A hybrid EEG-EMG BMI improves the detection of movement intention in cortical stroke patients with complete hand paralysis

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***Abstract*— Motor rehabilitation based on brain-machine interfaces (BMI) has been shown as a feasible option for stroke patients with complete paralysis. However, the pathologic EEG activity after a stroke makes the detection of movement intentions in these patients challenging, especially in those with damages involving the motor cortex. Residual electromyographic activity in those patients has been shown to be decodable, even in cases when the movement is not possible. Hybrid BMIs combining EEG and EMG activity have been recently proposed, although there is little evidence about how they work for completely paralyzed stroke patients. In this study we propose a neural interface, relying on EEG, EMG or EEG+EMG features, to detect movement attempts. Twenty patients with a chronic stroke affecting their motor cortex were recruited, and asked to open and close their paralyzed hand while their electrophysiological signals were recorded. We show how EEG and EMG activities provide complementary information for detecting the movement intentions, being the accuracy of the hybrid BMI significantly higher than the EEG-based system. The obtained results encourage the integration of hybrid BMI systems for motor rehabilitation of patients with paralysis due to stroke.**

I. Introduction

Chronic stroke patients with complete paralysis have few or null rehabilitation options [1], and brain-machine interfaces (BMI) have been recently proposed as one of the only therapeutic options to help them regaining their lost motor function [2]. These BMI interventions aim at reorganizing the motor pathways by creating a contingent link between the damaged brain and the peripheral nerves and muscles [2]. For that, the brain activity is monitored (generally with electroencephalography–EEG), and when the patients attempt to move their paralyzed limb, an external device helps them to perform an actual movement. Despite BMI therapies could overcome the results of traditional physiotherapy for severely paralyzed patients, the degree of recovery after BMI training is still limited, and further improvements are necessary before these interventions become a standard treatment for stroke rehabilitation [3].

One important limitation of BMI systems for stroke rehabilitation is the difficulty to accurately detect the intentions of movement from the ongoing EEG activity. Different factors contribute to this problem. Firstly, stroke patients produce uncontrolled compensatory activity during movement attempts, which causes a large amount of EEG artifacts that mask the relevant brain activation [4]. Secondly, their cortical activation during the attempts of movement is reduced, especially in patients with damages that involve the motor cortex [5]. For these reasons, the classification accuracies that are achieved with EEG-based BMIs in patients with cortical stroke are significantly lower than in patients with subcortical lesions or in healthy controls [6].

To try to provide more robust control signals for BMI-based rehabilitation, hybrid approaches combining brain and muscle activity have been proposed [7]. Even in stroke patients with complete hand paralysis, it has been shown that residual electromyographic (EMG) activity can be classified to detect movement intentions [8]. In a pilot approach, we developed a hybrid BMI that allowed a chronic stroke patient to control a robotic exoskeleton by detecting his intentions to move with via EEG and EMG activity [9]. However, the amount of information that each type of signal is providing is still not fully understood, and further research is required to improve new hybrid BMI developments.

In this study, we analyzed data of 20 chronic patients with stroke lesions that involved the motor cortex. Their EMG and EEG activity were recorded while the patients attempted to move their completely paralyzed hand. Three approaches were tested to detect the movement intentions of the patients: (1) relying on EEG only, (2) relying on EMG only, (3) relying on EEG and EMG. The accuracy of each approach is compared to evaluate if the information provided by each type of activity can be complementary and improve the performance of the BMI.

II. Methods

A. Patients

Twenty chronic stroke patients were considered in the study (7 female, age 48.5±14.5 years, time since stroke 54.9±61.0 months). All of them had a stroke that involved the motor cortex, and complete hand paralysis with no residual finger extension in the affected arm (12.8±8.4 average score in the modified upper-limb Fugl-Meyer assessment, excluding coordination, speed and reflexes; max. 54 points). The experiments were performed at the University of Tübingen (Germany). The study was approved by the Ethics Committee of the Faculty of Medicine of the University of Tübingen, and all the patients provided written informed consent before participation.

B. Experimental protocol and data acquisition

The patients participated in one experimental session, where their electroencephalographic (EEG) and electromyographic (EMG) activity was monitored while they attempted

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to move their completely paralyzed hand. Each patient executed between 4 and 6 blocks that included 17 trials each, in which they were asked to try to open and close the affected hand. Audiovisual cues were presented to the patients to indicate them when to rest (random duration between 4-5 seconds), when to attempt the movement (for 4 seconds), and the inter-trial intervals (random duration between 8-9 seconds).

