This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSRE.2016.2597157, IEEE Transactions on Neural Systems and Rehabilitation Engineering

EEG analysis during active and assisted repetitive movements: evidence for differences in neural engagement

Giulia Tacchino, Marta Gandolla, Stefania Coelli, Riccardo Barbieri *Member, IEEE*, Alessandra Pedrocchi, *Member, IEEE* and Anna M. Bianchi, *Member, IEEE*

***Abstract*—Two key ingredients of a successful neuro-rehabilitative intervention have been identified as intensive and repetitive training and subject's active participation, which can be coupled in an active robot-assisted training. To exploit these two elements, we recorded electroencephalography, electromyography and kinematics signals from 9 healthy subjects performing a 2×2 factorial design protocol, with subject's volitional intention and robotic glove assistance as factors. We quantitatively evaluated primary sensorimotor, premotor and supplementary motor areas activation during movement execution by computing Event-Related Desynchronization (ERD) patterns associated to mu and beta rhythms. ERD patterns showed a similar behavior for all investigated regions: statistically significant ERDs began earlier in conditions requiring subject's volitional contribution; ERDs were prolonged towards the end of movement in conditions in which the robotic assistance was present. Our study suggests that the combination between subject volitional contribution and movement assistance provided by the robotic device (i.e., active robot-assisted modality) is able to provide early brain activation (i.e., earlier ERD) associated with stronger proprioceptive feedback (i.e., longer ERD). This finding might be particularly important for neurological patients, where movement cannot be completed autonomously and passive/active robot-assisted modalities are the only possibilities of execution.**

***Index Terms*— assistive devices, EEG, EMG, ERD/ERS, neurorehabilitation.**

I. Introduction

Stroke represents a major cause of disability worldwide despite the advances achieved in the management of its acute phase. The majority of individuals affected by stroke manifests residual impairments in both the contralesional upper and lower limbs [1], [2]. Relevant limitations in daily life activities result from even mild impairment of the upper limb function, especially of the hand. This has been demonstrated to negatively influence the quality of life of a stroke survivor [3].

This work was supported by the Think and Go project funded by Lombardy Region (POR FSE 2007/2013) and Fondazione Cariplo.

G. Tacchino, M. Gandolla, S. Coelli, R. Barbieri, A. Pedrocchi and A. M. Bianchi are with the Department of Electronics, Information and Bioengineering, Politecnico di Milano, Piazza Leonardo da Vinci 32, 20133, Milan, Italy (email: giulia.tacchino@polimi.it, marta.gandolla@polimi.it, stefania.coelli@polimi.it, riccardo.barbieri@polimi.it, alessandra.pedrocchi@polimi.it, annamaria.bianchi@polimi.it).

In this context, hand functional rehabilitation plays a key role. Even after extensive therapeutic interventions in acute phase, the probability of regaining functional use of the impaired hand is still low, estimated around 12% [4]. Therefore, effective rehabilitative interventions to restore hand functions even in the chronic phase of the disease (i.e., when the patient is discharged from the hospital) can have a dramatic impact on quality of life, improving independence, social integration, and work abilities.

Different key ingredients of a successful neuro-rehabilitative intervention have been identified in literature. On one side, it has been suggested to deliver high therapy doses performed as intensive and repetitive task practice [5]. Repetitive training can be easily carried out through robotic-based rehabilitation sessions, which need low supervision and allow the execution of precise, safe and repeatable therapeutic exercises [2]. Contrasting results are reported in literature with respect to the clinical impact of robotic assistive therapy for upper limbs with respect to usual care [6], [7]. However, all authors agree on the beneficial effect of a high therapy dose, where the more is the best, and one of the key advantages of neurorehabilitation performed through robotic devices is the possibility to deliver much higher therapy doses, and to deliver them not only in specialized centers, but also in home environments. In fact nowadays, once at home, the frequency and intensity of training is too low to enhance neural reorganization and functional changes. In this context, the use in a domestic environment of a robotic device would guarantee the appropriate amount of rehabilitation therapy, safeguarding at the same time repeatability of the training and safety.

On the other hand, subject's active participation to the rehabilitative therapy has been identified as a crucial element to induce neural plasticity and promote motor recovery on the top of movement execution in itself [8], [9]. Dealing in particular with robotic-assisted therapy, Hu and colleagues demonstrated that combining the voluntary effort from stroke patients with a robotic-based training (active robot-assisted modality performed through an electromyography (EMG)-driven robot) would result in a more significant motor improvement with respect to a training in which the robot passively moves the subject's hand [9]. Motor improvements have been quantified through clinical scores and EMG

1534-4320 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSRE.2016.2597157, IEEE Transactions on Neural Systems and Rehabilitation Engineering

parameters, but changes in cortical activity correlated with the training modality (active or passive robot-assisted) have not been assessed. When coming to neurological patients, involving the correct brain areas through an active participation to the therapy should improve motor learning [10], [11], even if with a certain inter-subjects variability (e.g., [8]), and therefore brain activity might be an effective marker to access patient's involvement and to investigate the effectiveness of a rehabilitation process. Brain activity in different motor conditions can be non-invasively investigated with optimal time resolution with electroencephalography (EEG) [12]. EEG-based parameters can be used to detect the timing and the extent of the sensorimotor rhythms modulations induced by movement execution. Event-Related Desynchronization (ERD) quantifies the reduction in power of mu (8 – 13 Hz) and beta (15 – 25 Hz) rhythms, which is an electrophysiological correlate of activated neural networks when sensorimotor input are processed and motor commands are generated [13]. In addition, post-movement Event-Related Synchronization (ERS) quantifies a power enhancement of the sensorimotor oscillations at the end of movement execution [14].

Formaggio and colleagues [15], [16] investigated the topography and the time course of ERD/ERS patterns in healthy participants during the performance of active, imagined and highly standardized passive robot-assisted movements. They found a bilateral activation of the primary sensorimotor cortex (SMC) during unilateral hand movements for both active and passive conditions. However, they did not address in their experimental paradigm the issue of subject's active participation to the motor training performed by the robotic device. Ramos-Murguialday and colleagues [17] investigated the effect of contingent feedback on the control of a Brain Computer Interface (BCI)–based neuroprosthesis. The subject's intention was included in the control loop as a "trigger signal" derived from ERD of the sensorimotor rhythms due to movement imagination. Norman and colleagues [18] investigated for the first time the effect of an active robot-assisted condition on ERD/ERS patterns of sensorimotor rhythms within the context of a two level factorial design, with the robotic assistance and the motor activity treated as binary categorical factors. Their analysis focused on the pre-movement interval. The authors describe pre-movement ERD for active conditions, confirming what is known in literature for self-paced movements [12]. Moreover, they also show a pre-movement ERD during predictable passive movements, which they interpret as a cortical preparation for the impending somatosensory input the movement will produce. However, once the "trigger signal" (i.e., ERD due to movement imagination [17] or pre-movement ERD before a predictable passive movement [18]) is produced, the activated robot performs the requested movement independently of whether the subject's active motor engagement in the task is maintained or not. It is therefore fundamental to measure whether the subject remains engaged throughout movement execution or if his/her effort is only devoted to activate the robotic device. To this aim it is necessary to: i) evaluate modulations of the SMC activity (e.g., through ERD/ERS patterns) for the whole movement execution period, and not only during the pre-movement phase; and ii) check for effective voluntary contribution from the subject (e.g., through EMG recordings). Indeed, EMG measures allow to access subjects' active participation, and therefore can be exploited to design and verify an active robot-assisted therapy in which the subject's voluntary effort is effectively combined with the robot activity for the whole movement duration.

