Continuous decoding of Motor Attempt and Motor Imagery from EEG Activity in Spinal Cord Injury Patients

Eduardo López-Larraz, Javier M. Antelis, Luis Montesano, Angel Gil-Agudo, Javier Minguez

***Abstract*— Spinal cord injury (SCI) associates brain reorganization with a loss of cortical representation of paralyzed limbs. This effect is more pronounced in the chronic state, which can be reached approximately 6 months after the lesion. As many of the brain-computer interfaces (BCI) developed to date rely on the user motor activity, loss of this activity hinders the application of BCI technology for rehabilitation or motor compensation in these patients. This work is a preliminary study with three quadriplegic patients close to reaching the chronic state, addressing two questions: (i) whether it is still possible to use BCI technology to detect motor intention of the paralyzed hand at this state of chronicity; and (ii) whether it is better for the BCI decoding to rely on the motor attempt or the motor imagery of the hand as mental paradigm. The results show that one of the three patients had already lost the motor programs related to the hand, so it was not possible to build a motor-related BCI for him. For the other patients it was suitable to design a BCI based on both paradigms, but the results were better using motor attempt as it has broader activation associated patterns that are easier to recognize.**

I. INTRODUCTION

Spinal cord injury (SCI) is a devastating disease that leads to loss of motor and sensory functions. The vertebrae damage results in an interruption of some of the pathways that connect the brain to the limbs and as a consequence, the brain areas responsible for the control of those limbs become unused. Several research studies have explored the changes produced in the brain of SCI patients after years of chronic injury. Some studies have shown that brain plasticity produces a long-term brain reorganization: the cortical representations of intact body areas expand to the representations of body areas affected by such deafferentiation. However, conflicting results have been obtained and therefore, there is no accepted theory comprising all obtained results. On one hand, it has been indicated that SCI patients presented weak (or none) brain activity on the motor cortex during attempts of moving paralyzed limbs (Müller-Putz with electroencephalography –EEG– [1], and Turner with functional magnetic resonance imaging –fMRI– [2]). These results could be explained by a significant reduction in gray matter in the motor cortex of chronic SCI patients [3]. On the other hand, studies [4] (EEG), and [5] (fMRI), suggest that motor brain activity on SCI patients was altered, but there were still recognizable patterns present in motor tasks.

E. López-Larraz, J.M. Antelis, L. Montesano and J. Minguez are with the I3A and Universidad de Zaragoza, Spain. J. Minguez is also with Bit&Brain Technologies SL, Spain. E-mail: {edulop, antelis, montesano, jminguez}@unizar.es. A. Gil-Agudo is with Hospital Nacional de Parapléjicos de Toledo, Toledo, Spain. E-mail: amgila@sescam.jccm.es.
This work has been partially supported by projects HYPER-CSD2009-00067 and DPI2009-14732-C02-01 funded by the Spanish Government.

Brain-computer interface (BCI) is a technology that has recently emerged to translate user intentions into commands with applications in many fields, such as in neuro-robotic or neuro-prosthetic device control [6], [7], [8]. Many of the BCIs developed to date are based on the decoding of motor intentions using the activity of the motor cortex. Thus, for the application of this technology to SCI patients, it is necessary that these patients could produce certain recognizable motor brain patterns. As SCI patients present an association of brain reorganization together with a loss of motor representation of paralyzed limbs, there are questions that need to be addressed: (i) is there a time limit from which this technology cannot be used? ; and (ii) which is the most suitable motor paradigm that encodes motor intention?

This paper addresses both questions in a preliminary study with three patients close to the chronic state (4.5 and 5 months after the lesion). Addressing the first issue, patients were selected before the chronic state (clinical evidence indicates that SCI patients reach the chronic state between six months and one year after the damage). For the second issue, motor brain activity can be elicited either by motor attempt (MA) of a paralyzed limb or by motor imagery (MI) [5] (both with different neural circuits and partially different activity). Both paradigms have been used in the design of BCIs and in their application to SCI patients [1], [9]. However, there is no clear evidence of which is more suitable for an online BCI. In the experimental paradigm, the patients performed MA and MI grasping tasks with the right hand while EEG was recorded. Time-frequency analyses were carried out on the EEG to explore the activation patterns over the motor cortex. Additionally, a BCI was built for both motor paradigms and performance was compared for different patients.

