On Recalibration Strategies for Brain-Computer Interfaces Based on the Detection of Motor Intentions

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Abstract Coupling motor intentions decoded from cortical activities with coherent proprioceptive feedback is of interest for the motor rehabilitation of neurological patients with lesions in the central nervous system. For these interventions to be effective, repeated sessions need to be carried out to achieve functional long-lasting plastic changes of cortical circuits. Electroencephalography-based Brain-Computer Interfaces typically show significant decreases in accuracy when used across multiple sessions with fixed parameters. Therefore, it is important to look for optimal strategies to recalibrate these classifiers. Here we compare different recalibration strategies for systems decoding motor intentions based on electroencephalographic data of neurological patients.

1 Introduction

The analysis of electroencephalographic signals preceding voluntary motor actions allows the decoding of valuable task-related cortical changes [1, 2]. This information can be used to characterize cortical activities in neurological patients and to identify when a subject is intending to perform a movement online [3].

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Brain-computer interfaces (BCI) based on motor-related electroencephalographic (EEG) signals may be used to promote motor neurorehabilitation in patients with neurological conditions affecting the links between the brain and the peripheral muscles. BCIs in this case associate motor-related EEG patterns with proprioceptive feedback that can be mechanical or electrical. Systems based on low-latency detections of motor intentions are expected to boost the BCI impact of the patients' function [4]. However, these interventions may only produce meaningful functional benefits when applied repeatedly for a certain period of time.

Since EEG signals vary substantially across different recording sessions due to their intrinsic non-stationary behavior and vulnerability against subtle perturbations of the recording conditions (electrode-skin impedances, electromagnetic interferences, patients' arousal, etc.) [5], BCI performances can vary substantially across days.

Up to date, the most frequently used strategy to calibrate EEG-based decoders of motor-related cortical states is to carry out an initial screening session that provides enough examples to train the BCI system for the subsequent interventions (see for example [6]). However, no studies have been performed comparing different recalibration strategies for BCI systems relying on the detection of motor intentions.

This abstract compares results of three different recalibration strategies for BCI systems based on the detection of pre-movement cortical changes in multiple recording sessions.

2 Methods

2.1 Patients, Recordings and Protocol

Data from four stroke patients (all males, age 54 +/− 12 years, mean +/− SD) was used. Patients participated in an experiment involving the execution or attempt of a set of reaching voluntary movements in eight sessions along one month. A self-paced paradigm was used: in each session, patients were asked to perform self-paced movements (~1 movement every 10–15 s). The experimental protocols in which the patients took part were approved by the Ethical Committee of the ''Universidad Rey Juan Carlos'' (stroke patients), and warranted their accordance with the Declaration of Helsinki. All patients signed a written informed consent.

EEG was recorded from F3, F1, Fz, F2, F4, FC5, FC3, FC1, FCz, FC2, FC4, FC6, C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, CP6, P3, P1, Pz and P4 (according to the international 10/10 system). The data were amplified and digitized at a sampling rate of 256 Hz, and notch-filtered at 50 Hz. In addition to the EEG signals, the arm and hand movements were measured with three gyroscopes placed on the hand dorsum, the distal third of the forearm, and the middle of the arm to measure the limb kinematics. These data were used to extract the movement events by estimating the moments at which self-initiated movements started (a threshold at 7 % the maximum angular velocity of each session was used to locate the movement onsets).

2.2 EEG-Based Detection of Motor Intentions

Features were extracted by computing the event related desynchronization (ERD) and the movement-related cortical potentials (MRCP). For this, only channels from the frontal, fronto-central, central, centro-parietal, and parietal rows were considered. To model the resting state, the interval [−4, −2] s with respect to the movement onset was used. For the movement state, the interval [−0.5, 0.5] s was used. ERD features were the power values within [7–30] Hz calculated using an autoregressive model. MRCPs features were the signal amplitudes after filtering the EEG signals in the range [0.1–1] Hz. Sparse discriminant analysis was used to select the most discriminant features and as the pseudo-online classifier of motor intentions.

To obtain training examples of rest and movement intention classes, and to extract the features, a one-second long sliding window was applied with a step of 250 ms between −4 and −1 s for the rest class and between −0.5 and +0.5 s for the movement class (with 0 being the onset of the movements as estimated with gyroscopes).

In those recalibration schemes in which data from a same session was used for calibration and validation, a trial-based leave-one-out cross-validation was used: for each trial, the rest of the trials of the same session were used to train the classifier. Training trials were in turn applied a tenfold cross-validation procedure to obtain the optimal threshold: in each iteration, 90 % of the training set was used to obtain a classifier which was applied on the other 10 % of the data and then the optimal threshold was obtained for the whole training dataset. The criterion to select the optimal threshold was to maximize the percentage of good trials (as defined in Sect. 2.4).

2.3 Recalibration Schemes Compared

Three schemes were compared. In *Scheme 1,* the classifier of each session was trained with data from the previous session (for session 1, data from the last session was used). In *Scheme 2,* the classifier was trained with data from the same session. Finally, in *Scheme 3* the classifiers were trained with both, data from the current session and from all previous sessions (for session 1, data from only the first session was used).

2.4 Classifier Validation and Statistics

To analyze the performance of the different recalibration schemes, the percentage of good trials (GT %) in each classified session was computed. In this case, good trials were those in which no false activations were given during the resting phase and, in addition, one activation was generated in the interval [−0.5, 0.5] s with respect to the onset of the movements estimated with the gyroscopes. GT % allows a simplified analysis of the detection results combining false activations and true positives.

To test the statistical differences between the three recalibration schemes, a Friedman test with Nemenyi post-hoc was used. *P*-values under 0.05 were considered significant.

3 Results

Table 1 summarizes the results (GT %) obtained with the decoder of motor intentions using the three recalibration schemes. These results are in line with what has been presented in previous studies on BCIs based on motor intention detection [7]. Decoding results were significantly different between the schemes, with *Scheme 3* (use of historical data in combination with data from the current session) returning the best results. Post-hoc paired comparisons showed that *Scheme 3* provided significantly better results than *Scheme 1* ($p = 0.013$).

No statistically significant differences were found between the recalibration schemes in terms of the detection latencies achieved (Table 2 shows average results). The absolute value of the mean latency for *Scheme 3* (3 ms) was lower than for the other two schemes (−57 ms and −70 ms), which may indicate that *Scheme 3* achieved a more accurate model of the motor intention condition (which was defined as the EEG epochs finishing at t = 0 ms).

Table 1 Average (across sessions) GT % for each patient and for each of the three recalibration schemes compared

	Scheme 1	Scheme 2	Scheme 3
P01	67.8	82.0	86.0
P02	71.6	89.6	92.1
P03	37.5	40.9	51.0
P04	48.0	57.6	68.4
Avg.	56.2	67.5	74.4

Table 2 Average (across sessions and patients) detection latencies for each patient and for each of the three recalibration schemes compared

	Scheme 1	Scheme 2	Scheme 3
Avg.	−57 +/− 234	−70 +/− 204	3 +/− 205

4 Conclusion

According to the results presented here, combining data from different sessions (including data from the session in which the BCI is to be applied) constitutes the best solution for recalibrating BCI systems based on motor intentions for interventions carried out along multiple sessions.

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