Our study investigates the neural correlates of subjects' active participation to functional robotic-based movements through ERD/ERS patterns derived from EEG recordings on healthy volunteers. Our experimental paradigm includes four tasks that exploit the robotic support and the volition intention as the main factors of a factorial design, which has been shown to be a suited statistical approach by previous EEG [18] and fMRI studies [19], [20]. In this framework, ERD/ERS patterns during whole movement execution have been analyzed in order to investigate the effect of subject's volitional effort and robotic assistance combination on SMC activity. We used a robotic glove for hand neuro-motor rehabilitation to assist functional hand movements, and we performed EMG recordings to check for effective voluntary contribution from the subject. We believe that EMG analysis represents an important complement of EEG investigation when active and passive robot-assisted modalities are compared. In fact, when dealing with neurological patients, it cannot be given from granted that active participation recommendations are effectively executed. Therefore, residual muscular activity as measured by superficial EMG signals is a precious accessible information to detect and quantify the patient effort, also when movement kinematics is affected [21], [22].

II. Materials and Methods

A. Participants

9 right-handed healthy subjects (7 females, 2 males, mean age 26.3 ± 1.9 years) with no neurological or orthopedic impairment volunteered for this study. All subjects gave informed written consent.

B. Experimental set-up

Electroencephalographic (EEG), electromyographic (EMG) and kinematic signals were recorded while using the robotic glove Gloreha (GLOve REhabilitation HAnd, www.gloreha.com), developed and produced by Idrogenet Srl (Lumezzane, BS, Italy). A picture of a volunteer wearing the complete equipment is shown in Figure 1. Gloreha is a device for neuromotor rehabilitation of the hand composed by two main elements: a comfortable and light glove, and a chassis containing electric actuators and an electronic board.

1534-4320 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSRE.2016.2597157, IEEE Transactions on Neural Systems and Rehabilitation Engineering

The device allows the execution of all the combinations of fingers joints flexo-extension. Specifically, fingers movement is performed thanks to 5 electric actuators and an electronic board, placed in the chassis, not accessible to the operator. Each actuator is linked to a wire. In a compartment of the chassis the operator can adjust the length of the 5 cables that generate the fingers movement to set the starting position of the hand, which is also the maximum level of extension the glove will reach during the therapy.

EMG signals were recorded with a multi-channel signal amplifier system (Porti™, Twente Medical System International). The sampling frequency was set to 2048 Hz. 10 superficial self-adhesive electrodes arranged in a bipolar configuration have been placed on the forearm in a circular configuration, placed 2-3 cm under the elbow [23]–[27]. Indeed, in this configuration electrodes are not placed specifically on a single muscle, instead the information recorded from electrodes is rather global, and the overall signal is processed to retain the patient muscular activation. The ground electrode was placed on the opposite wrist, and a Velcro band was placed over the 10 electrodes (Figure 1, B). Design of EMG electrodes set-up was driven by the priority of the easy use and donning, allowing at the same time to record the muscular activity from a variety of muscles that control hand movements.

An electrogoniometer was placed on the index finger to track the kinematics of the performed movement. The electrogoniometer signal was acquired at 2048 Hz sampling frequency with the same multi-channel signal amplifier system used for EMG signals acquisition.

EEG signals were recorded by means of a Sam32 amplifier (MICROMED, Mogliano Veneto, Italy). 19 Ag/AgCl surface electrodes were placed on the scalp according to the 10-20 International System (i.e. Fp1, Fp2, F7, F3, Fz, F4, F8, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, P8, O1, O2) [28]. The impedance of every electrode was kept below 5kΩ. The ground electrode was placed on the right earlobe; all channels were offline re-referenced using CAR procedure (Common Average Reference). To allow an offline synchronization between Porti system and the Sam32 amplifier, 2 additional superficial self-adhesive electrodes were connected to the Sam32 amplifier to simultaneously record an EMG signal. These electrodes were arranged in a bipolar configuration and were placed on the forearm close to the previously described EMG electrodes (Figure 1, B). The sampling frequency was set to 256 Hz for both EEG and EMG data acquired with the Sam32 amplifier. An antialiasing low-pass filter and a notch filter were set at 120 Hz and 50 Hz respectively.

C. *Experimental protocol and tasks description*

Subjects were comfortably seated in front of a computer screen with their right arm resting on a table. The experimental protocol was composed by 4 tasks conceived according to a 2×2 factorial design. In particular, the first factor was the robotic glove support [with levels L1 = glove and L2 = NO glove] and the second factor was the volitional intention [with levels L1 = active movement and L2 = NO active movement]. The selected motor task was a complete right Hand Close/Open movement (HCO).

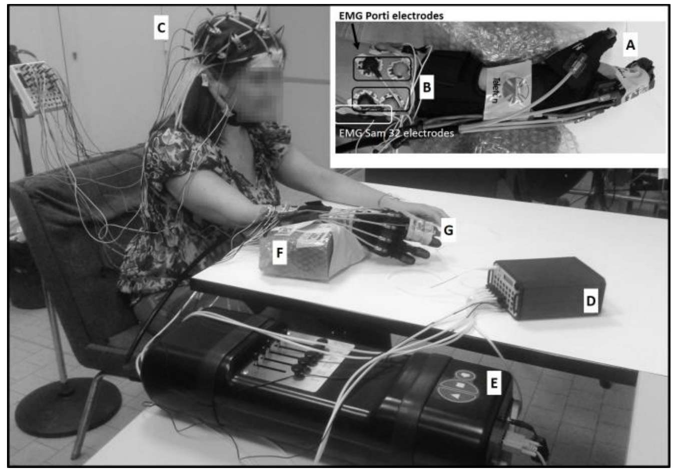

Fig. 1. Volunteer wearing the complete equipment for the experiment. Gloreha device is composed by a glove (A) and a chassis (E) containing electric actuators and an electronic board. Signals from EMG electrodes (B) and from the electrogoniometer (G) are acquired through a multi-channel signal amplifier system (Porti™, Twente Medical System International) (D). EEG signals are recorded through 19 Ag/AgCl electrodes (C) by using a Sam32 amplifier (MICROMED). A support for the wrist/forearm (F) is used while executing the experimental protocol.

According to the factorial design, the four tasks were structured as follows:

- task A (glove/active movement) = HCO supported by the robotic glove concurrently with voluntary movement contribution by the subject;

- task B (glove/NO active movement) = HCO supported by the robotic glove while the subject remains relaxed, resulting in a purely passive movement;

- task C (NO glove/active movement) = voluntary HCO movement without using the robotic glove;

- task D (NO glove/NO active movement) = no movements executed by the subject.

In tasks A, B and C subjects performed 20 movements, alternating 10 hand closing movements and 10 hand opening movements. A rest phase of 10 s was inserted between each hand closing and the following hand opening movement. The duration of both movements was set through the Gloreha software, and was proportional to the time required to perform the hand movement based on single-subject anatomy, given a fixed motor velocity (around 5 s for all subjects). Gloreha motors were specifically set for each subject in order to achieve a comfortable movement. Between tasks A and B, the glove was not removed from the hand of the subject in order to guarantee the maximum of movement repeatability. The beginning of close/open movements was triggered by the glove in both tasks A and B, while auditory cues were used for task C (brief 1000 Hz tone). While performing task C, each subject was instructed to execute a slow HCO movement attempting to reproduce the movement timing in terms of

1534-4320 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSRE.2016.2597157, IEEE Transactions on Neural Systems and Rehabilitation Engineering

movement duration similar to that defined by the glove. Accordingly, the time interval between consecutive auditory cues was set equal to 15 s, reproducing approximately 5 s of movement followed by 10 s of rest. The same auditory cues were used in task D to verify that EEG power modulations were not induced by the auditory stimuli, and to obtain an epoch definition comparable with the other tasks, despite no movements were executed in task D. All subjects were instructed to remain completely relaxed during tasks B and D and to equally voluntarily contribute in terms of muscles activity during tasks A and C. For synchronization purposes, two complete voluntary right hand close/open movements were executed prior to each task. Before starting the effective acquisition, each subject practiced the protocol until comfortable with the tasks.

