Single Joint Movement Decoding from EEG in Healthy and Incomplete Spinal Cord Injured Subjects

Andrés Úbeda[1], Álvaro Costa[1], Eduardo Iáñez[1], Elisa Piñuela-Martín[2],
Ester Márquez-Sánchez[2], Antonio J. del-Ama[2], Ángel Gil-Agudo[2] and José M. Azorín[1]

***Abstract*— In this paper, linear regression models will be used to decode individual joint angles from low frequency EEG components. To that end, isotonic flexion/extension knee movements will be analyzed. Particularly, the decoding performance of healthy and incomplete spinal cord injured subjects will be assessed to determine the behavior of this methodology with motor disabled people. When studying cortical activity during walking, the appearance of muscular artifacts severely influences the EEG signals recorded. The analysis of single joint movements should decrease the noise provoked by the gait process itself. Additionally, different time windows prior to the decoded angle will be assessed to obtain a more reliable decoder. The results show that decoding performance is significantly above chance for most of the subjects (both healthy and disabled) and suggests that meaningful information of the movement planning starts around 2.5 seconds prior to the decoded angle.**

I. INTRODUCTION

A Brain-Machine Interface (BMI) generates commands by processing the electrical activity of the brain [1] and enables handicapped people to interact with their environment by bypassing neuromuscular control [2]. BMIs are a very useful support to motor rehabilitation procedures of people that suffer movement limitations [3]. Regarding lower limb rehabilitation, the BMI could be combined with other sensors and with lower limb exoskeletons to assist the movement and provide cortical indices during the performance of the gait process.

Although walking is automatically based on reflexes governed at the spinal level, there are evidences that suggest that the motor cortex is particularly active during specific phases of the gait cycle [4]. As an example, a synchrony in the frequency domain has been found between the primary motor cortex and the tibialis anterior (TA) muscle indicating a cortical involvement in human gait function [5]. Also, strong Event Related Desyncronization (ERD) components are found while performing normal walking [6]. In another study, independent component analysis of EEG has revealed unique spatial and spectro-temporal electrocortical properties for different lower limb motor tasks [7]. Recent works show that it is possible to obtain kinematic information of the gait cycle by applying linear regression models to electroencephalographic (EEG) slow cortical potentials (SCP) [8], [9], i.e., cortical information in the frequency band below 2 Hz. In those works, joint angle and angular velocities (from hip, knee and ankle of both legs) are decoded and compared to actual measurements obtained from an infrared optical motion capture system. The decoding performance generally reaches high accuracies, suggesting that this procedure may be suitable to extract relevant kinematic information from cortical activity. These data must be interpreted with caution as decoding performance may not be enough, particulary for those subjects who achieve worse correlations, to perform a direct online decoding of joint kinematics.

Another important issue that should be taken into account is the influence of motion artifacts during walking [10]. These artifacts should be clearly characterized if lower limb kinematics are directly decoded during the gait process. To avoid this influence, or at least significantly reduce it, we propose a simpler experiment where only individual joint movements are decoded. In this paper, this approach is particularized to an isotonic flexion/extension of the knee performed by both healthy and incomplete spinal cord injured patients. One of the goals of this approach is proving that decoding performance is still significant in the absence of motion artifacts and assessing that the decoding methodology can be translated to a clinical scope. This work is part of the BioMot project (Grant Agreement number IFP7-ICT-2013-10-611695) whose main goal is to analyze dynamic sensorimotor interactions in realistic human locomotion and design an artificial cognitive system for embodiment into bioinspired wearable assistive devices.

II. MATERIALS AND METHODS

A. Participants

Four individuals with incomplete spinal cord injury (iSCI) were recruited from the inpatients services at the National Hospital for Spinal Cord Injury in Toledo. The following inclusion criteria was applied: adults with SCI lesion above D7-D8, with ASIA C or D were selected. All patients were able to maintain standing position and ambulate for 30 meters without external assistance and had enough functionality and strength in the upper limbs to use a walker or crutches. Patients with orthotastism disfunction, any surgery intervention in the three months prior to participate in the study, upper limb pain, spasticity greater than three measured by the Asworth Scale and pressure sores in the upper and lower

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[1] Brain-Machine Interface Systems Lab, Miguel Hernández University, Av. de la Universidad s/n, 03202 Elche, Spain {aubeda, acosta, eianez, jm.azorin}@umh.es

