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Continuous decoding of intention to move from contralesional hemisphere brain oscillations in severely affected chronic stroke patients

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Abstract— **Decoding motor information directly from brain activity is essential in robot-assisted rehabilitation systems to promote motor relearning. However, patients who suffered a stroke in the motor cortex have lost brain activity in the injured area, and consequently, mobility in contralateral limbs. Such a loss eliminates the possibility of extracting motor information from brain activity while the patient is undergoing therapy for the affected limb. This work proposes to decode motor information from EEG activity of the contralesional hemisphere in patients who suffered a hemiparetic stroke. Four stroke patients participated in this study and the results proved the feasibility of decoding motor information while patients attempted to move the affected limb.**

I. INTRODUCTION

Demographic data analysis shows an increasing concern in finding solutions and optimizing interventions for stroke survivors [1], [2]. Robot-assisted rehabilitation therapies have emerged as a very promising therapeutic approach with numerous advantages [3], including the enhancement of muscle strength, improvement of motor coordination and dexterity [4], and promotion of neural circuit strength to recover lost mobility [5]. Robot-assisted rehabilitation also provides a reliable and safe way for the execution of intensive and repetitive rehabilitation movements of the affected limbs, while reducing the need of assistance from the therapist.

Force and kinematic sensors are usually used in robotics-based motor rehabilitation as control signals whenever stroke survivors still present residual movements [6], [7]. Alternatively, information from the peripheral nervous system (PNS), such as muscle activity (EMG), can be used (alone or combined with force or kinematics sensors) to drive and control the movement-assisted devices [8], [9], [10], [11]. This is advantageous as it provides a certain level of control to the patient undergoing therapy. However, this strategy does not directly involve the central nervous system (CNS), and therefore it could slow down or even inhibit motor relearning [12].

For patients without any residual movement in the affected joints, EMG (if present) and electroencephalographic (EEG) signals combined or alone might be the only non-invasive remaining signals that could be used to trigger, in a natural way, the robot movements and therefore close the loop between brain and end effector (paralyzed limb). Recently, several groups developed BCI approaches for motor rehabilitation in stroke patients, in which proprioceptive and visual feedback become the key factors to close the brain-end effector loop and produce some rehabilitation effects [13], [14].

The use of information obtained directly from CNS is essential to allow the patient to control, in a fully natural and active way, both the device and the rehabilitation process. Thus, strengthening of neural circuits is induced along with the reorganization of the cortex (brain plasticity), allowing for the recovery of lost mobility. Consequently, to promote motor relearning, information such as motor planning or intention must be directly extracted form the CNS while the patients are using a movement-assisting device. Although recent studies with healthy subjects have proposed the decoding of motor information directly from the brain activity non-invasively recorded with EEG [15], [16], the limitation when dealing with stroke patients is the damage in the brain neural networks connections. This damage could cause absence or limitation of detectable motor-related brain activity in injured and vicinity areas that could connect intention with action (contralateral muscle activity). It has been proved that during the execution of movement both the contralateral and ipsilateral cortex are active [17], [18] due to subcortical and intercallosal connections [19], [20]. Furthermore, it has been demonstrated that arm kinematic information could be decoded from brain ipsilateral areas [21], suggesting the use of the healthy hemisphere to decode limb movement in patients with unilateral stroke, and thus use this information in robot-mediated therapy.

This work studies the decoding of motor intention using EEG activity of the contralesional hemisphere only, in four severely affected chronic stroke patients. In particular, sensorimotor rhythm oscillations in the healthy motor cortex were used to decode movement (intention to move) of the unaffected and affected arm. In addition, a continuous decoding strategy is presented, based on estimation of motor information, to simulate a real case scenario in which the patient could control a rehabilitation robot on-line with contralesional brain activity only.

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II. METHODS

A. Subjects

Four male patients (age range $55-65$ years) who suffered subcortical ischemic stroke (two in the left and two in the right hemisphere) participated in this study. All patients suffered a stroke at least two years before the experiments, i.e., being in the chronic phase. Patients were unable to use the upper limb for any activity of daily living, having no residual finger extension on the paretic side. All patients were able to complete the tasks using the healthy side.

