A Hybrid Brain-Machine Interface based on EEG and EMG activity for the Motor Rehabilitation of Stroke Patients

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Abstract—Including supplementary information from the brain or other body parts in the control of brain-machine interfaces (BMIs) has been recently proposed and investigated. Such enriched interfaces are referred to as hybrid BMIs (hBMIs) and have been proven to be more robust and accurate than regular BMIs for assistive and rehabilitative applications. Electromyographic (EMG) activity is one of the most widely utilized biosignals in hBMIs, as it provides a quite direct measurement of the motion intention of the user. Whereas most of the existing non-invasive EEG-EMG-hBMIs have only been subjected to offline tests or are limited to one degree of freedom (DoF), we present an EEG-EMG-hBMI that allows the simultaneous control of 7-DoFs of the upper limb with a robotic exoskeleton. Moreover, it establishes a biologically-inspired hierarchical control flow, requiring the active participation of central and peripheral structures of the nervous system. Contingent visual and proprioceptive feedback about the user's EEG and EMG activity is provided in the form of velocity modulation during functional task training. We believe that training with this closed-loop system may facilitate functional neuroplastic processes and eventually elicit a joint brain and muscle motor rehabilitation. Its usability is validated during a real-time operation session in a healthy participant and a chronic stroke patient, showing encouraging results for its application to a clinical rehabilitation scenario.

I. INTRODUCTION

Hybrid brain machine interfaces (hBMI), understood as systems that directly decode the user's intention from brain and possibly other type of signals (electromyogram (EMG), electrooculogram (EOG), kinematics, force, etc) to control an actuator, are recently getting more attention in the field of assistive and rehabilitative technologies for motor-disabled people.

Despite conventional non-invasive BMI therapies have shown noteworthy results in rehabilitative [1], [2], [3], [4], [5] applications, they have limitations such as low reliability and accuracy when it comes to complex functional task training. Although the inclusion of additional non-physiological information such as kinematics, may improve BMI performance, it is not a direct link to the nervous system and might be less efficient producing functional neuroplasticity in a rehabilitative solution. On the other hand, EMG has been widely employed to control prostheses, rehabilitation exoskeletons or functional electrical stimulation systems, as it provides a more direct and robust measurement of the user’s motion intention than brain signals. However, issues such as the absence of sufficient residual EMG activity or muscle fatigue may hinder the exploitation of myoelectric interfaces. Thus, hBMIs have emerged as systems that build on the advantages and alleviate the restraints of each of the single signal-based approaches, resulting in a more robust system.

A few studies have already demonstrated that introducing supplementary input information coming from the muscles can lead to a higher decoding accuracy [6], [7], [8], [9], [10], [11] or the inclusion of more degrees of freedom (DoFs) [12], reflected in a richer and smoother control of assistive or rehabilitation devices. Nonetheless, the way in which the control is shared between the input signals is not trivial and varies among applications. Although numerous input processing methods (sequential or simultaneous) and fusion algorithms (e.g. outputs of the EMG- and EEG-classifiers are fused with equally balanced weights or using a Bayesian approach [6]) have been proposed, it still remains a challenge to find a fusion strategy that takes into account all the variables playing a role on the control.

We present a hBMI system that consists of an EEG-based binary classifier and an EMG-based continuous decoder of trajectories. To the best of our knowledge, the only study that carried out a real-time testing of a similar hBMI is [13], in which 4 able-bodied subjects and a spinal cord injury patient operated a hBMI to control the elbow joint angle (1 DoF) during a functional task with an exoskeleton. Our approach goes a step further and allows the real-time control of 7 DoFs of the upper limb. Moreover, it follows a biologically-inspired hierarchical control flow involving both central and peripheral structures of the nervous system. Additionally, it puts emphasis on the correction of pathological muscle activity, which is of paramount importance to ensure an effective transfer to activities of daily living and hence, a proper motor rehabilitation [14]. The usability of the hBMI is evaluated in a real-time operation session with a healthy individual and a chronic stroke patient.

