Is EMG a viable alternative to BCI for detecting movement intention in severe stroke?

Sivakumar Balasubramanian, Eliana Garcia-Cossio, Niels Birbaumer, Etienne Burdet*, and Ander Ramos-Murgialday*

Abstract—**Objective: In light of the shortcomings of current restorative brain computer interfaces (BCI), this study investigated the possibility of using EMG to detect hand/wrist extension movement intention to trigger robot-assisted training in individuals without residual movements. Methods: We compared movement intention detection using an EMG detector with a sensorimotor rhythm based EEG-BCI using only ipsilesional activity. This was carried out on data from 30 severely affected chronic stroke patients from a randomized control trial using an EEG-BCI for robot-assisted training. Results: The results indicate the feasibility of using EMG to detect movement intention in this severely handicapped population; probability of detecting EMG when patients attempted to move was higher ($p < 0.001$) than at rest. Interestingly, 22 of the 30 (or 73%) patients had sufficiently strong EMG in their finger/wrist extensors. Furthermore, in patients with detectable EMG, there was poor agreement between the EEG and EMG intent detectors, which indicates that these modalities may be detecting different processes. Conclusion: A substantial segment of severely affected stroke patients may benefit from EMG-based assisted therapy. When compared to EEG, a surface EMG interface requires less preparation time, is easier to don/doff, and is more compact in size. Significance: This study shows that a large proportion of severely affected stroke patients have residual EMG, which yields a direct and practical way to trigger robot-assisted training.**

Index Terms—**Stroke, EMG, BCI, Neurorehabilitation, Movement intention**

I. INTRODUCTION

FOLLOWING a stroke, intense movement training can promote sensorimotor recovery in the upper-extremity (UE) [1]–[5]. A critical factor driving motor improvements is the patient's active participation during therapy [6], [7], which can be maximised by encouragining patients to use their residual movement capability during training [8]. However, such approaches will not work for patients with no residual movements. Instructing such severely impaired patients to concentrate on movement training or imagery does not ensure that they actually focus on planing and preparing movements adequately. Ideally, one would observe neural activity, extract signatures of movement intention, and use that as a trigger to provide assisted movement, the contingent feedback, and reward. This is the rationale behind any neurorehabilitation approach using *restorative BCI* [9]–[11], which aims to actively engage severely affected patients in training. A restorative BCI system uses EEG, MEG or invasively recorded brain activity to detect movement intention and controls a robot that drives the affected limb [12]–[20]. EEG-BCI systems have generally used motor imagery or movement attempts to measure event-related desynchronisation (ERD) of the sensorimotor rhythm (SMR) [14], [17] to detect movement intention; a recent study has also used slow cortical potentials and the Bereitschafts potential [16].

Several studies have demonstrated the feasibility of BCI systems for robot-assisted rehabilitation [12]–[20], and provided evidence for its effectiveness to reduce impairments and improve the sensorimotor function [21]. However, several factors prevent its routine clinical application:

1) EEG's low information rate [22], poor signal-to-noise ratio, and large trial-to-trial variability [23] mean that the reliable movement intention detection sometimes requires delays. Given the precise timing requirements for Hebbian learning mechanisms in the context of the BCI literature [24], variable delay between intention, movement and feedback may impede learning.
2) EEG-BCI system design for movement intent detection in stroke survivors can be difficult due to variable reorganisational processes in motor areas over time. An EEG signature providing reliable feedback at one time period may change during subsequent periods.
3) Current EEG systems are cumbersome for everyday use and require a long preparation time.

In view of these difficulties with EEG-BCI to trigger robot-assisted movements, we propose inferring the presence/absence of movement intention (for on/off control) in severely affected stroke patients through a binary decoder using EMG from the muscles typically involved in a target movement. A binary decoder detects the presence or absence of intention and can be used for assisted movements through on/off control (e.g. [14], [25]). A continuous decoder estimates the level of effort from the subject and uses that to continuously modulate the assisted movement [26]–[28] (e.g. control the velocity of specific degrees-of-freedom). In this context, the main advantage of a binary decoder with on/off control over the continuous decoder is when the intent related

S. Balasubramanian is with the Department of Bioengineering, Christian Medical College Vellore 632002, Tamil Nadu, India.

E. Garcia-Cossio is with the Institute of Medical Psychology and Behavioral Neurobiology, University of Tubingen, Germany and neuroCare Group, Munich, Germany.

N. Birbaumer is with the Institute of Medical Psychology and Behavioral Neurobiology, University of Tubingen, Germany and Wyss Center for Bio and Neuroengeneering, Geneva, Switzerland.

E. Burdet is with the Department of Bioengineering, Imperial College of Science, Technology and Medicine, UK.

A. Ramos-Murgialday is with the Institute of Medical Psychology and Behavioral Neurobiology, University of Tubingen, Germany and the Neurotechnology Laboratory, Tecnalia, San Sebastian, Spain.

* Shared senior authorship.

signal has a lot of variability. Here, a continuous decoder would require more filtering to produce an accurate and smooth control signal to execute assisted movements, which will proportionally increase the delay between intention and movement execution. On the other hand, a binary decoder with some temporal-filtering might suffer less from this issue.

Most existing work in EMG-based therapy protocols have been typically carried out on patients with some residual movements, with the exception of [29] and [16]. DiPietro et. al [29] recruited three severely affected patients for an EMG-triggered robot-assisted therapy study, one of whom had no residual movement but some residual EMG in UE muscles that could be used for triggering assisted movements [29]. Bhagat et. al [16] studied two severely affected stroke patients without residual movements, who had some EMG, which was used to gate the EEG-BCI detector's output. However, it is currently not clear if EMG-triggered assisted therapy is a viable option for severely affected stroke patients with no residual movement.

Recently, we had investigated the ability of UE surface EMG for decoding different movements in 41 severely affected stroke patients [30]. Patients performed different bilateral UE movements (e.g. shoulder flexion, elbow extension, wrist extension, etc.), while EMG from both UE was recorded from several muscles. None of the 41 patients were able to extend their wrist or fingers, about 85% of them could not extend the elbow, and 70% could not flex or rotate the shoulder. The EMG data was used to classify these different movements using an artificial neural network. We observed that the hand/wrist movements could be decoded correctly with at least 65% accuracy in about 21% of the 41 stroke patients [30]. The current work extends [30] by specifically investigating the feasibility of using EMG as an on/off control for triggering robotic assistance for hand therapy. In particular, it attempts to answer questions about: (a) the proportion of severely affected stroke patients that could benefit from an EMG triggered assisted training, and (b) how well an EMG detector agree with a EEG-BCI detector on movement intention.

