Decoding of hand movement velocities in three dimensions from the EEG during continuous movement of the arm

P. Ofner[1] and G.R. Müller-Putz[1]

[1]*Graz University of Technology, Institute for Knowledge Discovery, Graz, Austria*

Correspondence: P. Ofner, Graz University of Technology, Krenngasse 37, 8010 Graz, Austria. E-mail: patrick.ofner@tugraz.at

Abstract. Brain-computer interface (BCI) systems can be used to control limb neuroprostheses in order to restore limb functionality of paralyzed persons. Traditionally, only invasive BMI (brain machine interfaces) are thought to provide an adequate signal-to-noise ratio and bandwidth to control an upper limb neuroprosthesis accurately in a continuous manner with sufficient degrees-of-freedom. This paper supports work which already showed that it is possible to decode the velocity of executed arm/hand movements from electroencephalographic signals but using a different movement paradigm and suppressing eye movements. It was possible to decode movement velocities with a high correlation with actual executed movements. This could pave the way to a new type of prostheses control using a direct link betweeen natural hand movement imagination and prostheses movement.

Keywords: EEG, movement decoding, brain machine interface, brain-computer interface, neuroprosthesis

1. Introduction

It is desired to have control of an upper limb neuroprosthesis so that it could be moved precisely in three dimensions and with low cognitive load with a brain-computer interface (BCI) using electroencephalographic (EEG) signals. [McFarland et al., 2010] showed an approach using topographically and spectrally focused features. However this method needs months of user training because users need to learn to modulate these features. [Bradberry et al., 2010] proposes a direct and continuous three-dimensional (3D) decoding of movements. Recently, [Bradberry et al., 2011] pursues this work to an online control of a cursor in two dimensions with natural motor imagination (MI) which needs negligible user training. However, the risk of influencing EEG signals with eye movements (EM) is very high. In [Bradberry et al., 2010] subjects had been instructed to fixate gaze on an LED while executing a center-out reaching task, but the fixation of gaze is difficult when approaching different targets with the arm because visual feedback is necessary. In [Bradberry et al., 2011] EM were not inhibited at all. We carried out an experiment similar to [Bradberry et al., 2010], but used continuous, accidental and self-chosen movements instead of a center-out reaching task. Furthermore, because of no need for visual feedback, it was easier for subjects to suppress eye movements.

2. Material and Methods

Five healthy, right-handed subjects were comfortably seated in an armchair and were instructed to perform natural, round (not jaggy) and in speed varying movements with the right arm in front of the upper body in all three dimensions. During movements, subjects were asked to fixate gaze on a cross on a computer screen in front of them. We recorded ten trials each lasting 65 s and used only the last 60 s of each trial for further analysis to exclude any movement onset effects. The start of a trial was indicated by a short beep tone. After each trial, a subject specific break followed to avoid fatigue of the arm.

For EEG signal recording 49 electrodes covering frontal and sensorimotor areas were used. Reference was placed on the left ear, ground on the right ear. In addition, three electrodes recorded the electrooculogram (EOG). Signals were acquired with g.USBamp amplifiers (g.tec, Graz, Austria) with a sampling frequency of 512 Hz after band-pass filtering between 0.01 Hz and 200 Hz with an eighth-order Chebyshev filter and applying a notch filter at 50 Hz. After recording, we removed linear trends from trials. Because of computational convenience, we filtered all signals with a 100 Hz zero-phase, fourth-order, low-pass Butterworth filter and down sampled data to 256 Hz. To measure the x/y/z coordinates of the hand we used the Kinect system (Microsoft, Redmond, USA) together with the OpenNI/NITE software freely available from http://www.openni.org. For analysis, we rotated the coordinate system so that the x-axis was going from right to left, the y-axis from down to up and the z-axis from front to back relative to the subject.