II. METHODS

A. Participants and Signal Recording

Three male quadriplegic patients (age range 33 ± 1 years) participated in this study. A summary of their type of lesion and time elapsed since injury is included in Table I.

Patients were selected as a homogeneous group according to age, time elapsed since injury, and type of lesion criteria. All patients were unable to perform grasping movements, although some mobility in elbows and shoulders was retained. All patients were hospitalized at the *Hospital Nacional de Parapléjicos de Toledo*, where the experimentation sessions took place. Patients were duly informed before the experimentation session, and all gave informed consent.

EEG was recorded using a commercial gTec system, consisting of 16 active EEG electrodes. The electrodes were placed at AFz, FC3, FCz, FC4, C5, C3, C1, Cz, C2, C4, C6, CP3, CP1, CPz, CP2 and CP4 (according to the international 10/10 system). The ground and reference electrodes were placed on FPz and on the left earlobe, respectively. The EEG was digitized at a sampling frequency of 256Hz, and power-line notch-filtered to remove the 50Hz line interference.

TABLE I

PATIENTS CHARACTERISTICS

	Year of birth	Time since lesion (days)	Level of Injury	ASIA Impairment Scale
$P01$	1978	150	C6	B
$P02$	1977	156	C4/C5	A
$P03$	1979	136	C4/C5	A

B. Experimentation Paradigm and Protocol

During the recording sessions, the patients were seated in a wheelchair, facing a computer screen. The experiment consisted of two different tasks: (i) motor attempt (MA) of grasping with the right hand, and (ii) motor imagery (MI) of grasping with the right hand. For MI, patients were instructed to perform a kinesthetic imagery of the movement to involve the motor cortex [10].

Visual cues were present on the screen as guidance during the different stages of the experiment. The first cue instructed patients to relax the body and to be prepared for the next cue (three seconds). The second cue indicated the start of the attempt or the imagination of movement (lasting three seconds). The third cue indicated the trial end (lasting three seconds). During the first and second cues, the patients were asked to avoid blinking or compensating movement with the rest of the arm, while during the third cue they where allowed to relax and blink. The experiment was executed in six blocks of 4.5 minutes each, divided into three blocks of MA trials, and three blocks of MI trials. Blocks of MA and MI were alternated. Thirty trials were recorded for each block, resulting in a total of 180 trials (90 for each condition). After each block patients could rest as long as necessary to avoid fatigue.

Note that in both MA and MI cases, there is an intrinsic delay between the time instant when the patient was cued and the time in which he actually started the action. However, since there is no motor output or any measurement indicating the actual starting time with certainty, the delay can not be reliably measured. This issue will be taken into account in the subsequent analyses.

C. EEG Data Preprocessing and ERD/ERS Analysis

EEG trials lasted nine seconds, with the time reference set from -3 to 6 seconds with respect to the presentation of the second cue (initiation of MA/MI). All EEG trials were trimmed to the [-3,3] window and bandpass-filtered from 0.5 to 50Hz using a zero-phase shift filter. Two different spatial filters, a Laplacian and a common average reference (CAR), were applied independently to the EEG of each patient to obtain reference-free trials with better discriminability between rest and MA/MI classes.

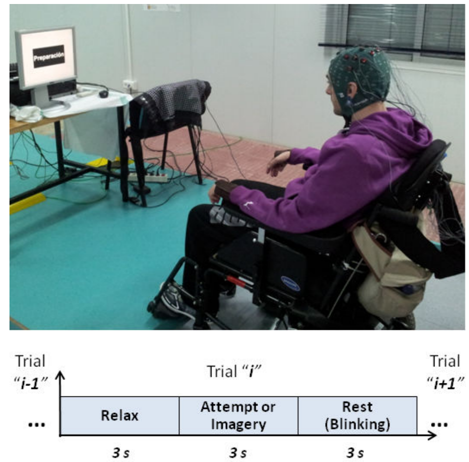

Fig. 1. Snapshot of the experimental setup showing a participant with the EEG system and temporal sequence of one trial during the execution of the experiment.