B. Experimental procedure

The experimental protocol was approved by the ethics committee of the University of Tubingen, Medical Faculty, and written consent was obtained from each patient. The subjects were seated in a chair in front of a computer screen with both forearms resting comfortably on their lap. The task was to move -or to attempt to move- the unaffected -or affected- arm from the initial position to any self-selected 3D location presented on the screen as colored circles (reaching task), and then to return to the initial position (see figure 1). The experiment comprehended two conditions. Condition one referred to *movement of the unaffected arm*, while condition two referred to *attempts to move the affected arm*. The users were provided with audio and visual cues. The first cue instructed the users to relax the body and to adopt the initial position for three seconds. The second cue marked the start of the movement of the unaffected arm or the attempt to move the affected arm. After another three seconds, the third cue indicated to relax adopting the initial position, blink and rest for another three seconds. During the motion phase (between the second and third cues), subjects were asked to avoid blinking or compensating movement with the torso or other parts of the body. This was controlled visually by the therapist and then off-line by visual inspection of the EMG data. The experiment was executed in four blocks of six minutes each. Fourty trials were recorded in each block, resulting in a total of 160 trials (80 for each condition). After each block the patient could rest as long as necessary to avoid fatigue.

C. Data acquisition

EEG activity was recorded from 64 active electrodes arranged according to the 10/10 international system using an actiCAP system (from Brain Products GmbH, Germany), with the ground at AFz and referenced to the left earlobe. Sixteen bipolar Ag/AgCl electrodes (eight on each arm) from Myotronics-Noromed (Tukwila, WA, USA) were used for surface EMG data acquisition and placed on the muscles involved in the movement: 1) extensor carpi ulnaris; 2) extensor digitorum; 3) on the flexor carpi radialis, plamaris longus, flexor carpi ulnaris (flexion); 4) on the external head of the biceps (flexion); 5) the external head of the triceps; 6) frontal side of the deltoid; 7) lateral side of the deltoid; and 8) posterior side of the deltoid over the teres minor and infraspinatus muscles. EEG and EMG data were recorded at a sampling rate of 2500 Hz with no filtering.

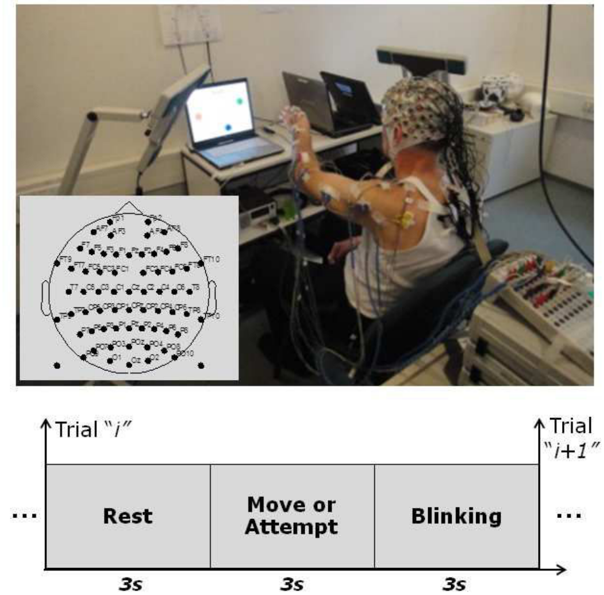


Fig. 1. Snapshot of the experimental setup showing a participant with the EEG and EMG electrodes, and temporal sequence of one trial during the execution of the experiment.

D. EEG and EMG data preprocessing

EEG and EMG trials lasted nine seconds each, with the time reference set from -3 to 6 seconds with respect to the presentation of the second cue (movement initiation). For each trial the actual movement onset was determined using the EMG signals. For each subject, the EMG signal with the higher amplitude and most consistent activity (low amplitude in the relax period and sustained high amplitude during the moving period) across all trials was selected by visual inspection. The selected EMG channel was high-pass filtered with a cutoff frequency of 10 Hz, and subjected to the Hilbert transform to obtain the movement onset for each trial. Finally, all EEG and EMG trials were epoched from -3 to 3 seconds relative to the EMG-based movement onset.

EEG data were bandpass-filtered from 0.5 to 60 Hz using a zero-phase shift filter and re-sampled to 160 Hz. In order to remove the effects of volume conduction, Laplacian spatial filtering [22] was applied to obtain artifact-free EEG signals.

E. Task-related power modulation

The temporal evolution of the power spectra of different frequency bands of the artefact-free EEG activity was computed with a time-frequency analysis using the complex Morlet‘s wavelet [23]. The time-frequency representation (TFR) was computed for all trials in each condition from 2 to 40 Hz with a frequency resolution of 1 Hz. Subsequently, the statistical significance of the percentage of power spectra decrease/increase relative to the baseline in the time interval from -3 to 0 s was computed with a bootstrap analysis [24] at the $\alpha = 0.01$ significance level.

