Proceedings of the 6th International Brain-Computer Interface Conference 2014 DOI:10.3217/978-3-85125-378-8-35

Online detection and classification of movement kinetics

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Abstract

Over the past years brain-computer interface (BCI) technology has been proposed as a means for neurorehabilitation. To induce Hebbian-associated-like plasticity, the movement-related cortical potential (MRCP) can be detected from the continuous brain activity to trigger timely appropriate inflow of somatosensory feedback from electrical stimulation. The aim of this study was to detect the MRCP online from the continuous brain activity and decode two types of movements that were performed with different levels of force and speed (2x50 movements). 5 healthy subjects and 1 stroke patient performed/attempted to perform the movements. The system correctly detected and classified 65±3 % and 51 % of the movements for the healthy subjects and patient, respectively. The findings suggest that it is possible to detect movements and decode kinetic information online. This may have implications for stroke rehabilitation where task variability may be introduced to optimize the retention of relearned movements.

1 Introduction

Stroke is the main cause of adult disability in high-income countries worldwide; therefore, several techniques have been proposed to reverse motoric impairments [1]. Over the past years, brain-computer interfaces (BCIs) have been proposed as tools that can be used in neurorehabilitation [2, 3]. Recently, it was shown that plasticity could be induced by using the movement-related cortical potential (MRCP) as a control signal in a BCI that provides somatosensory feedback from electrical stimulation [4, 5]. The MRCP is a low-frequency brain potential associated with executed and imagined movements [6]. The potential can be observed in the electroencephalogram (EEG) up to two seconds before a voluntary movement; therefore, it has been proposed for BCIs that are used for induction of Hebbian-associated-like plasticity [4, 5]. The MRCP also contains kinetic information of the executed or imagined movement such as the level of force and speed [6, 7]. This kinetic information may be utilized in designing more sophisticated rehabilitation protocols where variety of tasks is required. It has been shown that variety of tasks in a rehabilitation paradigm is good for maximizing the retention of relearned motor skills [8]. To implement this in BCI protocols, we need to detect the movement intention and classify different task parameters (force and speed) to activate

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correlated somatosensory feedback (through functional electrical stimulation). The detection and decoding of the MRCP have been performed offline in a previous study [7].

The aim of this study was to implement and test the feasibility of detecting the MRCP and discriminating between fast movements with a high level of force and slow movements with a low level of force.

2 Methods

2.1 Subjects

Five healthy volunteers (1 female and 4 males: 29±5 years old) and one stroke patient with lower limb paresis (77 years old, male, infarction, right side affected, 46 days since event) participated. All the subjects gave their informed consent before participation, and the procedures were approved by the local ethical committee (N-20130081).

2.2 Experimental protocol

Each subject was seated in a chair with the right foot fixed to a pedal with an attached force transducer. The experiment was divided into two sessions; training and testing. The training session started with recording of the maximum voluntary contraction (MVC) force followed by 50 repetitions of cued isometric dorsiflexions of the ankle for each of two movement types. The two tasks were [7]: i) 3 s to reach 20% of MVC and ii) 0.5 s to reach 60% of MVC. The subjects spend ~5 min to familiarize with each task. The order of the two tasks was randomized, but they were not mixed. To assist the subjects in performing the movements with the correct level of force and speed, they were visually cued by a custom made program (Knud Larsen, SMI, Aalborg University), where force was used as input. They were asked to produce force to match a ramp trace.

After the training session, the detector (Section 2.4) and classifier (Section 2.5) were built and the testing session started. In this session, the subjects performed 50 movements of each movement type randomly and in their own pace (they were instructed to separate two consecutive movements with at least 5 s, and the experimenter guided them at the end of the session, so an equal amount of movements were performed). After they performed a movement they verbally expressed the movement type that was performed; this was noted and compared to the outcome of the computer prediction.

2.3 Signal acquisition

Ten channels of monopolar EEG were recorded (EEG amplifiers, Nuamps Express, Neuroscan) continuously from FP1, F3, Fz, F4, C3, Cz, C4, P3, Pz, and P4 according to the International 10-20 system (32 Channel Quick-Cap, Neuroscan). The signals were sampled at 500 Hz and analog to digital converted with 32 bits accuracy. The signals were referenced to the right ear lobe. Electrooculography (EOG) was recorded from FP1. The impedance of the electrodes was below 5 kΩ during the experiment.

2.4 Detection, feature extraction and classification

In the training and testing session, the EEG signals were bandpass filtered from 0.05-10 Hz with a 2nd order Butterworth filter. A surrogate channel of the nine EEG channels was obtained by applying an optimized spatial filter to improve the signal-to-noise ratio (SNR) as proposed by Niazi et al. [9]. The movements were detected using a template matching technique [7, 9] where a template of the

 DOI:10.3217/978-3-85125-378-8-35

initial negative phase of the MRCP was matched to the surrogate channel. The template was extracted from an average of the 2x50 movements that were performed in the training session. The length of the template was 2 s, and it was extracted from the peak of maximum negativity and 2 s prior to this point. The detection threshold was obtained for each subject using a receiver operating characteristic (ROC) curve. The ROC curve was generated through 3-fold cross-validation of the training data. The detection threshold was selected to maximize the true positive rate (TPR), but on the expense of more false positive detections (FPs). Detections occurred when the cross-correlation, computed between the template and the surrogate channel, exceeded the detection threshold, and the EOG activity was lower than 125μV. Detector decisions were made every 200 ms. To reduce the number of FPs, the detector was disabled for 3 s after detection. The detection was evaluated through the TPR and number of FPs/min. Six temporal features were extracted from the initial negative phase of the MRCP from the detection onset and 2 s prior this point. These features were: i+ii) slope and intersection of a linear regression fitted to the entire interval (-2 s until the detection onset), iii+iv) slope and intersection of a linear regression fitted to the last 0.5 s of the interval (-0.5 s until the detection onset), v) maximum negative amplitude and vi) mean amplitude.

