Brain and muscle derived features to discriminate simple hand motor tasks for a rehabilitative BCI: comparative study on healthy and post-stroke individuals

Journal of Neural Engineering

CrossMark

OPEN ACCESS

RECEIVED
8 March 2024

REVISED
29 July 2024

ACCEPTED FOR PUBLICATION
17 October 2024

PUBLISHED
28 November 2024

PAPER

Brain and muscle derived features to discriminate simple hand motor tasks for a rehabilitative BCI: comparative study on healthy and post-stroke individuals

Valeria de Seta[1,2,3], Emma Colamarino[1,2], Floriana Pichiorri[2], Giulia Savina[1,2], Francesca Patarini[1,2], Angela Riccio[2], Febo Cincotti[1,2], Donatella Mattia[2] and Jlenia Toppi[1,2,*]

[1] Department of Computer, Control, and Management Engineering, Sapienza University of Rome, Rome, Italy
[2] Neuroelectric Imaging and BCI Lab, IRCCS Fondazione Santa Lucia, Rome, Italy
[3] Neuro-X Institute, EPFL, Lausanne, Switzerland
[*] Author to whom any correspondence should be addressed.

E-mail: jlenia.toppi@uniroma1.it

Keywords: Brain Computer Interface, EEG, EMG, stroke, cortico-muscolar coherence, movement-related cortical potential, event-related desynchronization

Supplementary material for this article is available online

Abstract

Objective. Brain–Computer Interfaces targeting post-stroke recovery of the upper limb employ mainly electroencephalography to decode movement-related brain activation. Recently hybrid systems including muscular activity were introduced. We compared the motor task discrimination abilities of three different features, namely event-related desynchronization/synchronization (ERD/ERS) and movement-related cortical potential (MRCP) as brain-derived features and cortico-muscular coherence (CMC) as a hybrid brain-muscle derived feature, elicited in 13 healthy subjects and 13 stroke patients during the execution/attempt of two simple hand motor tasks (finger extension and grasping) commonly employed in upper limb rehabilitation protocols. *Approach*. We employed a three-way statistical design to investigate whether their ability to discriminate the two movements follows a specific temporal evolution along the movement execution and is eventually different among the three features and between the two groups. We also investigated the differences in performance at the single-subject level. *Main results*. The ERD/ERS and the CMC-based classification showed similar temporal evolutions of the performance with a significant increase in accuracy during the execution phase while MRCP-based accuracy peaked at movement onset. Such temporal dynamics were similar but slower in stroke patients when the movements were attempted with the affected hand (AH). Moreover, CMC outperformed the two brain features in healthy subjects and stroke patients when performing the task with their unaffected hand, whereas a higher variability across subjects was observed in patients performing the tasks with their AH. Interestingly, brain features performed better in this latter condition with respect to healthy subjects. *Significance.* Our results provide hints to improve the design of Brain–Computer Interfaces for post-stroke rehabilitation, emphasizing the need for personalized approaches tailored to patients' characteristics and to the intended rehabilitative target.

1. Introduction

Brain–Computer Interface (BCI) systems have been employed in the last 15 years in the field of post-stroke motor rehabilitation, for their capability to decode movement-related brain activity in real-time and feed it back to the subject visually or via more complex effectors ranging from neuromuscular stimulation to exoskeletons [1–4].

Most of the BCI systems employed for post-stroke rehabilitation record brain activity non-invasively via electroencephalography (EEG). Recently, hybrid BCIs exploiting physiological signals other than brain activity, such as muscular activity derived from surface electromyography (EMG), have been used in a rehabilitative context to increase classification performance [5] or more interestingly to monitor motor abnormalities [6].

The EEG correlates of motor activity employed as control features in BCI systems are potentially numerous ranging from modulation of EEG rhythms [7], event-related potentials [8] and measures of brain connectivity or brain-muscle connectivity [9, 10] in hybrid approaches. Each of them is optimally elicited via ad-hoc paradigms and encodes slightly different neurophysiological information. Sensorimotor rhythms are oscillations in the EEG occurring in the alpha (8–12 Hz) and beta (13–30 Hz) bands and can be recorded over the sensorimotor areas, whose amplitude typically decreases (i.e. desynchronizes) during movement execution. Such event-related desynchronization (ERD) is typically followed by an increase in amplitude described as event-related synchronization (ERS) [11]. The movement-related cortical potential (MRCP) occurs naturally right before the movement attempt, reaching the maximum negativity near the movement onset [12, 13]. It was shown to be able to decode movement intention [14] and to discriminate between different upper-limb movements [15]. Finally, cortico-muscular coherence (CMC) is a measure of synchronization between central and peripheral activations, and it can be considered a simple form of hybrid functional connectivity measuring the spectral coherence between EEG and EMG signals [10]. All of these brain and brain-muscles correlates of movement have been described in post-stroke populations, showing deviations from the healthy condition sometimes related to the degree of motor impairment [6, 16–19].

As such, these correlates have been tested in BCI contexts for clinical applications [20–23]. However, as of today, there is no clear indication of which neurophysiological signal best suits for BCI control in a post-stroke motor rehabilitation context.

Previous studies compared the performances of different brain features, such as ERD/ERS and MRCP, primarily focusing on pre-movement detection [24–27] or decoding movements across different limbs [28, 29]. These studies demonstrated that an MRCP-based approach or a combined approach based on both brain correlates tends to outperform strategies based on ERD/ERS features alone. The abilities of ERD/ERS and MRCP to discriminate between different movements of the same limb were investigated separately with different purposes and experimental designs. Such studies revealed that EEG-based spectral features alone do not yield robust classification [30], whereas MRCP allows classification accuracies above chance level when discriminating between different movements [15, 31]. Recent studies have explored the ability of CMC to discriminate among different movements of the same arm in healthy subjects [32–34] also comparing its performance with that obtained using ERD/ERS features [35]. They have reported that CMC manages to discriminate between different movements of the same limb, outperforming the use of only brain features.

To the best of our knowledge, a comparison of the ability of different neural correlates to discriminate between different movements of the same limb in both healthy and stroke subjects has not been investigated before. Furthermore, no study has focused on how each feature performs in different time frames along task execution.

In this study, we compared two different EEG-derived features, namely ERD/ERS and MRCP, and one EEG-EMG-based feature named CMC, elicited in 13 healthy subjects (control group—CTRL) and 13 stroke patients (experimental group—EXP) during the execution of simple hand motor tasks, namely the finger extension (Ext) and grasping (Grasp). The possibility of discriminating different movements of the same limb, which is crucial for neuroprosthetic control [36], is relevant for rehabilitative BCIs. In fact, with the intent of following the patient along motor recovery, rehabilitation approaches target goal-oriented and ecologic exercises, particularly when mediated by end effectors such as neuromuscular stimulation [37]. In this context, appropriate timing of feedback delivery is crucial for the brain plasticity phenomena underlying motor relearning [21]. We defined an ad-hoc signal processing pipeline for each of the features and investigated in a three-way statistical design whether their capability to discriminate two simple movement types using only a two-dimensional space:

i) follows a specific temporal evolution along the movement execution,
ii) is different among the two brain and the hybrid features and is consistent at the single-subject level separately for the two groups,
iii) is different between the stroke and healthy subjects and eventually correlates with motor impairment.

We hypothesize, according to the different neurophysiological meaning of the explored features, that each feature performs better in a specific time frame according to the dynamics of the required task and that participants in the EXP group will show differences in the feature which performs the best.

The ultimate objective is to provide useful hints to design future BCI systems targeting post-stroke motor recovery, pursuing a trade-off between system performances and salient neurophysiological content of the proposed rehabilitative exercise.

2. Material and methods

2.1. Participants

Thirteen patients (EXP group) with a diagnosis of stroke and thirteen right-handed healthy subjects (CTRL group) participated in the study.

Healthy subjects did not present any evidence or known history of neuromuscular disorders, whereas for stroke participants the following inclusion criteria were applied: (1) a history of first-ever unilateral, cortical, subcortical, or mixed stroke, caused by ischemia or haemorrhage (confirmed by magnetic resonance imaging), that occurred 3–12 months prior to study inclusion; (2) upper limb hemiparesis that was caused by the stroke; and (3) age between 18 and 80 years. The exclusion criteria were presence of other chronic disabling diseases, such as orthopaedic injuries that could impair reaching or Grasp; spasticity of each segment of the upper limb scored higher than 4 on the modified ashworth scale (MAS) [38]. The two groups did not show any age difference (two-sided independent sample t-test, $p = 0.31$).

Clinical and functional evaluation was performed by expert physiotherapists before data acquisition (same day). The upper extremity section of the Fugl-Meyer assessment scale (FMA-UE, motor domains only ranging from 0—maximum impairment to 66—normal function) [39] was performed to describe patients' residual arm function. The manual muscle test (MMT) [40] was evaluated to assess strength in the paretic upper limb by testing shoulder abduction, elbow flexion/extension and wrist flexion/extension. The National Institute of Health Stroke Scale (NIHSS) [41] was performed to assess general impairment derived from stroke. Handedness was assessed in all participants by means of the short form of the Edinburgh handedness inventory [42]. Information about participants' demographic and clinical data are reported in table 1, more details on the single-subject characteristics of the EXP group are provided in table S1 of the supplementary materials. The dataset used for the purposes of this study was obtained within a research project conducted in accordance with the Declaration of Helsinki and approved by the local ethics board at Fondazione Santa Lucia, IRCCS, Rome, Italy (CE PROG.752/2019), whose results were partially published in [6, 20]. All the participants signed an informed consent.

2.2. Experimental design

Participants were involved in an experimental protocol already described in [6] and designed to elicit all three features. All participants were seated in a comfortable chair with their forearms placed on the table. Visual cues were presented on a screen on the desk in front of them via Matlab's Psychtoolbox. The experiment was administered according to a block design approach, including 4 blocks of 40 trials each, with a break among them. In each block, the subject was asked to perform one specific task among the four proposed: execution/attempt of finger extension and grasping with the right and the left hand separately in healthy participants, and with the unaffected (UH) and affected hand (AH) in stroke participants. Each block comprised 20 task trials of the same movement type and 20 rest trials presented according to a semi-random sequence with an inter-trial interval, consisting of a fixation cross in the middle of the screen, set at 3 s. Task trials had 8 s duration and started with 4 s of preparatory period, after which a go stimulus occurred, and the participant had to perform the task for 4 s.