F. Feature selection

Channels located on the contralesional motor cortex and frequency bins in the motor-related bands (α and β) presenting significant de-synchronization in the time window from 0 to 3 s were individually identified by visual inspection for each subject. The spectral power at those frequency-channel pairs was computed using a 16th order autoregressive model [25] over a window of size δ_w for the EEG activity, constituting features x_t at time t for motion intention detection. Power spectral-based features from channels in the motor cortex and from motor-related bands have been used for the detection of imagined or executed movements of different parts of the limbs [26]. However, this work only uses channels from the contralesional motor cortex to decode both conditions (movements of the healthy side and attempt to move the paretic side).

G. Classifier

The features x_t were used to classify the arm movement from the EEG measurements at time t using a Support Vector Machine (SVM) with a radial basis function kernel, due to its extensive use in different BCI applications [27]. The features x_t extracted in the time interval $t \in [-3, 0)$ were labeled as rest, while features extracted in $t \in [0, 3]$ were labeled as motion. Features were z-score normalized. The classification performance was evaluated by a ten-fold cross validation procedure, where the full set of trials was sampled without replacement to create independent training and test sets for each fold.

The training of the classifier used only non-overlapping features of the training trials, that is, x_t was sampled according to δ_w ($t \in \{-3 + \delta_w, -3 + 2\delta_w ..., 3\}$). Note that, due to the window required to compute the power spectra, features with $t \in [0, \delta_w]$ span over rest and motion. These features were excluded from the training set. The output of the classifier was computed every $50ms$ in each test trial. Note that at time t, the features are computed using exclusively the EEG activity up to t. Different δ_w (3, 2, 1, 0.75, 0.5 and 0.25 s) were evaluated to assess the impact of the time window in the classifier performance.

To measure performance, the decoding accuracy (DA) was defined as the percentage of correctly classified labels.

III. RESULTS

A. Task-related power modulation analysis

Figures 2 and 3 show for both conditions and in all subjects the relative power maps for the contralesional electrode with maximum desyncrhonization and its corresponding ipsilesional channel. The maps consistently show for the four subjects that there is no statistically significant de-synchronization in the ipsilesional channel, as expected due to the lesion. However, in both conditions there is a significant power decrease in the α and β bands of the contralesional channel. This observed desynchronization is stronger in movements of the unaffected arm (Figure 2) than in attempting to move the affected arm (Figure 3). These results are consistent with studies using healthy participants and show statistically significant involvement of the healthy motor cortex in the execution of movements of the unaffected arm, but more interestingly, they also show that, although in a minor degree, the healthy motor cortex is also involved in the attempt to move the affected arm.

B. Motion detection results

The first analysis studies the window size δ_w providing the best results in terms of classifier accuracy. Figure 4 summarizes the results of DA for different windows sizes. As expected, the larger the window, the better the estimation of the power spectra and, consequently, the accuracy of the classifier. The smaller window (0.25s) results in random classification (50%). A time window of 0.75s increases the average classification rate up to 71% in average for all the subjects. Wider windows slightly improve accuracy (e.g., almost 80% for a 3s window). However, in rehabilitation therapies it is necessary to detect motion intention within a reasonable time and, therefore, 0.75s is a good trade-off between accuracy and latency for the classifier.

Regarding the difference between the affected and unaffected arms, there are no significant differences in the decoding accuracy for any participant. This suggests that, despite the weaker desynchronization observed when moving the affected arm, the corresponding power spectral features obtained in the contralesional hemisphere still contains movement intention information. Furthermore, the window size does not play an important role for the two different conditions. In any case, these results show the feasibility to decipher motor information from the contralesional hemisphere while performing movements of the affected limb.

The next analysis studies the classification accuracy along time, i.e., the rate obtained at each point in time in the interval $[-3, 3]$. Results were obtained with window size δ_w of 0.75s. Figure 5 shows the percentage of correct classification for the four participants. Note that the first prediction time is at -2.25 s, as at this instant the first full time window of EEG activity (0.75 s) becomes available, which is required to compute the power spectral features. For all the subjects, the percentage of classification for $t < 0$ (no motion) for the class rest is 72% and 71% for the affected and the unaffected arm, respectively. While during motion ($t > 0$), the percentage of classification for the class movement -or attempt to move- is 69% and 71%, respectively. This confirms a similar performance for condition 1 than for condition 2.