In our previous study [14], [30], we had evaluated an EEG-BCI to trigger robot-assisted movements in severely affected stroke patients with no visible finger extension. A majority of these patients had residual EMG in the finger extensors that improved with therapy. While this muscle activity may not be suitable for continuous control of robotic assistance, we hypothesized that it can be used as an on/off trigger for robot-assisted therapy. In order to test this hypothesis, we analysed the EMG activity from the forearm muscles of all study participants from [14]. We also used this data to compare the agreement between EMG and EEG-BCI-based motion intention detection.

II. Methods

The EMG and BCI data analysed in this study were collected as part of a previously published randomised controlled trial evaluating the effectiveness of BCI for chronic stroke rehabilitation in 32 severely affected patients [14]. The study was carried out at the University of Tübingen, Germany and was approved by the ethics committee of the Faculty of Medicine [14]. The details of the study participants are listed in Table I; two patients in the control group we excluded after recruitment as they did not satisfy the inclusion/exclusion criteria.

TABLE I

Demographic data and Fugl-Meyer assessment (FMA), at the time of enrollment, for the patient groups. Motor part of the modified upper-limb cFMA (hand and arm parts combined having a maximum score of 54 points); F - female; M - male; L - left; R - right.

Group	Experimental	Control
Gender	9M/7F	9M/5F
Age (yrs)	49.3±12.5	50.3±12.2
Time since stroke (months)	66±45	71±72
Lesion side	8R/8L	8R/6L
cFMA scores	11.15±6.92	13.28±10.71

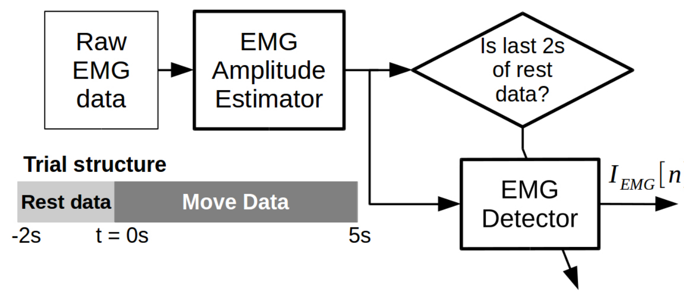

Fig. 1. **Schematic of the EMG amplitude estimator and detector.**

We investigated robot-assisted therapy for the arm and hand triggered by movement intention detected from an EEG-BCI system [14]. The BCI system was a two-state detector that used the ipsilesional SMR to detect an intention to move. In the experimental group, robotic assistance was contingent upon the BCI detection of movement intention. In the control group it was random, and uncorrelated to the BCI output. In the experimental group, movement intention was detected from a desynchronisation in the SMR, which produced a binary output every 40 ms. When the five consecutive detector outputs were the same, then a command was sent to the robot to either assist or stop hand movements. In the control group, the BCI detector output changed state every 40 ms with a probability of 10% and if the last five consecutive outputs of the BCI detector were the same, the robot was commanded either to assist or stop hand movements.

During the BCI triggered robot-assisted training, EMG from the following four UE muscles were recorded bilaterally: (1) *extensor carpi ulnaris* (2) *extensor digitorum* (3) long head of the *biceps* (flexion) (4) the external head of the *triceps* [14]. The current study did not make use of the raw EEG data, but only used the binary output of the SMR-based EEG-BCI two-state detector.

A. EMG-based movement intention detector

An algorithm was implemented for detecting EMG signals in the forearm muscles (*extensor carpi ulnaris* and *extensor* *digitorium*) of the affected limb during the BCI robot-assisted therapy sessions. This EMG detector worked on the assumption that in the "rest" state there is negligible EMG activity in the target muscles, while in the "move" state there will be more EMG activity. There are various possible approaches to design an EMG activity detector [31], but we implemented a simple Hodges detector [32] as described below.

The raw EMG data (sampled at 500 Hz) was first bandpass filtered (forward and backward) using a fourth order Butterworth filter with cut-off frequencies 10 Hz and 225 Hz. The EMG amplitude for the two channels (*extensor carpi ulnaris* and *extensor digitorum*) were estimated every 40 ms using the root mean square amplitude on a 200 ms window. Let,

$$\mathbf{a}(n) = [a_1(n), a_2(n)]^T, \ \ 0 \leq n < N_t$$

represent EMG amplitude data from a given trial, where $a_i(n)$ is the amplitude estimate of the i^{th} EMG channel at time index n, and N_t is the total number of data points in a trial.

The EMG detector was trained using the last 2 sec of "rest" state data (Fig. 1) by estimating the mean μ_i and standard deviation σ_i of the EMG amplitudes of the individual channels for a trial:

$$\mu_i = \frac{\sum_{n=N_1}^{N_2-1} a_i(n)}{N_2 - N_1}; \quad \sigma_i = \left[\frac{\sum_{n=N_1}^{N_2-1} \left[a_i(n) - \mu_i\right]^2}{N_2 - N_1 - 1}\right]^{\frac{1}{2}} \quad (1)$$

μ_i and σ_i correspond to the mean and standard deviation of $a_i(n)$ in the "rest" state, N_1 and N_2 are the indices corresponding to the start and end of the last 2 sec of "rest" state data. Data from the first 1 sec from the "rest" state was ignored because it could still contain EMG from the previous trial as the patient relaxes. The mean and standard deviation for the individual channels were then used to define the amplitude threshold that determined the presence or absence of EMG in channel i:

$$\tau_i = \mu_i + 2\sigma_i, \ \ i \in \{1, 2\} \quad (2)$$

The detector first used a simple rule to generate a binary output $\tilde{I}(n)$, which was set to 1 if (at least) one of the channels had activity above the threshold, i.e. $a_1(n) > \tau_1$ or $a_2(n) > \tau_2$, else it was set to 0. The movement intention $I_{EMG}(n) \in \{0, 1\}$ was then obtained after performing a temporal-filtering on $\tilde{I}(n)$, same as the one used with the EEG-BCI detector. At any given time instant n, $I_{EMG}(n)$ was set to 1 if the last 5 consecutive values of $\tilde{I}(n)$ were 1, and it was set to 0 if the last 5 consecutive values of $\tilde{I}(n)$ were 0, else it was set to $I_{EMG}(n-1)$; the inital value of $I_{EMG}(n)$ was set to 0 ($I_{EMG}(0) = 0$).

