Inter-muscular coherence features to classify upper limb simple tasks *

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***Abstract*— The application of Hybrid Brain-Computer Interfaces (BCI) for post-stroke hand motor rehabilitation requires the investigation of new electromyographic (EMG) features, potentially able to identify pathological synergies to be discouraged. Inter-muscular coherence (IMC) is gaining attention as a descriptor of the mechanisms behind abnormal motor control in stroke patients. With the ultimate goal to exploit IMC features to control BCIs, this work aims at (a) characterizing finger extension and grasping tasks by IMC features, (b) assessing IMC feature performance in classifying different conditions. Classification results (accuracy equal to 0.81 ± 0.19) pave the way for IMC feature application in hybrid BCI control.**

I. Introduction

Stroke is one of the leading causes of long-term disability [1]. Depending on the brain lesion location and extension, it can result in a wide range of motor deficits impacting on the ability of stroke survivors to carry out daily living activities [2]. The most common deficit remains hemiparesis of the upper limb. Muscle weakness, changes in muscle tone, and impaired motor control induce disabilities in common activities such as reaching and picking up objects [3], decreasing survivors' quality of life. Technology-based approaches [4] have been proposed to return independence to stroke subjects, promoting the evidence-based, personalized rehabilitation and allowing also to increase therapy's intensity whilst reducing time and resources allocated. Electroencephalographic (EEG) and electromyographic (EMG) techniques may reveal, respectively, brain and muscle patterns elicited by a given rehabilitative exercise, allowing to assess the post-stroke recovery by means quantitative and objective measures. EEG-based Brain-Computer Interfaces (BCI) which record, decode, and translate into a real-time feedback the brain activity, have already been demonstrated as contributing to significantly better motor functional outcomes in stroke patients with severe motor impairments of the upper limb [5]. Hybrid BCI approaches have been already explored combining residual EMG activity and motor-related brain activation in order to provide a contingent reward which aims at re-establishing the link between the central nervous system and the periphery that is disrupted by the stroke [2]. From the muscular side, promoting the motor function recovery requires to reinforce muscular patterns that most resemble the physiological activation, that is to discourage pathological synergies, abnormal muscle activation, co-activation [6], antagonist hyperactivity, spasticity and muscle weakness that patients often experience after stroke. To this aim, research efforts are still needed to identify potential EMG features that significantly encompass such pathological changes. Inter-muscular coherence (IMC) is gaining attention as descriptor of the mechanisms behind abnormal motor overflow in stroke patients [7]. At the state of the art tasks such as reaching [8] and elbow flexion [7] have been characterized by IMC features in stroke population. In this work, we investigated IMC on simple hand tasks, most commonly employed within BCI contexts (e.g. hand opening and closing). Before addressing the issue in stroke patients, we analyzed EMG data from healthy subjects from multiple muscles in a wide frequency range. This study aims at exploring simple tasks (i.e. hand finger extension and grasping) in a population of healthy subjects in order to a) characterize the relevant frequency and spatial IMC features extracted from EMG data collected by twelve upper limb muscles and b) investigate IMC ability in discriminating between task (i.e. finger extension and grasping) and rest conditions.

II. Materials and Methods

A. Participants

Twenty healthy volunteers (9 females/11 males, age 27.8 ± 2.4 years), all right-handed and with no previous history of neuromuscular disorders, have been enrolled in the study. All subjects were informed of the experimental protocol and gave their informed consent to the study, conducted in agreement with the principles outlined in the Declaration of Helsinki.