D. Kinematic data processing

Kinematic signals were processed to identify movement onsets and offsets. The electrogoniometer signal was low-pass filtered to obtain a smooth signal through a 5th order Butterworth filter (5 Hz cut-off frequency). Movement onsets and offsets were identified by means of a dedicated software designed and implemented in MATLAB (Version R2015b; Mathworks Inc., Natick, MA), taking advantage of signal shape. Two thresholds (th) have been defined separately on filtered electrogoniometric signal (EG) for each subject and task as:

$$\text{th} = \min\{EG_i\} \pm 0.3 * [\max\{EG_i\} - \min\{EG_i\}] \qquad (1)$$

where i represents EG samples within the considered subject/task. Electrogoniometric signal portions which overcome the high threshold include open movement offsets and close movement onsets, determined as local maxima derived respectively from the beginning and the end of the signal portion. In turn, signal portions below the low threshold include close movement offsets and open movement onsets, determined as local minima derived respectively from the beginning and the end of the signal portion (Figure 2).

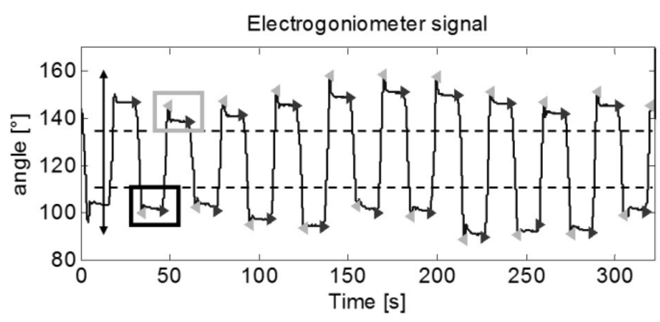

Fig. 2. Electrogoniometric signal processing for the detection of movement onsets/offsets using two thresholds (horizontal dashed lines). Electrogoniometric signal portions which overcome the high threshold include open movement offsets and close movement onsets, determined as local maxima derived respectively from the beginning and the end of the signal portion (grey rectangle). Signal portions below the low threshold include close movement offsets and open movement onsets, determined as local minima derived respectively from the beginning and the end of the signal portion (black rectangle).

E. EMG data processing

EMG signals of all 5 channels acquired by the Porti system were separately high-pass filtered with a 5th order Butterworth filter to remove the offset (10 Hz cut-off frequency), rectified and low-pass filtered by using a 5th order Butterworth filter (1 Hz cut-off frequency) to obtain 5 pre-processed EMG signals (pEMG). Given that EMG electrodes are disposed following a spatial criteria, and not directly on measured muscles, it is possible that only some channels bring information about muscles contraction. Therefore, separately for each subject, we considered only those pre-processed signals that met the following inclusion criterion:

$$max\{pEMG\} - min\{pEMG\} > 10 * min\,\{pEMG\} \qquad (2)$$

Since in this configuration electrodes are not placed specifically on a single muscle, instead the information recorded from electrodes is rather global, all considered pre-processed EMG signals were averaged together to obtain an overall EMG signal [25]–[27]. Overall EMG signal was then windowed with respect to EG derived movement onsets and offsets, and the signal of each window was resampled to obtain the same number of samples for each movement to allow EMG features comparison.

Literature offers many indices, both in time and in frequency, to evaluate the EMG measurement quality and reproducibility [29]. In this work, the following EMG features were chosen to compare the four experimental conditions: i) area under the overall EMG curve; ii) overall EMG peak amplitude; iii) overall EMG Root Mean Square (RMS).

The area under the EMG curve has been calculated as the sum of the resampled overall rectified EMG signal within the time window between movement onsets and offsets. The EMG peak amplitude was computed as the maximum value of the overall EMG signal obtained in a single movement window. Finally, the RMS was calculated as follows:

$$RMS = \sqrt{\frac{1}{N} * \sum_{i=1}^{N} EMG_i^2} \qquad (3)$$

where N represents the number of samples of each task repetition, and EMG_i the overall EMG value assumed in correspondence of the ith sample.

All EMG features were then compared between tasks by using generalized linear models with EMG features as dependent variables, Gloreha (G) and volitional intention (V) as predictive factors, and subjects as covariate. Statistical analysis has been performed in SPSS, version 22.0, and p-values < 0.05 were considered as statistically significant.

F. EEG data processing

EEG data were exported in MATLAB environment. EEGLAB toolbox [30] and custom scripts were used for an offline processing of the recorded signals. Data were band-pass filtered in the range 2 - 40 Hz by means of a finite impulse response filter of order 2000. Then a down-sampling to 128 Hz was performed. Stereotyped artefacts in the EEG recordings (i.e. eye blinks and movements, cardiac activity and scalp muscle contraction) were identified and removed

1534-4320 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSRE.2016.2597157, IEEE Transactions on Neural Systems and Rehabilitation Engineering

using infomax independent component analysis from EEGLAB toolbox.

Recordings from 1 subject were discarded due to a large number of EEG segments highly corrupted by movement artifacts. Therefore, the subsequent analyses were performed on the recordings of the remaining 8 subjects (7 females and 1 male). Due to the temporal window going from muscles activation to kinematic effective movement (i.e., electromechanical delay [31]), EEG analysis for the active conditions (i.e., tasks A, C) was performed using overall EMG derived onsets/offsets rather than movement timing determined by kinematic measurements. Muscular activity onsets and offsets were detected from the overall EMG signal as relative minima/maxima of the signal envelope obtained with a 1st order low-pass Butterworth filter application [25], [27]. Overall EMG derived onsets/offsets were synchronized with EEG measurements by means of the two voluntary contractions performed prior every task. The synchronization process was based on alignment of muscular contraction onsets as derived by EMG signals measured with the two devices (i.e., Porti and Sam32). Synchronization procedure was carried out for each subject and task, and carefully visually checked. Movement onsets and offsets from kinematics were imported on EEG signals recorded during task B (i.e., glove/NO active movement). Hand closing movements were not considered for the subsequent analyses. This was due to the fact that the resting position of the hand for closing movements is with the hand open, thus a muscular contraction is intrinsically necessary to maintain the resting position.

Large inter-individual differences in the frequency bands of mu and beta rhythms have been reported in literature [12]. We used Event-Related Spectral Perturbation (ERSP) maps to identify subject-specific frequency bands reactive to movement execution in order to determine the upper and lower limits of the bandpass filters to be used for ERD/ERS computation [32]. To this purpose, we computed ERSP maps for electrode C3 and for tasks A, B, C. ERSP maps provide a time-frequency representation of mean event-related changes in spectral power with respect to a reference period (baseline). The time-frequency decomposition was performed through EEGLAB toolbox using three-cycle Morlet wavelets, as seen in literature [33]. A correct identification of the baseline is crucial for estimating meaningful ERSP maps. Therefore, as suggested in [12], for each subject we identified the best baseline interval as the 1-s-long segment before movement onset showing a clear peak in the power spectrum associated to mu rhythm. The identification of this spectral peak in the signal power spectrum indicates that the SMC is not engaged in either sensorimotor information processing nor in motor commands generation. Indeed, this spectral peak disappears during movement planning and execution. ERSP maps were computed on 8-s-long epochs (from -2 s to 6 s with respect to onset events), containing the whole movement. EEG power values were calculated for 195 linearly spaced frequencies (from 1.5 Hz to 50 Hz) and along 200 time bins. The subject-specific frequency bands reactive to movement were identified as those bands showing statistically significant changes in power values during the complete execution of the movement with respect to the baseline. The statistical analysis was performed using a two-tailed permutation test (alpha level was set to 0.05). For each ERSP map, the False Discovery Rate method was used to correct the vector of p-values for multiple comparisons (i.e., 195 frequency values x 200 time bins). The time course of ERD/ERS was computed using the band power method [12], [13]. For each subject and task, EEG signals were separately band-pass filtered within the previously identified subject-specific frequency bands. Filtered signals were then squared in order to obtain power values as function of time. For those tasks in which a movement was executed (i.e., tasks A, B and C) we identified the segments of the squared signals that were included between onset and offset events. To allow a comparison between movements and subjects, we normalized the time scale of each segment, without affecting frequency domain properties. Accordingly, all segments were stretched or shrunk in order to overlap all the onset and all the offset times, thus all the movements were represented with the same duration in time, which was fixed equal to 5 s. Effective onset and offset events are not available for task D, as any movement is executed in this task. Therefore, each auditory cue and the 5th second after it were considered as onset and offset events respectively. Then, separately for each task, the processed squared signals were cut into epochs defined between 0.5 s before and 8 s after onset events. Within each epoch, the time instants $t = 0$ s and $t = 5$ s always identify the onset and the offset events respectively. Epochs were then averaged across trials. As in [12], relative ERD/ERS were expressed as the percent change of the signal power relative to the mean power in the baseline period.