B. Statistical Analysis

The data from every trial corresponding to hand opening movements in all training sessions were analysed using the EMG detector to estimate $I_{EMG}(n)$ (where n indicates time instant). The EMG ($I_{EMG}(n)$) and EEG-BCI ($I_{BCI}(n)$) based movement intentions were used to answer the following two questions:

Q1: Do stroke patients with no visible hand movements produce movement related surface EMG in their hand muscles during the "move" state?

Q2: Do movement intentions detected by EMG (I_{EMG}) and the EEG-BCI (I_{BCI}) detectors agree with each other?

The first question was investigated by comparing the mean values of $I_{EMG}(n)$ in the "rest" $\left(p_{EMG}^{Rest}\right)$ and "move" $\left(p_{EMG}^{Move}\right)$ states, which can be interpreted as the probability of detecting EMG in these states, respectively. If EMG activity is detected when the patient is attempting to open the hand, then p_{EMG}^{Move} would be greater than p_{EMG}^{Rest}. The mean values of p_{EMG}^{Move} and p_{EMG}^{Rest} from all trials across all sessions were estimated for all 30 patients and compared using the Wilcoxon signed-rank test at 1% significance level [33].

The second question was investigated by estimating the Cohen's Kappa (κ) agreement statistic [34] between $I_{EMG}(n)$ and $I_{BCI}(n)$ in the "move" state for each individual patient. The joint probability distribution of both EMG and BCI detector outputs $P(I_{EMG}, I_{BCI})$ for a patient was first estimated; the data from all trials for each patient was used for this purpose. Following this, the overall κ was computed using

$$\kappa = \frac{p_o - p_e}{1 - p_e} \quad (3)$$

where $p_o = P(1,1) + P(0,0)$ is the observed probability of agreement between the EMG and BCI detectors, and p_e is the hypothetical probability of agreement

$$p_e = P(1,\cdot) \times P(\cdot,1) + P(0,\cdot) \times P(\cdot,0) \quad (4)$$

where '$\cdot$' indicates that the joint probability is summed across that particular variable resulting in a marginal probability; for instance, $P(1,\cdot)$ is the marginal probability of $I_{EMG} = 1$. It should be noted that $\kappa = 1$ indicates complete agreement while $\kappa = -1$ complete disagreement.

III. Results

An example of the EMG amplitude estimator and detector outputs along with the BCI output are shown in Fig. 2. The dotted vertical line separates the "rest" (left of the dotted line) and "move" (right of the dotted line) states. The EMG detector was trained on two seconds of data immediately preceding the dotted line, while the entire trial data was then run through the detector to identify the presence of EMG. Unlike the EMG detector output which can be non-zero in both "rest" and "move" states, the BCI detector's output was suppressed during the "rest" state [14], and thus its output was uniformly zero in this state. The two plots in Fig. 2 show two trials with good (bottom plot) and poor agreement (top plot) between the EMG and BCI detector outputs in the "move" state.

A. Is there a detectable EMG that can characterise movement intention in severe stroke patients?

The mean value of the EMG detector's output in the "rest" $\left(p_{EMG}^{Rest}\right)$ and "move" $\left(p_{EMG}^{Move}\right)$ states were compared to identify the presence of movement intention-related EMG in severe stroke patients. The summary plot of the parameters p_{EMG}^{Rest} and p_{EMG}^{Move} evaluated from the entire dataset from all patients, across all hand training sessions, is shown in Fig. 3. Overall, the mean probability of detecting EMG in the "move" state was found to be higher than that in the "rest"

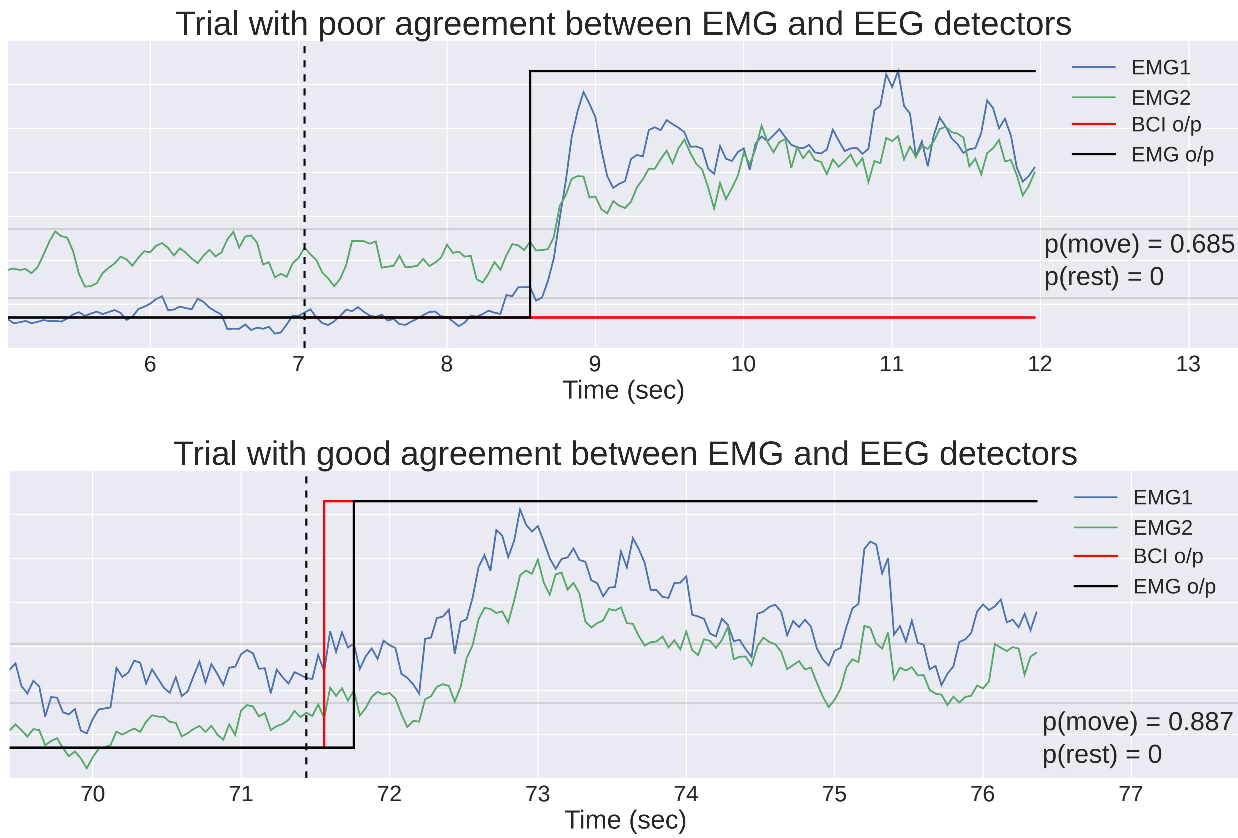

Fig. 2. **Sample outputs of two hand opening trials showing the amplitude estimates from the EMG channels, along with the EEG-BCI and EMG detector outputs. The top plot shows a case where there is poor agreement between EMG and BCI detectors, while the bottom plot is a case where there is good agreement.**

state (Wilcoxon singed-rank test: $p < 0.001; N_{EMG} = 30$); $N_{EMG} = 30$ corresponds to the 30 study participants.