[2] Biomechanics and Technical Aids Department, National Hospital for Paraplegics, Finca de la Peraleda S/N, 45071, Toledo, Spain {epinuela, emarquezs}@externas.sescam.jccm.es, {ajdela, amgila}@sescam.jccm.es

TABLE I
DESCRIPTION OF PARTICIPANTS

Subject	Age	Sex	Laterality	Measured Leg	Patient Description
C07	39	Male	Right	Left	Incomplete SCI C4-C5, ASIA D. Spasticity: Ashworth 1
C08	62	Male	Left	Left	Incomplete SCI D1-D12, ASIA D. Spasticity: Ashworth 1
C09	39	Female	Right	Left	Incomplete SCI L4-L5, ASIA D. Spasticity: Ashworth 1
C10	36	Female	Right	Left	Incomplete SCI D3, ASIA C. Spasticity: Ashworth 1+
A05	33	Male	Right	Right	Healthy
A06	24	Male	Right	Right	Healthy
B11	36	Male	Right	Right	Healthy
B12	44	Female	Right	Right	Healthy

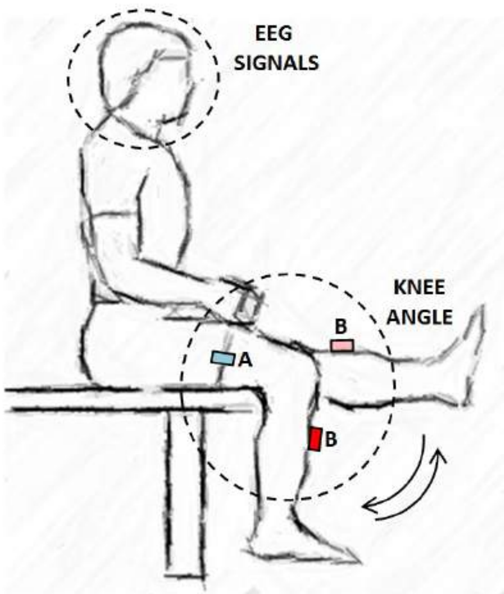

Fig. 1. Subjects perform isotonic flexion/extension knee movements. Inertial sensors A and B are used to measure knee angles and EEG signals are recorded simultaneously (Background image modified from Gwin and Ferris, 2012)

limbs were excluded from the experiments. Additionally, 4 healthy users participated in the study. The ethical board reviewed and approved the experimental procedures and all participants signed the corresponding informed consent.

Table I shows the description of the healthy and iSCI patients that participated in the study. The column "Measured Leg" specifies the leg used to perform the isotonic movements. In the case of healthy subjects, the dominant leg was used to perform the movements. In the case of iSCI patients, the movements were performed with the leg most affected by the lesion.

B. Experimental Setup

The experimental test is based on the performance of isotonic flexion/extension knee movements as shown in Figure 1. For each session, subjects performed six runs consisting of 30 seconds of continuous movements each. Subject C10 only performed five runs due to fatigue.

Brain signals were acquired using two commercial amplifiers of g.USBamp (g.Tec, GmbH, Austria) with the g.GAMMAcap, which has active electrodes to increase the signal/noise ratio. The acquisition of EEG signals was done using 32 electrodes with a sampling frequency of 1200 Hz. The electrodes used are composed of a sintered Ag/AgCl crown with a 2-pin safety connector (g.LADYbird, g.Tec, GmbH, Austria). Additionally, an antistatic wrist strap was used to remove external noises during the experiments.

To measure knee angles, an inertial sensor system was used. It consists of a set of seven inertial sensors (Technaid S.L) where two of them are used to obtain the angles of a knee. To that end, one inertial sensor was placed on the external side of each thigh and another one on the front of the each leg. Joint angles were calculated based on Euler angles and using the orientation matrices of the sensors. Orientation data were acquired through a HUB that is connected to the PC USB port with a data acquisition frequency of 30 Hz.