We subdivided each averaged epoch into consecutive and not overlapping 0.5-s-long time windows and we computed the mean ERD/ERS value for each window. Topographical maps of ERD/ERS patterns for all time windows and for both mu and beta bands were computed for all subjects and tasks. ERD/ERS time course analysis was restricted to C3, F3 and Cz electrodes as they record neural activity respectively from contralateral (i.e., left) SMC and Premotor Cortex (PM), and from bilateral Supplementary Motor Area (SMA) within the 10-20 montage [34]. As seen in literature [15], [16], [18], for each task we performed a paired sample two-tailed t-test to verify whether the mean ERD/ERS values computed in each window were significantly statistically different with respect to the baseline condition. Furthermore, mean ERD/ERS values were compared between tasks in each time window by using generalized linear models with ERD/ERS features as dependent variables, Gloreha (G) and volitional intention (V) as predictive factors, and subjects as covariate. All statistical analyses have been performed in SPSS, version 22.0, and p-values < 0.05 were considered as statistically significant.

1534-4320 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSRE.2016.2597157, IEEE Transactions on Neural Systems and Rehabilitation Engineering

III. RESULTS

A. Kinematic and EMG data analysis

All subjects were able to perform the required tasks, and the algorithms applied to kinematic measures and to the overall EMG signal were able to correctly detect movement and muscular contraction onsets/offsets, which were carefully visually checked.

The EMG features (i.e. area under the overall EMG curve, overall EMG peak amplitude, overall EMG RMS) were analyzed to verify the hypothesis that, from a muscular activation point of view, tasks where subjects' contribution was required (i.e. tasks A, C) were significantly different in terms of muscular contraction from those where subjects were asked to relax (i.e. tasks B, D). As expected, only the volitional intention factor (V) resulted to be statistically significant for all features. Specifically, volitional intention factor (V) generalized linear model associated p-values resulted to be minor than 0.001 for all EMG features, while glove factor (G) generalized linear model associated p-values resulted to be equal to 0.431, 0.871, and 0.993 respectively for area under the overall EMG curve, overall EMG peak amplitude, and overall EMG RMS. In other words, on a statistical base, muscular activity was modified when the subjects were asked to voluntary contribute to the movement with respect to when the subjects were required to remain relaxed, independently by the fact of wearing/non-wearing the robotic glove.

B. EEG data analysis

The subject-specific frequency bands reactive to movement for mu and beta rhythms, as obtained from ERSP maps, are reported in Table 1. The mu rhythm fell within the range 7 - 14 Hz with a predominance in the range of upper alpha frequencies (i.e., 10 – 13 Hz). The beta rhythm fell within the range 16 - 28 Hz with a predominance in the range of low beta frequencies (i.e., 16 – 24 Hz). The baseline intervals specifically determined for each subject and used for the computation of ERSP maps and ERD/ERS time course are also reported in Table 1. ERSP maps from a representative subject obtained for electrode C3 and for all tasks are shown in Figure 3. In the tasks in which a movement was executed (i.e., tasks A, B and C), two distinct frequency bands, which correspond to mu and beta rhythms, showed reactivity to movement execution. Indeed, the signal power within these bands was significantly smaller with respect to baseline interval. In the subsequent paragraphs all time values are expressed relative to movement onset instant (t = 0 s).

TABLE I
SUBJECT-SPECIFIC FREQUENCY BANDS REACTIVE TO MOVEMENT EXECUTION AND BASELINE INTERVALS USED FOR ERD/ERS COMPUTATION.

Subject ID	mu band [Hz]	beta band [Hz]	Baseline interval (s) with respect to onset time
S1	8 - 13	16 - 22	[-3 -2]
S2	10 - 14	18 - 25	[-3 -2]
S3	12 - 14	16 - 22	[-3 -2]
S4	9 - 13	19 - 24	[-3 -2]
S5	11 - 14	17 - 22	[-2 -1]
S6	7 - 11	16 - 21	[-1.5 -0.5]
S7	9 - 13	21 - 26	[-2 -1]
S8	7 - 9	23 - 28	[-2 -1]

Mu frequency band

As expected, ERD for task D (i.e., NO glove/NO active movement) was not statistically different from the baseline for all the considered electrodes along the whole movement duration. On the contrary, for the tasks requiring movement execution, whether active (tasks A, C) or passive (task B), ERD was statistically significantly different from the baseline for nearly the whole movement duration (Figure 4, A). The four tasks present different ERD timing (Table 2).

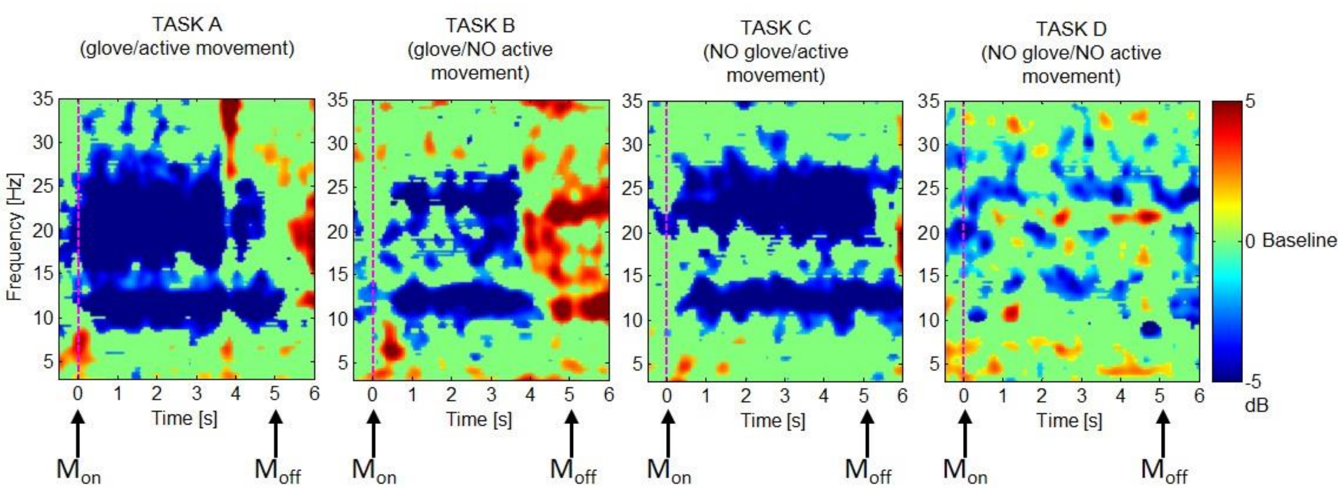

Fig. 3. ERSP maps obtained from a representative subject (S2) and used to identify subject-specific frequency bands associated to mu and beta rhythms that showed reactivity to movement execution. ERPS maps are represented for electrode C3 and for all tasks (A, B, C and D). Spectral power values are converted in logarithmic units and then expressed in dB, ranging from -5 to 5 dB. The pink dashed line represents onset event (M_{on}), which corresponds to the time instant t = 0 s. The offset event is labelled as M_{off}. Statistically significant differences in power values with respect to the baseline are represented in red and blue colors for positive and negative deviations from the baseline activity, respectively.