B. Data Collection and Experimental Protocol

EMG data were collected, sampled at 2400 Hz and recorded by the g.HIamp amplifier (g.tec medical engineering GmbH Austria). EMG signals were recorded from twelve muscles (six for each side): extensor digitorum (ED), flexor digitorum superficialis (FD), triceps (TRI), biceps brachii (BIC), lateral deltoid (DELT), pectoralis major (PEC). Three maximum voluntary contractions were recorded for each muscle before the session. During the acquisition all subjects were seated in a comfortable chair with their forearms on the armrests. Visual cues were presented on a screen in front of the subject. Subjects were instructed to perform two tasks: finger extension (Ext) and grasping (Grasp), separately executed in a randomized order with both right and left hand. Each task was repeated twice

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for a total of eight recordings. Each recording comprised thirty repetitions (trials) of the task. The total trial duration was 7s with an inter-trial interval of 3.5 s. For each trial, in the first 3s subjects were invited to rest, then after the visual stimulus they had to gradually extend their fingers or grasp taking all remaining 4s.

C. *Data Analysis*

EMG data were down-sampled at 1000 Hz, band-passed filtered [3 500]Hz with a Butterworth zero phase filter and notch filtered at 50Hz to remove the power-line interference. Data were segmented in trials lasting 7s (3s of rest and 4s of task) and for each trial the windows [0 2]s and [4 6]s were defined as windows representing rest and task conditions, respectively. For each muscle, all trials (separately for task and rest conditions) were concatenated, resulting in a matrix [(2s x 60 trials) x 12 muscles]. For each condition and possible couple of muscles, the IMC was computed using the Matlab R2019b (The MathWorks, Inc., Natick, Massachusetts, USA) built-in function mscohere (1s window length and no overlap). IMC values were filtered by the chance level defined according to the equation in [9] (α =0.01, False Discovery Rate (FDR) correction). Frequency bands were defined according to the literature until 60 Hz and in steps of 50 Hz until 500 Hz: [6 12]Hz, [13 30]Hz, [31 60]Hz, [61 100]Hz, [101 150]Hz, [151 200]Hz, [201 250]Hz, [251 300]Hz, [301 350]Hz, [351 400]Hz, [401 450]Hz, [451 500]Hz. For each frequency band, the maximum IMC value and its frequency (Hz) were extracted from data of task condition. For the rest condition, the IMC value at the peak frequency of task condition was considered.

Seventeen subjects were included in the following analysis. Three subjects were excluded due to artefacts. Moreover, signals recorded from the pectoralis major muscles (both left and right side) were excluded because of the electrocardiographic signal contamination.

D. *IMC pattern characterization*

For each task (Ext with the left hand, ExtL; Ext with the right hand, ExtR; Grasp with the left hand, GraspL; Grasp with the right hand, GraspR), couple of muscles and frequency band, IMC weights were compared across subjects between task and rest conditions (paired t-test, α=0.01 FDR correction). The outcomes in form of patterns of significant t-values were visualized (see following figures).

E. *IMC Classification*

For each task (ExtL, ExtR, GraspL, GraspR) a classification model based on IMC features was built to evaluate the ability of IMC features in discriminating task and rest condition (binary classification), relevant in view of targeting the stroke population. For each subject the feature vector consisted of the IMC values computed for each couple of muscles and frequency band [792 features=66 muscle couples x 12 bands]. Since the feature vector included IMC values for (i) couples of muscles belonging to the upper limb involved in the movement, to the contralateral upper limb and couples of muscles belonging to right and left upper limb, (ii) all frequency bands in the EMG spectrum, different types of spatial and frequency constraints were tested. Concerning spatial constraints, two scenarios were considered: (1) all couples of muscles and (2) couples of muscles belonging to the upper arm involved in the movement (e.g. right side muscles if the movement was ExtR or GraspR). Concerning the frequency constraints, three scenarios were considered: (1) features belonging to all (twelve) frequency bands, (2) features belonging to the low frequency bands [6 150]Hz, (3) features belonging to the high frequency bands [151 500] Hz. For each of the possible feature domains (6 scenarios = 2 types of spatial constraints x 3 types of frequency constrains), in order to further reduce the feature domain dimension and identify significant features, a feature selection algorithm (stepwise linear discriminant analysis [10] with input model empty and maximum number of features set equal to 2 was applied before building the classification model. A support vector machine classifier with a linear kernel was implemented as classification model in the framework of a leave-one (subject) out cross-validation. Specifically, for each iteration (iterations equal to the number of participants) IMC weights of a single subject were the testing dataset, while the classifier was trained with data of all other subjects. For each iteration the classification accuracy was computed. To investigate differences among constraints (2 spatial constraints and 3 frequency constraints) imposed to the global feature matrix [num of subjects x 792 features], for each task (ExtL, ExtR, GraspL, GraspR) classification accuracies (dependent variables) were analyzed by the repeated measure two-way analysis of variance (ANOVA). Spatial constraint and frequency constrain were the two factors (independent variables) of the analysis. The Tukey HSD post hoc analysis was applied to assess pairwise differences. The threshold for statistical significance was set to $p<0.05$. Results are presented as mean ± standard error (SE) across subjects.