C. Signals Preprocessing

First, knee angles are resampled to match EEG signals. Information from 16 electrodes distributed over the central and parietal cortex has been used to decode knee angles according to this distribution: FC5, FC1, FC2, FC6, C3, Cz, C4, CP5, CP1, CP2, CP6, P3, Pz, P4 , PO3 and PO4. EEG signals have been manually analyzed to reject blinks. Afterwards, EEG signals have been low-pass filtered with a 2nd-order Butterworth filter below 2 Hz. Finally, EEG data from each electrode and the knee angle have been standardized by subtracting, for each time sample (t), the mean ($\bar{V}$) of the signal and dividing the result by the standard deviation (SD_V) as shown in (1). This standardization has been computed for each individual run.

$$EV[t] = \frac{V[t] - \bar{V}}{SD_V} \tag{1}$$

D. Decoding Method

To decode the knee angle, a multidimensional linear regression has been applied according to the formula (for further details refer [11]):

$$x\left[t\right] = a + \sum_{n=1}^{N} \sum_{k=0}^{L} b_{nk} S_n \left[t - G * k\right] \tag{2}$$

where $x[t]$ is the kinematics state (knee angle) at time t and Sn is the voltage measured at electrode n. L are the

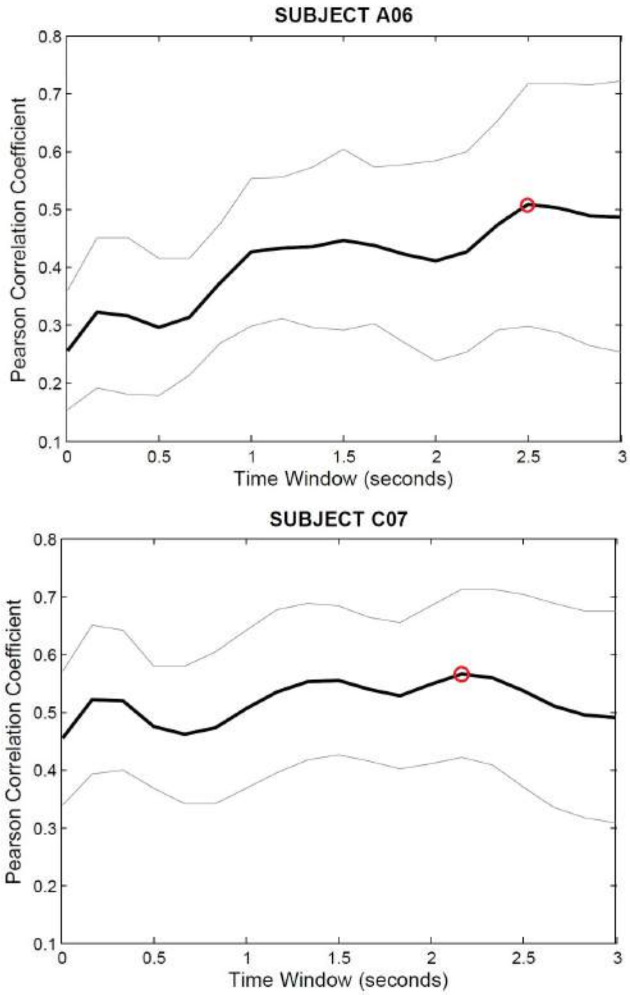

Fig. 2. Decoding performance (mean$\pm$std) after performing a parameter sweep for the gap between lags (G) for one healthy subject (A06) and one spinal cord injured subject (C07). The circle marks the decoding performance peak.