1534-4320 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSRE.2016.2597157, IEEE Transactions on Neural Systems and Rehabilitation Engineering

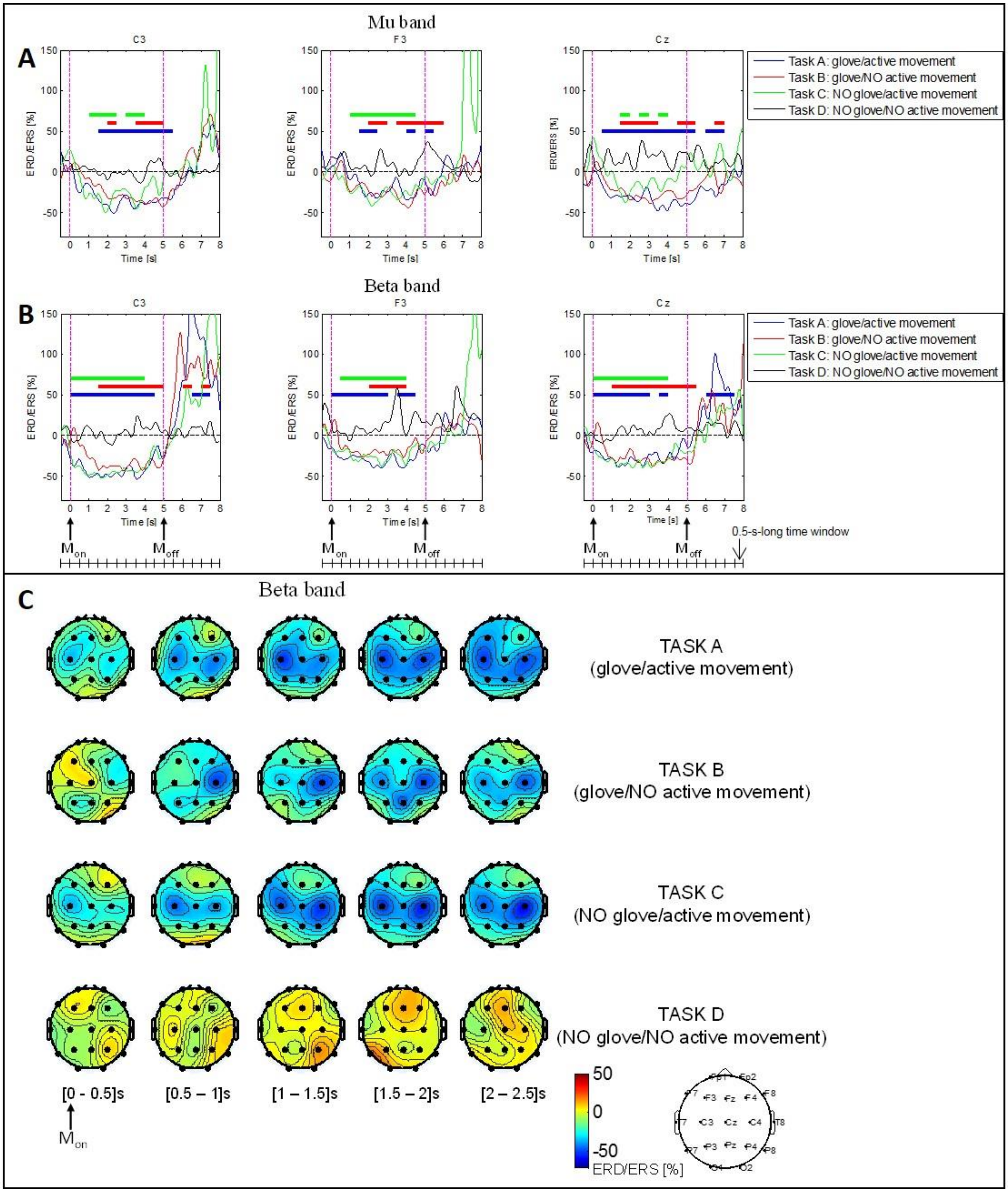

Fig. 4. Average across subjects of ERD/ERS time course (panels A and B) and ERD/ERS topographical maps (panel C) for the four tasks (i.e., task A: glove/active movement; task B: glove/NO active movement; task C: NO glove/active movement; task D: NO glove/NO active movement). ERD/ERS time course in the mu (panel A) and in the beta (panel B) frequency bands is displayed for electrodes C3, F3 (i.e., SMC and Premotor Cortex contralateral to movement) and Cz (SMA). Vertical pink dashed lines indicate movement onset and offset (time instants t = 0 s and t = 5 s respectively). Horizontal bars with the same color schema of the tasks represent the 0.5-s-long time windows in which ERDs achieved statistical significance relative to baseline. Topographical maps of beta ERD/ERS (panel C) display the mean ERD/ERS values computed within five consecutive 0.5-s-long time windows after movement onset (i.e., from 0 to 0.5s; from 0.5 to 1s; from 1 to 1.5s; from 1.5 to 2s; from 2 to 2.5s).

1534-4320 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSRE.2016.2597157, IEEE Transactions on Neural Systems and Rehabilitation Engineering

TABLE II
BEGINNING INSTANT [S] OF THE FIRST 0.5-S-LONG TIME WINDOW, STARTING FROM MOVEMENT ONSET (T = 0 S), IN WHICH ERD ACHIEVED STATISTICAL SIGNIFICANCE (P-VALUE < 0.05) RELATIVE TO BASELINE.

	Mu band						Beta band					
	time [s]			ERD [%]			time [s]			ERD [%]		
Task	C3	F3	Cz	C3	F3	Cz	C3	F3	Cz	C3	F3	Cz
A (glove/active movement)	1,5	1,5	0,5	-38	-25	-25	0	0	0	-34	-22	-21
B (glove/NO active movement)	2	2	1,5	-33	-28	-26	1,5	2	1	-40	-20	-30
C (NO glove/active movement)	1	1	1,5	-29	-23	-33	0	0,5	0	-34	-19	-23
D (NO glove/NO active movement)	-	-	-	-	-	-	-	-	-	-	-	-

The mean ERD value, expressed as percentage unit, is reported for each time window and for all electrodes (i.e., C3, F3 and Cz) and tasks (i.e., A, B, C and D).

In particular, the four conditions differ in terms of the first time window in which ERD becomes statistically significantly different from baseline. Indeed, in primary sensorimotor and premotor cortices (i.e., C3 and F3 electrodes), power decrease in the mu frequency band (i.e., ERD) associated to conditions requiring subject's active contribution to the movement (i.e., tasks A, C) was found earlier in terms of timing with respect to power decrease associated to the condition where only robotic assistance was present (i.e., task B). As for supplementary motor area (i.e., Cz electrode), ERD associated to the task involving both volitional intention and robotic assistance (i.e., task A) shows the earlier statistically significant power decrease. For all considered electrodes, a statistically significant ERD was maintained throughout the end of movement execution (time instant t = 5 s) when the robotic assistance was present (i.e., tasks A, B).