The temporal evolution of the power spectra of the artifact-free EEG activity was computed for all trials with a time-frequency analysis, using the complex Morlet's wavelet [11]. ERD/ERS maps were computed taking as baseline interval the time window $[-2, 0]$s. The statistical significance of the ERD/ERS values was verified by applying a $t-$percentile bootstrap statistic to calculate confidence intervals with $\alpha = 0.05$ [12]. This type of analysis has been reported as a good descriptor of brain activity related to motor tasks [13].

D. BCI for MA/MI detection

The feature selection process was based on the previous ERD/ERS analysis. Channels close to the motor cortex and frequency bins in the motor-related bands (α and β) were individually identified by visual inspection for each patient. The spectral power at those frequency-channel pairs was computed using a 16th order autoregressive model [14]. The window length (δ_w) used to compute the power spectra has an impact on the quality of the features x_t at time t for MA/MI detection. Different δ_w (0.25, 0.5, 0.75, 1, 1.5, 2 and 2.5 s) were evaluated to assess the impact of the time window in the classifier performance.

The features x_t were used to detect the grasping MA or MI from the EEG measurements at time t, using a Support vector machine (SVM) with a radial basis function kernel. This classifier has been previously used in different BCI applications [15]. 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 marked as MA or MI. 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. Features were z-score normalized, according to the train set on each iteration of the cross-validation procedure.

The training of the classifier used only non-overlapping features of the training trials, i.e., x_t was sampled according to δ_w ($t \in \{-3 + \delta_w, ..., 3\}$). As there might exist a delay between cue presentation ($t = 0$) and MA/MI beginning (Sec. II-B), features with $t \in [0, 0.5]$ were excluded from the training set, since they were labeled as MA/MI but could contain rest activity. Subsequently, that interval could probably be misclassified during online operation. The performance of the classifier was obtained as the percentage of correctly predicted labels. Labels were predicted every $50ms$ in each test trial. Note that at time t, the features are computed using exclusively the EEG activity from $[t-\delta_w, t)$.

III. Results

A. ERD/ERS Analysis

For each patient, Figure 2 displays the ERD/ERS maps in the frequency range $[0, 50]$Hz for both MA (left column) and MI (right column). In patients $P01$ and $P02$, significant desynchronization patterns occurred in α and β frequency bands over the left motor cortex (contralateral area to the grasping hand) for both tasks. The highest ERD patterns for $P01$ were in channel CP1 with a CAR filter, while for $P02$ these were obtained in channel C1 with a Laplacian filter. For both patients, the ERD patterns produced in MA were more significant and with a larger portion of the time-frequency map than in MI. However, for patient $P03$ (patient with most recent injury) there was no significant ERD/ERS in any of the tasks (since there was no significant activity for all combinations of filters and channels close to the motor cortex, channel C3 with a Laplacian filter is displayed in his corresponding figures). Thus, $P01$ and $P02$ are still able to produce significant brain activity during both motor tasks, while $P03$ did not produce any recognizable brain pattern over the motor cortex by means of MA or MI.

This result indicates that there might be other factors apart from the time of lesion that affect the loss of cortical representation in the motor cortex of paralyzed limbs. In addition, $P01$ and $P02$ could be potential users of a BCI based on the ERD/ERS, while for $P03$ it would be very difficult to build a decoder as there are no differentiable features of the motor intention. $P03$ would need a different mental paradigm behind the BCI, not dependent of motor rhythms, or would have to undergo training intervention to restore motor brain patterns [16] prior to BCI usage.

B. Continuous decoding

The first analysis assessed the impact of different δ_w in the classifier accuracy. The results indicated that higher δ_w provided higher accuracies, but entailed higher delays in the detection of the MA/MI onset. After several tests, δ_w was set to 0.75s for $P01$, and 0.5s for $P02$, as these values represented the best trade-off between accuracy and delay. $P03$ did not provide better-than-random results with any δ_w, so he was excluded from the remaining decoding analysis.