II. METHODS

A. Experimental design

One healthy subject (male, age: 26) and a chronic stroke patient (male, age: 62, 2 years from stroke, severe left hemiparesia, modified upper limb Fugl-Meyer Assessment (mFMA) = 59/114 and combined hand and arm FMA = 7/54)
volunteered to participate in the study. Both of them were naïve to the operation of BMIs and gave written consent to the procedures as approved by the Ethics Committee of the Faculty of Medicine of the University of Tübingen, Germany. The participants underwent a calibration session and a real-time hBMI operation session on separate days. Notice that since the protocol that we designed includes the use of both upper limbs, for simplicity we will refer to the non-dominant side of the healthy participant as the paretic side and to the dominant one as the healthy side.

The actuator of the hBMI was the IS-MORE exoskeleton (Tecnalia-San Sebastian, Spain). It is a 7-DoF upper limb robotic exoskeleton (see Fig. 1), which allowed the displacement and rotation of the forearm on a 2D horizontal plane parallel to the mat’s plane (3 proximal DoFs: (i) \( p_x \) position; (ii) \( p_y \) position; (iii) \( \theta_{xy} \) angle), the pronation and supination of the wrist (1 distal DoF: (iv) \( \phi_{wrist} \) angle) and the flexion and extension of the thumb, the index and the group of middle, ring and pinky fingers measured as the angle of rotation with respect to the metacarpophalangeal joints (3 distal DoFs: (v) \( \delta_{thumb} \); (vi) \( \psi_{index} \); (vii) \( \alpha_{finger} \). The exoskeleton was placed over a 70 x 50cm mat surrounded by three shelves marked with different colors, which constituted the three targets the participants had to reach during the experiments (see Fig. 1).

Participants started the real-time operation task with their paretic arm and hand relaxed in a comfortable rest position. Then participants were asked, upon auditory cues, to reach one of the three targets around the workspace (see Fig. 1), while supinating the wrist and opening their hand. They were given 7 seconds to reach the final configuration. If the target was not reached, the trial was considered unaccomplished and an inter-trial interval of 3-5 seconds started, followed by a 2 second-preparation time. After this, a new trial from the current position towards the same target began. Once the target was reached, participants were instructed to go back to the initial rest position following the same procedure. In each block, participants had to reach each target twice. The healthy subject completed 5 blocks while the patient was able to operate the hBMI during 3 blocks.

The calibration session was divided into an EEG screening and an EMG calibration. The reason for this was that the EMG calibration was performed with the healthy upper limb. This implied that no EEG activity that reflected the movement volition of the paretic upper limb was available in order to select the electrodes on the ipsilesional hemisphere that would control the hBMI.

In the EEG screening, participants were presented with two auditory and visual cues indicating to relax or to (try to) open and close their paretic hand for 5 seconds. Participants completed 4 blocks of 8 repetitions of each condition.

In the EMG calibration, the participants performed the same task explained above but in this case, with their healthy arm. Both participants completed 5 blocks during this calibration phase.

During both phases, the motors of the exoskeleton were on, which means that the subjects had to actively follow the movement driven by the robot. Although this condition avoided that factors such as weight and friction had an impact on the EMG activity, the risk that the patients remained passive existed too. That’s why participants were repetitively reminded that the movement had to be followed actively and as naturally as possible. Finally, whereas the speed and direction of the calibration movements were predefined and fully-assisted, during the real-time operation, the movement was partially influenced by their paretic EMG activity.

It is important to clarify that even if the exoskeleton allowed the movement in 7 DoFs and the healthy participant controlled all of them during the hBMI operation, he had to reach the target position only in the 3 proximal DoFs in order to accomplish the trial and move on to the next target. In the case of the stroke patient, instead, the control of the exoskeleton was done only in the three proximal DoFs because the motors of the exoskeleton didn’t have enough torque to overcome the high spasticity in the distal DoFs, being the movements of these joints unreliable. Therefore, for both participants, only the performance of the control of the 3 proximal DoFs is reported in this paper.