Beta frequency band

The ERD/ERS time course in the beta frequency band (Figure 4, B) during movement execution period (from 0 to 5 s) is similar to that observed in the mu band, but more evident and relevant differences among tasks in terms of timing of the first statistically significant ERD were detected. As reported in Table 2 for C3 electrode, a statistically significant ERD in the conditions requiring subject's active contribution (i.e., tasks A, C) began when the movement started (time instant t = 0 s). On the contrary, a statistically significant ERD began at 1.5 s when only robotic assistance was present (i.e., task B). A similar behavior was observed for electrodes F3 and Cz. Moreover, the volitional intention factor (V) resulted to be statistically significant in the time interval between 0 and 1 s for C3 electrode (p-value = 0.006) and during the time interval between 0 and 0.5 s for electrodes F3 and Cz (p-value = 0.011 and p-value = 0.015 respectively). In other words, ERD behavior in terms of timing is influenced by subject's active contribution to the movement at the beginning of the executed movement. The differences in terms of ERD timing among the four tasks can also be visually appreciated on the topographical maps of ERD/ERS patterns (Figure 4, C). Indeed, especially during the 0 - 0.5 s time interval, SMC and PM contralateral to movement, and the bilateral SMA show a statistically significant ERD only for tasks involving subject's active contribution to the movement (i.e., tasks A, C). In agreement with previous reported findings [12], [15], [16], the topographical maps highlight a bilateral ERD highly focused over the SMC contralateral and ipsilateral to the movement (i.e., C3 and C4 electrodes respectively). This bilateral ERD began at 0.5 s for tasks A and C, while it began at 1.5 s for task B.

IV. DISCUSSION

The aim of this study was to describe brain activity implications in primary sensorimotor, premotor and supplementary motor areas when considering active participation to a robotic assisted movement. In particular, the influence of the two factors on neural activity has been investigated by means of a 2 x 2 factorial design, which combines volitional contribution of the subject to the movement and robotic assistance as factors. The effective volitional contribution of the subject during movement execution has been monitored with superficial EMG, confirming a significantly higher muscular activity in conditions where volitional contribution of the subject was requested (i.e., tasks A, C). In addition, the muscular activation analysis demonstrated that the volitional contribution of the subjects in terms of muscular activations was comparable in tasks where volitional effort was required. Therefore, any differences in terms of brain activity have to be linked to motor control loop perturbation rather than a muscular performance difference.

A. *Neural correlates of subjects' active participation to functional robotic-based movements*

We observed neural activity (i.e., ERD) in correspondence of the analyzed electrodes during movement execution for both active (i.e., tasks A, C) and passive (i.e., task B) conditions, as previously observed in EEG [15], [16], and fMRI literature [19]. However, ERD patterns observed in the present study differed among experimental conditions mainly in terms of timing.

ERD patterns observed in beta and mu frequency bands show a similar behavior for primary sensorimotor and premotor cortices, and supplementary motor area, and namely a statistically significant ERD in the conditions requiring subject's active contribution (i.e., tasks A: glove/active

1534-4320 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

movement and task C: NO glove/active movement) began earlier with respect to the condition where only robotic assistance was present (i.e., task B: glove/NO active movement). Given that ERD has been proven to be a physiological correlate of activated brain areas, our results demonstrate that the activation of SMC, PM and SMA begins earlier in time when the volitional intention factor is present (i.e., tasks A, C) with respect to when only robotic assistance is present (i.e., task B). Although presenting the same behavior (i.e., ERD starting earlier in time for conditions where volitional intention is present), beta and mu bands ERD have different onsets. In particular, beta band ERD begins earlier in time with respect to mu band ERD. We hypothesize that this difference lies on the separate functional networks to which the sensorimotor rhythms are associated. Indeed, it has been demonstrated that the mu rhythm reflects predominantly somatosensory cortical functions, while the beta rhythm is associated with motor cortical functions [35]. ERD magnitude has been demonstrated to correlate with the extent of cortical activation, and specifically a stronger ERD corresponds to a higher cortical activation, as demonstrated by a recent EEG-fMRI study [36]. We observed comparable ERD values after movement onset in those conditions in which the volitional intention factor was present (i.e., tasks A, C), thus suggesting a comparable level of cortical activation. In addition, the EMG analysis demonstrated that the subjects' muscular contribution was equivalent in these tasks. Indeed, the presence of the volitional factor is coupled with beta band ERD to start at movement onset which can be associated to movement planning in an externally triggered movement, particularly for what is concerning PM and SMA areas. Beta band ERD associated with glove/NO active movement condition might reflect brain activation related to movement execution itself, rather than movement planning, as the resulting movement is purely passive. This is in line with what has been suggested in literature, and namely that the volitional intention factor was found to play an important role in the movement execution, when the motor scheme and proprioceptive predictions for the upcoming movement are generated [19].

We observed a stronger and long lasting ERD towards the end of movement in those conditions in which the robotic assistance was present (i.e., tasks A, B) with respect to the condition in which the movement was not supported by the glove (i.e., task C). In line with literature findings [37], this enhancement of ERD pattern during the last part of the movement could originate from reinforced afferent proprioceptive feedback related to the final position imposed by the robotic glove. Primary somatosensory cortex receives ascending inputs from spinal circuits, typically through the thalamic pathway [38] and specifically, part of the primary somatosensory cortex, Brodmann area 3a, receives substantial input from muscle proprioceptors [39].

B. *Hypothesis for an impact on rehabilitation treatment design*

We hypothesize that the earlier SMC activation immediately after movement onset is due to the volition intention, and primarily mediated by primary motor cortex, while the more prolonged SMC activation in the last part of the movement is due to the reinforced afferent proprioceptive feedback given by the glove, primarily mediated by primary sensorimotor cortex. This is in line with the interaction between artificially altered sensory feedback and volitional movement as revealed by fMRI activation shown to be located in primary sensorimotor cortex that has been interpreted as the differential effect of proprioception during concurrent voluntary movement in healthy subjects [19]. The same effect has been shown for post-stroke patient, where the ability to plan the movement (as mediated by supplementary motor area) and to perceive functional electrical stimulation as support for drop foot correction as a part of his/her own control loop (as mediated by angular gyrus) has been demonstrated to be important for motor relearning to take place [20], [40].

Although the use of robotic assisted treatments for neurological rehabilitation is controversial, our study suggests that the movement planning after an externally triggered movement, as mediated by subject volitional contribution, coupled with the effective movement execution, which is supported by the robotic device, is able to provide early brain activation (i.e., earlier ERD) coupled with stronger proprioceptive feedback (i.e., longer ERD). In particular, the planned movement should correspond to proper somatosensory feedback for the motor scheme to be strengthen as suggested by Hebbian-based plasticity [41], [42]. This might be particularly important for neurological patients where the movement cannot be completed by themselves, and thus the passive robot-assisted or the active robot-assisted modalities are the only possibilities for the design of a rehabilitation treatment. Therefore, based on the results obtained in the present study, the implications for the design of a rehabilitative therapy are the following: i) an active-assisted training, whether performed by a robotic device or by a therapist, induces an earlier activation of the relevant brain areas (i.e., SMC, PM, SMA) with respect to a passive-assisted training; ii) after movement onset, which is when the motor scheme for the upcoming movement is generated, the brain activations induced by the active-assisted modality are comparable to those induced by a voluntary movement; iii) towards the end of the movement, reinforced afferent proprioceptive feedback might force a more prolonged brain activity.

C. *Study limitations and future sights*

Brain activity implications when considering active participation to a robotic assisted movement have been investigated in 8 healthy volunteers. We did not include patients with neurological trauma in the study, since we wanted to understand how active-assisted and passive-assisted motor training can modulate the sensorimotor rhythms in a physiological context. Although a small number of subjects

1534-4320 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSRE.2016.2597157, IEEE Transactions on Neural Systems and Rehabilitation Engineering

participated to the study, the reported results are statistically robust. Additional investigations on a larger population are recommended to confirm the achieved findings. The rather small number of movement repetitions per task (i.e., 10 movements), even if comparable with that used in a previous study [16], has been determined based on a compromise between a reasonable duration of the experiment and the goodness and robustness of results. The experiment was conducted in controlled conditions, so the quality of data was accurately checked. As the four tasks were executed consecutively, the number of repetitions was determined in order to prevent the subject from being bored and from fatigue effects. Due to the need of not removing the robotic glove between tasks A and B, so to guarantee the maximum of movement repeatability, we did not randomized the experimental order of tasks, and therefore it might have been subjected to a certain carryover effect.

As a future research, we plan to investigate the neural correlates of active-assisted and passive-assisted motor training in neurological patients with particular attention to ERD timing.