The next analysis studied the classification accuracy along time in both tasks. The classifier provided a decision value every 50ms of the interval $(-3+\delta_w, 3]$. Figures 3a-d show the percentage of correct classification for both conditions of $P01$ and $P02$. Note that the first prediction time for $P01$ was at -2.25s, as this is the first time instant where a full time window (0.75s) was available. For $P02$, in contrast, the first value was at -2.50s, since the δ_w was set to 0.5s.

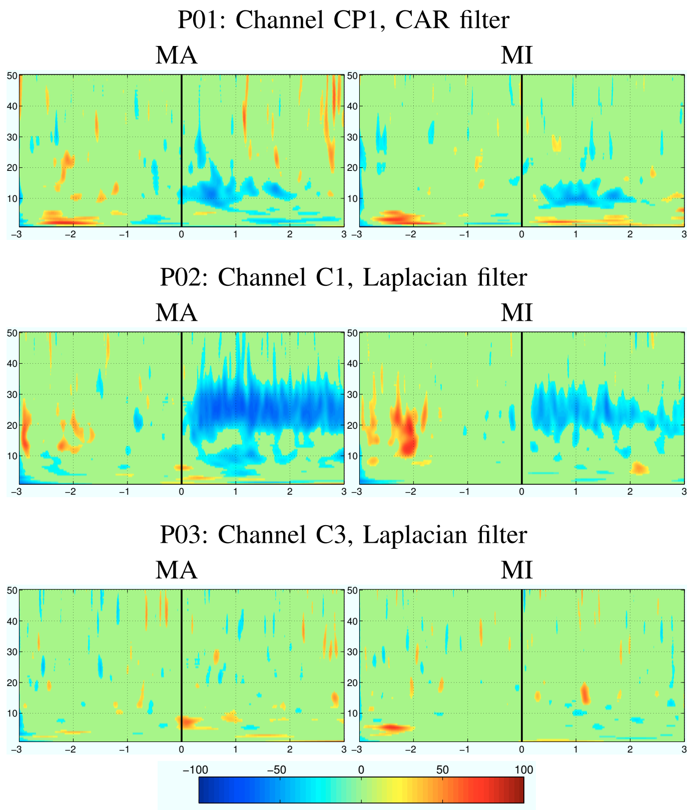

Fig. 2. Significant ERD/ERS maps for all patients for motor attempt (left), and motor imagery (right). Y-axis represents frequency (Hertzs); X-axis indicates time (in seconds) with respect to the cue given to start MA or MI.

Figures 3a-d show the decoded class at each point in time for the different patients. The horizontal lines mark an accuracy of 70%. It has been argued that this is the minimum accuracy for a correct and reliable BCI operation [17] and, therefore, the lines indicate whether the decoding of the task achieved this value. Although labels change at $t=0$, it is important to recall that there is an implicit delay originated by two different factors: (i) the latency of the brain due to the mental processing of the stimulus and action preparation (as mentioned in Sec. II-B), and (ii) the use of sliding windows, which establishes the classifier decision in time instant t based on the features from time interval $[t-\delta_w, t)$. Thus, mixed labels around $t=0$ are expected due to the lack of a perfect synchronization signal across trials.

For $P01$, the classification accuracy of rest was slightly under 70%, while for MA it achieved more than 80% approximately at $t=1$ and then started to degrade (Fig. 3a). Regarding MI, the accuracy was lower both in rest and MI. Rest detection rate was always slightly under 70% and MI was only above this threshold for a short period of time approximately at $t=1$ (Fig.3b). The decoding of $P02$ achieved better results than $P01$. For MA, detection rates where, on average, above 85% both for rest and MA. Furthermore, the accuracy was more stable along time and the change between labels was sharper around $t=0.4$ (Fig. 3c). For MI, average accuracy was lower than in MA, but still higher than the aacuracy achieved for patient $P01$,