B. Data acquisition and processing

A set of 32 EEG channels with a high density of electrodes over the motor cortex (FP1, FP2, F7, F3, Fz, F4, F8, FC3, FC1, FC2, FC4, C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, CP6, P7, P3, Pz, P4, P8, O1, O2) and two EOG channels were collected at 1KHz (Brain Products GmbH, Germany). Additionally, EMG data from several upper and forearm muscles were acquired with the same system and sampling frequency. Six bipolar electrodes (Myotronics-Noromed, USA) were placed over the Abductor Pollicis Longus, the Biceps, the Triceps and the Frontal, Middle and Back portions of the Deltoid while two high-density arrays of 24 channels each (Tecnalia-Serbia, Serbia) were utilized to record the activity from the extensor and flexor muscles of the forearm. The reference and ground electrodes were located over the olecranon and the clavicle, respectively. Kinematic data of the 7-DOFs was recorded at 20Hz with a camera attached to the bottom of the exoskeleton and motor encoders (more details in [15]).

EEG signals were bandpass filtered (4th order Butterworth filter at 5-48Hz), down-sampled to 100Hz and spatially
filtered with a short-Laplacian filter. The resulting signals were modelled as an autoregressive process of order 20 using 0.5sec-long windows and a step window of 50ms and then the mean power spectral density was computed. The most discriminative perilesional channels and frequency bands were identified offline and used as input features to the decoder. EEG features were normalized using the last 4 minutes of data during the real-time operation.

EMG data was filtered using a 4th order Butterworth bandpass filter (10-500Hz) and a 50Hz comb filter. Five time-domain features (Mean of absolute value, Variance, Waveform Length, Root-mean-square error and the Logarithm of the Variance) were extracted from each of the selected EMG channels during the calibration process. Features were normalized to zero mean and unit variance using the mean and standard deviation computed on the last minute of EMG data during the online operation phase.

Kinematic data was low-pass filtered with a 4th order Butterworth filter (1.5Hz).

C. hBMI calibration

As explained in Section II-A, the calibration session consisted of the following two parts:

i) An EEG screening phase, in which participants either relax or (try to) open and close their paretic hand. R-squared values comparing the EEG activity during the movement execution (attempt) and the relax conditions were computed offline. The frequency band and the two electrodes on the ipsilesional motor area with highest r-squared values were selected. Features were extracted on those electrodes and bands, as explained in Section II-B, and used as input to the EEG-decoder to control the hBMI. The collected data and a linear discriminant analysis were employed to build a binary classifier that would classify the EEG activity either as “Movement” or “Rest”.

ii) An EMG calibration phase, during which the participants wore the exoskeleton on their healthy arm and performed the same functional task that would be trained during the hBMI operation session. For each participant, the channels with highest amount of information were selected offline from the high-density arrays as follows: First, channels were bipolarized along the straight direction and both diagonals. The decoding performance (measured by the correlation coefficient (CC)) was computed iteratively, starting with all the possible channels and getting rid of the channel with the lowest regression coefficient in each loop. Finally, the minimum amount of channels, up to a maximum of 50, that would suffice to achieve a CC = max(CC) - 5% * (max(CC) - min(CC)) were selected. After this dimensionality reduction process, an EMG decoder was trained using all the bipolar electrode channels and the selected subset of the high-density array channels. In order to have a decoder based on non-compensatory EMG activity only, it was trained with data from the healthy arm and then used to decode the activity from the paretic arm. A ridge regression algorithm with a regularization parameter $\lambda = 10^4$ chosen experimentally was used to build such a decoder and thereby, to continuously map the input EMG signals into the predicted kinematics in real-time during the hBMI operation.

D. hBMI operation

The control strategy of our hBMI followed a top-down approach by establishing an “EEG-gated EMG control” type. Both decoders worked continuously and simultaneously and a hierarchical control based on the natural motor command flow was implemented (see Fig. 1). First of all, to ensure the active participation of the patient, the movement volition detection from the EEG signal was required to initiate the movement. Thus, the output of the EEG decoder would determine at all times whether the control of the hBMI was handed over to the muscles or not. For example, outputs of the EEG decoder classified as “Rest” during a trial period would prevent the exoskeleton from moving, independently of the EMG decoder output. However, if during the trial time the subject was desynchronizing the sensorimotor rhythms (i.e. output classified as “Movement”), the movement of the exoskeleton would be triggered. In this case, the final direction and speed of the exoskeleton would be partially determined by the kinematics predicted by the EMG decoder (50% for the case of the healthy participant and 40% for the patient, chosen experimentally) and by an assistive component, which would always redirect the exoskeleton towards the target position. Written mathematically, the fusion formula of the assistive and the predicted components into the final kinematic command sent to the exoskeleton in each DoF $i = 1:7$ would be the following:

$$V_{final,i} = \gamma \ast V_{EMG,i} + (1 - \gamma) \ast V_{assistive,i}$$  \hspace{1cm} (1)

where for each DoF $i$, $V_{final,i}$ is the final velocity sent to the exoskeleton, $V_{EMG,i}$ the velocity predicted from the EMG activity, $V_{assistive,i}$ the assistive component computed using a linear-quadratic regulator (LQR) and $\gamma \in [0,1]$ the weight determining the amount of influence of the EMG activity in the control of the direction and the speed of the movement.

Additional filtering measures were applied to the output of the EEG and EMG decoders in order to achieve a smoother and more stable real-time control: First of all, the movement of the exoskeleton was not triggered (or stopped) until the EEG-decoder output was classified five consecutive times as “Movement” (or “Rest”), following the procedure in [1]. On top of that, a weighted moving average filter with a backwards window of 180ms and linearly decaying weights starting from the most recent value was applied to the kinematics predicted by the EMG decoder. The outputs of the decoders were ignored for the control during the rest and the preparation periods, in which the movement of the exoskeleton was blocked.

An adaptive strategy was followed for the EEG decoder, which was retrained at the end of each trial with the last two minutes of data collected from each condition period (“Rest” and “Movement”). A supervised approach was followed by utilizing the ground-truth labels marked by the experimental design. However, regardless of the performance drop due
to the session-to-session and arm-to-arm transfers, the EMG decoder was kept fixed during the whole intervention since the aim was to provide the participants with feedback about how correct and natural their muscle activation patterns were, based on the EMG recorded from the healthy arm during the calibration.

E. Performance evaluation

We utilized several metrics to evaluate the performance of the subjects when operating the hBMI in real-time. Five metrics previously reported in [1] were computed to assess the ability of the participants to modulate their SMR rhythms to control the hBMI:

- **Percentage of time the exoskeleton was moving during a trial.** This performance metric reflects the ability of the subject to decrease the SMR power during a trial.
- **Percentage of maximum consecutive time the exoskeleton moved during a trial.** This metric reflects the longest time period the participant was able to maintain a SMR desynchronization within a trial.
- **Number of movement onsets or transitions from the “Rest” to the “Movement” condition.** This measures how many times the participant lost control over the SMR modulation.
- **Latency to the first movement onset.** This represents the reaction time of the participant in producing the necessary SMR modulation to trigger the movement for the first time at the beginning of a trial.
- **True positive rate (TPR) and false positive rate (FPR),** being the TPR the percentage of outputs classified as “Movement” during a trial and the FPR the percentage of outputs classified as “Movement” during a resting period.

Regarding the evaluation of the control based on the EMG activity modulation, the performance metrics that we used for such analysis are the following:

- **Number of trials needed to reach a target,** which reflects the number of unaccomplished trials that the participant performed before reaching the target.
- **Spectral Arc Length (SPARC),** which is a measurement of how smooth the movement of the exoskeleton was in each DoF. It was presented in [16] and the closer to zero the values, the smoother the trajectory was.
- **Correlation coefficient (CC)** between the assistive velocity component and the EMG-based predicted velocity during the periods in which the exoskeleton was in motion.
- **Normalized root-mean-squared-error (NRMSE)** computed by comparing the assistive velocity component and the EMG-based predicted velocity component during the intervals in which the exoskeleton was moving.

Despite the SPARC, CC and NRMSE were computed for each of the DoFs individually, the mean across the proximal DoFs are reported in the results.

The values of all the aforementioned metrics were computed for each of the participants and blocks of the hBMI operation session. Finally, a Wilcoxon test was applied to each metric to compare the performance of the two participants in each category.

III. RESULTS

Due to the low number of blocks performed by the participants, motor skill learning was not expected to happen. Nevertheless, both participants were able to modulate their brain and muscle activity to successfully operate the hBMI and hence, reach the presented targets.
The employed EMG decoder enabled the continuous and real-time control of the speed and direction of the movement in 7 DoFs concurrently, which constitutes an advance over previous classification or decoding approaches of a few seconds 4 and 6.