Acknowledgments

The present research was part of the THINK&GO project supported by Regione Lombardia and Fondazione Cariplo. We would like to thank Idrogenet for lending us the robotic glove Gloreha and for their technical support in the study.

References

[1] J. J. Daly and R. L. Ruff, “Construction of efficacious gait and upper limb functional interventions based on brain plasticity evidence and model-based measures for stroke patients,” ScientificWorldJournal, vol. 7, pp. 2031–2045, 2007.

[2] N. Takeuchi and S.-I. Izumi, “Rehabilitation with Poststroke Motor Recovery: A Review with a Focus on Neural Plasticity,” Stroke Res. Treat. Stroke Res. Treat., vol. 2013, p. e128641, Apr. 2013.

[3] P. S. Lum, S. Mulroy, R. L. Amdur, P. Requejo, B. I. Prilutsky, and A. W. Dromerick, “Gains in Upper Extremity Function After Stroke via Recovery or Compensation: Potential Differential Effects on Amount of Real-World Limb Use,” Top. Stroke Rehabil., vol. 16, no. 4, pp. 237–253, Jul. 2009.

[4] P. S. Lum, S. B. Godfrey, E. B. Brokaw, R. J. Holley, and D. Nichols, “Robotic approaches for rehabilitation of hand function after stroke,” Am. J. Phys. Med. Rehabil. Assoc. Acad. Physiatr., vol. 91, no. 11 Suppl 3, pp. S242-254, Nov. 2012.

[5] K. N. Arya, S. Pandian, R. Verma, and R. K. Garg, “Movement therapy induced neural reorganization and motor recovery in stroke: a review,” J. Bodyw. Mov. Ther., vol. 15, no. 4, pp. 528–537, Oct. 2011.

[6] A. C. Lo, P. D. Guarino, L. G. Richards, J. K. Haselkorn, G. F. Wittenberg, D. G. Federman, R. J. Ringer, T. H. Wagner, H. I. Krebs, B. T. Volpe, C. T. J. Bever, D. M. Bravata, P. W. Duncan, B. H. Corn, A. D. Maffucci, S. E. Nadeau, S. S. Conroy, J. M. Powell, G. D. Huang, and P. Peduzzi, “Robot-Assisted Therapy for Long-Term Upper-Limb Impairment after Stroke,” N. Engl. J. Med., vol. 362, no. 19, pp. 1772–1783, May 2010.

[7] N. Norouzi-Gheidari, P. S. Archambault, and J. Fung, “Effects of robot-assisted therapy on stroke rehabilitation in upper limbs: systematic review and meta-analysis of the literature,” J. Rehabil. Res. Dev., vol. 49, no. 4, pp. 479–496, 2012.

[8] A. A. Blank, J. A. French, A. U. Pehlivan, and M. K. O’Malley, “Current Trends in Robot-Assisted Upper-Limb Stroke Rehabilitation: Promoting Patient Engagement in Therapy,” Curr. Phys. Med. Rehabil. Rep., vol. 2, no. 3, pp. 184–195, Jun. 2014.

[9] X. L. Hu, K.-Y. Tong, R. Song, X. J. Zheng, and W. W. F. Leung, “A comparison between electromyography-driven robot and passive motion device on wrist rehabilitation for chronic stroke,” Neurorehabil. Neural Repair, vol. 23, no. 8, pp. 837–846, Oct. 2009.

[10] D. L. Turner, A. Ramos-Murguialday, N. Birbaumer, U. Hoffmann, and A. Luft, “Neurophysiology of robot-mediated training and therapy: a perspective for future use in clinical populations,” Front. Neurol., vol. 4, p. 184, 2013.

[11] Z. Warraich and J. A. Kleim, “Neural Plasticity: The Biological Substrate For Neurorehabilitation,” PM&R, vol. 2, no. 12, pp. S208–S219, Dec. 2010.

[12] G. Pfurtscheller and F. H. Lopes da Silva, “Event-related EEG/MEG synchronization and desynchronization: basic principles,” Clin. Neurophysiol., vol. 110, no. 11, pp. 1842–1857, Nov. 1999.

[13] G. Pfurtscheller and A. Aranibar, “Evaluation of event-related desynchronization (ERD) preceding and following voluntary self-paced movement,” Electroencephalogr. Clin. Neurophysiol., vol. 46, no. 2, pp. 138–146, Feb. 1979.

[14] G. Pfurtscheller, “Event-related synchronization (ERS): an electrophysiological correlate of cortical areas at rest,” Electroencephalogr. Clin. Neurophysiol., vol. 83, no. 1, pp. 62–69, Jul. 1992.

[15] E. Formaggio, S. F. Storti, I. B. Galazzo, M. Gandolfi, C. Geroin, N. Smania, L. Spezia, A. Waldner, A. Fiaschi, and P. Manganotti, “Modulation of event-related desynchronization in robot-assisted hand performance: brain oscillatory changes in active, passive and imagined movements,” J. NeuroEngineering Rehabil., vol. 10, no. 1, pp. 1–10, Feb. 2013.

[16] E. Formaggio, S. F. Storti, I. B. Galazzo, M. Gandolfi, C. Geroin, N. Smania, A. Fiaschi, and P. Manganotti, “Time–Frequency Modulation of ERD and EEG Coherence in Robot-Assisted Hand Performance,” Brain Topogr., vol. 28, no. 2, pp. 352–363, May 2014.

[17] A. Ramos-Murguialday, M. Schürholz, V. Caggiano, M. Wildgruber, A. Caria, E. M. Hammer, S. Halder, and N. Birbaumer, “Proprioceptive Feedback and Brain Computer Interface (BCI) Based Neuroprostheses,” PLoS ONE, vol. 7, no. 10, p. e47048, Oct. 2012.

[18] S. L. Norman, M. Dennison, E. Wolbrecht, S. C. Cramer, R. Srinivasan, and D. J. Reinkensmeyer, “Movement Anticipation and EEG: Implications for BCI-Contingent Robot Therapy,” Trans. Neural Syst. Rehabil. Eng., 2016.

[19] M. Gandolla, S. Ferrante, F. Molteni, E. Guanziroli, T. Frattini, A. Martegani, G. Ferrigno, K. Friston, A. Pedrocchi, and N. S. Ward, “Re-thinking the role of motor cortex: context-sensitive motor outputs?,” NeuroImage, vol. 91, pp. 366–374, May 2014.

[20] M. Gandolla, N. S. Ward, F. Molteni, E. Guanziroli, G. Ferrigno, and A. Pedrocchi, “The Neural Correlates of Long-Term Carryover following Functional Electrical Stimulation for Stroke,” Neural Plast., 2016, p. 4192718.

[21] R. M. Singh and S. Chatterji, “Trends and Challenges in EMG Based Control Scheme of Exoskeleton Robots - A Review,” Int. J. Sci. Eng. Res., pp. 1–8, 2012.

[22] N. S. K. Ho, K. Y. Tong, X. L. Hu, K. L. Fung, X. J. Wei, W. Rong, and E. A. Susanto, “An EMG-driven exoskeleton hand robotic training device on chronic stroke subjects: Task training system for stroke rehabilitation,” in 2011 IEEE International Conference on Rehabilitation Robotics, 2011, pp. 1–5.

[23] C. Castellini and P. van der Smagt, “Evidence of muscle synergies during human grasping,” Biol. Cybern., vol. 107, no. 2, pp. 233–245, Apr. 2013.

[24] S. Muceli and D. Farina, “Simultaneous and proportional estimation of hand kinematics from EMG during mirrored movements at multiple degrees-of-freedom,” IEEE Trans. Neural Syst. Rehabil. Eng. Publ. IEEE Eng. Med. Biol. Soc., vol. 20, no. 3, pp. 371–378, May 2012.