For a given trial, the EMG detector used data from the "rest" state to estimate the thresholds (τ_i) for detecting EMG. Thus, even if there is no EMG in the "move" state, p^{Move}_{EMG} may be higher than p^{Rest}_{EMG} because the "move" state data was not used to estimate the thresholds. In order to get an estimate of the difference one could expect due to chance, between p^{Rest}_{EMG} and p^{Move}_{EMG}, a set of simulated data was generated and analysed using the same EMG detector. The details of this analysis are provided in Appendix A. The detector's performance on this noise data was captured by two parameters, p^{Rest}_{Noise} and p^{Move}_{Noise}. As seen in Fig. 3, even for the simulated noise data the probability of detecting signal above threshold was higher in the "move" state compared to the "rest" state (Wilcoxon singed-rank test: $p < 0.001; N_{Noise} = 30$). Moreover, the probability of detecting EMG was also higher than that of noise (Wilcoxon rank-sum test: $p < 0.001; N_{EMG} = 30, N_{Noise} = 30$)[1] indicating that the difference between the "rest" and "move" states for EMG was more than that could be expected due to chance. *These results indicate there was residual intent-related surface EMG in these severely affected patients during the "move" state, and suggests that EMG is a viable solution for detecting movement intention in severe stroke patients.*

Although Fig. 3 provides an overall summary of the differences between the "rest" and "move" states, it does not provide any information about individual patients across different sessions. This information is provided in Table II, which displays the mean values of p^{Rest}_{EMG} and p^{Move}_{EMG} for the individual patients estimated across all trials and sessions. Overall, for 73% (22/30) of the study participants, the median p^{Move}_{EMG} was greater than p^{Rest}_{EMG} and the 99^{th} percentile of the median p^{Move}_{Noise}, i.e. *a large percentage of patients showed movement intent-related surface EMG that could serve as a trigger for assisted movement therapy.*

Additionally, Table II also provides a measure of the accuracy of the EMG detector displaying the mean accuracy across sessions for each patient (along with the standard deviation across sessions). The accuracy in a given session was defined as the proportion of the session's trials where the EMG detector detected more EMG in the "move" state than the "rest" state, i.e. p^{Move}_{EMG} is greater than both p^{Rest}_{EMG} and 99^{th} percentile of p^{Move}_{Noise}. The detector's mean accuracy was found to be highly correlated to mean p^{Move}_{EMG} (Spearman correlation $r = 0.997$, $p < 0.001$), indicating that patients with larger residual EMG were able to generate the signal more consistently across trials compared to patients with low residual EMG. A similar accuracy analysis for the EEG-BCI detector could not be carried out as its output was suppressed (set to '0') in the "rest" state [14].

[1] N_{EMG} and N_{Noise} are the sample sizes for the EMG and noise data.

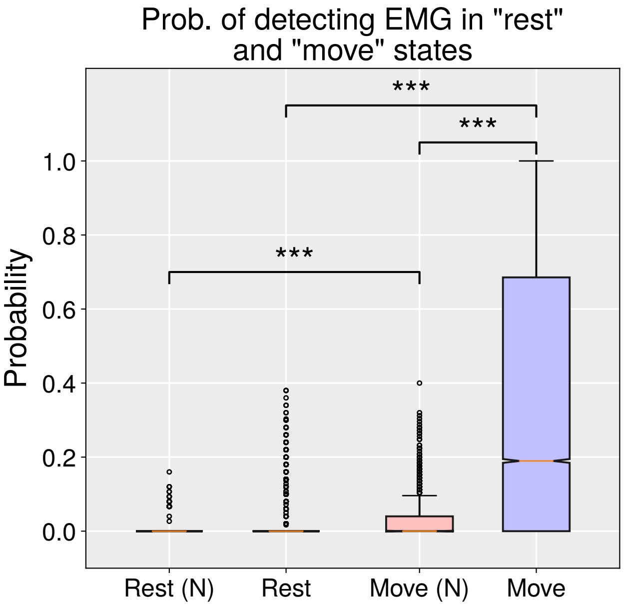

Fig. 3. **Probability of detecting EMG in the "rest" and "move" states from all patients across all hand training sessions. The boxplots in blue correspond to probabilities estimated from actual EMG data from patients, while the boxplots in red correspond to simulated noise data; '(N)' in the x-axis indicates noise. '***' indicates a significant difference between the mean proability of detection at $p < 0.001$.**

TABLE II

Data analaysis summary from individual patients listing the mean values of p_{EMG}^{Rest} and p_{EMG}^{Move}, and the overall Cohen's κ agreement statistic between the EMG and EEG-BCI detectors. The '*' in the "Move" column indicates that the median p_{EMG}^{Move} estiamted across all sessions was larger than that of p_{EMG}^{Rest} and p_{Noise}^{Move} and the 99^{th} percentile of median p_{Noise}^{Move} (E: Experiment group; C: Control group)

Patient	Rest	Move	Accuracy Mean (Std)	Agreement
E1	0.008	0.102	0.435 (0.107)	0.015
E2	0.008	0.241*	0.589 (0.171)	0.044
E3	0.011	0.583*	0.908 (0.034)	0.282
E4	0.016	0.747*	0.973 (0.019)	0.207
E5	0.019	0.566*	0.876 (0.109)	0.178
E6	0.011	0.459*	0.806 (0.069)	0.066
E7	0.011	0.512*	0.837 (0.105)	0.084
E8	0.007	0.351*	0.778 (0.089)	0.140
E9	0.008	0.096	0.463 (0.044)	0.014
E10	0.018	0.194*	0.625 (0.117)	0.090
E11	0.004	0.878*	0.985 (0.011)	0.099
E12	0.008	0.088	0.449 (0.103)	0.005
E13	0.010	0.147*	0.574 (0.060)	0.161
E14	0.011	0.115*	0.500 (0.079)	0.012
E15	0.016	0.200*	0.584 (0.186)	0.060
E16	0.040	0.203*	0.629 (0.078)	0.026
C1	0.008	0.227*	0.653 (0.079)	–
C2	0.012	0.535*	0.862 (0.055)	–
C3	0.017	0.069	0.424 (0.055)	–
C4	0.008	0.083	0.378 (0.074)	–
C5	0.005	0.694*	0.903 (0.107)	–
C6	0.047	0.154*	0.540 (0.037)	–
C7	0.013	0.115	0.446 (0.074)	–
C8	0.013	0.093	0.432 (0.067)	–
C9	0.012	0.079	0.442 (0.080)	–
C10	0.007	0.384*	0.783 (0.104)	–
C11	0.008	0.655*	0.914 (0.072)	–
C12	0.015	0.316*	0.727 (0.093)	–
C13	0.012	0.483*	0.796 (0.141)	–
C14	0.007	0.184*	0.589 (0.106)	–