Table 1. Demographic and clinical characteristics of the participants (mean ± standard deviation). C = chronic; FMA = Fugl-Meyer assessment scale, upper limb section; H = haemorrhagic; I = ischemic; L = left, LH = left hand, MAS = modified ashworth scale, MMT = manual muscle test, MH = mixed hand, MO = months, NIHSS = National Institute of Health Stroke Scale, R = right, RH = right hand, S = subacute, YR = years.

GROUP	EXP (N = 13)	CTRL (N = 13)
AGE (YR)	55.8 (±16.5)	48.5 (±19.3)
HANDEDNESS	10RH + 2MH + 1LH	13 RH
TIME FROM EVENT (MO)	5.5 (±4.5)	—
TYPE (S/C)	10 S + 3 C	—
ETIOLOGY (I/H)	7I + 6 H	—
SIDE OF LESION (R/L)	8 L + 5 R	—
FMA	42.9 (±14)	—
NIHSS	2.4 (±1.4)	—
MAS	1.6 (±1.5)	—
MMT	19.3 (±4.9)	—

Besides, rest trials lasted 4 s in which the participant had to relax. Participants were instructed to perform the task as fast as they could and hold it at 15% of maximum voluntary contraction (MVC) of the target muscle until the end of the trial. MVCs lasting 5 s were recorded for each muscle at the beginning of the experiment. All details about the block-design paradigm and the timeline of each trial are reported in figure 1.

EEG and EMG data were acquired simultaneously during the paradigm administration and sampled respectively at 1 kHz and 2 kHz. EEG signals were recorded from the scalp with 61 active electrodes arranged according to an extension of 10–20 International System (reference on left mastoid and ground on right mastoid) by means of BrainAmp amplifiers (Brain Products GmbH, Germany); surface EMG data were recorded through Pico EMG sensors (Cometa S.r.l., Italy) from 16 muscles collected in bipolar fashion: extensor digitorum (ED), flexor digitorum superficialis (FD), triceps brachii (TRI), biceps brachii (BIC), pectoralis major (PEC), lateral deltoid (Lat_DELT), anterior deltoid (Ant_DELT) and upper trapezius (TRAP) of both sides (L: left, R: right). EEG and EMG data were

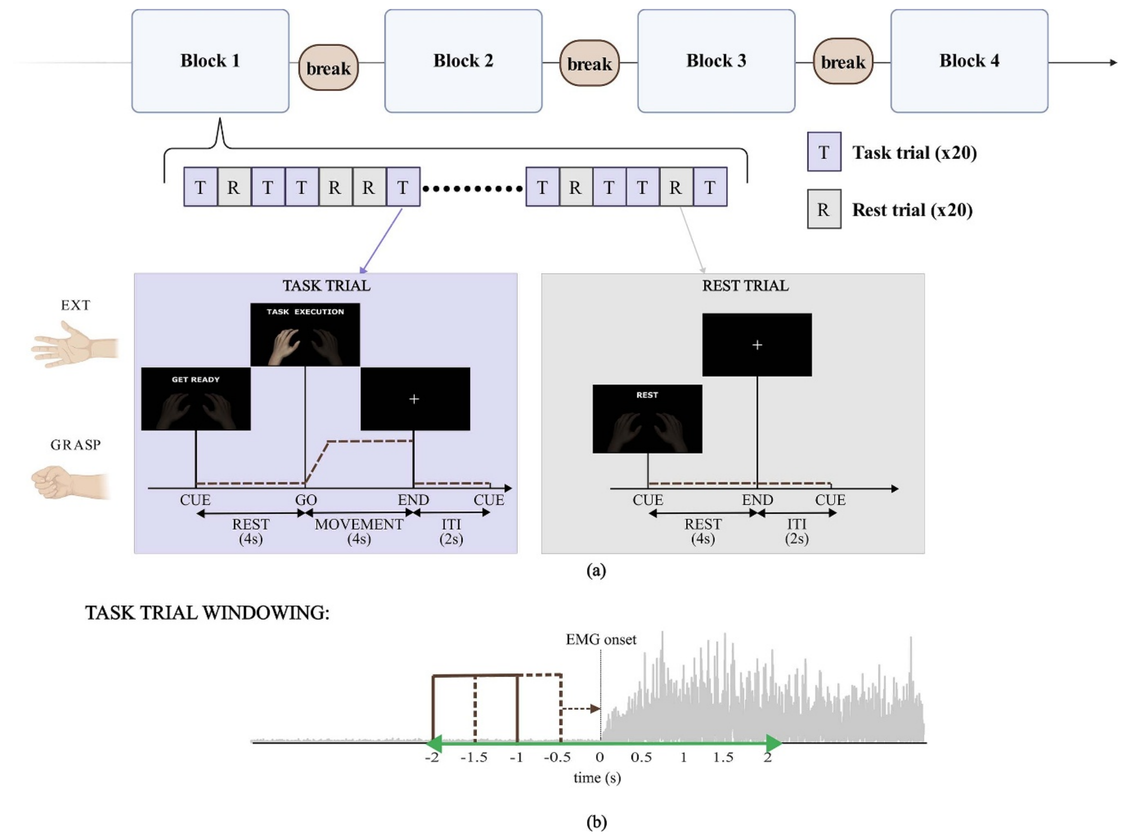

Figure 1. (a) Experiment timeline: the experiment was organised into four blocks with a break among them, each consisting of 20 task and 20 rest trials. In each block, participants performed one of the proposed tasks (i.e. ExtR, ExtL, GraspR, GraspL), with the sequence of tasks randomised across participants. A closer look at the timeline of task and rest trials is presented: the brown dashed line illustrates the activation profile required for the correct execution of the task, corresponding to the target muscle (ED for Ext and FD for Grasp), as well as the rest period. (b) Depiction of the selected time interval for task trials used to extract the features: task trials were aligned to the EMG onset, and the time interval [−2,2]s with respect to the EMG onset was selected. A sliding window approach was used to epoch such interval in 7 1 s-windows shifted of 0.5 s, features were extracted in each window to evaluate their evolution along motor preparation and execution/attempt phases.

synchronized through the BrainVision TriggerBox (Brain Products GmbH, Germany).

2.3. Data analysis

The methodological approach followed in this study is illustrated in figure 2. EEG and EMG data were processed offline (upper dashed box in figure 2) with custom scripts in Matlab 2021b (The MathWorks, Inc.), then each of the three features under analysis, i.e. ERD/ERS, MRCP and CMC, was extracted and used to classify the movement type according to a sliding window approach (lower dashed box in figure 2).

Ad-hoc pre-processing pipelines were performed according to the literature for the extraction of each feature type, and they are described in the following paragraphs (2.3.2, 2.3.3 and 2.3.4). The same pre-processing pipeline was applied to the EEG signals used to extract ERD/ERS and CMC features (in light blue and magenta in the flow chart of figure 2), whereas MRCP features were derived from EEG signals pre-processed through a dedicated pre-processing pipeline (in green in the flow chart of figure 2).

Artifact rejection was performed for each pipeline as described in the subsequent paragraphs and only artifact-free trials common to the three pipelines were considered for the analysis. The number of rejected task trials was on average 2.17 and 2.58 for healthy and stroke participants respectively.

The analysis (feature extraction + movement classification) was executed for task trials only in the temporal window [−2,2]s defined according to the EMG onset (figure 1(b)). The use of EMG onset as a temporal reference allowed the alignment of all the task trials with respect to the beginning of the movement and thus defining a window of interest centred on it. A sliding window approach (1 s-windows shifted by 0.5 s) was applied to task trials in such interval to consider features' evolution along the motor task period (preparation + execution/attempt).

2.3.1. EMG onset detection

To identify the movement onset, EMG signals were downsampled to 1000 Hz, band-pass filtered [3–500]Hz and a notch filter at 50 Hz was applied to remove power-line artefacts. The electrocardiographic component was rejected through template