EEG activity was recorded with a 16-electrodes Acticap system (BrainProducts GmbH, Germany) from Fp1, Fp2, F3, Fz, F4, T7, C3, Cz, C4, T8, CP3, CP4, P3, Pz, P4, and Oz locations, with the ground in AFz and reference in FCz. Vertical and horizontal electrooculographic (EOG) derivations were also recorded to capture eye movements. EMG activity was recorded using bipolar Ag/AgCl electrodes (Myotronics-Noromed, USA) from four muscles: *extensor carpi ulnaris*, *extensor digitorum*, *biceps* and *triceps*. All signals were synchronously sampled at 500 Hz.

C. Movement detection scheme

We designed a pseudo-online simulation of a brain/muscle/brain+muscle machine interface to detect when the patients attempted to move their hand. All the methods were applied in the same way as they would be used in a real-time setup, including causal filtering, sliding windows and auto-regressive models for feature extraction.

We followed a block-based N-fold cross-validation (with N being the number of blocks performed by each patient). In each fold, one block was separated for testing, and the rest of them were used for training the system. The signals from the training blocks were trimmed down to 7-second trials (i.e., from -3 to +4 seconds, with respect to the presentation of the cue that asked the patients to move). These training trials were processed to extract examples of activity corresponding to *rest* and *movement attempt*, using one-second windows from the EEG and/or the EMG signals. These examples were used to train a classifier that was subsequently tested on the remaining test block. The mean of all the folds was afterwards computed for each patient.

D. Removal of artifacts

Before training the classifier, and to avoid using information relying on artifacts, an automated rejection procedure was applied to the training datasets. Trials were considered to have artifacts if: (1) presented muscle activation during the rest periods (in any of the EMG channels); (2) presented motion or muscular artifacts in the EEG (measured by z-scoring the power in delta and gamma frequencies and rejecting the trials that exceeded in more than 3 std of the power during rest). In addition, ocular contaminations were removed using linear regression with the EOG derivations. Further details of the artifact rejection procedure can be found elsewhere [4].

E. Feature extraction and training

We aimed at comparing how reliable EEG, EMG and the combination of EEG and EMG signals are for detecting the attempts of movement of the patients. In each training trial, 5 one-second windows were extracted as examples of the *rest* class (i.e., from the time interval [-2, 0] s, with a sliding step of 0.25 s), and 5 one-second windows for the *movement attempt* class (i.e., from the time interval [1, 3] s, with a sliding step of 0.25 s). Feature vectors were built by computing the features from EEG, EMG or EEG+EMG.

1) EEG features: The EEG signals were bandpass filtered between 0.1 and 48 Hz (4th-order Butterworth filter), and re-referenced with a Laplacian montage. The features were extracted from the electrodes placed over the ipsilesional hemisphere (i.e., contralateral to the involved hand): i.e., C3, CP3, P3 if the right hand was involved; C4, CP4, P4 if the left hand was involved. The average power in the alpha ([7-13] Hz) and in the beta ([14-30] Hz) frequency bands was computed using an order-20 autoregressive model based on the Burg algorithm. For each one-second window, 6 features were obtained (i.e., 2 frequency ranges, 3 EEG channels).

2) EMG features: The EMG signals were high-pass filtered at 20 Hz (4th-order Butterworth filter). The features were extracted from the *extensor carpi ulnaris* and *extensor digitorum* muscles by computing the waveform-length of the one-second windows. For each one-second window, 2 features were obtained (i.e., one for each muscle).

The system for detecting the movement intention was evaluated three times: (1) using EEG features only, (2) using EMG features only, (3) combining EEG and EMG features. The feature vectors were normalized to have zero mean and unit variance. Then, they were fed to a linear-discriminant analysis (LDA) classifier, which computed the hyper-plane that best separates the features from the two classes (i.e., *rest* and *movement attempt*).

F. Performance evaluation

The classification of the test data was done simulating an online scenario. A one-second sliding window was evaluated every 20 ms (from -3 to 4 s), extracting the features and obtaining an output of the classifier. The features in the test data were calculated with the same procedure as explained in Section II-E. The feature normalization and the EOG correction of the test windows was done by applying the parameters previously computed from the training data.