B. How well do the EMG and BCI detectors agree on movement intention?

The Cohen's κ statistic estimated from patients in the experimental group is shown in Table II. κ was estimated only for the experimental group because in the control group the BCI detector's output was changed randomly and was not correlated to the patient's SMR. Overall in the experimental group, the agreement between the EMG and BCI detectors was positive but small (median $\kappa = 0.075$), indicating that there was little agreement between EMG and BCI detector outputs. κ was practically zero (< 0.1) for most patients, but there were some patients with slight to fair agreement between EMG and BCI ($0.1 < \kappa < 0.3$, Table II). Thus, *even when there was significant movement intent-related EMG, there was only a slight agreement between BCI and EMG detector outputs*.

IV. Discussion

There has been a growing interest in restorative BCI to actively engage stroke patients with no residual motor control in neurorehabilitation. BCI systems detect movement intention, and close the loop by providing movement-related afferent feedback, synchronised to the cortical processes for movement planning, through a robotic device [12]–[20] or electrical stimulation [24]. Existing systems primarily use EEG to detect voluntary movement intention to provide assisted movements [12]–[20].

The results of the current study demonstrate that EMG provides a feasible alternative or ajunct to voluntarily engage severely affected patients in training. EMG is a peripheral manifestation of a movement attempt, and thus a proxy for brain activity related to motion intention. Using EMG, rather than EEG, to trigger robot-assisted movements has several advantages:

1) EEG detectors use an empirical approach of choosing any set of signals showing feature changes when a patient attempts a movement. These changes in signal features may not be a direct correlate of movement attempt [24], but may reflect only non-specific arousal changes during movement preparation, such as the late components of negative slow brain potentials occuring before the actual "Bereitschafts potential" [35]. On the other hand, EMG in a target muscle is the resulting final evidence of an attempted movement. Thus, for a given task, if there are still residual connections from the brain to target muscles, EMG is an indicator of a movement attempt.
2) EMG is more task-specific than EEG as it relies on the activities of specific muscles involved in a given task; EEG does not have the spatial resolution for identifying individual muscle groups.
3) EMG is easier to record than EEG as the setup required is smaller, simpler, and easier to don and doff. EMG also require minimal time for calibration.
4) EMG is more reliable than EEG. Muscles act as natural amplifiers and EMG has lesser attenuation compared to

EEG. EMG from the UE muscles are also less affected by other physiological signals such as ECG or EOG.

The data presented here involves 30 of the 32 stroke survivors with severe impairments with no voluntary finger extension [14]. Presence of residual EMG was not an inclusion criteria, although, EMG activity was part of the patient screening process [14]. With a simple threshold method and by using only two muscles from the paretic side, we observed 22 out of 30 subjects (or 73%) to have significant EMG activity for detecting motion intention. This suggests that **a large portion of this patient population may be able to use specific target muscles (e.g. wrist and finger extensors) to interactively train assisted movements**. For the rest 27% of patients with extremely small or no residual EMG, EMG-triggered therapy would not be suitable. Such patients would require an EEG-BCI system for assisted therapy, until sufficient voluntary control or EMG reappears.

A comparison between EEG and EMG movement intent detection revealed that there was poor agreement between the two modalities. Out of the 16 subjects (Table II), only two had Cohen's κ greater than 0.2. The lack of agreement was least expected given that a majority of patients had EMG in their forearm muscles. This poor agreement may indicate that EEG detects different processes, possibly not directly related to movement generation. Another possiblity could be the poor detection accuracy/reliability of the EEG or EMG detectors employed in the current study. Table II shows that three of the four patients with EMG detection probability greater than 80% had the highest values for Cohen's κ. Contamination and bias of EEG (and EEG-BCIs) due to different sources of artefacts, especially when used for motor rehabilitation is well known [36]. Furthermore, the poor SNR of residual EMG signals could have reduced the accuracy and reliability of the EMG detector (Table II). These issues were, at least partly, addressed through the use of temporal filters (200 ms time window) for both EEG and EMG detectors. However, it is likely that a different EEG modality or more sophisticated EEG/EMG detectors could have resulted in better agreement between cortical and muscle activities. For instance, movement-related cortical potential (MRCP) is another popular EEG modality to detect movement intention [37], [38]. Recent developments on sophisticated methods for improved MRCP detection [39], [40] could have improved the overall EEG and EMG agreement. Similarly, a more optimal EMG detector [31], [41]–[45] could also lead to a better agreement.

Early detection of movement intent, well before movement onset, afforded by EEG is believed to be a crucial factor for optimal recovery with restorative BCIs [39], [40]. This early detection allows close temporal coupling between movement intent and afferent feedback from assisted movements, which has been shown to strengthen cortical connections involved in movement planning and execution [37], [46]. Interestingly, cortical excitability has also been shown to increase with externally induced cortical and peripheral stimuli when there is tight temporal coupling between them – paired associative stimulation [47]–[49]. These neuroplastic proceses are probably the result of Hebbian learning mechanisms such as spike time dependent plasticity (STDP) [24], [49].

EMG-triggered assisted movement therapy is likely to operate through the same Hebbian learning mechanisms as EEG-BCI triggered therapy. However, the delay between cortical and EMG activity might reduce the effectiveness of the learning process due to suboptimal timing of the stimulus [24]. Although, single neuron studies have demonstrated the importance of timing between pre- and post-synaptic activities, the role of precise timing is not clear in network-level structures which are modulated continuously [24]. Furthermore, there is evidence in the current literature demonstrating that both cortical changes [50], [51] and functional recovery can occur following EMG-triggered assisted movements [51]–[53]; thus, indicating that EMG-triggered movements can serve as associative cues for strengthening learning. Mcgie et. al found that motor evoked potentials were upregulated following both EEG-BCI-triggered and EMG-triggered FES [50]. Francisco et. al showed that stroke patients training with EMG-triggered FES performed better than patients receiving standard physical therapy [52]. A review by de Kroon et. al found that EMG-triggered FES may be more effective than non-triggered stimulation for upper-limb training in stroke [53]. All these studies have relied on EMG-triggered electrical stimulation to produce assisted movements of a target joint, which is different from robot-assisted movements in terms of the afferent feedback sent to the brain. Electrical stimulation produces contractions in the target muscles and thus provides additional afferent feedback (from the muscle spindles and Golgi tendon organs) on top of feedback resulting from the limb movement. This difference could influence the recovery induced by these two modalities when used in a intent-triggered assisted paradigm. However, a recent study by Mrachacz-Kersting indicates that these two feedback modalities might be equally effective in increasing cortical excitability following a 30 min intervention using an EEG-BCI triggered ankle dorsiflexion movement [38].

