAL TESTS

Ch	S0	S1	S2	S3	S4
F3	<i>B1 B2 MPB1sB2s MPs</i>	B1 <i>MP</i> <i>B2s</i>	NP B1 B2 MP B1s B2s MPs	<i>B1</i> <i>B1s</i> <i>B2s</i> <i>MPs</i>	<i>NP B1 B2 B1s</i> MPs*
FC1	<i>B1 B2 MPB1sB2s MPs</i>	<i>B2s</i>	NP B1 B2 <i>B2s</i>	B1 B2 <i>B1s</i> <i>B2s</i> <i>MPs</i>	<i>NP B1 B2 MP B1s</i> MPs*
FC5	<i>B1 B2 MP B2s</i>	<i>B1</i>	<i>B1 B2 MP B2s MPs</i>	<i>B1s</i> <i>B2s</i> <i>MPs</i>	<i>B1 B2 MP B1s B2s</i> MPs*
Cz	<i>NP B1 B2 MPB1sB2s MPs</i>	<i>B1 B2 MP B1s B2s</i>	<i>NP B1 B2 MP B1s B2s</i>	NP* B1*B2* MP <i>B1s</i> <i>B2s</i> <i>MPs</i>	<i>NP B2 MP*B1s B2s</i> MPs
C3	<i>NP B1 B2 MPB1sB2s MPs</i>	NP B1 MP B1s <i>B2s</i>	<i>NP B1 B2 MP B1s B2s</i>	NP* B1*B2* MP <i>B1s</i>	<i>NP B1 B2 B1s B2s</i> MPs*
T7	<i>NP B2 MP MPs</i>	B2MP*B1s	<i>NP B1 B2 MP B2s MPs</i>	<i>B1</i> <i>B1s</i> B2s	<i>NP B1 B2 MP B2s</i> MPs
CP1	<i>NP B1 B2 MPB1sB2s</i>	<i>NP B2 MP</i>	<i>NP B1 B2 MP B2s</i>	NP* B1*B2* MP* <i>B1s</i> <i>B2s</i>	<i>NP B1 B2 B2s</i> MPs
CP5	<i>B1 B2s MPs</i>	<i>NP B1</i> MP B1s* <i>B2s</i> <i>MPs</i>	<i>NP B1 B2 MP B1s B2s MPs</i>	NP B2* MP <i>B1s</i>	<i>B1 B2 MP B1s B2s</i>
P3	<i>NP B1 B2 MPs</i>	<i>NP B1</i> B1s <i>MPs</i>	<i>NP B1 B2 MP B1s B2s MPs</i>	NP* B1 B2* MP <i>MPs</i>	<i>B2 B1s B2s MPs</i>
Lap	<i>NP B1 B2 MPB1sB2s MPs</i>	<i>B1 MP MPs</i>	<i>NP B1 B2 MP B2s MPs</i>	NP* B1 B2 MP <i>B2s</i>	<i>B2 MP MPs</i>
	S5	S6	S7	S8	S9
F3	<i>B1 B2 B1sB2s</i>	NP B1 B2* B1s <i>B2s</i>	<i>NP B2 MP B1s</i>	<u><i>NP B1 B2 MP B1s B2s MPs*</i></u>	B1 <i>B1s B2s</i>
FC1	<i>NP B1 MPB1sB2s</i>	NP*B1 B2* B1s <i>B2s</i> MPs	<i>B1 B2 MP MPs</i>	<u><i>NP MP B1s B2s MPs*</i></u>	<i>NP B1 B2 MP B1s B2s MPs</i>
FC5	<i>MPB1sB2s</i>	NP B2 B1s <i>B2s</i> MPs	<i>NP B1 B2 MP B1s MPs*</i>	<u><i>MP* B1s* B2s MPs*</i></u>	<i>NP B1 B2 MP B1s B2s MPs</i>
Cz	<i>B1sB2s</i>	NP B2 <i>B2s</i> <i>MPs</i>	<i>B1 B2 MP B1s B2s MPs</i>	<u><i>B1 MP B1s B2s MPs*</i></u>	<i>NP B1 B2 B1s B2s MPs</i>
C3	<i>NP B1s</i>	<i>B1 B2</i> <i>B2s</i> <i>MPs</i>	<i>NP B1 B2 MP B1s</i>	<u><i>MP B1s B2s MPs*</i></u>	<i>NP B1 B2 MP B2s MPs</i>
T7	<i>NP MP B2s MPs</i>	NP* B2* MP <i>B2s</i> MPs	<i>NP B1 B2 MP B1s B2s</i>	<u><i>NP* B1 MP* B1s* B2s* MPs</i></u>	<i>NP B1 B2 MP B1s B2s MPs</i>
CP1		NP <i>MP B1s B2s</i>	<i>NP MP B1s B2s MPs</i>	<u><i>NP B1 B2 MP B1s B2s MPs</i></u>	<i>NP B1 B2 MP B1s B2s MPs</i>
CP5	<i>NP B1s MPs</i>	<i>NP B1 B2 MP B1s B2s</i>	<i>NP B1 B2 MP B2s MPs</i>	<u><i>MP* B1s* B2s MPs*</i></u>	<i>NP B1 B2 MP B1s B2s MPs</i>
P3	NP <i>MPB1sB2s</i>	NP*B1 B2 <i>B2s</i> MPs*	<i>NP B2 MP B2s MPs*</i>	<u><i>NP B2 MP B1s B2s MPs*</i></u>	<i>NP B1 B2 B1s B2s MPs</i>
Lap	<i>B2s</i>	<i>NP B1 B2 MP B1s</i> MPs*	<i>NP B2 MP B1s B2s MPs</i>	<u><i>NP B1 B2 B1s B2s MPs</i></u>	<i>B1 B2 MP B1s B2s MPs</i>

S0-9=Subject 0-9; Ch=Channel; NP=Negative Peak value; B1= average early Bereitschaftspotential; B2= average late Bereitschaftspotential, MP= average Motion Monitoring Potential; B1s= average slope early Bereitschaftspotential; B2s= average slope late Bereitschaftspotential; MPs= average slope Motion Monitoring Potential. The name of the feature is in *italic* if the equivalence test for that feature rejected the null hypothesis, **bold** if the Welch's t-test, or Mann-Whitney U test rejected the null hypothesis with p<.05, or p<.01 if marked by *. Omitted features names are of inconclusive test result. The results of subject 8 are underlined for the noisy channels.