III. Results

A. *IMC pattern characterization*

The results of the statistical comparison between task and rest conditions in the frequency band ranging from 101Hz to 150Hz are shown in Fig.1 (ExtL panel a, GraspL panel b). For the task ExtL (Fig.1 panel a) significant connections (IMC higher in task than in rest condition) mainly involve the couples of muscles of the left upper limb as ED-FD, ED-TRI and FD-TRI. The statistical comparison points out significant connections also in the contralateral upper limb (i.e. right) for the couples ED-FD, ED-TRI, BIC-TRI. Significant connections mainly among muscles of the left upper limb are as well shown for the GraspL task (Fig.1 panel b). The couples of muscles ED-FD, FD-TRI, BIC-TRI and DELT-BIC result as those having the highest t-values. As observed for the ExtL, contralateral connections involve ED-FD and FD-TRI. However, some connections could be false positives, as well-known in the using of bivariate estimators. Same characterizations were obtained for all frequency bands and tasks. All of them have three main common points: no connections are highlighted in the frequency band [6 12]Hz; the connection ED-FD of the upper limb involved in the movement is unvarying among tasks and bands; going up in the frequency bands the number of connections increases both between left and right muscles and among muscles of the contralateral side to that of the task.

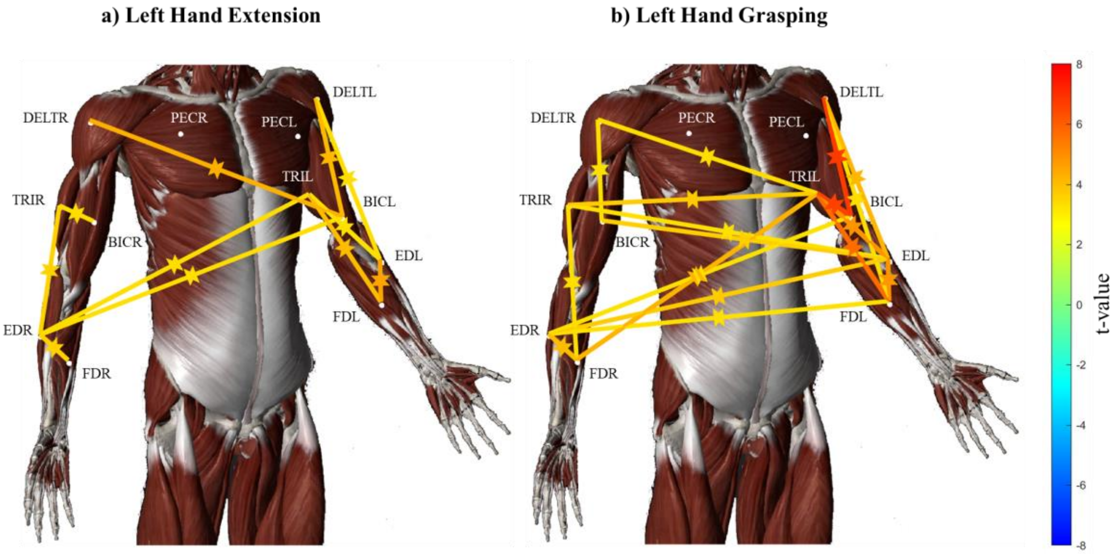

Figure 1. Inter-muscular coherence grand average patterns (17 healthy subjects) obtained from the statistical comparison (paired t-test, α=0.01, False Discovery Rate correction) between left hand finger extension and rest condition (panel a) and between left hand grasping and rest condition (panel b). Positive t-values describe inter-muscular coherence values higher in task than in rest condition. Negative t-values describe inter-muscular coherence values higher in rest than in task condition. Frequency band ranges from 101Hz to 150 Hz.

B. *IMC classification*

Fig. 2 shows for each task and scenario (combination among spatial and frequency constraints) the classification accuracies, presented in a bar chart as average and standard error across subjects. Results reveal the ability in discriminating task and rest conditions with performances higher than 75% even not considering any spatial or frequency constraint. However, applying the constraints increases performances. Statistical analysis results are presented in Table 1. The repeated measures two-way ANOVA highlights significant differences for the factor *frequency constraint* in task GraspL and GraspR. The post-hoc analysis applied to the significant factor points out differences (i) between low frequency bands and high frequency bands and between low frequency bands and no-applied constraints for the task GraspL, showing poorer classification performance in low frequency bands (0.59) than in high frequency bands (0.90), and (ii) between low frequency bands and high frequency bands for the task GraspR. Although not statistically significant, the trend of classification performances for Ext task seems to be opposite: poorer performance (0.79) in high frequency bands than in low frequency bands (0.88).