We emphasize that the work presented is a secondary analysis of data collected from a randomized controlled trial that investigated the effect of BCI-based robot-assisted training of the UE [14]. Thus, the study outcomes should only be taken as a preliminary result on the feasibility of EMG as a proxy for movement intention in severely affected stroke patients. Nevertheless, the positive results obtained here motivate further investigation of the use of EMG detector proposed in this paper to trigger robot-assisted neurorehabilitation of the hand in severely affected stroke survivors.

V. Conclusion

The current study evaluated the feasiblity of using surface EMG as an adjunct or alternative to EEG-based movement intention detection in severely affected stroke paients with no visible movement. This was done through analysis of data from a previously published randomized controlled trial on EEG-BCI triggered robot-assisted rehabilitation of the arm/hand of severely affected chronic stroke patients. Overall, the results from the study indicate that EMG is a viable alternative or adjunct to EEG for detecting movement intention, with almost 73% (22/30) of the patients showing sufficient surface EMG in their finger/wrist extensor muscles. Given the potential practical advantages of EMG compared to EEG, it is worth further investigating this approach for assisted neurorehabilitation. Additionally, we also observed that there was poor agreement between the EEG and EMG based intention detectors, which may indicate that they detect different processes.

Appendix A
EMG Detector Performance on Noise Data

For any a given trial, the EMG detector was trained using data from the "rest" state. Thus, even if there is no EMG in the "move" state, p_{EMG}^{Move} may be higher than p_{EMG}^{Rest} because the "move" state data was not used to determine the detector parameters. In order to get an estimate of the difference between p_{EMG}^{Rest} and p_{EMG}^{Move} due to the training-testing effect, a set of simulated data was generated and analysed using the same EMG detector. The simulated data consisted of 3000 different realisations of two independent channels of Gaussian white noise (8 sec in duration sampled at 500Hz); the first 3 seconds of data is assumed to be the "rest" state, while the rest 5 seconds is "move" state. The 3000 trials were splits into 30 sets of 100 trials, simulating 30 different subjects performing 100 trials. Each trial in the dataset was bandpass filtered between 10Hz and 225Hz (same as the one used on the raw EMG data), and its amplitude was estimated. The amplitude estimate was input to the EMG detector to evaluate the detector's performance p_{Noise}^{Rest} and p_{Noise}^{Move}, which are the probabilities of detecting a noise amplitude above the detector threshold in the "rest" and "move" states, respectively. This results in 3000 pairs of p_{Noise}^{Rest} and p_{Noise}^{Move} corresponding to 100 trials for 30 subjects.

Acknowledgments

This research was supported in part by the European Commission grants EU-FP7 HUMOUR (ICT 231554), CONTEST (ITN 317488), EU-H2020 COGIMON (ICT 644727), COST ACTION TD1006 European Network on Robotics for NeuroRehabilitation, Deutsche Forschungsgemeinschaft (DFG), Baden-Württemberg Stiftung (GRUENS, ROB-1), the Natural Science Fundation of China (NSFC 31450110072), Bundes Ministerium für Bildung und Forschung BMBF MOTORBIC (FKZ 13GW0053), AMORSA (16SV7754) and by the UKIERI grant UKUTP201100135.

References

[1] B. French, L. Thomas, M. Leathley, C. Sutton, J. McAdam, A. Forster, P. Langhorne, C. Price, A. Walker, and C. Watkins, "Does repetitive task training improve functional activity after stroke? A Cochrane systematic review and meta-analysis," *Journal of Rehabilitation Medicine*, vol. 42, no. 1, pp. 9–14, Jan 2010.

[2] G. Kwakkel, R. van Peppen, R. C. Wagenaar, S. Wood Dauphinee, C. Richards, A. Ashburn, K. Miller, N. Lincoln, C. Partridge, I. Wellwood, and P. Langhorne, "Effects of Augmented Exercise Therapy Time After Stroke: A Meta-Analysis," *Stroke*, vol. 35, no. 11, pp. 2529–2539, Nov 2004.

[3] G. Kwakkel, "Impact of intensity of practice after stroke: issues for consideration." *Disability and rehabilitation*, vol. 28, no. 13-14, pp. 823–30, Jan 2006.

[4] P. Langhorne, F. Coupar, and A. Pollock, "Motor recovery after stroke: a systematic review," *The Lancet Neurology*, vol. 8, no. 8, pp. 741–754, Aug 2009.

[5] R. P. Van Peppen, G. Kwakkel, S. Wood-Dauphinee, H. J. Hendriks, P. J. Van der Wees, and J. Dekker, "The impact of physical therapy on functional outcomes after stroke: what's the evidence?" *Clinical Rehabilitation*, vol. 18, no. 8, pp. 833–862, Dec 2004.

[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. 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," *New England Journal of Medicine*, vol. 362, no. 19, pp. 1772–1783, May 2010.

[7] L. E. Kahn, M. L. Zygman, W. Z. Rymer, and D. J. Reinkensmeyer, "Robot-assisted reaching exercise promotes arm movement recovery in chronic hemiparetic stroke: a randomized controlled pilot study." *Journal of neuroengineering and rehabilitation*, vol. 3, no. 1, p. 12, Jun 2006.

[8] L. Marchal-Crespo and D. J. Reinkensmeyer, "Review of control strategies for robotic movement training after neurologic injury," *Journal of NeuroEngineering and Rehabilitation*, vol. 6, no. 1, p. 20, 2009.

[9] N. A. Bhagat, A. Venkatakrishnan, B. Abibullaev, E. J. Artz, N. Yozbatiran, A. A. Blank, J. French, C. Karmonik, R. G. Grossman, M. K. O'Malley, G. E. Francisco, and J. L. Contreras-Vidal, "Design and Optimization of an EEG-Based Brain Machine Interface (BMI) to an Upper-Limb Exoskeleton for Stroke Survivors." *Frontiers in neuroscience*, vol. 10, no. 6, p. 122, Dec 2016.