[25] M. Gandolla, S. Ferrante, D. Baldassini, M. C. Cottini, C. Seneci, and A. Pedrocchi, “Artificial Neural-Network EMG Classifier for Hand Movements Prediction,” in XIV Mediterranean Conference on Medical and Biological Engineering and Computing 2016, E. Kyriacou, S. Christofides, and C. S. Pattichis, Eds. Springer International Publishing, 2016, pp. 634–637.

[26] M. Gandolla, S. Ferrante, D. Baldassini, M. C. Cottini, C. Seneci, F. Molteni, E. Guanziroli, and A. Pedrocchi, “EMG-Controlled Robotic Hand Rehabilitation Device for Domestic Training,” in XIV Mediterranean Conference on Medical and Biological Engineering and

1534-4320 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSRE.2016.2597157, IEEE Transactions on Neural Systems and Rehabilitation Engineering

Computing 2016, E. Kyriacou, S. Christofides, and C. S. Pattichis, Eds. Springer International Publishing, 2016, pp. 638–642.

[27] M. Gandolla, S. Ferrante, G. Ferrigno, D. Baldassini, F. Molteni, E. Guanziroli, M. Cotti Cottini, C. Seneci, and A. Pedrocchi, "Artificial neural-network EMG classifier for functional hand grasp movements prediction," Submitt. J. Int. Med. Res.

[28] H. H. Jasper, "The ten-twenty electrode system of the International Federation," Electroencephalogr. Clin. Neurophysiol., vol. 10, no. 2, pp. 371–375, 1958.

[29] B. Larsson, B. Månsson, C. Karlberg, P. Syvertsson, J. Elert, and B. Gerdle, "Reproducibility of surface EMG variables and peak torque during three sets of ten dynamic contractions," J. Electromyogr. Kinesiol. Off. J. Int. Soc. Electrophysiol. Kinesiol., vol. 9, no. 5, pp. 351–357, Oct. 1999.

[30] A. Delorme and S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," J. Neurosci. Methods, vol. 134, no. 1, pp. 9–21, Mar. 2004.

[31] P. R. Cavanagh and P. V. Komi, "Electromechanical delay in human skeletal muscle under concentric and eccentric contractions," Eur. J. Appl. Physiol., vol. 42, no. 3, pp. 159–163, Nov. 1979.

[32] C. Neuper and G. Pfurtscheller, "Evidence for distinct beta resonance frequencies in human EEG related to specific sensorimotor cortical areas," Clin. Neurophysiol. Off. J. Int. Fed. Clin. Neurophysiol., vol. 112, no. 11, pp. 2084–2097, Nov. 2001.

[33] Y. Liao, Z. A. Acar, S. Makeig, and G. Deak, "EEG imaging of toddlers during dyadic turn-taking: Mu-rhythm modulation while producing or observing social actions," NeuroImage, Feb. 2015.

[34] G. Pfurtscheller and A. Berghold, "Patterns of cortical activation during planning of voluntary movement," Electroencephalogr. Clin. Neurophysiol., vol. 72, no. 3, pp. 250–258, Mar. 1989.

[35] R. Hari and R. Salmelin, "Human cortical oscillations: a neuromagnetic view through the skull," Trends Neurosci., vol. 20, no. 1, pp. 44–49, Jan. 1997.

[36] H. Yuan, T. Liu, R. Szarkowski, C. Rios, J. Ashe, and B. He, "Negative covariation between task-related responses in alpha/beta-band activity and BOLD in human sensorimotor cortex: an EEG and fMRI study of motor imagery and movements," NeuroImage, vol. 49, no. 3, pp. 2596–2606, Feb. 2010.

[37] M. Alegre, A. Labarga, I. G. Gurtubay, J. Iriarte, A. Malanda, and J. Artieda, "Beta electroencephalograph changes during passive movements: sensory afferences contribute to beta event-related desynchronization in humans," Neurosci. Lett., vol. 331, no. 1, pp. 29–32, Oct. 2002.

[38] J. Padberg, E. Disbrow, and L. Krubitzer, "The organization and connections of anterior and posterior parietal cortex in titi monkeys: Do new world monkeys have an area 2?," Cereb. Cortex, vol. 15, no. 12, pp. 1938–1963, 2005.

[39] K. P. Körding and D. M. Wolpert, "Bayesian integration in sensorimotor learning," Nature, vol. 427, no. 6971, pp. 244–247, Jan. 2004.

[40] M. Gandolla, F. Molteni, N. S. Ward, E. Guanziroli, G. Ferrigno, and A. Pedrocchi, "Validation of a Quantitative Single-Subject Based Evaluation for Rehabilitation-Induced Improvement Assessment," Ann. Biomed. Eng., vol. 43, no. 11, pp. 2686–2698, Nov. 2015.

[41] D. O. Hebb, The Organization of Behavior. New York: Wiley, 1949.

[42] J. W. Stinear and T. G. Hornby, "Stimulation-induced changes in lower limb corticomotor excitability during treadmill walking in humans," J. Physiol., vol. 567, no. Pt 2, pp. 701–711, Sep. 2005.

Giulia Tacchino received the M.S. degree in Biomedical Engineering and the European Ph.D. degree in Bioengineering from the Politecnico di Milano in 2011 and 2016, respectively. She is a Post-Doc Research Fellow at the Department of Electronics, Information and Bioengineering of the Politecnico di Milano. Her research activity is focused on the characterization of EEG signals during motor protocols.

Marta Gandolla (MSc in Biomedical Engineering – 2009; European PhD cum laude in Bioengineering - 2013 from the Politecnico di Milano) is Post-Doc Research Fellow at the Neuroengineering and Medical Robotics Laboratory since 2013. Her research interest is about innovative methods design based on electrical stimulation and/or robotic systems for the rehabilitation and assistance of neurological patients. Moreover, she is interested in central mechanisms of neurological rehabilitation and re-learning.

Stefania Coelli received the M.S. degree in Biomedical Engineering in 2014 from the Politecnico di Milano. She was a research fellow for the THINK&GO project at the Politecnico di Milano. Since November 2015 she is a Ph.D. candidate in Bioengineering at the Department of Electronics, Information and Bioengineering of the Politecnico di Milano.

Riccardo Barbieri received the M.S. degree in Electrical Engineering from the University of Rome "La Sapienza", Rome, Italy, in 1992, and the Ph.D. in Biomedical Engineering from Boston University, Boston, MA, in 1998. He is Associate Professor in the Department of Electronics, Information and Bioengineering at the Politecnico di Milano. He is also affiliated with the Massachusetts General Hospital, the Massachusetts Institute of Technology, and the Wyss Institute for Biologically Inspired Engineering at Harvard University in Boston. His research interests are in the development of signal processing algorithms for the analysis of biological systems.

Alessandra Pedrocchi received the M.S. degree in electrical engineering and the Ph.D. degree in bioengineering from the Politecnico di Milano in 1997 and 2001, respectively. She is currently an Assistant Professor at the Department of Electronics, Informatics and Bioengineering of the Politecnico di Milano, where she teaches Neuroengineering in the Biomedical Engineering Department. She works in the NeuroEngineering and Medical Robotics laboratory (www.nearlab.polimi.it) studying neurorobotics, bioartificial interfaces for in vitro neurons and advanced technologies for neurorehabilitation. She has been working in the following international projects: MUNDUS EU-project, REALNET EU-project and Erasmus Mundus European MSc in Advanced Rehabilitation Technologies.

Anna M. Bianchi is full professor in Biomedical Engineering at the Department of Electronics, Information and Bioengineering of the Politecnico di Milano. She received the Laurea in Electronic Engineering from the same University. In the period 1987-2000 she was research assistant at the IRCCS S. Raffaele Hospital in Milano; in 2001 joined Politecnico di Milano. She is teacher of Biomedical Signal Processing and Medical Informatics and since 2004 is in the board of the same PhD program. She is member of the IEEE-EMBS and member of the technical committees on Cardiopulmonary Systems and on Neuroengineering. She is fellow of EAMBES.

1534-4320 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.