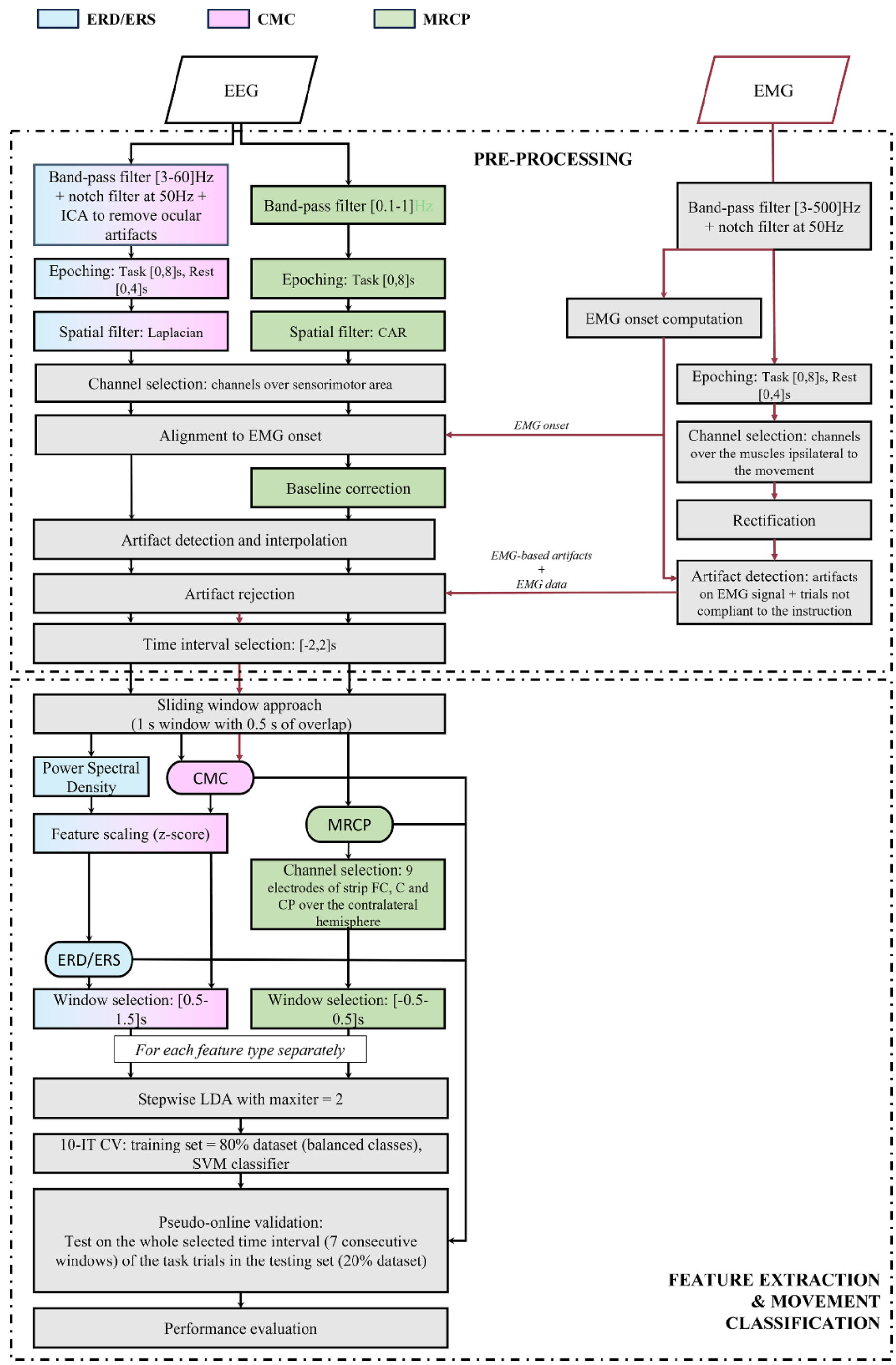

Figure 2. Outline of the methodological steps of the analysis. The colours of the boxes indicate the EEG processing steps applied ad-hoc for the extraction of each type of feature: light blue for ERD/ERS features, light green for MRCP features and magenta for CMC features. Grey boxes are related to processing steps common to the three features. Brown arrows highlight the EMG processing pipeline.

matching and subtraction method, resulted to be the method to achieve the best performance in terms of the lowest root mean square error in both time and frequency domain EMG features estimation [43]. Specifically, the approach, presented in [44] was applied and tailored to our data in terms of (i) the signal used for the QRS detection, set in our analysis as the signal band-passed filtered (10–40 Hz) collected from the left side PEC muscle and, (ii) statistical measure used to compute the template, set as the median of the QRS complexes. The EMG data of the target muscle (ED for Ext movements and FD for Grasp movements) have been processed to obtain the EMG onset for each task trial applying the Hodges and Bui algorithm [45] as in [20]. Task trials in which EMG onset resulted to occur before 2.5 s and after 6.5 s with respect to the cue onset were considered not compliant with the instruction given by the visual cues and thus marked as to reject.

2.3.2. ERD/ERS

For ERD/ERS computation, EEG signals were band-pass filtered [3–60]Hz and a notch filter at 50 Hz was applied to remove power-line noise. Independent Component Analysis was used to remove ocular artifacts and data were segmented into 8 s epochs for task trials and 4 s epochs for rest trials from the cue onset. To obtain reference-free signals and to enhance the signal-to-noise ratio, a nearest neighbour Laplacian was applied to EEG signals [46]. A subset of EEG channels over the sensorimotor area (FC5, FC3, FC1, FCz, FC2, FC4, FC6, C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, CP6, P3, Pz, P4) was considered for the extraction of ERD/ERS features, according to evidence from the literature [47, 48].

To obtain EEG artefact-free trials, a voltage threshold ($\pm 100\ \mu$V) was defined and all trials in which more than 1 channel exceeded the threshold were marked as to reject, otherwise, a spherical interpolation was performed to replace the noisy channel and the trial was included in the analysis. EEG data of task trials were aligned with respect to the EMG onset and the time interval [−2,2]s was selected and further divided into 7 consecutive 1 s-windows with 0.5 s of overlap. For rest trials, the artifact detection was performed by epoching the 4 s-trials in 1 s-windows and the first artifact-free window was considered for further analyses.

To obtain ERD/ERS features, Welch periodogram (Hann windows of 250 ms duration with 50% overlap) was used to compute the power spectrum of the EEG signals. The computation was repeated for all the 7 windows of task trials and the only one window of rest trials. Power spectrum values were averaged in two frequency bands of interest, normally associated with brain correlates of voluntary movements [7]: alpha (8–12 Hz) and beta (13–30 Hz) bands.

To visualize the temporal dynamics of such brain correlate for each motor task, the mean power spectrum of all the 24 EEG channels in each band was compared (paired t-test, $\alpha = 0.05$, false discovery rate—FDR correction) in task and rest condition for each sliding window, and the grand-average topographical scalp maps of the 7 task windows were displayed.

ERD/ERS features were then extracted by means of a *z*-score normalization of the PSD values in each task trial according to the mean and the standard deviation across trials of the PSD values obtained in the rest condition. Such normalization was performed to ensure that the difference between the two motor tasks was not attributable to variations in resting-state activity across different runs. The ERD/ERS computation was executed for each channel, frequency band and window of task trials. Thus, the initial ERD/ERS feature space was 48 dimensional (24 EEG channels $\times$ 2 frequency bands) for each window.

2.3.3. MRCP

For MRCP extraction, EEG signals were band-pass filtered [0.1–1]Hz, segmented in the period [0,8]s according to task trials' cue onset, and re-referenced according to the common average reference [49]. Then, a subset of EEG channels over the frontal and central sensorimotor area (F5, F3, F1, Fz, F2, F4, F6, FC5, FC3, FC1, FCz, FC2, FC4, FC6, C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, CP6) was selected because the activity of the frontocentral cortex is the major source for MRCPs [50]. Data were aligned with respect to the EMG onset and the time interval [−2.5, 2]s was selected for MRCP feature extraction. The first 500 ms were used for baseline correction and then removed from the epochs. Trials with more than 1 EEG channel in the baseline exceeding in absolute value the amplitude of 100 μV were marked as to reject, otherwise, a spherical interpolation was performed to replace the noisy channel with a weighted average of its neighbours.

To extract MRCP features, 21 electrodes of strip FC, C and CP over the bilateral sensorimotor areas were selected and the grand-average temporal evolution along the time interval of interest was displayed for each motor task. Baseline-corrected EEG data were downsampled to 20 Hz and the amplitudes of the time samples in the 1 s-window were considered as MRCP features in each consecutive window and trial. Thus, the initial MRCP feature space was 420 dimensional (21 EEG channels $\times$ 20 time samples).

2.3.4. CMC

CMC was computed using the EEG signals, pre-processed as for ERD/ERS features, and the filtered EMG signals segmented in 8 s epochs for task trials and 4 s epochs for rest trials with respect to the cue onset. A semi-automatic approach was used to detect the artefacts in the EMG signals: a statistical criterion based on the comparison between the EMG characteristics [51] of each trial and the median EMG characteristics of all trials (reference characteristic) was applied separately for task and rest conditions. Once the EMG artifacts were detected by the statistical criterion, trials were visually inspected and validated for rejection. As for the EEG data, also the EMG data were aligned with respect to the EMG onset and the time interval [−2,2]s of task trials was selected.

For the extraction of the hybrid EEG-EMG feature, only the 8 EMG channels over the muscles ipsilateral to the movement (e.g. the 8 muscles of the right upper limb in ExtR and GraspR) were selected. EMG signals were rectified [52] and the cortico-muscular coupling between each EEG-EMG pair was computed as in [33]. For each movement, the characteristic frequency of each EEG-EMG pair was extracted in three frequency bands of interest shown to be most informative for CMC features [6, 33]: alpha (8–12 Hz), beta (13–30 Hz) and gamma (31–60 Hz).

To evaluate the morphology of the feature along the time interval of interest the grand-average cortico-muscular patterns with the significant connections in task condition compared to rest condition were computed as in [6] for each sliding window, band and motor task.

The single-trial CMC values at the three characteristic frequencies of each EEG-EMG pair were computed in both task and rest conditions. In each of the 7 consecutive sliding windows, CMC features were extracted as the CMC values in task condition scaled by the mean and the standard deviation of the CMC values in rest trials (z-score standardization), such normalization was performed to ensure that the difference between the two motor tasks was not attributable to variations in resting-state activity across different runs. Thus, the initial CMC feature space had dimension 576 (24 EEG channels $\times$ 8 EMG channels $\times$ 3 frequency bands).

2.4. Movement classification

2.4.1. Classifier training and testing

To discriminate Ext from Grasp movements in each limb, data in one of the seven 1 s-windows was selected to train the classifier. Such window was chosen a priori according to the literature as follows: [0.5,1.5]s with respect to EMG onset (holding phase) for ERD/ERS and CMC-based classification [11, 53] and the 1 s-window centred on the movement onset (window [−0.5,0.5]s) for MRCP-based classification [54]. A feature selection algorithm based on the stepwise regression [55] with an empty initial model was applied to reduce the dimensionality of each feature space to a maximum of 2 features (maxiter = 2) before training a support vector machine (SVM) classifier with a linear kernel.

We set the maximum number of features equal to 2 as the best compromise between accuracy and system usability, matching the use of BCI technology in a clinical context. We have demonstrated in a previous study how the classification performances obtained using 10 features (Area Under the receiver operating characteristic Curve, AUC = 0.9) were almost comparable to those achieved with 2 features (AUC = 0.85) when distinguishing hand Grasp from Ext [32]. For each feature space, a single-subject 10-iteration cross-validation was applied to train the SVM classifier: in each iteration, the 80% of Ext and Grasp observations, randomly selected between the two classes to train a balanced classifier, was used as training set.

To test the ability of the trained classification model to discriminate between the two motor tasks, at each iteration a pseudo-online validation was performed testing the classifier, not only in the window used to train the classification model but along the 7 consecutive windows of the observations excluded from the training set (test set equal to 20% of the whole dataset's observations). The chance level was determined by performing a permutation test, which involved randomly shuffling the labels in both the training and test sets. This process was repeated multiple times to generate a distribution of classification accuracies under the null hypothesis, allowing us to estimate the probability of achieving a given accuracy by chance.