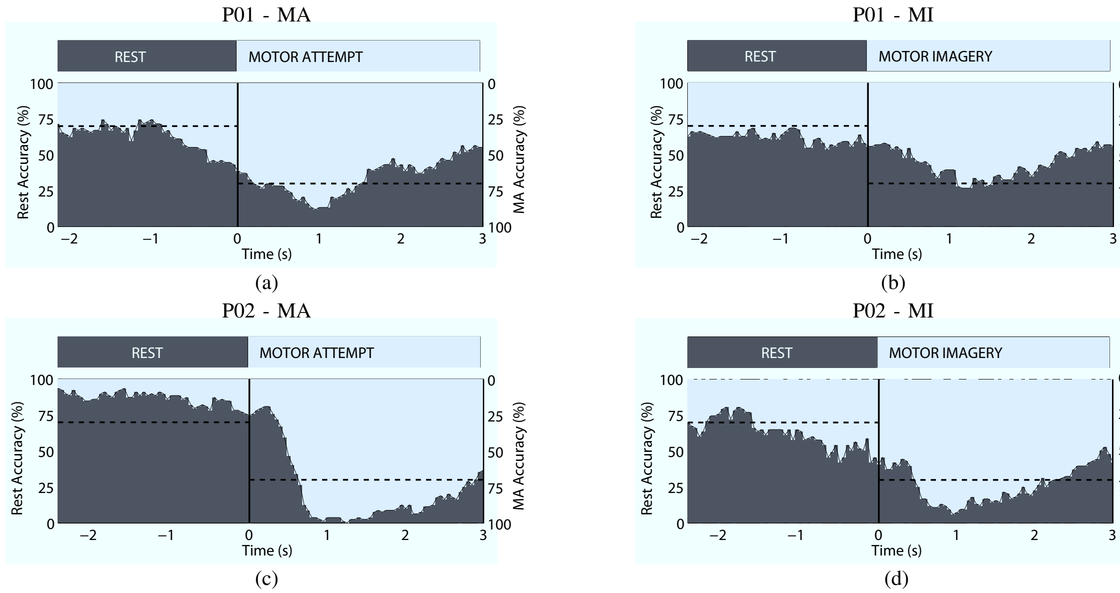

Fig. 3. Time-course of classification accuracies. Upper row presents results for P01, and lower row for P02. Left column corresponds to MA, while right column corresponds to MI. Dark areas represent the accuracy of rest interval, while bright areas represent accuracy of MA/MI. The horizontal lines represent an accuracy of 70%.

since accuracies were more often above the 70% threshold, especially when detecting the MI class (Fig. 3d).

In summary, for the two patients where the power spectra contained significant differences in terms of ERD/ERS, it was possible to build a continuous decoder that could provide control signals for a BCI. In addition, the usage of motor attempt task (MA) resulted in better decoding performance than the use of motor imagery task (MI).

IV. Conclusions and future work

This paper studied the feasibility of building a motor-related BCI for SCI patients through a preliminary study with three quadriplegic patients close to reaching the chronic state. The results point out that, even though the three patients have not reached the chronic state, one of them already did not present significant ERD/ERS neither in MA or MI paradigms. As this patient's lesion was the most recent, it seems that there might be other factors apart from time affecting the loss of cortical motor representation of paralyzed limbs in SCIs. For the other two patients, significant but different ERD patterns were found between MA and MI (in line with [5]) indicating that both tasks were candidates for BCI design. Subsequent analysis of the decoders for both tasks revealed that MA led to higher accuracies, maybe due to the fact that the significance of the ERD/ERS is higher in this paradigm for both patients.

References

[1] G.R. Müller-Putz, D. Zimmermann, B. Graimann, K. Nestinger, G. Korisek, and G. Pfurtscheller, "Event-related beta EEG-changes during passive and attempted foot movements in paraplegic patients," *Brain Research*, vol. 1137, pp. 84 – 91, 2007.

[2] J.A. Turner, J.S. Lee, O. Martinez, A.L. Medlin, S.L. Schandler, and M.J. Cohen, "Somatotopy of the motor cortex after long-term spinal cord injury or amputation," *IEEE Trans. on Neural Systems and Rehabilitation Engineering*, vol. 9, no. 2, pp. 154 –160, june 2001.