Discussion and Conclusion

This study takes place in the context of the exploration and designing of new EMG features to control a hybrid BCI system for hand rehabilitation after stroke. The target of that hybrid BCI system is to provide stroke subjects with a feedback based on the EMG patterns that most resemble physiological activations. Simple tasks, such as the finger extension and grasping, have been characterized by means of the inter-muscular coherence features. Results confirm the findings in [7] [11] [12] about the frequency bands characterized by significant IMC values. However, our results highlight also the relevance of IMC features in frequency bands over 60Hz, as expected basing on the characteristics of the EMG spectrum. Moreover, the analysis of the IMC patterns highlighted both common features for Ext and Grasp tasks such as the connection between FD and ED muscles and task-specific features, such as the couple BIC-DELT (flexor muscles of the upper limb) for the Grasp task. Connections observed among muscles of the contralateral upper limb (with respect to that involved in the movement) highlight the requirement of monitoring more muscles than just ED and FD muscles (as main agonist/antagonist of the explored tasks). This especially in view of the rehabilitative application for stroke subjects in which compensation mechanisms with the healthy upper limb may characterize the movement execution. From the classification point of view, results underline the IMC feature ability in discriminating between task (i.e. Grasp and Ext) and rest conditions with a global accuracy (mean ± SE across tasks and constraint scenarios) of 0.81 ± 0.19. Even though performance results are quite low as compared with classification models based on amplitude features (e.g. root mean square), they hold promise as they are based on features extracted from a bivariate analysis containing, therefore, the simultaneous information from two muscles. Although the promising results of this work, many issues are still open. Further investigations are required to refine the coherence estimator in order to assess the relevance of the observed connections (e.g. between right and left upper limbs) by means more advanced approaches, i.e. with lower false positive rate in coherence detections. Moreover, the peculiarities of the context require to get deeper knowledge in task relevant features before moving towards the designing of inter-muscular coherence-based BCIs to support post-stroke rehabilitative protocols of the upper limb. Therefore, results need to be compared with those obtained from stroke subjects while they attempt to perform same movements (i.e. finger extension and grasping), even investigating the relationship with functional impairment level.