2.4.2. Performance evaluation

For each type of feature, the accuracy [56] was computed to evaluate its ability to classify two different hand movements along the analysed windows. Performance values were averaged across the 10 iterations for each participant and side.

Moreover, single-subject performances were evaluated for each feature-based classification with a specific focus on the window utilized for training the classification model. Such evaluation aimed to determine intra-subject differences related to the type of feature used to discriminate Ext from Grasp movement.

2.5. Statistical analysis

2.5.1. Temporal evolution of the performance along trial duration

To investigate the dynamic of each type of feature in discriminating Ext from Grasp movement along the whole selected time interval (2 s of movement preparation and 2 s of movement execution) in both healthy and stroke participants, a one-way repeated measures ANOVA (rmANOVA) was performed for each type of feature, side and group separately, considering as within main factor the WINDOW (7 levels: one for each sliding window) and as dependent variable the accuracy value.

To compare the ability of ERD/ERS, MRCP and CMC features to discriminate finger extension from grasping in both healthy and stroke participants, a one-way rmANOVA was performed for each window, side, and group separately. The FEATURE TYPE (3 levels: ERD/ERS, MRCP, CMC) was considered as within main factor and the accuracy as the dependent variable.

2.5.2. Between-groups differences in classification performance

A one-way ANOVA was applied to the accuracy values obtained by each feature-based classification considering as factor the three groups: CTRL—control group executing the task with the right hand; EXP UH—stroke group executing the task with the UH; EXP AH—stroke group attempting the task with the AH. The test was repeated in each of the 7 consecutive windows analysed.

The statistical significance level was set to $p < 0.05$ in all the statistical tests, a Tuckey's post-hoc test was performed to assess differences among the levels of the main factor of the ANOVAs performed. All the results were corrected for multiple comparisons according to the FDR procedure [57].

3. Results

3.1. Features morphology

The topographical representations of the three different types of features obtained in stroke participants during Ext and Grasp attempts with the AH are illustrated in figure 3. ERD in beta band appears to be stronger and more widespread across the sensorimotor area for Ext compared to Grasp movement. During Ext movement attempts, ERD is present during the movement preparation phase and intensifies during the motor execution phase. In contrast, during Grasp movement attempts, ERD occurs only during the motor execution phase, figure 3(a).

The MRCP waveforms show a peak around 0 s (EMG onset), more prominent in the hemisphere contralateral to the movement (left hemisphere). Differences in peak amplitude, latency, and topographical distribution are observed between the two motor tasks, figure 3(b).

Besides, CMC patterns in beta band show significant connections during the movement execution phase. Few connections and low CMC values due to a high inter-subject variability as well as to the reduction in CMC weight were obtained during the movement attempted with AH, as observed in previous studies [6]. Differences in network density and type of muscles involved in the CMC pattern during the movement attempt phase are shown between the two motor tasks, figure 3(c).

The topographical representations of the three features for healthy participants and stroke participants during the movements executed with the UH are shown in figures S1 and S2 of supplementary materials, whereas the morphology of the features in the other frequency bands of interest is reported in figures S3-S5. For the sake of brevity, for the CTRL group only results related to motor tasks performed with the right hand (dominant hand) were reported in the study.

3.2. Temporal evolution of the classification performance along trial duration and across-features differences

As for the CTRL group, the rmANOVA revealed significant differences in accuracy values concerning the main factor, WINDOW, for the three features separately (ERD/ERS: $F(6,72) = 12.78$, $p < 0.01$; MRCP: $F(6,72) = 5.56$, $p < 0.01$; CMC: $F(6,72) = 28.37$, $p < 0.01$). The temporal evolution of Ext-vs-Grasp classification accuracies observed across the seven consecutive time windows separately for the three features is depicted in figure 4(a) whereas the results of the post-hoc analysis on the main factor WINDOWS for the 3 features are reported in figure 4(b).

Accuracy levels during the motor preparation phase ([−1.5,0.5]s with respect to EMG onset), closely approximated the chance level without any statistically significant difference among each other. Moving forward to windows related to movement execution (time interval [0,1.5]s), an increase in the accuracy was observed. As for ERD/ERS, the first window in which the accuracy resulted as significantly different from the previous ones was the fifth (centred on 0.5 s) where performances moved from slightly above chance level to 70%–80% and remained almost constant up to the end of the trial. No differences were found among the last 3 windows as revealed by the post-hoc test. As for the CMC, the first statistical difference along the trial was described in the window containing the EMG onset ($t = 0$ s) in which the accuracy reached values around 85% and remained stable around 85%–90% for the entire trial duration (no differences among the last 4 windows as revealed by the post-hoc test). MRCP-based classification displayed accuracy values close to chance level for all the windows except for the window centred in 0 s (i.e. movement onset) where a prominent peak in accuracy (74%) was found as statistically different with respect to all the other windows. To summarise, the first significant classification accuracy values were obtained in the window centred in 0.5 s for ERD/ERS while in the window centred in 0 s for MRCP and CMC.

Results of the rmANOVAs on the accuracy for the main factor FEATURE TYPE are shown in figure 4(c) for each temporal window. No statistical differences among the three feature types were observed during the movement preparation phase (first three windows). CMC-based classification showed the highest accuracy with respect to the ERD/ERS during the time interval [0,1]s. The worst performances were found for MRCP-based classification in all the movement execution windows except for the window centred in 0 s in which no significant differences were found among MRCP accuracies, ERD/ERS and CMC ones.

The EXP group, when executing movements with the UH, reported Ext-vs-Grasp classification performance trends resembling that of the CTRL group in the preparation ([−1.5,0.5]s) and the holding phase ([0.5,1.5]s), as shown in figure 5(a). The only deviations from the CTRL group worth noting are related to the factor FEATURE TYPE (figure 5(c)). We did not find any significant difference between CMC and the other two features at the movement onset. Here, the accuracies were around 70%–80% for all the three features highlighting an increase on average of the performances based on MRCP and a delay in movement detection based on CMC when the task is executed by the EXP group with UH with respect to CTRL. In fact, CMC reached performances of 95% only in the window centred on 0.5 s, where both CMC and ERD/ERS were statistically different from MRCP which was at chance level. CMC

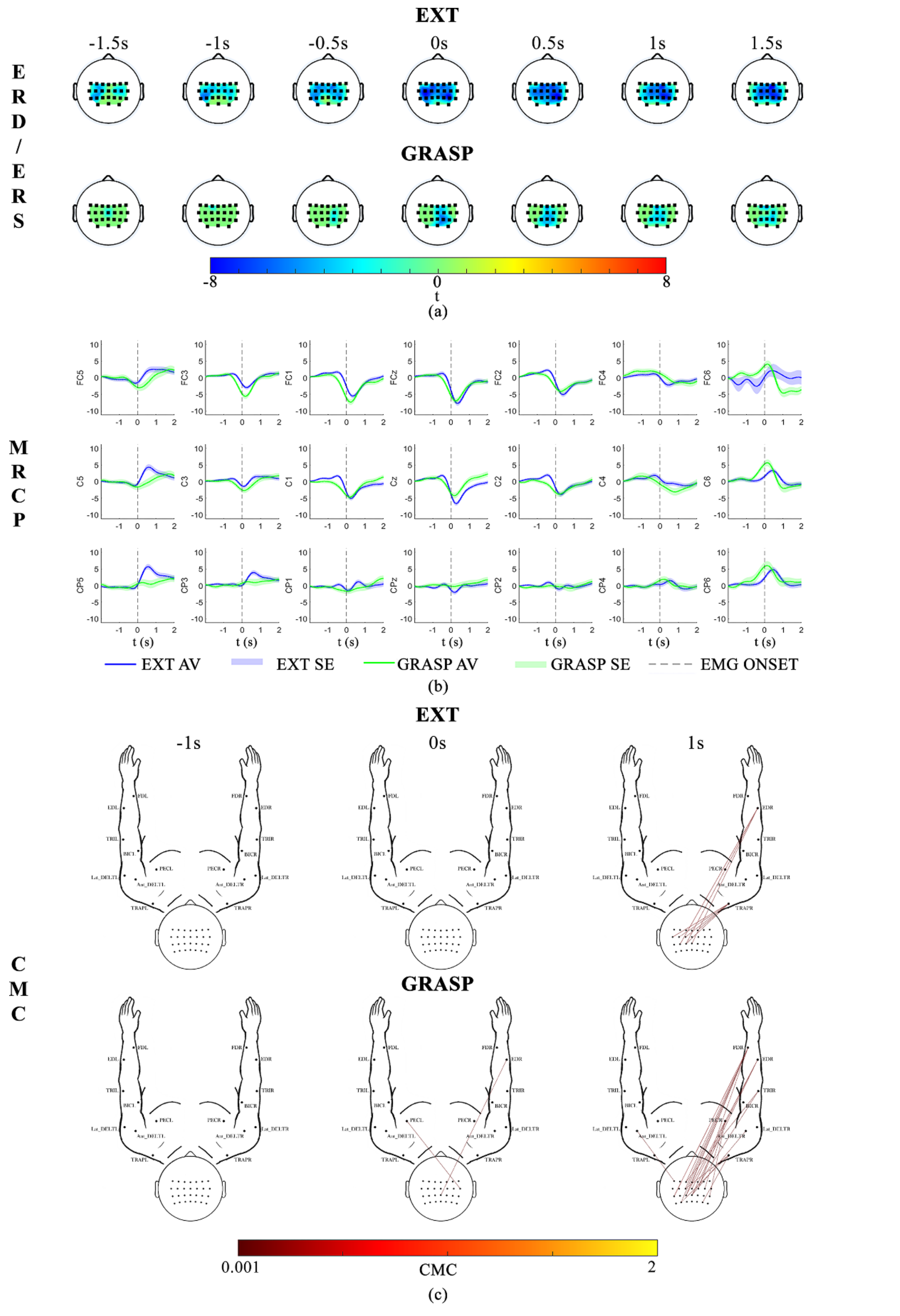

Figure 3. Grand-average ($N = 13$) topographical representation of the three features under analysis in the EXP group during Ext and Grasp movements attempted with the affected hand (AH). (a) Topographical scalp maps of the event-related desynchronization/synchronization (ERD/ERS) in beta (13–30 Hz) frequency band in the 7 sliding windows under analysis. Hot colours code for t-values when task > rest (synchronisation), blue colours code for t-values when task < rest (desynchronization). (b) Movement related cortical potential (MRCP) waveforms (mean—AV ± standard error—SE) in the time interval of interest ($[-2,2]$s with respect to the EMG onset) for the 21 EEG channels of the sensorimotor area. (c) Corticomuscular coherence (CMC) patterns estimated in beta (13–30 Hz) frequency band in three windows within the interval of interest, centred at -1 s, 0 s and 1 s with respect to EMG onset. The 2D body model is seen from the above: scalp with the nose pointing up the top and arms in front of the participant. Only statistically significant CMC values are represented (paired t-test between task and rest trials, α =0.05 FDR correction). The colour bar codes for the CMC average value (across participants) in the task trial. The EEG time series recorded over different scalp positions from patients with right-sided lesions were flipped along the midsagittal plane so that the ipsilesional side was common to all stroke participants. A similar procedure was also applied to EMG data in all stroke participants with left affected hand (right hemisphere lesion). Both flipping procedures thus ensured to label the left hemisphere and contralateral right hand as 'affected' in all the stroke participants, independently from their actual lesion side. EXT: finger extension movement, GRASP: grasping movement.