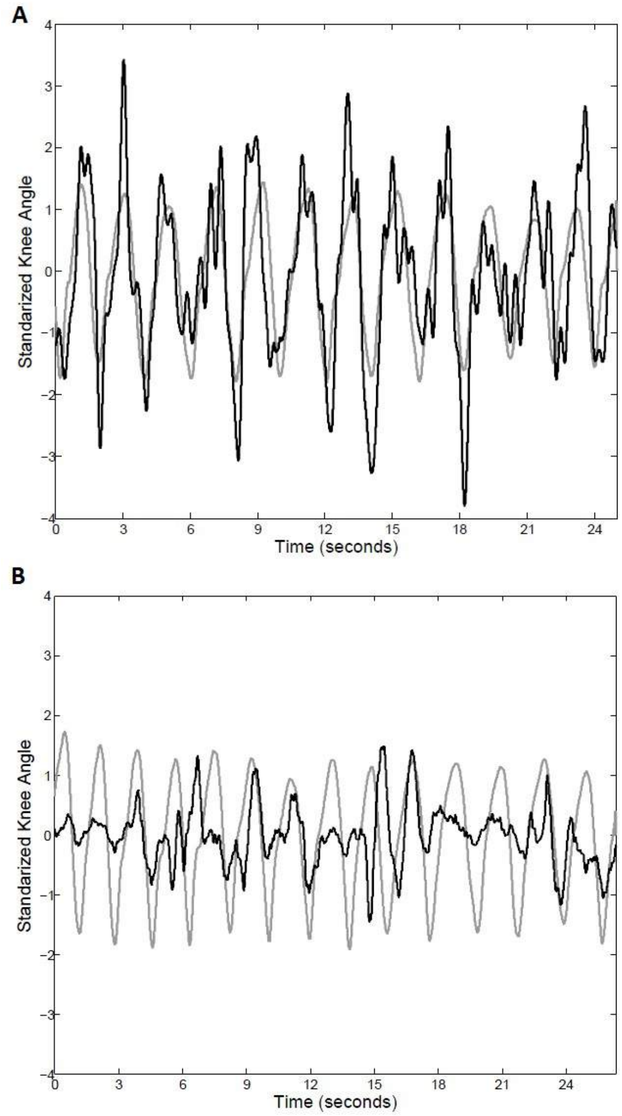

Fig. 3. Examples of the reconstruction of the knee angle for subject C07. In grey, knee angle measured through the inertial sensors. In black, decoded knee angle. A shows the decoded knee angle for the best gap (time window of 2.167 s and Pearson Correlation Coefficient of 0.7651) and B for the worst (time window of 667 ms and Pearson Correlation Coefficient of 0.313).

number of lags, G is the gap between lags, N the number of channels and a and b are the weights of the linear regression. L was defined as 10 and N corresponds to 16 (number of sensors introduced in the decoder). Different gaps (G) have been studied to evaluate the proper time window (prior to the decoded angle) used in the analysis. The decoded knee angle for each run and speed has been compared to the actual knee angle measured with the inertial sensors systems to compute the final decoding correlation. To that end, an fold cross-validation has been computed for each subject. The number of folds were selected depending on the number of runs performed by each subject.

III. RESULTS AND DISCUSSION

In order to assess the most appropriate time window for the analysis, a parameter sweep has been performed for the gap between lags (G). Figure 2 shows two examples of the decoding performance (mean$\pm$std) obtained for a G between 1 and 360, i.e., a processing time window between 8.3 milliseconds and three seconds. From this Figure, it is apparent that the decoding performance peaks in windows between 2 and 2.5 seconds prior to the decoded knee angle. According to previous literature, movement related potentials involved in voluntary movements, such as the Bereitschaftspotential (BP), occur approximately 2 seconds prior to movement onset [12]. This is consistent with our results, which show a higher cortical involvement in a similar time range for most of the subjects. In particular, the decoding performance peak was found in around 2.4517 seconds window lengths averaged across all subjects. This average value is obtained after discarding one of the subjects (C09) who obtained a peak in windows around 833 milliseconds, far away from the usual values. Figure 3 shows an example of the decoded knee angle for one of the best subjects (C07). As it can be seen, the

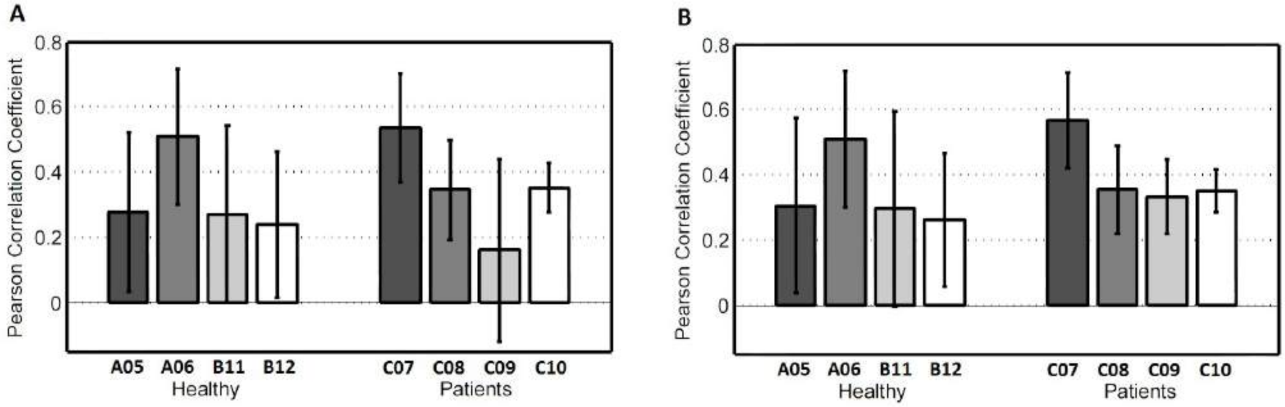

Fig. 4. Decoding performance (mean±std) for each individual subject. A - Decoding correlations for the average gap (2.4517 seconds). B - Decoding correlations for the optimal gap of each subject.

