3D Trajectory Reconstruction of Upper Limb Based on EEG

J.-H. Kim[1], R. Chavarriaga[2], J. d. R. Millán[2], S.-W. Lee[1]

[1]*Korea University, Seoul, Korea;* [2]*EPFL, Lausanne, Switzerland*

Correspondence: Seong-Whan Lee, Korea University, Seoul, Korea. E-mail: sw.lee@korea.ac.kr

Abstract. The main goal of this paper is to simultaneously decode movement velocity of both hand and elbow from electroencephalography (EEG) signals. The result can support motor rehabilitation using a robotic arm and assist people with disabilities to control an upper limb neuroprosthesis in natural movement. In recent works, researchers have estimated hand movement velocity from EEG signals. However, such studies are insufficient to apply motor rehabilitation, since they only considered hand movement trajectory. Sometimes patients take wrong elbow movement in motor rehabilitation even though their hand movements are correct. In this study, we explore to decode not only hand but also elbow velocity from EEG signals when subjects move upper limb.

Keywords: BCI, Arm Movement Trajectory, EEG, Upper Limb Rehabilitation, Elbow Movement Trajectory

1. Introduction

Recent research shows the possibility of decoding hand movement trajectory using low frequency (< 1 Hz) components of the EEG signals [Bradberry et al., 2010]. In addition, multiple studies have also shown that these components also convey information about movement onset, directions and velocity [Lew et al., 2012].

When patients are trained with end effector-based robot-assisted rehabilitation system, they often lack supervision to verify that movements are performed in the correct manner. To this end, it is useful to assess the kinematics of the different joints of the arm. In turn, monitoring of the neural correlates of these joints –and eventual discrepancies with the observed behavior- can be useful to better understand and assist motor neurorehabilitation. In this work we apply previously reported methods to decode the kinematics of both hand and elbow. Although this preliminary study was performed with able-bodied subjects, we hypothesize that this approach may be useful for evaluating and supporting motor neurorehabilitation.

2. Material and Methods

2.1. Experiments

Three healthy right-handed male subjects participated in the experiment. Subjects sat comfortably in front of a panel containing four target buttons (up, down, left and right) on the vertical plane, and a home position button on the horizontal plane. They were instructed to perform the center-out task from home button to reach the targets buttons. The experiment was composed of 5 runs of 20 trials each. A resting period of 3 s was interleaved between trials. Subjects began each trial with their right hand on the home button. After 2 s, an auditory cue informed the subject which target to reach. Targets were equally and randomly selected among the four directions. Following another 2 s, a beep sound informed the subject to reach the target button. After some time, other cue requests the subject to move the hand back to the home button. The protocol is detailed in [Lew et al., 2012].

The EEG was acquired using 64 channels arranged in the 10/20 system electrodes at a sampling rate of 4096 Hz (ActiveTwo, BioSemi). Hand and elbow 3D position were recorded using a motion tracking device (accuTrack 500, Atracsys) at a sampling rate of 4111 Hz. Both recording streams were synchronized via hardware triggers.

2.2. Data Processing

The continuous EEG data were down-sampled to 128 Hz and common average referencing (CAR) was used to remove the global background activity based on all the recorded channels. A zero-phase, fourth-order, low-pass Butterworth filter with a cutoff frequency of 1 Hz was then applied to the EEG data. The continuous EEG data was segmented into trials and the average value of the baseline period - defined as the 500 ms time window prior to the auditory cue - of each trial was subtracted from the EEG of that trial.

To decode the movement velocity of the upper limb, we used a linear model method [Bradberry et al., 2010],

$$x[t] - x[t-1] = a_x + \sum_{n=1}^{N} \sum_{k=0}^{L} b_{nkx} S_n[t-k] \tag{1}$$

$$y[t] - y[t-1] = a_y + \sum_{n=1}^{N} \sum_{k=0}^{L} b_{nky} S_n[t-k] \qquad (2)$$

$$z[t] - z[t-1] = a_z + \sum_{n=1}^{N} \sum_{k=0}^{L} b_{nkz} S_n[t-k] \qquad (3)$$

where $x[t] - x[t-1]$, $y[t] - y[t-1]$, and $z[t] - z[t-1]$ represent the velocities of movement at time t in the x, y and z axis. L(=10) is the number of time lags and $S_n[t-k]$ represents the voltage difference measured at EEG sensor n at time lag k, and the a and b variables are weights obtained through multiple linear regression. N is the number of electrodes used in analysis. For decoding we use 21 electrodes covering the motor areas: FC5, FC3, FC1, FCz, FC2, FC4, FC6, C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4 and CP6, according to the International System 10/20.
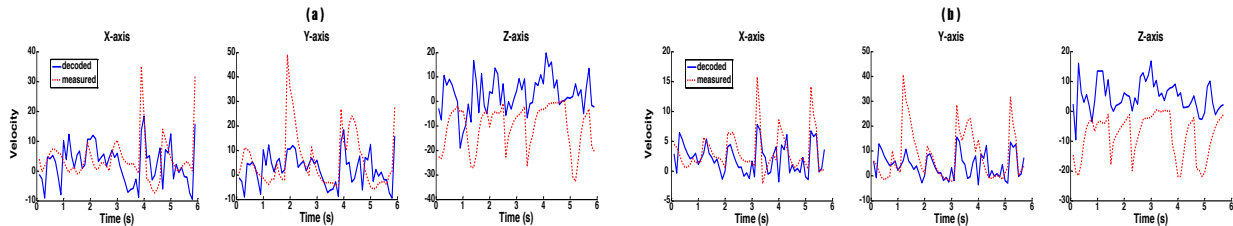

Figure 1.   *Decoder example : The comparison between the measured velocity (dotted line) and decoded velocity (solid line) from subject 3 in the time domain. (a) Velocity of hand movement. (b) Velocity of elbow movement.*

3. Results

We reconstructed three-dimensional hand and elbow movements from EEG signals using the linear model as shown in Fig. 1. We quantified the decoding accuracy using the mean of the correlation coefficient *r* between measured and reconstructed hand and elbow velocity across 10 cross-validation folds. Mean correlations value for hand velocities are 0.31, 0.27 and 0.15 for x, y and z coordinates respectively. Corresponding correlation values for elbow velocity are 0.31, 0.3 and 0.16. We obtained similar decoding accuracy for both hand and elbow movement velocity, with lower correlation values for the z coordinate (all p < 0.02).

4. Discussion

This paper shows that it is possible to decode both hand and elbow movement trajectory from low frequency EEG signals. In [Bradberry et al., 2010] r-values for x/y/z-axes were 0.19, 0.38 and 0.32, which are similar to decoding accuracy comparing this study result. But decoding accuracy of each axis is different. The worst decoding accuracy is x-axis in [Bradberry et al., 2010] and is z-axis in this study.

In the future, we will study the decoding of kinematic parameters when subjects perform both motor execution and imagination of the upper limb. Also, we will implement the online decoding of the movements and perform experiments with subjects with motor disabilities to compare with the results obtained in able-bodied subjects.

Acknowledgements

References

Bradberry TJ, Gentili RJ, Contreras-Vidal JL. Reconstructing three-dimensional hand movements from noninvasive electroencephalographic signals. *J Neurosci,* 30(9):3432-3437, 2010.

Lew E, Chavarriaga R, Silvoni S, Millán JdR. Detection of self-paced reaching movement intention from EEG signals. *Front Neuroeng,* 5(13):1-17, 2012.