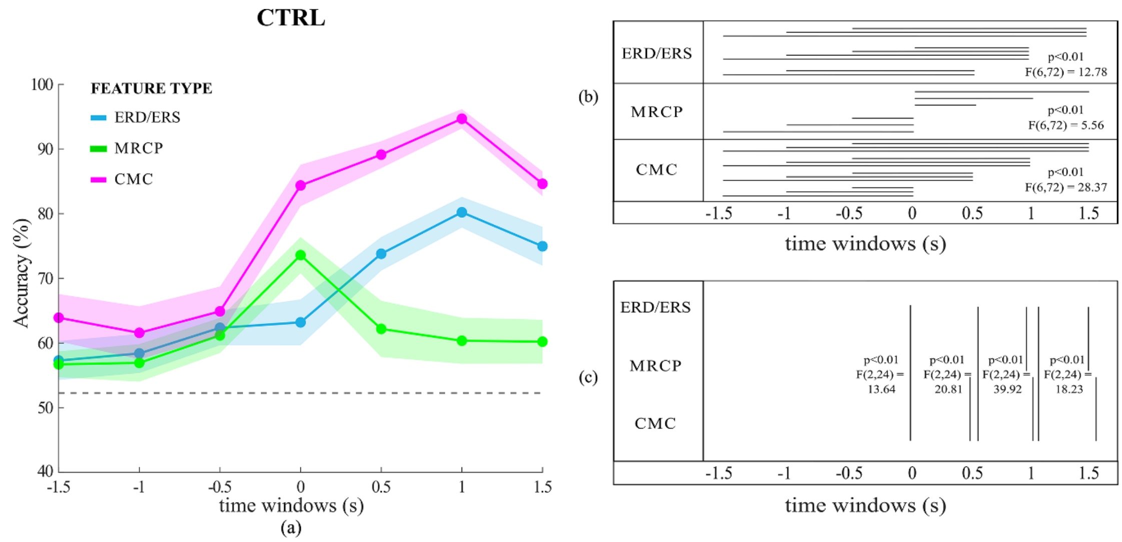

Figure 4. (a) Temporal trend of the Ext-vs-Grasp classification accuracies obtained in the 13 healthy participants (CTRL group) during tasks performed with the right hand along the 7 consecutive windows tested for the three feature types. The time represents the centre of each window with respect to the EMG onset ($t = 0$ s), the chance level for classification accuracy is represented by a dashed horizontal line. (b) Results of the one-way rmANOVA with main factor WINDOW for the three feature types separately; (c) results of the one-way rmANOVA with main factor FEATURE TYPE for each of the 7 consecutive windows. Lines show statistically significant differences as revealed by Tuckey's post-hoc test ($p < 0.05$, FDR corrected for multiple comparisons).

outperformed ERD/ERS-based classification in the last window (holding phase) centred in 1.5 s.

Figure 5(d) shows the trends of the performances in discriminating the two motor tasks obtained in the EXP group when attempting the movements with the AH. The temporal trends obtained are similar to those previously described when patients moved the UH. The only changes lay in the absence of a significant difference between CMC and ERD/ERS during the movement execution windows (figure 5(f), [0,1.5]s) when the movement is attempted with the AH and in a generalised increase of ERD/ERS-based performances in the preparation phase.

3.3. Investigating differences in classification performance among the three features at the single-subject level

As expected, the best classification accuracy was achieved on average in the window used to train the classification model (window suggested by literature: window centred in the EMG onset for MRCP-based classification, window centred in 1 s for ERD/ERS and CMC-based classifications).

To investigate the intra-subject differences related to the type of feature used, tables 2 and 3 show the performance achieved by testing the ability of each feature-based classification to discriminate Ext from Grasp movement within that window.

In the CTRL group, overall, using CMC features showed the highest average performance and the lowest inter-subject variability (95% on average with a standard error of 1%) with respect to the other two classifications based on ERD/ERS and MRCP which reached 80% and 74% respectively. Looking at the accuracies obtained for each participant in CTRL group for the three features reported in table 2, we noticed a strong consistency within the group testified by the fact that the accuracies obtained at the single-subject level reflected the trend obtained on average in the group. Few exceptions were noticed for participants H6 and H10 where ERD/ERS-based classification performed as well as CMC-based one (90%–100%) and for participants H1 in which MRCP-based classification performed as well as CMC-based one (90%).

Similar results were obtained in the EXP group for movements performed with UH: CMC-based classification resulted to achieve on average the highest accuracy and the lowest inter-subject variability, with some participants in which CMC-based and ERD/ERS-based classification showed to perform similarly. Whereas lower accuracy and higher inter-subject variability were obtained when using MRCP features, as shown in table 3.

For movements attempted with the AH by the EXP group, the classification accuracy in discriminating the two motor tasks within the best window resulted to be higher on average of 80% regardless of the feature type.

In each participant, at least one of the features led to performance equal to or higher than 90%. In most of the patients, CMC-based classification had not the highest accuracy as in the CTRL and EXP UH but the values were comparable with those obtained for ERD/ERS. MRCP-based classification showed high accuracy in most patients, in some cases outperforming those obtained by means of ERD/ERS (S1, S2, S3, S4, S10) and CMC (S1), as shown in table 3.

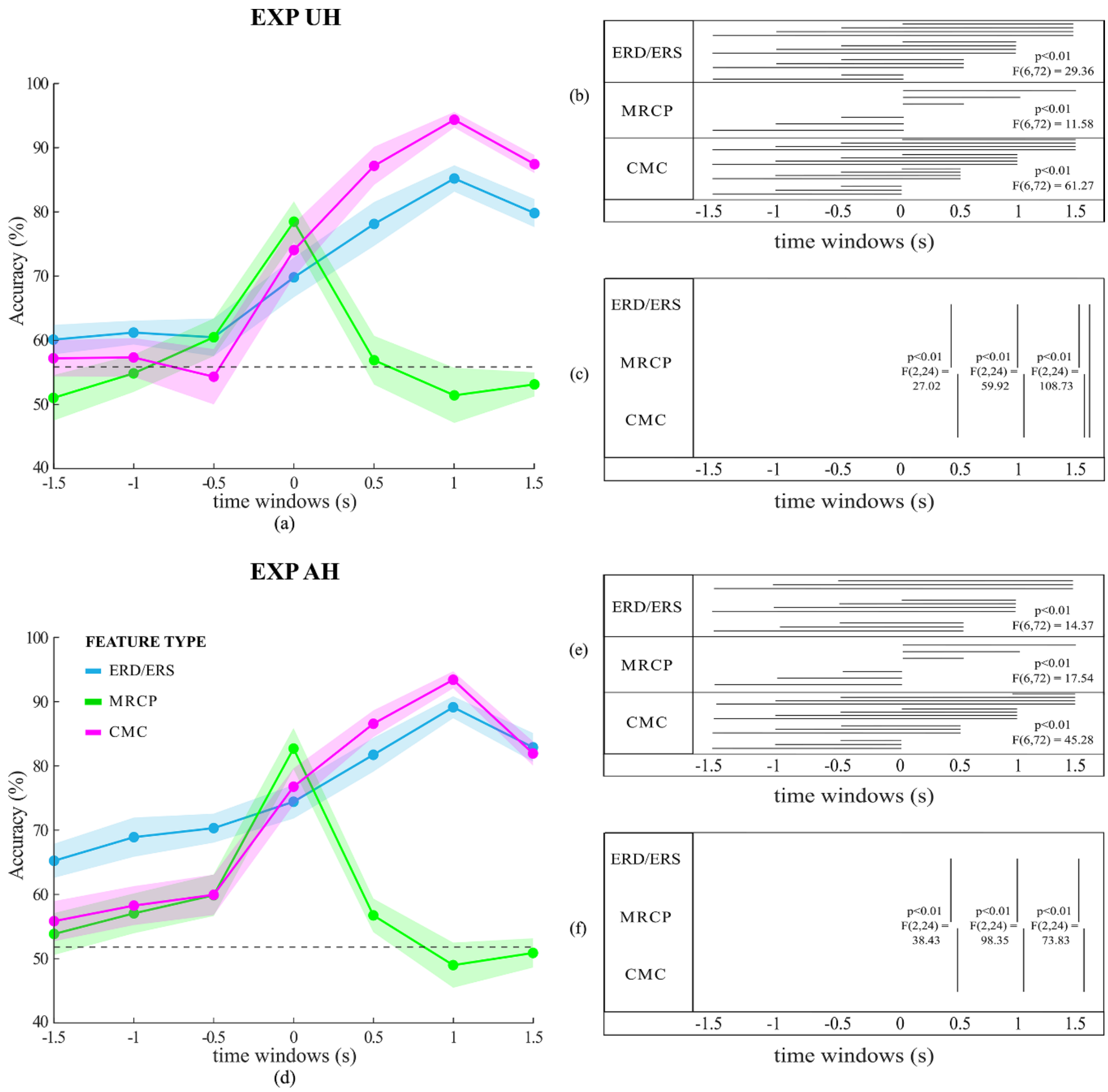

Figure 5. (a), (d) Temporal trend of the Ext-vs-Grasp classification accuracies obtained in the 13 stroke participants (EXP group) during tasks performed with (a) the unaffected hand (UH) and (d) the affected hand (AH) along the 7 consecutive windows tested for the three feature types. The time represents the centre of each window with respect to the EMG onset ($t = 0$ s), the chance level is represented by a dashed horizontal line. (b), (e) results of the one-way rmANOVA with main factor WINDOW for the three feature types separately during UH (b) and AH (e); (c), (f) results of the one-way rmANOVA with main factor FEATURE TYPE for each of the 7 consecutive windows during UH (c) and AH (f). Lines show statistically significant differences as revealed by Tuckey's post-hoc test ($p < 0.05$, FDR corrected for multiple comparisons).