Finally, the results from the EMG performance evaluation are presented in Fig.4. The mean number of trials needed to reach a target was 3.455 for the healthy participant and 3.833 for the patient. The mean SPARC values across blocks were -2.637 (healthy) and -2.778 (patient), while the mean CC values were 0.308 (healthy) and -0.107 (patient) and the mean NRMSE resulted in 0.109 (healthy) and 0.159 (patient). In spite of the significantly lower (CC: p = 0.0001; NRMSE: p = 0.014) decoding accuracy achieved by the stroke patient due to the pathological EMG activity, the higher assistance level given to the patient during the hBMI operation helped him to achieve scores for the SPARC and number of trials per target metrics similar to the healthy participant.

**IV. DISCUSSION**

This study presents and validates the usability of a novel hBMI system that follows a top-down approach. The hierarchical control strategy was inspired by the biologically natural motor command flow. In a healthy individual, motor commands are initiated at the brain level and then they travel through the spinal cord to reach the peripheral nerves and finally the muscles, whose fibers are activated by the motor units to produce the desired movement. Therefore, it seems natural to think that an effective hBMI control strategy should constantly require an initial command from the brain to later on transfer the control to the muscles. In this way, the active participation of the brain is necessary at all times for the movement to occur, which prevents the patient from remaining passive (i.e. no desynchronization happening in the brain) while the exoskeleton assists the movement of his/her limb. Moreover, by including the muscles in the control of the hBMI, various problems generally present in stroke patients such as muscle weakness and the existence of abnormal muscle synergies are tackled. Therefore, thanks to the supplementary information coming from the muscles, the proposed hBMI not only offers the possibility of achieving a higher decoding accuracy and a more dexterous and smoother control of the actuator, but it also envisages the possibility of a joint brain and muscle rehabilitation.

The same EEG decoder algorithm as the presented here was utilized before in a double blind sham-controlled clinical trial in 32 chronic stroke patients [1] and it was proven to be a valid algorithm to induce motor recovery. Although initially the stroke patient had some trouble to trigger the movement of the exoskeleton at the beginning of the trial, he rapidly learned and got better, eventually achieving a performance equal to or even better than that of the healthy participant. Therefore, in this preliminary study, both participants could control the onset of the movement with notable ease and the results confirm a high EEG modulation performance, which is encouraging for its use in future clinical trials.
DoFs. The lower EMG decoding performance achieved by the stroke patient can be explained by the existence of pathological EMG activity in the paretic limb. Thus, the kinematics predicted by the EMG decoder trained with healthy activity didn’t correlate with the assistive component, which constantly redirected the movement towards the target. However, since the weight of the assistive component on the control of the exoskeleton was set at a higher value for the stroke patient (60%) than for the healthy participant (50%), the former could successfully reach the targets and achieve scores of path smoothness and number of trials per target comparable to the healthy individual. Hence, in spite of the modest performance values of the EMG-based control, both participants were able to bring the exoskeleton to the desired final position. Continuously controlling a 7-DoF myoelectric interface during functional tasks might not be intuitive even for healthy subjects and especially at the beginning. A longer training period is necessary for the participants to adapt to the EMG model and achieve a skillful control of the exoskeleton.

Finally, it should be mentioned that in these experiments, all the DoFs were controlled following the same control strategy. However, in case a patient didn’t have any residual EMG at all in some or all the involved muscles, the control could start being based solely on EEG activity and would progressively shift towards a hybrid control, as the muscles recovered certain degree of activity as a result of the training. Alternative strategies that would take factors such as muscle fatigue into account could be developed too.

V. CONCLUSION

A new hBMI rehabilitation system was presented and its usability was validated with one healthy participant and a chronic stroke patient in a real-time operation session. This hBMI rehabilitation system establishes a hierarchical EEG- and EMG-based control strategy with the goal of evoking a joint brain and muscle rehabilitation in stroke patients. Therefore, by being built upon neurophysiological principles and by constantly requiring the active participation of central and peripheral structures of the nervous system, this hBMI constitutes a potential tool to boost the recovery of lost motor function at proximal and distal segments of the upper limb. Nevertheless, further experiments with a large population of stroke patients are necessary to assess the effectiveness of the presented hBMI in eliciting motor rehabilitation.

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