The classification rate does not change abruptly at $t = 0$, but it evolves rather smoothly from one class to another, which results in a lower accuracy at approximately $t = 0$ than what was obtained for the rest of the time axis. Indeed, the classification rates from 0 to ≈0.5 s are approximately 50% for both arms. There are several reasons that may explain this behavior. Firstly, sensorimotor rhythms start to modulate after the corresponding cue and prior to the actual beginning of the movement measured from the EMG sensors. Secondly, approximately at $t = 0$ there is a dynamic change in the power spectra. As explained in Section II-G, the estimated power spectra does not belong to a single class (motion or rest) and, consequently, it may be less discriminative. This effect is boosted by the fact that these periods of time were

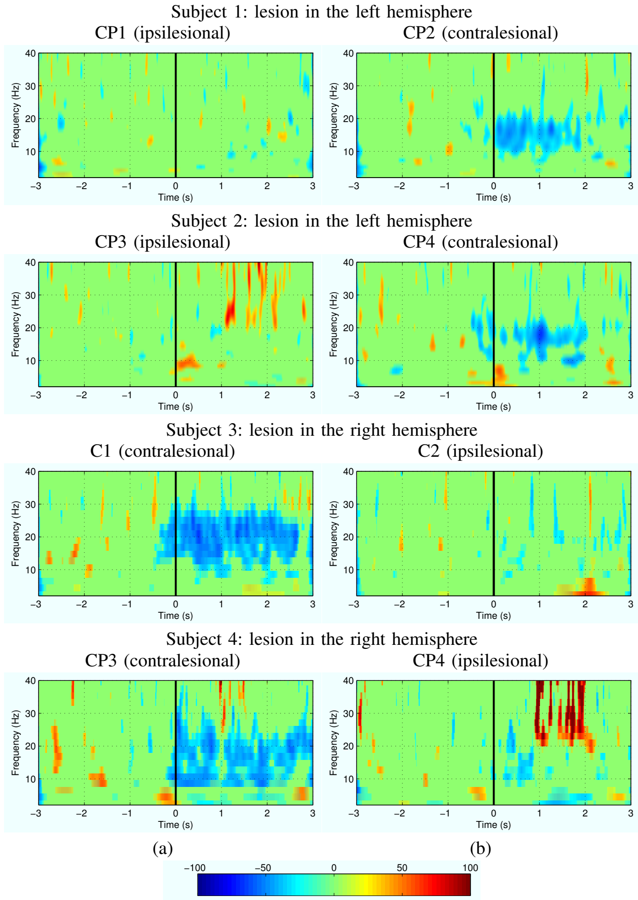


Fig. 2. Significant relative power maps for all subjects for condition 1: Movements of the unaffected arm. For subjects one and two, the lesion is in the left hemisphere and significant de-synchronization was observed in the right hemisphere (contralesional). Subjects three and four presented lesions in the right hemisphere and significant de-synchronization was observed in left hemisphere (contralesional).

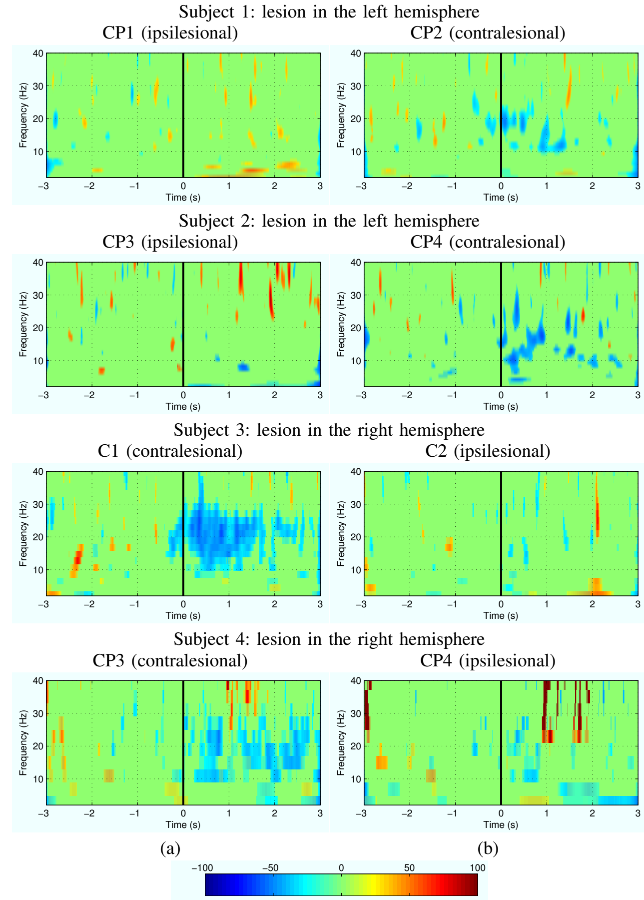


Fig. 3. Significant ERD/ERS maps for all subjects for condition 2: Attempting to move the affected arm. For subjects one and two, the lesion was in the left hemisphere and significant de-synchronization was observed in the right hemisphere (contralesional). Subjects three and four presented lesions in the right hemisphere and significant de-synchronization was observed in left hemisphere (contralesional).