Table 2. Single-subject classification accuracies in healthy participants (CTRL group) obtained within the optimal window (used for training the classifier) by the event-related desynchronization/synchronization (ERD/ERS)-based classification, movement related cortical potential (MRCP)-based classification and the cortico-muscular coherence (CMC)-based classification of Ext-vs-Grasp movements performed with the right hand. The last two columns contain the mean value obtained in the group and the related standard error (SE).

	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11	H12	H13	Mean	SE
ERD/ERS	81%	73%	80%	86%	84%	96%	79%	78%	75%	92%	63%	73%	83%	80%	2%
MRCP	89%	53%	73%	61%	79%	80%	71%	78%	74%	82%	74%	83%	60%	74%	3%
CMC	90%	100%	100%	90%	93%	100%	100%	87%	100%	91%	87%	93%	100%	95%	1%

3.4. Between-groups differences in classification performance

Figure 6 shows the comparison of the temporal dynamics of the classification performance for each feature type separately in the three groups under analysis (CTRL, EXP UH and EXP AH). The only statistical difference highlighted by the ANOVA was found in the window [0.5,1.5]s for the ERD/ERS-based classification between the CTRL and EXP AH group.

4. Discussion

This study explored the potential of three distinct neurophysiological counterparts of the hand

Table 3. Single-subject classification accuracies in stroke participants (EXP group) obtained within the optimal window (used for training the classifier) by the ERD/ERS-based classification, the MRCP-based classification and the CMC-based classification of Ext-vs-Grasp movements performed with the unaffected hand (UH) and attempted with the affected hand (AH). The last two columns contain the mean value obtained in the group and the related standard error (SE).

		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	Mean	SE
UH	ERD/ERS	88%	86%	85%	76%	95%	85%	92%	74%	80%	85%	95%	93%	74%	85%	2%
	MRCP	80%	68%	90%	84%	75%	83%	60%	54%	82%	80%	90%	88%	88%	79%	3%
	CMC	100%	94%	96%	95%	94%	98%	83%	93%	92%	93%	99%	98%	93%	94%	1%
AH	ERD/ERS	83%	90%	88%	90%	100%	90%	100%	88%	85%	78%	90%	92%	85%	89%	2%
	MRCP	95%	95%	95%	93%	92%	66%	79%	73%	78%	85%	60%	78%	85%	83%	3%
	CMC	87%	100%	91%	97%	93%	90%	100%	93%	88%	98%	96%	95%	86%	93%	1%

movements to discriminate between two simple motor tasks i.e. finger extension from grasping in both healthy and stroke participants.

We found that the temporal dynamics of discriminant accuracy across the consecutive time windows were in accordance with the expectations derived from the physiology of movement and related literature. In particular, ERD/ERS and CMC-based classification showed a significant increase in performance during the motor execution phase [20, 58], whereas MRCP-based classification showed a prominent peak in accuracy at movement onset [54]. This is in line with what was previously described in healthy subjects during hand Grasp movements, where movement-vs-rest differences were found almost 400 ms before and 150 ms after movement onset for MRCP and ERD/ERS, respectively [59]. Our results showed slightly delayed temporal dynamics that was probably due to different experimental protocols i.e. contrast between 2 movements versus a single movement against rest.

The temporal dynamics of ERD/ERS, MRCP and CMC features' accuracies were similar between healthy subjects and stroke patients when executing the movement with the unaffected hand in the preparation and holding phase, whereas they diverged when the affected hand was involved. Specifically, in healthy subjects CMC-based classification managed to distinguish between the two movements not only at movement onset but throughout the movement execution phase, showing a faster temporal dynamic compared to ERD/ERS-based classification for which a similar profile, even if shifted in time and lower in general for accuracy, was observed.

The classification accuracies observed in healthy participants in the window used to train the classifier (on average 95% for CMC-based classification, 80% for ERD/ERS-based classification and 74% for MRCP-based classification) were similar to previous data on discriminative abilities of CMC [34] and MRCP [15, 31]. However, a direct comparison with the performances obtained in these previous studies is challenging due to the different number of classes considered. Our classification performance encourages the use of ERD/ERS to distinguish different movements of the same hand, such as finger extension from grasping [60]. Indeed, our classification accuracies resulted to be higher than those reported in a similar study assessing the ability of ERD/ERS and CMC to discriminate upper limb movements [35].

At the single subject level, CMC outperformed both ERD/ERS and MRCP consistently in healthy participants. Stroke participants, especially when executing the movement with the affected hand, were characterized by a higher variability across subjects in terms of which feature provided the best accuracy. In the EXP group, CMC performances at movement onset decreased on average whereas ERD/ERS and MRCP accuracies increased on average. For both ERD/ERS it was observed that higher classification accuracies were obtained in EXP AH with respect to CTRL in the window used to train the classifier.

The higher classification accuracy observed for CMC-based classification, more consistently among healthy subjects, is not unexpected. Indeed, CMC is an intrinsically hybrid feature which encodes communication between the cortical (EEG) activity and the muscular (EMG), and it is fairly obvious that in the attempt to distinguish one movement from another in the same body district (i.e. Ext from Grasp), the information coming from the muscles is capital.

In the context of BCI applications for post-stroke motor recovery, the necessity to record EEG and EMG simultaneously adds relevant complexity to both the set-up and the necessary algorithms for data processing. However, this study demonstrated the superior discriminative power of CMC with respect to the other EEG-derived features. This was especially consistent in healthy subjects while it showed some pitfalls in the case of stroke patients when executing the movement with the AH. Specifically, ERD/ERS and MRCP outperformed CMC in some patients and the temporal evolution of CMC-based accuracy was slower in this group. These findings confirm that CMC is affected by the stroke-derived hemiparetic condition, in line with the vast literature showing a correlation between such motor impairment and CMC parameters [61, 62]. Furthermore, CMC encodes information that is relevant to characterise common post-stroke movement

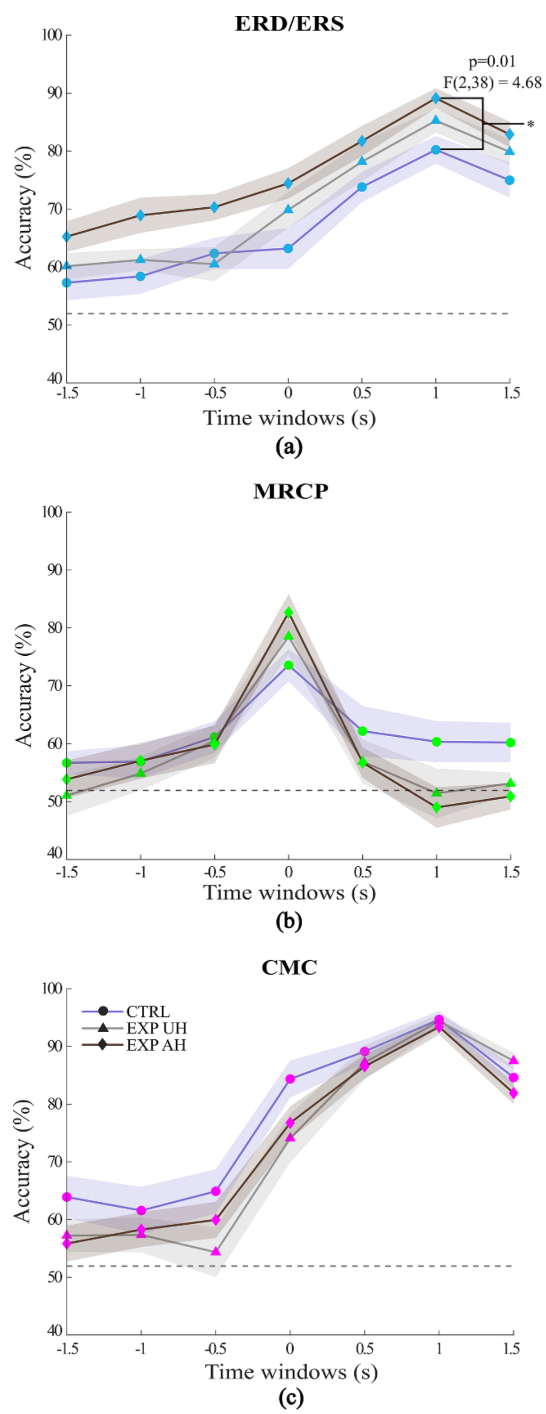

Figure 6. Temporal trends of the Ext-vs-Grasp classification accuracies obtained along the 7 consecutive windows in 13 healthy participants (CTRL group), in 13 stroke participants when performing the movement with the unaffected hand (EXP UH) and when attempting the movement with the affected hand (EXP AH) for each feature-based classification: (a) ERD/ERS (b) MRCP and (c) CMC-based classification. The time represents the centre of each window with respect to the EMG onset ($t = 0$ s), the chance level is represented by a dashed horizontal line. The asterisk shows a statistically significant difference as revealed by Tuckey's post-hoc test ($p < 0.05$, FDR corrected for multiple comparisons).

abnormalities [6] that may constitute one of the targets of BCI-based post-stroke rehabilitation (e.g. to contrast abnormal muscular recruitment, spasticity, and co-contractions), thus justifying the additional complexity of the recording setup and data processing in a rehabilitative context.

The observation that the 'best' discriminating feature in the optimal time window varied among stroke patients, being sometimes identified in ERD/ERS or MRCP, prompts us to consider the need to personalize BCI approaches for rehabilitation in order to facilitate adherence and participation to the treatment itself. The ability to efficiently deliver correct and contingent feedback in rehabilitation contexts is important to guarantee consistency, adherence to treatment and ultimately enhance neuroplasticity subserving favourable motor outcomes.