Next, we applied a fifth-order, low-pass Butterworth filter at 1 Hz, and computed the temporal difference of all EEG/EOG data. To decode movement x/y/z velocities, we used three linear models consisting of all EEG/EOG channels, respectively, and ten time lags in 10 ms intervals [Bradberry et al., 2010]. We found the parameters of the linear models with multiple linear regressions. To assess the quality of the movement velocity decoder we applied a 30-fold cross validation to all ten minutes of movement and computed the Pearson correlation coefficient between the measured velocities and the decoded velocities from the EEG and EOG, respectively, for each cross validation fold.

3. Results

Table 1 and 2 show mean values and standard deviations of the Pearson correlation coefficient across all cross validation folds of each subject and the grand average over all subjects when decoding velocities from the EEG and EOG, respectively. The average x/y/z Pearson correlation coefficients were 0.70/0.77/0.62 and 0.35/0.33/0.23 when decoding from EEG and EOG, respectively.

Table 1. *Mean values and standard deviations of Pearsons correlation coefficient across validation folds of each subject when decoding from EEG.*

EEG	*Subject 1*		*Subject 2*		*Subject 3*		*Subject 4*		*Subject 5*		*subject mean*	*subject std*
	mean	*std*	*mean*	*std*	*mean*	*std*	*mean*	*std*	*mean*	*std*		
x	0.53	0.09	0.71	0.08	0.79	0.07	0.74	0.11	0.73	0.10	**0.70**	**0.09**
y	0.84	0.06	0.78	0.09	0.71	0.09	0.78	0.09	0.71	0.13	**0.77**	**0.05**
z	0.71	0.08	0.54	0.16	0.67	0.06	0.50	0.16	0.67	0.12	**0.62**	**0.08**

Table 2. *Mean values and standard deviations of Pearsons correlation coefficient across validation folds of each subject when decoding from EOG.*

EOG	*Subject 1*		*Subject 2*		*Subject 3*		*Subject 4*		*Subject 5*		*subject mean*	*subject std*
	mean	*std*	*mean*	*std*	*mean*	*std*	*mean*	*std*	*mean*	*std*		
x	0.27	0.17	0.46	0.17	0.15	0.18	0.44	0.20	0.42	0.19	**0.35**	**0.12**
y	0.42	0.12	0.28	0.18	0.13	0.14	0.48	0.18	0.33	0.18	**0.33**	**0.12**
z	0.25	0.17	0.17	0.16	0.20	0.14	0.18	0.16	0.33	0.14	**0.23**	**0.06**

4. Discussion

Our results confirm that it is possible to decode hand movement velocities from EEG. In [Bradberry et al., 2010] correlation coefficients of 0.19/0.38/0.32 for x/y/z-axes were reached. These results were surpassed in our work (cf. Table 1). Reasons could be that we used a different movement modality (accidental vs. target directed) and a broader frequency band for decoding (0.01 – 1 Hz vs. 0.5 – 1 Hz). The risk that our promising results are due to eye activity can be neglected, because subjects fixated their gaze and decoding from EOG yields lower correlations than decoding from EEG (cf. Table 1 and 2).

Further work will show the applicability of this decoder for online controlling neuroprostheses using natural MI.

Acknowledgements

This work is supported by the European ICT Programme Project FP7-224631.

References

Bradberry TJ, Gentili RJ, Contreras-Vidal JL. Reconstructing Three-Dimensional Hand Movements from Noninvasive Electroencephalographic Signals. *The Journal of Neuroscience*, 30(9): 3432-3437, 2010.

Bradberry TJ, Gentili RJ, Contreras-Vidal JL. Fast Attainment of Computer Cursor Control with Noninvasively Acquired Brain Signals. *Journal of Neural Engineering*, 8(3), 2011.

McFarland DJ, Sarnacki WA, Wolpaw JR. Electroencephalographic (EEG) Control Of Three-Dimensional Movement. *Journal of Neural Engineering*, 7(3): 2010