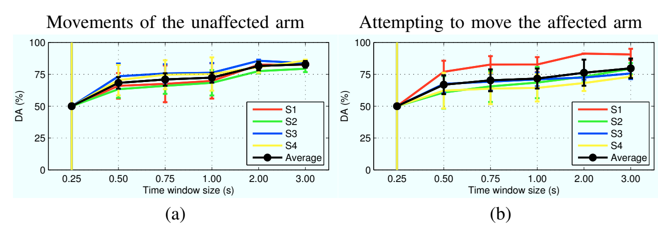
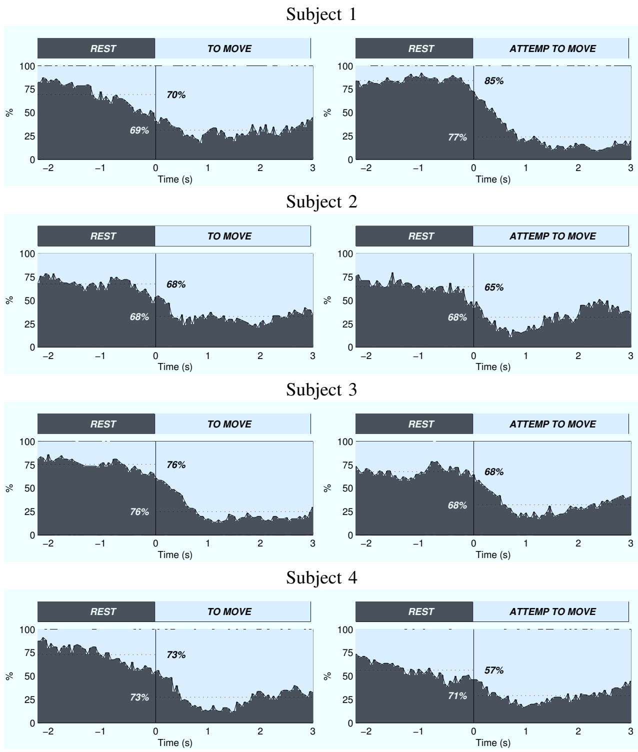


Fig. 4. Decoding accuracy (DA) from different time windows sizes for all subjects. (a) Results for movements of the unaffected arm (condition 1). (b) Results for attempting to move the affected arm (condition 2).

not used during training. Another interesting observation is that the accuracy during the movement -or attempt to move-period tends to decrease after $t \approx 2$ s. This may be due to the fact that the sensorimotor rhythms decay as a consequence of the automatism process in the brain (this can also be observed in the reduction suffered after $t \approx 2$ s in the ERD patters showed in Figure 3).

IV. CONCLUSIONS

This paper studied the use of EEG activity directly from the motor cortex to measure the involvement (attempt to move the affected arm) of severely affected chronic stroke patients with no residual finger extension in motor rehabilitation therapies. A significant de-synchronization was shown in the contralesional cortex while moving the affected arm, which was present in all patients and could be used to control a rehabilitation robot. Furthermore, the decoding performance during the ipsilateral decoding (paretic attempt to move) was similar to the one obtained during contralateral decoding of the healthy arm and can be classified continuously using contralesional brain sensorimotor brain oscillations during movement of the paretic arm only. This allows for the reliable and stable neural control of motor rehabilitation prosthetics, even in the absence of ipsilesional brain activity during an attempt to use the paralyzed limb, providing more therapeutical-assisstive options to severely affected stroke patients. The rehabilitative effect of using only contralesional areas to control the robot might not facilitate brain reorganization towards ipsilesional areas as recommended by data [28], [29], but could be used as a very interesting rehabilitation tool, assessing the involvement of the patient (intention to move) in the transition to regain ipsilesional control.



Movements of the unaffected arm (a) | Attempting to move the affected arm (b)

Fig. 5. Time-course of classification rates in percentage for all the subjects. (a) Results for movements of the unaffected arm (condition 1). (b) Results for attempting to move the affected arm (condition 2).

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