It is also worth mentioning that ERD/ERS, differently from the other two features, has been widely employed in paradigms based on motor imagery [9, 22, 63] rather than execution, more easily applicable in very severe patients with no residual motor activity.

All this information should be considered when designing paradigms for rehabilitative BCIs, evaluating the importance of fast/contingent feedback, the need to verify the maintenance of a given motor task over time, and the capability of the target patient population to perform the required task.

Our most unexpected finding is probably related to the higher classification accuracies for ERD/ERS in stroke patients with respect to healthy subjects, observed in the window used to train the classifier and a general trend, even if not significant, for MRCP at movement onset. As said, only EEG-derived features performed generally less well than the EEG-EMG feature to distinguish between two movements in the same body segment. Both the sensory-motor event-related frequency modulation and the MRCP are recorded at the scalp level and reflect phenomena involving largely overlapping neural populations for both the Grasp and Ext movements. However, these features in stroke subjects that perform the movements with their impaired hand are capable of discriminating between the two movements better than in healthy subjects. Our interpretation, corroborated by available evidence [16, 64, 65], is that the effort required on behalf of patients to perform the movements increases their discriminability at the scalp level. Indeed, the required movements were performed quite effortlessly by healthy subjects, likely involving the minimum necessary neural resources. Conversely, for hemiparetic patients, the very act of exercising their affected hand holds a higher salience which eventually results in the recruitment of larger neural populations. Moreover, the presence of a lesion in the brain affecting areas devoted to hand motor control likely resulted in a differential involvement of nearby brain areas depending on the specific type of hand movement required. The trend of MRCP classification accuracy, higher in patients when attempting the movement with the AH, supports these hypotheses. Indeed, although the impact of stroke on

MRCP peak amplitude remains controversial [19, 66], most studies reported an increase in MRCP peak negativity after stroke [18, 67], with a subsequent reduction during motor recovery [19].

As regards the capability of the selected features to classify the movements before movement onset (an aspect which might be of interest in rehabilitative and assistive context e.g. to control movement effectors [25, 68]), our results were altogether unsatisfying (except for 70% of accuracy with ERD/ERS). Our interpretation of this negative finding is that the preparation phases for the two movements are hardly discriminable, while at movement onset (for MRCP) and during maintenance (for ERD/ERS and CMC), the sensory afferents play a crucial role in movement discrimination.

A further limit of our study is that the use of a sliding window approach rather than real-time movement classification may not entirely replicate real-world BCI applications, thus an online study should be performed for the direct translation of findings to practical rehabilitation scenarios. In addition, the training of the classifier was conducted on a window selected a priori for all the patients on the basis of previous knowledge of motor tasks [11, 53, 54]. Future works should generalise this point by tailoring offline the training window on a single patient.

Furthermore, as the dataset dimension is limited, our machine learning approach only includes training and testing datasets, with a consequent impact on the generalisability of the results. Larger studies will allow the construction of a validation dataset in addition to the training and test datasets, on which the hyperparameters of the model can be tuned providing an unbiased evaluation of the model fitted to the training dataset.

The block-design approach for data collection might have affected the classification performances reported in this manuscript. To mitigate this risk, we randomized the blocks' order across participants and normalised the data through z-score with respect to the rest period.

5. Conclusions

This study provides valuable insights into the potential of different neurophysiological correlates in discriminating hand movements, especially in the context of post-stroke rehabilitation. Three distinct neurophysiological counterparts of hand movement, extracted from the same dataset in stroke patients showed distinct characteristics in terms of classification accuracies along the different time windows explored. This underlines the importance of a comprehensive observation of the motor-related brain phenomena beyond the mere pursue of the highest accuracy. Indeed, while accuracy is definitely pivotal in determining the efficacy of assistive BCI (i.e. BCIs for communication and control), several other factors should be taken into account in rehabilitative contexts (e.g. feedback modality). Our results emphasize the need for personalized BCI approaches, tailored to patients' motor impairment and characteristics. The personalization of control features is crucial to enhance patient engagement and adherence to treatment. Moreover, it underlines the importance of evaluating the temporal dynamics of such feature-based movement classifications in order to choose a feature that can provide a fast and contingent feedback right after the movement attempt or continuous feedback during movement maintenance, according to the required application. Future works should test in real-time the ability of the investigated features to discriminate different movement types in stroke patients. Moreover, other movements even more complex should be included to increase the knowledge about such features and investigate their potentiality in BCI for rehabilitation purposes. From a methodological point of view, more complicated classifiers (e.g. non-linear) should be tested in order to assess whether the results obtained from the features comparison are dependent on the approach used or could be generalized.

Data availability statement

The data cannot be made publicly available upon publication because they are not available in a format that is sufficiently accessible or reusable by other researchers. The data that support the findings of this study are available upon reasonable request from the authors.

Acknowledgment

We thank Giorgio Tartaglia (neurophysiology technician) for the support in data recording.

This work was partially supported by the Italian Ministry of Health (GR-201812365874, RF-2018-12365210, Ricerca Corrente 2024) and by Sapienza University of Rome—Progetti di Ateneo 2020 (RM120172B8899B8C).

ORCID iDs

Valeria de Seta https://orcid.org/0000-0001-8796-8775
Emma Colamarino https://orcid.org/0000-0002-5375-8339
Floriana Pichiorri https://orcid.org/0000-0003-1225-7025
Giulia Savina https://orcid.org/0009-0005-1778-706X

Angela Riccio https://orcid.org/0000-0002-4098-9461
Donatella Mattia https://orcid.org/0000-0002-3092-2511
Jlenia Toppi https://orcid.org/0000-0002-8279-1699

References

[1] Raffin E and Hummel F C 2018 Restoring motor functions after stroke: multiple approaches and opportunities *Neuroscientist* **24** 400–16
[2] Peksa J and Mamchur D 2023 State-of-the-art on brain-computer interface technology *Sensors* **23** 6001
[3] Yang S, Li R, Li H, Xu K, Shi Y, Wang Q, Yang T and Sun X 2021 Exploring the use of brain-computer interfaces in stroke neurorehabilitation *BioMed Res. Int.* **2021** e9967348
[4] Pichiorri F and Mattia D 2020 Brain-computer interfaces in neurologic rehabilitation practice *Handbook of Clinical Neurology* vol 168, ed N F Ramsey and J R Del Millán (Elsevier) ch 9, pp 101–16
[5] Hong K-S and Khan M J 2017 Hybrid brain–computer interface techniques for improved classification accuracy and increased number of commands: a review *Front. Neurorobot.* **11** 275683
[6] Pichiorri F, Toppi J, De Seta V, Colamarino E, Masciullo M, Tamburella F, Lorusso M, Cincotti F and Mattia D 2023 Exploring high-density corticomuscular networks after stroke to enable a hybrid brain-computer interface for hand motor rehabilitation *J. Neuroeng. Rehabil.* **20** 5
[7] Pfurtscheller G, Pregenzer M and Neuper C 1994 Visualization of sensorimotor areas involved in preparation for hand movement based on classification of μ and central β rhythms in single EEG trials in man *Neurosci. Lett.* **181** 43–46
[8] Deecke L, Scheid P and Kornhuber H H 1969 Distribution of readiness potential, pre-motion positivity, and motor potential of the human cerebral cortex preceding voluntary finger movements *Exp. Brain Res.* **7** 158–68
[9] Hamedi M, Salleh S-H and Noor A M 2016 Electroencephalographic motor imagery brain connectivity analysis for BCI: a review *Neural Comput.* **28** 999–1041
[10] Mima T and Hallett M 1999 Corticomuscular coherence: a review *J. Clin. Neurophysiol.* **16** 501
[11] Pfurtscheller G and Lopes Da Silva F H 1999 Event-related EEG/MEG synchronization and desynchronization: basic principles *Clin. Neurophysiol.* **110** 1842–57
[12] Mrachacz-Kersting N, Ibáñez J and Farina D 2021 Towards a mechanistic approach for the development of non-invasive brain-computer interfaces for motor rehabilitation *J. Physiol.* **599** 2361–74
[13] Toro C, Deuschl G, Thatcher R, Sato S, Kufta C and Hallett M 1994 Event-related desynchronization and movement-related cortical potentials on the ECoG and EEG *Electroencephalogr. Clin. Neurophysiol.* **93** 380–9
[14] Bai O, Rathi V, Lin P, Huang D, Battapady H, Fei D-Y, Schneider L, Houdayer E, Chen X and Hallett M 2011 Prediction of human voluntary movement before it occurs *Clin. Neurophysiol.* **122** 364–72
[15] Ofner P, Schwarz A, Pereira J and Müller-Putz G R 2017 Upper limb movements can be decoded from the time-domain of low-frequency EEG *PLoS One* **12** e0182578
[16] Thibaut A, Simis M, Battistella L R, Fanciullacci C, Bertolucci F, Huerta-Gutierrez R, Chisari C and Fregni F 2017 Using brain oscillations and corticospinal excitability to understand and predict post-stroke motor function *Front. Neurol.* **8** 187
[17] Yilmaz O, Birbaumer N and Ramos-Murguialday A 2015 Movement related slow cortical potentials in severely paralyzed chronic stroke patients *Front. Hum. Neurosci.* **8** 1033
[18] Honda M, Nagamine T, Fukuyama H, Yonekura Y, Kimura J and Shibasaki H 1997 Movement-related cortical potentials and regional cerebral blood flow change in patients with stroke after motor recovery *J. Neurol. Sci.* **146** 117–26
[19] Butt M, Naghdy G, Naghdy F, Murray G and Du H 2021 Effect of robot-assisted training on EEG-derived movement-related cortical potentials for post-stroke rehabilitation–a case series study *IEEE Access* **9** 154143–55
[20] De Seta V, Toppi J, Colamarino E, Molle R, Castellani F, Cincotti F, Mattia D and Pichiorri F 2022 Cortico-muscular coupling to control a hybrid brain-computer interface for upper limb motor rehabilitation: a pseudo-online study on stroke patients *Front. Hum. Neurosci.* **16** 1016862
[21] Mrachacz-Kersting N *et al* 2016 Efficient neuroplasticity induction in chronic stroke patients by an associative brain-computer interface *J. Neurophysiol.* **115** 1410–21
[22] Pichiorri F *et al* 2015 Brain–computer interface boosts motor imagery practice during stroke recovery *Ann. Neurol.* **77** 851–65
[23] Wolpaw J R, Birbaumer N, McFarland D J, Pfurtscheller G and Vaughan T M 2002 Brain–computer interfaces for communication and control *Clin. Neurophysiol.* **113** 767–91
[24] Wang K, Xu M, Wang Y, Zhang S, Chen L and Ming D 2020 Enhance decoding of pre-movement EEG patterns for brain–computer interfaces *J. Neural Eng.* **17** 016033
[25] Sburlea A I, Montesano L and Minguez J 2015 Continuous detection of the self-initiated walking pre-movement state from EEG correlates without session-to-session recalibration *J. Neural Eng.* **12** 036007
[26] Seeland A, Manca L, Kirchner F and Kirchner E A 2015 Spatio-temporal comparison between ERD/ERS and MRCP-based movement prediction *Proc. Int. Joint Conf. on Biomedical Engineering Systems and Technologies (BIOSTEC)* vol 4 (SCITEPRESS—Science and Technology Publications, Lda) pp 219–26
[27] Ibáñez J, Serrano J I, Del Castillo M D, Monge-Pereira E, Molina-Rueda F, Alguacil-Diego I and Pons J L 2014 Detection of the onset of upper-limb movements based on the combined analysis of changes in the sensorimotor rhythms and slow cortical potentials *J. Neural Eng.* **11** 056009
[28] Wang J, Bi L and Fei W 2023 EEG-based motor BCIs for upper limb movement: current techniques and future insights *IEEE Trans. Neural Syst. Rehabil. Eng.* **31** 4413–27
[29] Liu T, Huang G, Jiang N, Yao L and Zhang Z 2020 Reduce brain computer interface inefficiency by combining sensory motor rhythm and movement-related cortical potential features *J. Neural Eng.* **17** 035003
[30] Quandt F, Reichert C, Hinrichs H, Heinze H J, Knight R T and Rieger J W 2012 Single trial discrimination of individual finger movements on one hand: a combined MEG and EEG study *NeuroImage* **59** 3316–24
[31] Schwarz A, Höller M K, Pereira J, Ofner P and Müller-Putz G R 2020 Decoding hand movements from human EEG to control a robotic arm in a simulation environment *J. Neural Eng.* **17** 036010
[32] de Seta V, Colamarino E, Cincotti F, Mattia D, Mongiardini E, Pichiorri F and Toppi J 2022 Cortico-muscular coupling allows to discriminate different types of hand movements *2022 44th Annual Int. Conf. IEEE Engineering in Medicine & Biology Society (EMBC)* pp 2324–7
[33] Colamarino E, de Seta V, Masciullo M, Cincotti F, Mattia D, Pichiorri F and Toppi J 2021 Corticomuscular and intermuscular coupling in simple hand movements to enable a hybrid brain–computer interface *Int. J. Neural Syst.* **31** 2150052
[34] Tang Z, Yu H, Lu C, Liu P and Jin X 2019 Single-trial classification of different movements on one arm based on ERD/ERS and corticomuscular coherence *IEEE Access* **7** 128185–97
[35] Lou X, Xiao S, Qi Y, Hu X, Wang Y and Zheng X 2013 Corticomuscular coherence analysis on hand movement distinction for active rehabilitation ed C-H Im *Comput. Math. Methods Med.* **2013** 908591