We evaluated the response of the classifier when trained with each set of features. Firstly, we obtained the true positives (TP) as the percentage of correct outputs during movement attempt (i.e., which we measured in the time interval [1.5, 4] s). Secondly, we calculated the false positives (FP) as the percentage of erroneous outputs during rest (i.e., measured in the time interval [-2, 0] s). Finally, we computed the average accuracy as the mean between TP and 1-FP (i.e., the true negatives).

G. Statistical comparisons

In order to evaluate if the different types of features had an influence on the classification accuracy, a Friedman's test was applied, considering the type of feature as factor (3 levels: EEG, EMG, EEG+EMG), and the accuracy as dependent

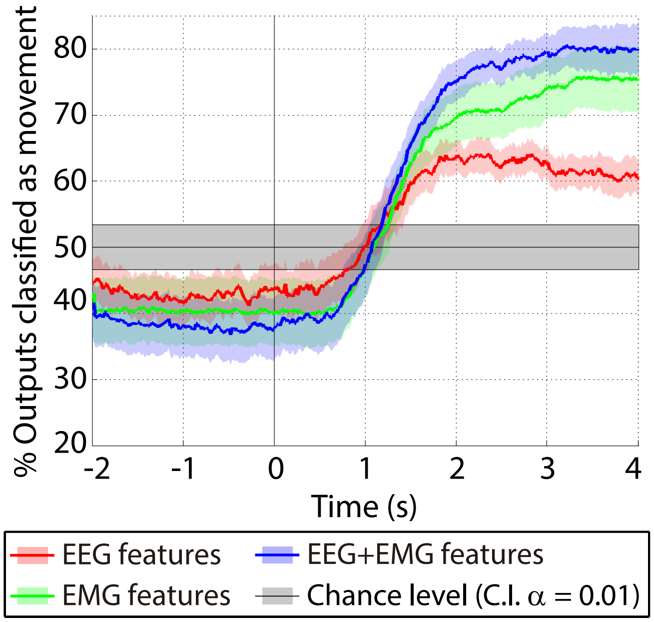

Fig. 1. Average outputs of the classifier when detecting the movement attempts with the three configurations of features: EEG, EMG, and EEG+EMG. The colored lines represent the percentage of classifier outputs detected as movement averaged for all the patients, with the shades indicating the standard error of the mean. The values before $t = 0$ represent false positives, while the values after $t = 0$ represent true positives. The shaded gray area indicates the confidence interval of the chance level (alpha=0.01, computed as in [10].)

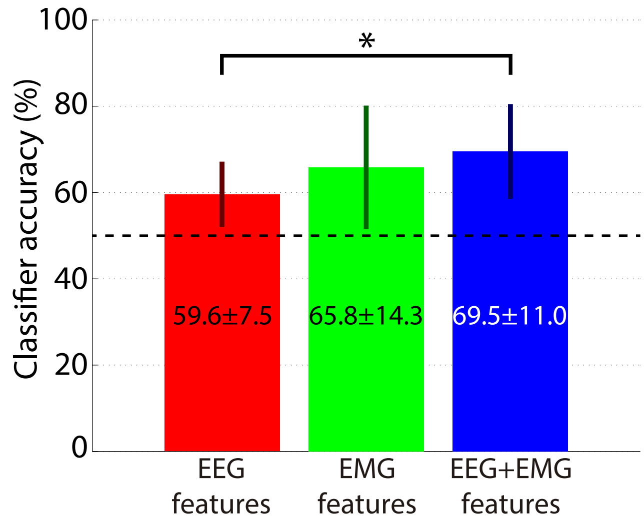

Fig. 2. Mean classification accuracy, averaging true positive and true negative values, for each type of features. The vertical bars indicate the standard deviation. Significant pairwise differences are denoted with an asterisk ($p < 0.05$ after correction).

variable. Paired post-hoc comparisons were performed using the Wilcoxon signed-rank test, with Bonferroni correction for multiple comparisons. Statistical significance was considered when corrected p-values were smaller than 0.05. Correlation between pairs of features was computed using the Spearman's correlation coefficient.

III. Results

Figure 1 shows the average time responses of the classifier in the test trials with each of the three feature configurations (i.e., EEG, EMG, EEG+EMG). As previously reported in [6], the performance of a BMI relying on ipsilesional activity of patients with cortical stroke is close to the chance level. However, despite having a complete paralysis of the hand, the patients produced some muscular activity that could be classified above chance. Furthermore, the combination of EEG and EMG features leads to an improvement in performance, both reducing false positives and enhancing the true positives.