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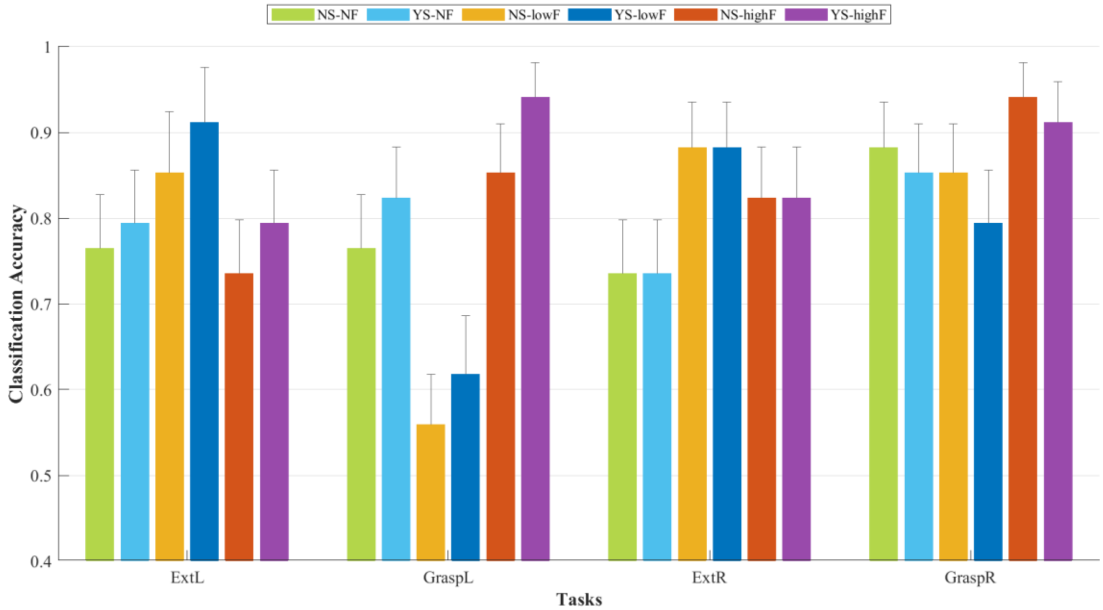

Figure 2. Classification accuracy, presented as mean ± standard error (17 healthy subjects), computed for each task, ExtL: left hand finger extension, GraspL: left hand grasping, ExtR: right hand finger extension, GraspR: right hand grasping, and scenario, i.e. combination among spatial and frequency constraints: NS-NF: no spatial and no frequency constraints; YS-NF: spatial constraints (IMC among muscles of the upper limb involved in the task) and no frequency constraints; NS-lowF: no spatial constraints and frequency constraints (frequency bands in the range 6-150Hz); YS-lowF: spatial constraints (IMC among muscles of the upper limb involved in the task) and frequency constraints (frequency bands in the range 6-150Hz); NS-highF: no spatial constraints and frequency constraints (frequency bands in the range 150-500Hz); YS-highF: spatial constraints (IMC among muscles of the upper limb involved in the task) and frequency constraints (frequency bands in the range 150-500Hz). A leave-one (subject) out cross-validation with a support vector machine classification model was implemented. Before training the classifier, the stepwise feature selection algorithm (num. of features set equal to 2) was applied to further reduce the dimension of the feature domain.

Table 1. For each task, results of the repeated measures two-way ANOVA. Significant comparisons have been marked (*).

	DEGREES OF FREEDOM	P-VALUE	F
Ext L			
spatial constraint	1	0.24	1.52
frequency constraint	2	0.13	2.18
interaction	2	0.89	0.12
GraspL			
spatial constraint	1	0.07	3.81
frequency constraint	2	< 0.01*	10.82
interaction	2	0.85	0.16
ExtR			
spatial constraint	1	1.00	0
frequency constraint	2	1.00	0
interaction	2	0.09	2.60
GraspR			
spatial constraint	1	0.26	1.36
frequency constraint	2	0.04*	3.55
interaction	2	0.85	0.16

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