[36] Ofner P, Schwarz A, Pereira J, Wyss D, Wildburger R and Müller-Putz G R 2019 Attempted arm and hand movements can be decoded from low-frequency EEG from persons with spinal cord injury *Sci. Rep.* **9** 7134
[37] Biasiucci A *et al* 2018 Brain-actuated functional electrical stimulation elicits lasting arm motor recovery after stroke *Nat. Commun.* **9** 2421
[38] Bohannon R W and Smith M B 1987 Interrater reliability of a modified ashworth scale of muscle spasticity *Phys. Ther.* **67** 206–7
[39] Fugl-Meyer A R, Jääskö L, Leyman I, Olsson S and Steglind S 1975 The post-stroke hemiplegic patient. 1. a method for evaluation of physical performance *Scand. J. Rehabil. Med.* **7** 13–31
[40] Fan E, Ciesla N D, Truong A D, Bhoopathi V, Zeger S L and Needham D M 2010 Inter-rater reliability of manual muscle strength testing in ICU survivors and simulated patients *Intensive Care Med.* **36** 1038–43
[41] Goldstein L B, Bertels C and Davis J N 1989 Interrater reliability of the NIH stroke scale *Arch. Neurol.* **46** 660–2
[42] Oldfield R C 1971 The assessment and analysis of handedness: the Edinburgh inventory *Neuropsychologia* **9** 97–113
[43] Xu L, Peri E, Vullings R, Rabotti C, Van Dijk J P and Mischi M 2020 Comparative review of the algorithms for removal of electrocardiographic interference from trunk electromyography *Sensors* **20** 4890
[44] Abbaspour S and Fallah A 2014 Removing ECG artifact from the surface EMG signal using adaptive subtraction technique *J. Biomed. Phys. Eng.* **4** 33–38 (available at: https://pmc.ncbi.nlm.nih.gov/articles/PMC4258854/)
[45] Hodges P W and Bui B H 1996 A comparison of computer-based methods for the determination of onset of muscle contraction using electromyography *Electroencephalogr. Clin. Neurophysiol.* **101** 511–9
[46] McFarland D J 2015 The advantages of the surface Laplacian in brain–computer interface research *Int. J. Psychophysiol.* **97** 271–6
[47] Nakamura A, Yamada T, Goto A, Kato T, Ito K, Abe Y, Kachi T and Kakigi R 1998 Somatosensory homunculus as drawn by MEG *NeuroImage* **7** 377–86
[48] Graimann B, Huggins J E, Levine S P and Pfurtscheller G 2002 *Visualization of Significant ERD/ERS Patterns in Multichannel EEG and ECoG Data Clin* (Neurophysiol) pp 11343–7
[49] Schwarz A, Ofner P, Pereira J, Sburlea A I and Müller-Putz G R 2017 Decoding natural reach-and-grasp actions from human EEG *J. Neural Eng.* **15** 016005
[50] Xu B, Deng L, Zhang D, Xue M, Li H, Zeng H and Song A 2021 Electroencephalogram source imaging and brain network based natural grasps decoding *Front. Neurosci.* **15** 797990
[51] Roland T 2020 Motion artifact suppression for insulated EMG to control myoelectric prostheses *Sensors* **20** 1031
[52] De Seta V, Toppi J, Pichiorri F, Masciullo M, Colamarino E, Mattia D and Cincotti F 2021 Towards a hybrid EEG-EMG feature for the classification of upper limb movements: *Comparison of Different Processing Pipelines 2021 10th Int. IEEE/EMBS Conf. on Neural Engineering (NER)* (IEEE) pp 355–8
[53] Riddle C N and Baker S N 2006 Digit displacement, not object compliance, underlies task dependent modulations in human corticomuscular coherence *NeuroImage* **33** 618–27
[54] Birbaumer N, Elbert T, Canavan A G and Rockstroh B 1990 Slow potentials of the cerebral cortex and behavior *Physiol. Rev.* **70** 1–41
[55] Rawlings J O, Pantula S G and Dickey D A 1998 *Applied Regression Analysis: A Research Tool* (Springer)
[56] Sokolova M and Lapalme G 2009 A systematic analysis of performance measures for classification tasks *Inf. Process. Manage.* **45** 427–37
[57] Benjamini Y and Yekutieli D 2001 The control of the false discovery rate in multiple testing under dependency *Ann. Stat.* **29** 1165–88
[58] Babiloni C, Carducci F, Cincotti F, Rossini P M, Neuper C, Pfurtscheller G and Babiloni F 1999 Human movement-related potentials vs desynchronization of EEG alpha rhythm: a high-resolution EEG study *NeuroImage* **10** 658–65
[59] Savić A M, Lontis E R, Mrachacz-Kersting N and Popović M B 2020 Dynamics of movement-related cortical potentials and sensorimotor oscillations during palmar grasp movements *Eur. J. Neurosci.* **51** 1962–70
[60] Seeber M, Scherer R and Müller-Putz G R 2016 EEG oscillations are modulated in different behavior-related networks during rhythmic finger movements *J. Neurosci.* **36** 11671–81
[61] Krauth R *et al* 2019 Cortico-muscular coherence is reduced acutely post-stroke and increases bilaterally during motor recovery: a pilot study *Front. Neurol.* **10** 126
[62] Guo Z, Qian Q, Wong K, Zhu H, Huang Y, Hu X and Zheng Y 2020 Altered corticomuscular coherence (CMCoh) pattern in the upper limb during finger movements after stroke *Front. Neurol.* **11** 410
[63] Choi K and Cichocki A 2008 *Control of a Wheelchair by Motor Imagery in Real Time Intelligent Data Engineering and Automated Learning (IDEAL)* (Springer) pp 330–7
[64] Jankelowitz S K and Colebatch J G 2005 Movement related potentials in acutely induced weakness and stroke *Exp. Brain Res.* **161** 104–13
[65] Wright D J, Holmes P, Russo F D, Loporto M and Smith D 2012 Reduced motor cortex activity during movement preparation following a period of motor skill practice *PLoS One* **7** e51886
[66] Yilmaz O, Cho W, Braun C, Birbaumer N and Ramos-Murguialday A 2013 Movement related cortical potentials in severe chronic stroke *2013 35th Annual Int. Conf. IEEE Engineering in Medicine and Biology Society (EMBC)* pp 2216–9
[67] Li H *et al* 2020 EEG changes in time and time-frequency domain during movement preparation and execution in stroke patients *Front. Neurosci.* **14** 827
[68] López-Larraz E, Antelis J M, Montesano L, Gil-Agudo A and Minguez J 2012 Continuous decoding of motor attempt and motor imagery from EEG activity in spinal cord injury patients *2012 Annual Int. Conf. IEEE Engineering in Medicine and Biology Society* pp 1798–801