Figure 2 displays the mean classification accuracies in a barplot. We found a significant effect of the type of features in accuracy $\chi^2(2) = 6.91; p = 0.03$. Post-hoc comparisons revealed significantly different accuracies between the classifier trained with EEG features and with EEG+EMG features.

To better understand such increase in performance, we performed a correlation analysis between all the pairs of features (Figure 3). The correlation between EEG features and EMG features was low in all the cases, which explains why the information added by the EMG complements the information of the EEG, leading to an improved classification accuracy. The two EMG features were highly correlated among themselves. The EEG features in the alpha band correlated well among themselves, the same as the beta features; however, the correlation between alpha and beta EEG features was lower.

IV. Discussion and Conclusions

This paper reported how the combination of ipsilesional brain activation with residual muscle activity boosts the performance for the detection of movement attempts in completely paralyzed patients with cortical stroke. We implemented a classifier that continuously monitored EEG and/or EMG activity, simulating an online neural interface to, for instance, control a rehabilitation robot. Our results demonstrate that EEG and EMG activity provide complementary information, and that both types of signals should be considered in future neuro-rehabilitative platforms based on brain-machine interface technology.

Previous studies have shown that patients with chronic paralysis due to stroke–and especially those with insults that affect the motor cortex–display modest EEG activation in the ipsilesional hemisphere during attempts of movement [5], [11]. For this reason, online classification of ipsilesional EEG signals to detect those movements provides accuracy values close to chance in these patients [6]. Although contralesional activity can also be exploited for brain-machine interfacing [12], such activity is more prone to contamination by muscular artifacts [4], and therefore should be considered with caution as it may provide a less accurate associative feedback, with a worse rehabilitative potential. Furthermore, the efficacy of reinforcing ipsilesional activity in BMI motor rehabilitation has been proven, but using contralesional or whole brain activity to induce functional plasticity, albeit promising, needs further investigation [2].

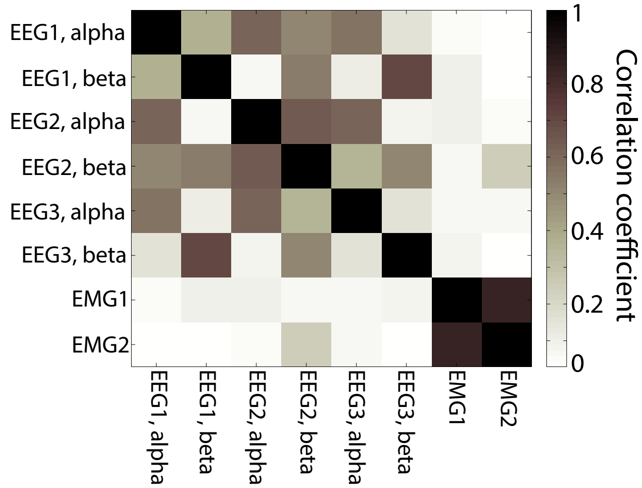

Fig. 3. Spearman correlation coefficient between all the pairs of features. EEG1 corresponds to C3 or C4 electrode, depending on the laterality of the stroke of each patient; EEG2 corresponds to CP3/CP4; EEG3 corresponds to P3/P4; EMG1 corresponds to the *extensor carpi ulnaris* muscle; and EMG2 corresponds to the *extensor digitorum* muscle.

Myoelectric interfaces, on the other hand, have been proposed with a great potential for decoding different types of arm movements [13], [14]. Stroke patients with complete hand paralysis can still elicit some residual muscle activation, at least in 45% of the patients [8], which could be decoded and used to control a rehabilitation robot or even to train them to reduce abnormal muscle co-contractions [15].

The combination of EEG and EMG in a hybrid BMI results advantageous in several aspects. Firstly, as shown in this article, the combination of both types of features guarantees a higher performance when classifying the patient intentions. Secondly, the hybrid strategy can be used to force the patients to activate the whole motor network, from brain to muscles, traveling through the spinal cord [9]. This may turn their sensory/motor pathways more excitable, which may, as a result, make the network more prone to reorganize by activity-dependent plasticity [16]. However, temporal contingency between brain/muscle commands and output might need further investigation to ensure positive motor related neuroplasticity.

Future research should focus on extending this approach to different movements of the arm, where the muscular activity can provide more selective information. Furthermore, the validation of the proposed hybrid BMI in a real rehabilitation intervention should be conducted to quantify the potential of the system to help the patients recover their lost motor function.

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