[10] U. Chaudhary, N. Birbaumer, and A. Ramos-Murguialday, "Braincomputer interfaces for communication and rehabilitation," *Nature Reviews Neurology*, vol. 12, no. 9, pp. 513–525, Aug 2016.

[11] J. J. Daly and J. R. Wolpaw, "Brain computer interfaces in neurological rehabilitation," *The Lancet Neurology*, vol. 7, no. 11, pp. 1032–1043, Nov 2008.

[12] K. K. Ang, K. S. G. Chua, K. S. Phua, C. Wang, Z. Y. Chin, C. W. K. Kuah, W. Low, and C. Guan, "A Randomized Controlled Trial of EEG-Based Motor Imagery Brain-Computer Interface Robotic Rehabilitation for Stroke," *Clinical EEG and Neuroscience*, vol. 46, no. 4, pp. 310–320, Oct 2015.

[13] 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.

[14] A. Ramos-Murguialday, D. Broetz, M. Rea, L. Läer, Ö. Yilmaz, F. L. Brasil, G. Liberati, M. R. Curado, E. Garcia-Cossio, A. Vyziotis, W. Cho, M. Agostini, E. Soares, S. Soekadar, A. Caria, L. G. Cohen, and N. Birbaumer, "Brain-machine interface in chronic stroke rehabilitation: A controlled study," *Annals of Neurology*, vol. 74, no. 1, pp. 100–108, Jul 2013.

[15] S. Silvoni, A. Ramos-Murguialday, M. Cavinato, C. Volpato, G. Cisotto, A. Turolla, F. Piccione, and N. Birbaumer, "Brain-Computer Interface in Stroke: A Review of Progress," *Clinical EEG and Neuroscience*, vol. 42, no. 4, pp. 245–252, Oct 2011.

[16] N. A. Bhagat, A. Venkatakrishnan, B. Abibullaev, E. J. Artz, N. Yozbatiran, A. A. Blank, J. French, C. Karmonik, R. G. Grossman, M. K. O'Malley, G. E. Francisco, and J. L. Contreras-Vidal, "Design and Optimization of an EEG-Based Brain Machine Interface (BMI) to an Upper-Limb Exoskeleton for Stroke Survivors." *Frontiers in neuroscience*, vol. 10, no. March, p. 122, Mar 2016.

[17] D. Brauchle, M. Vukelić, R. Bauer, and A. Gharabaghi, "Brain state-dependent robotic reaching movement with a multi-joint arm exoskeleton: combining brain-machine interfacing and robotic rehabilitation." *Frontiers in human neuroscience*, vol. 9, no. October, p. 564, Oct 2015.

[18] T. Ono, K. Shindo, K. Kawashima, N. Ota, M. Ito, T. Ota, M. Mukaino, T. Fujiwara, A. Kimura, M. Liu, and J. Ushiba, "Brain-computer interface with somatosensory feedback improves functional recovery from severe hemiplegia due to chronic stroke." *Frontiers in neuroengineering*, vol. 7, no. July, p. 19, Jul 2014.

[19] F. Pichiorri, G. Morone, M. Petti, J. Toppi, I. Pisotta, M. Molinari, S. Paolucci, M. Inghilleri, L. Astolfi, F. Cincotti, and D. Mattia, "Brain-computer interface boosts motor imagery practice during stroke recovery." *Annals of neurology*, vol. 77, no. 5, pp. 851–65, May 2015.

[20] B. Várkuti, C. Guan, Y. Pan, K. S. Phua, K. K. Ang, C. W. K. Kuah, K. Chua, B. T. Ang, N. Birbaumer, and R. Sitaram, "Resting State Changes in Functional Connectivity Correlate With Movement Recovery for BCI and Robot-Assisted Upper-Extremity Training After Stroke," *Neurorehabilitation and Neural Repair*, vol. 27, no. 1, pp. 53–62, Jan 2013.

[21] A. Ramos-Murguialday and N. Birbaumer, "Brain oscillatory signatures of motor tasks," *Journal of Neurophysiology*, vol. 113, no. 10, pp. 3663–3682, Jun 2015.

[22] B. Obermaier, C. Neuper, C. Guger, and G. Pfurtscheller, "Information transfer rate in a five-classes brain-computer interface," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 9, no. 3, pp. 283–288, 2001.

[23] O. Bai, V. Rathi, P. Lin, D. Huang, H. Battapady, D.-Y. Fei, L. Schneider, E. Houdayer, X. Chen, and M. Hallett, "Prediction of human voluntary movement before it occurs," *Clinical Neurophysiology*, vol. 122, no. 2, pp. 364–372, Feb 2011.

[24] C. Ethier, J. A. Gallego, and L. E. Miller, "Brain-controlled neuromuscular stimulation to drive neural plasticity and functional recovery." *Current opinion in neurobiology*, vol. 33, pp. 95–102, Aug 2015.

[25] N. Irastorza-Landa, A. Sarasola-Sanz, F. Shiman, E. López-Larraz, J. Klein, D. Valencia, A. Belloso, F. O. Morin, N. Birbaumer, and A. Ramos-Murguialday, "EMG Discrete Classification Towards a Myoelectric Control of a Robotic Exoskeleton in Motor Rehabilitation," 2017, pp. 159–163.

[26] 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," *Neurorehabilitation and Neural Repair*, vol. 23, no. 8, pp. 837–846, Oct 2009.

[27] X. L. Hu, K. Y. Tong, X. J. Wei, W. Rong, E. A. Susanto, and S. K. Ho, "Coordinated upper limb training assisted with an electromyography (EMG)-driven hand robot after stroke." *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference*, vol. 2013, pp. 5903–6, Jul 2013.

[28] A. Sarasola-Sanz, N. Irastorza-Landa, F. Shiman, E. López-Larraz, M. Spüler, N. Birbaumer, and A. Ramos-Murguialday, "Emg-based multi-joint kinematics decoding for robot-aided rehabilitation therapies," in *Rehabilitation Robotics (ICORR), 2015 IEEE International Conference on*. IEEE, 2015, pp. 229–234.

[29] L. Dipietro, M. Ferraro, J. Palazzolo, H. Krebs, B. Volpe, and N. Hogan, "Customized Interactive Robotic Treatment for Stroke: EMG-Triggered Therapy," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 13, no. 3, pp. 325–334, Sep 2005.

[30] A. Ramos-Murguialday, E. García-Cossio, A. Walter, W. Cho, D. Broetz, M. Bogdan, L. G. Cohen, and N. Birbaumer, "Decoding upper limb residual muscle activity in severe chronic stroke," *Annals of Clinical and Translational Neurology*, vol. 2, no. 1, pp. 1–11, Jan 2015.