The features were classified using a support vector machine (SVM) with a linear kernel. All trials from the training session were used to build the classifier that was used in the testing session. The classification accuracy was obtained for the correctly detected movements.

3 Results

The results are summarized in Table 1. The TPR was 85±4 % for the healthy subjects and 85 % for the stroke patient, and less than 1 FP/min was registered. The number of correctly detected and classified movement was higher for the healthy subjects (65±3 %) compared to the patient (51 %).

Healthy/stroke subject	Detection [%]	Detection and classification	FPs/min
H 1	87	62	0.6
H 2	90	70	0.6
H 3	82	65	0.2
H 4	78	61	0.1
H 5	89	67	2.4
Mean±SD	85±4	65±3	0.8±0.8
S 1	85	51	0.9

Table 1: Performance of the system for healthy subjects and the stroke patient. 'Detection' is the TPR, and the column to the right is the performance when the detected movement is classified.

4 Discussion

In this study, movements were detected and the kinetic information classified for healthy subjects with a performance of 65±3 % correctly detected and classified movements. The proposed techniques were also tested by a stroke patient where 51 % of the movements were correctly detected and classified.

The detection performance was slightly higher compared to what has been found in previous studies where an online system was simulated [7, 9]; this may be explained by the selection of the

 DOI:10.3217/978-3-85125-378-8-35

detection threshold. In the previous studies the detection threshold was based on the midpoint of the upward convex part of the ROC curve to obtain a tradeoff between the TPR and number of FPs. In this study, the detection threshold was selected to increase the TPR, but on the expense of more FPs. The number of FPs was accounted for by disabling the detector for 3 s after detection.

The performance of the classifier performed slightly worse than in the offline studies which may be explained by the lower detection threshold leading to an earlier detection of the movements and therefore less kinetic information can be extracted from the 2 s of data extracted prior the detection point. Detection latencies were not calculated in the current study, but it is expected to be in the range of ±100 ms [9].

The findings suggest that the BCI system can be used for neuromodulation where task variability can be introduced (two classes). The system performance is in the range of what has been reported to induce plastic changes [4], although it remains an open question what the lower limit is for inducing plasticity [3]. The effect on the induction of plasticity should be investigated to see if current BCI protocols for this purpose can benefit from the introduction of task variability.

5 Acknowledgement

The authors would like to thank Physiotherapist Christoffer Wang, Træningsenheden Aalborg, for recruiting the stroke patient.

References

[1] P. Langhorne, F. Coupar and A. Pollock, "Motor recovery after stroke: a systematic review," Lancet Neurology, vol. 8, pp. 741, 2009.

[2] J. J. Daly and J. R. Wolpaw, "Brain-computer interfaces in neurological rehabilitation," The Lancet Neurology, vol. 7, pp. 1032-1043, 2008.

[3] M. Grosse-Wentrup, D. Mattia and K. Oweiss, "Using brain-computer interfaces to induce neural plasticity and restore function," Journal of Neural Engineering, vol. 8, pp. 025004, 2011.

[4] I. K. Niazi, N. M. Kersting, N. Jiang, K. Dremstrup and D. Farina, "Peripheral electrical stimulation triggered by self-pace detection of motor intention enhances corticospinal excitability," IEEE Transaction on Neural Systems and Rehabilitation Engineering, vol. 20, pp. 595-604, 2012.

[5] N. Mrachacz-Kersting, S. R. Kristensen, I. K. Niazi and D. Farina, "Precise temporal association between cortical potentials evoked by motor imagination and afference induces cortical plasticity," J. Physiol. (Lond.), vol. 590, pp. 1669-1682, 2012.

[6] O. F. Nascimento, K. D. Nielsen and M. Voigt, "Movement-related parameters modulate cortical activity during imaginary isometric plantar-flexions," Experimental Brain Research, vol. 171, pp. 78-90, 2006.

[7] M. Jochumsen, I. K. Niazi, N. Mrachacz-Kersting, D. Farina and K. Dremstrup, "Detection and classification of movement-related cortical potentials associated with task force and speed," Journal of Neural Engineering, vol. 10, pp. 056015, 2013.

[8] J. W. Krakauer, "Motor learning: its relevance to stroke recovery and neurorehabilitation," Curr. Opin. Neurol., vol. 19, pp. 84-90, 2006.

[9] I. K. Niazi, N. Jiang, O. Tiberghien, J. F. Nielsen, K. Dremstrup and D. Farina, "Detection of movement intention from single-trial movement-related cortical potentials," Journal of Neural Engineering, vol. 8, pp. 066009, 2011.