decoded knee angle accurately follows the actual movement performed when the optimal time window is selected (2.167 s) (Figure 3A) and still has a good accuracy but with several mismatches when selecting a worse time window (667 ms) (Figure 3B).

Figure 4 shows the decoding performance (mean±std) obtained for both healthy and iSCI subjects. Figure 4A shows the decoding performance obtained for the average gap parameter (time windows of 2.4517 seconds). Figure 4B shows the decoding performance (mean±std) computed for the optimal gap (G) obtained for each subject. The decoding performance obtained for a fixed gap or time window is very similar to the decoding correlations computed for the optimal gaps of each subject. Only Subject C09 has a huge improvement in the decoding performance (Figure 4B) as the gap selected is remarkably different from the average gap computed. The similarities between both graphs suggest that a decoding time window of around 2.5 seconds is optimal across subjects (either healthy or iSCI) and could be generalized in future experiments. However, this assumption needs to be taken with caution and further research and experimental tests under different conditions should be performed to assure it.

Regarding average decoding performance, we found significant decoding correlations for most of the subjects when applying a fixed gap (Wilcoxon Sign-Rank Test, $p<0.05$), except from subjects A05, B11 and C09. This significance is expected to increase after computing the results with the optimal gap. In those cases, only decoding performance of Subject B11 is still not significant. Interestingly, there is no significant difference between decoding performance of healthy and iSCI subjects (Wilcoxon Sum-Rank Test, $p>0.05$). These findings suggest that incomplete spinal cord injuries do not affect the cortical activations derived from the generation of lower-limb movements. A possible explanation is that the subjects of this study still preserve a fine control of lower limb movements which may be translated into a similar behavior of motor cortical connections compared to healthy subjects.

The present study shows a significant decoding performance of single joint movements. Decoding correlations are, nevertheless, still low to perform a real time control of an exoskeleton. However, there is room for further progress in determining how the decoding performance behaves when applying these techniques to other joints, such as the ankle, and in other experimental conditions, like the performance of isotonic and isometric joint movements [7]. Additionally, more complex movements that involve a greater number of joints could be assessed, e.g., the analysis of slow pedaling or particular segments of the gait cycle. Further progress should be made in characterizing cortical behavior during lower limb activity. In this sense, an optimal lag and gap parametrization and the proper selection of electrodes are key factors to improve the decoding performance. The results also suggest that motion artifacts do not affect decoding performance to a great extent, as single joint movements should reduce or even eliminate this effect.

Another question that arises from the study is if these findings could provide support to a clinical application of the methodology in a neurorehabilitation task. This application could be based on the plasticity of the central nervous system and the learning processes to induce beneficial movements. The induced axonal growth due to neuroplastic phenomena could be triggered by matching the interactions of ascending and descending commands reproducing a coherent movement after a voluntary intention of movement, which might produce a neuroplastic change in the cortical pathways. To show this effect, future assessment of complete and incomplete SCI individuals should be undertaken.

IV. CONCLUSION

In this paper, linear regression models have been used to decode individual joint angles from low frequency EEG components. Particularly, isotonic flexion/extension knee movements have been performed by healthy and incomplete spinal cord injured subjects. The results show that decoding performance is significantly above chance for most of the subjects (both healthy and iSCI) and suggests that meaningful information of the movement planning starts around 2.5 seconds prior to the decoded angle. The results also indicate that iSCI subjects preserve a similar behavior of motor cortical connections compared to healthy subjects and, as a consequence, a fine control of lower limb movements.

Further research should be undertaken to characterize cortical behavior during lower limb activity. This includes a proper parametrization of the lag and the gap of the regression models, a deeper study of electrode selection and the assessment of different lower limb movements. Further research should aim at the application of this techniques in neurorehabilitation tasks, particularly applied to people who may be benefited from cortical plasticity.

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