[31] G. Staude, C. Flachenecker, M. Daumer, and W. Wolf, "Onset Detection in Surface Electromyographic Signals: A Systematic Comparison of Methods," *EURASIP Journal on Advances in Signal Processing*, vol. 2001, no. 2, pp. 67–81, 2001.

[32] P. W. Hodges and B. H. Bui, "A comparison of computer-based methods for the determination of onset of muscle contraction using electromyography." *Electroencephalography and clinical neurophysiology*, vol. 101, no. 6, pp. 511–9, Dec 1996.

[33] M. Hollander, D. A. Wolfe, and E. Chicken, *Nonparametric Statistical Methods*. Hoboken, NJ, USA: John Wiley & Sons, Inc., Jul 2015.

[34] L. G. Portney, M. P. Watkins, and W. P. Portney G, *Foundations of Clinical Research: Applications to Practice*, 2009, vol. 36.

[35] N. Birbaumer, T. Elbert, A. G. Canavan, and B. Rockstroh, "Slow potentials of the cerebral cortex and behavior." *Physiological Reviews*, vol. 70, no. 1, pp. 1–41, 1990.

[36] E. López-Larraz, C. Bibián, N. Birbaumer, and A. Ramos-Murguialday, "Influence of artifacts on movement intention decoding from eeg activity in severely paralyzed stroke patients," in *Rehabilitation Robotics (ICORR), 2017 International Conference on*. IEEE, 2017, pp. 901–906.

[37] N. Mrachacz-Kersting, S. R. Kristensen, I. K. Niazi, and D. Farina, "Precise temporal association between cortical potentials evoked by motor imagination and afference induces cortical plasticity," *The Journal of physiology*, vol. 590, no. 7, pp. 1669–1682, 2012.

[38] N. Mrachacz-Kersting, "Effect of feedback type on the effectiveness of a novel associative bci protocol targeting the tibialis anterior muscle," in *Converging Clinical and Engineering Research on Neurorehabilitation II*. Springer, 2017, pp. 13–17.

[39] R. Xu, N. Jiang, C. Lin, N. Mrachacz-Kersting, K. Dremstrup, and D. Farina, "Enhanced low-latency detection of motor intention from eeg for closed-loop brain-computer interface applications," *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 2, pp. 288–296, 2014.

[40] F. Karimi, J. Kofman, N. Mrachacz-Kersting, D. Farina, and N. Jiang, "Detection of movement related cortical potentials from eeg using constrained ica for brain-computer interface applications," *Frontiers in neuroscience*, vol. 11, p. 356, 2017.

[41] S. Solnik, P. Rider, K. Steinweg, P. DeVita, and T. Hortobágyi, "Teager–kaiser energy operator signal conditioning improves emg onset detection," *European journal of applied physiology*, vol. 110, no. 3, pp. 489–498, 2010.

[42] X. Zhang and P. Zhou, "Sample entropy analysis of surface emg for improved muscle activity onset detection against spurious background spikes," *Journal of Electromyography and Kinesiology*, vol. 22, no. 6, pp. 901–907, 2012.

[43] Q. Xu, Y. Quan, L. Yang, and J. He, "An adaptive algorithm for the determination of the onset and offset of muscle contraction by emg signal processing," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 21, no. 1, pp. 65–73, 2013.

[44] L. Vaisman, J. Zariffa, and M. R. Popovic, "Application of singular spectrum-based change-point analysis to emg-onset detection," *Journal of Electromyography and Kinesiology*, vol. 20, no. 4, pp. 750–760, 2010.

[45] J. Liu, D. Ying, and W. Z. Rymer, "Emg burst presence probability: A joint time–frequency representation of muscle activity and its application to onset detection," *Journal of biomechanics*, vol. 48, no. 6, pp. 1193–1197, 2015.

[46] N. Mrachacz-Kersting, N. Jiang, A. J. T. Stevenson, I. K. Niazi, V. Kostic, A. Pavlovic, S. Radovanovic, M. Djuric-Jovicic, F. Agosta, K. Dremstrup *et al.*, "Efficient neuroplasticity induction in chronic stroke patients by an associative brain-computer interface," *Journal of neurophysiology*, vol. 115, no. 3, pp. 1410–1421, 2016.

[47] K. Stefan, E. Kunesch, L. G. Cohen, R. Benecke, and J. Classen, "Induction of plasticity in the human motor cortex by paired associative stimulation," *Brain*, vol. 123, no. 3, pp. 572–584, 2000.

[48] N. Mrachacz-Kersting, M. Fong, B. A. Murphy, and T. Sinkjaer, "Changes in excitability of the cortical projections to the human tibialis anterior after paired associative stimulation," *Journal of neurophysiology*, vol. 97, no. 3, pp. 1951–1958, 2007.

[49] A. Suppa, A. Quartarone, H. Siebner, R. Chen, V. Di Lazzaro, P. Del Giudice, W. Paulus, J. Rothwell, U. Ziemann, and J. Classen, "The associative brain at work: Evidence from paired associative stimulation studies in humans," *Clinical Neurophysiology*, vol. 128, no. 11, pp. 2140–2164, 2017.

[50] S. C. McGie, J. Zariffa, M. R. Popovic, and M. K. Nagai, "Short-term neuroplastic effects of brain-controlled and muscle-controlled electrical stimulation," *Neuromodulation: Technology at the Neural Interface*, vol. 18, no. 3, pp. 233–240, 2015.

[51] Y. Hara, S. Obayashi, K. Tsujiuchi, and Y. Muraoka, "The effects of electromyography-controlled functional electrical stimulation on upper extremity function and cortical perfusion in stroke patients," *Clinical Neurophysiology*, vol. 124, no. 10, pp. 2008–2015, 2013.

[52] G. Francisco, J. Chae, H. Chawla, S. Kirshblum, R. Zorowitz, G. Lewis, and S. Pang, "Electromyogram-triggered neuromuscular stimulation for improving the arm function of acute stroke survivors: a randomized pilot study," *Archives of physical medicine and rehabilitation*, vol. 79, no. 5, pp. 570–575, 1998.

[53] J. de Kroon, M. IJzerman, J. Chae, G. Lankhorst, G. Zilvold, and G. Zilvold, "Relation between stimulation characteristics and clinical outcome in studies using electrical stimulation to improve motor control of the upper extremity in stroke," vol. 37, no. 2, pp. 65–74, 3 2005, this study was supported by the National Health Research Council of the Netherlands.

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