[3] P.J. Wrigley, S.M. Gustin, P.M. Macey, P.G. Nash, S.C. Gandevia, V.G. Macefield, P.J. Siddall, and L.A. Henderson, "Anatomical changes in human motor cortex and motor pathways following complete thoracic spinal cord injury," *Cerebr. Cortex*, vol. 19, no. 1, pp. 224–232, 2009.

[4] K. Gourab and B.D. Schmit, "Changes in movement-related β-band EEG signals in human spinal cord injury," *Clinical Neurophysiology*, vol. 121, no. 12, pp. 2017 – 2023, 2010.

[5] S. Hotz-Boendermaker, M. Funk, P. Summers, P. Brugger, M.C. Hepp-Reymond, A. Curt, and S.S. Kollias, "Preservation of motor programs in paraplegics as demonstrated by attempted and imagined foot movements," *NeuroImage*, vol. 39, no. 1, pp. 383 – 394, 2008.

[6] I. Iturrate, J. M. Antelis, A. Kübler, and J. Minguez, "A noninvasive brain-actuated wheelchair based on a P300 neurophysiological protocol and automated navigation," *IEEE Transactions on Robotics*, vol. 25, no. 3, pp. 614–627, 2009.

[7] C. Escolano, J.M. Antelis, and J. Minguez, "A Telepresence Mobile Robot Controlled With a Noninvasive Brain-Computer Interface," *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, vol. 42, no. 3, pp. 793–804, june 2012.

[8] J.dR. Millán, R. Rupp, G.R. Müller-Putz, R. Murray-Smith, C. Giugliemma, M. Tangermann, C. Vidaurre, et al., "Combining brain-computer interfaces and assistive technologies: state-of-the-art and challenges," *Frontiers in neuroscience*, vol. 4, 2010.

[9] G. Pfurtscheller, P. Linortner, R. Winkler, G. Korisek, and G. Müller-Putz, "Discrimination of motor imagery-induced EEG patterns in patients with complete spinal cord injury," *Comp Intel Neurosci*, 2009.

[10] C. Neuper, R. Scherer, M. Reiner, and G. Pfurtscheller, "Imagery of motor actions: Differential effects of kinesthetic and visualmotor mode of imagery in single-trial EEG," *Cognitive Brain Research*, vol. 25, no. 3, pp. 668 – 677, 2005.

[11] C. Tallon-Baudry, O. Bertrand, C. Delpuech, and J. Permier, "Oscillatory gamma-band (30-70 Hz) activity induced by a visual search task in humans.," *J Neurosci*, vol. 17, no. 2, pp. 722–734, Jan. 1997.

[12] B. Graimann and G. Pfurtscheller, "Quantification and visualization of event-related changes in oscillatory brain activity in the time frequency domain," *Progress in Brain Research*, , no. 159, pp. 79–97, 2006.

[13] G. Pfurtscheller and F.H. Lopes da Silva, "Event-related EEG/MEG synchronization and desynchronization: basic principles," *Clinical Neurophysiology*, vol. 110, no. 11, pp. 1842 – 1857, 1999.

[14] D.J. McFarland and J. Wolpaw, "Sensorimotor rhythm-based brain-computer interface (BCI): model order selection for autoregressive spectral analysis," *J. of Neural Eng.*, vol. 5, no. 2, pp. 155–162, 2008.

[15] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, "A review of classification algorithms for EEG-based brain computer interfaces," *Journal of Neural Engineering*, vol. 4, June 2007.

[16] S. Cramer, E. Orr, M. Cohen, and M. Lacourse, "Effects of motor imagery training after chronic, complete spinal cord injury," *Experimental Brain Research*, vol. 177, pp. 233–242, 2007.

[17] J. Perelmouter and N. Birbaumer, "A binary spelling interface with random errors," *Rehabilitation Engineering, IEEE Transactions on*, vol. 8, no. 2, pp. 227 –232, jun 2000.