Simultaneous Real-Time Detection of Motor Imagery and Error-Related Potentials for Improved BCI Accuracy

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Abstract

Brain-computer interfaces (BCIs), as any other interaction modality based on physiological signals and body channels (e.g., muscular activity, speech and gestures), are prone to errors in the recognition of subject's intent. An elegant approach to improve the accuracy of BCIs consists in a verification procedure directly based on the presence of error-related potentials (ErrP) in the EEG recorded right after the occurrence of an error. Two healthy volunteer subjects with little prior BCI experience participated in a real-time human-robot interaction experiment where they were asked to mentally move a cursor towards a target that can be reached within a few steps using motor imagery. These experiments confirm the previously reported presence of a new kind of ErrP. These "Interaction ErrP" exhibit a first sharp negative peak followed by a positive peak and a second broader negative peak (∼270, ∼330 and ∼430 ms after the feedback, respectively). The objective of the present study was to simultaneously detect erroneous responses of the interface and classifying motor imagery at the level of single trials in a real-time system. We have achieved online an average recognition rate of correct and erroneous single trials of 84.7% and 78.8%, respectively. The off-line post-analysis showed that the BCI error rate without the integration of ErrP detection is around 30% for both subjects. However, when integrating ErrP detection, the average online error rate drops to 7%, multiplying the bit rate by more than 3. These results show that it's possible to simultaneously extract in real-time useful information for mental control to operate a brain-actuated device as well as correlates of cognitive states such as error-related potentials to improve the quality of the brain-computer interaction.

1 Introduction

People with severe motor disabilities (spinal cord injury (SCI), amyotrophic lateral sclerosis (ALS), etc.) need alternative ways of communication and control for their everyday life. Over the past two decades, numerous studies proposed electroencephalogram (EEG) activity for direct brain-computer interaction [1]-[2]. EEG-based brain-computer interfaces (BCIs) provide disabled people with new tools for control and communication and are promising alternatives to invasive methods. However, as any other interaction modality based on physiological signals and body channels (e.g., muscular activity, speech and gestures), BCIs are prone to errors in the recognition of subject's intent, and those errors can be frequent. Indeed, even well-trained subjects rarely reach 100% of success. In contrast to other interaction modalities, a unique feature of the "brain channel" is that it conveys both information from which we can derive mental control commands to operate a brain-actuated device as well as information about cognitive states that are crucial for a purposeful interaction, all this on the millisecond range. One of these states is the awareness of erroneous responses, which a number of groups have recently started to explore as a way to improve the performance of BCIs [3]-[7].

In particular, [6] recently reported the presence of error-related potentials (ErrP) elicited by erroneous feedback provided by a BCI during the recognition of the subject's intent. In this off-line

study, six subjects were asked to mentally drive a cursor towards targets that can be reached within a few steps using motor imagery. However, since the subjects had no prior BCI experience, the system was not moving the cursor following the mental commands of the subject, but with a 20% error rate, to avoid random or totally biased behavior of the cursor. The main components of these "Interaction ErrP" are a negative peak 290 ms after the feedback, a positive peak 350 ms after the feedback and a second broader negative peak 470 ms after the feedback. This study shows the feasibility of simultaneously and satisfactorily detecting erroneous responses of the interface and classifying motor imagery for device control at the level of single trials. Indeed, the recognition rate of correct and erroneous single trials are 81.8% and 76.2%, respectively while the average recognition rate of the subject's intent is 73.1%. Finally, the average theoretical increase of the BCI performance (in terms of bit rate) when integrating ErrP detection is over 100%.
The objective of the present study is to simultaneously detect erroneous responses of the interface and classifying motor imagery at the level of single trials in a real-time BCI system. In this paper we report new experimental results recorded with two healthy volunteer subjects with little prior BCI experience during a simple real-time human-robot interaction that confirm similar results obtained off-line [6], as explained above. We have achieved online an average recognition rate of correct and erroneous single trials of 84.7% and 78.8%, respectively. The off-line post-analysis showed that the BCI error rate without the integration of ErrP detection is around 30% for both subjects. However, when integrating ErrP detection, the average online error rate drops to 7%, multiplying the bit rate by more than 3. These results confirm that it's possible to simultaneously extract in real-time useful information for mental control to operate a brain-actuated device as well as correlates of cognitive states such as error-related potentials to improve the quality of the brain-computer interaction.

2 Materials & Methods

To test the ability of BCI users to concentrate simultaneously on a mental task and to be aware of the BCI feedback at each single trial, we have simulated a human-robot interaction task where the subject has to bring the robot to targets 3 steps either to the left or to the right. This virtual interaction is implemented by means of a green square cursor that can appear on any of 20 positions along an horizontal line. The goal with this protocol is to bring the cursor to a target that randomly appears either on the left (blue square) or on the right (red square) of the cursor. The target is no further away than 3 positions from the cursor (symbolizing the current position of the robot). This prevents the subject from habituation to one of the stimuli since the cursor reaches the target within a small number of steps. Each target corresponds to a specific mental task. Subjects were asked to imagine a movement of their left hand for the left target and to imagine a movement of their right foot for the right target.
After the presentation of the target, the subject focuses on the corresponding mental task until the cursor moves. The system uses a 1 second window to determine the subject's intent. Then the system uses a 400 ms window to detect the presence of ErrP just after the presentation of the feedback (movement of the cursor). If no ErrP are detected, nothing happens and about 600 ms later, the system starts to accumulate data for the next classification of motor imagery. If ErrP are detected, the movement is canceled, and again after about 600 ms the system starts accumulating data for next step. Figure 1 illustrates this timing. At t=0, the target is 3 steps on the right of the cursor. The subject is therefore imagining a movement of his right foot. At t=1 second, the system makes a mistake and moves the cursor to the left while the subject was imagining a movement of his right foot. At t=1.4 second, the system detects ErrP and cancels the wrong movement. It is to note that the system is only canceling last movement, not replacing the wrong command (right) by the opposite one (left). After a delay of about 600 ms, the system starts accumulating data for the next motor imagery classification, i.e. for the next single trial.
In any case, the cursor is moving on average every 2 seconds, and some movements are canceled if ErrP are detected. When the cursor reached a target, it briefly turned from green to light green and then a new target is randomly selected by the system. If the cursor didn't reach the target

after 10 steps, a new target is selected. Two healthy volunteer subjects performed 10 sessions of 15 targets on 2 different days, the delay between the two days of measurements was about 2 weeks. The 20 sessions were split into 4 groups of 5. For the first day (Groups I & II) we used classifiers built with data recorded during a previous off-line study described above [6], and for the second day (Groups III & IV) we used the data of the first day to build classifiers. This rule applies for both motor imagery classification and for ErrP detection. The data acquisition and processing as well as the classification procedures can be found in [6]. For both subjects we used a 150 ms window starting 250 ms after the feedback for channels FCz and Cz for ErrP detection. For motor imagery classification, we used EEG channels Cz, C2, C4 and frequencies 12 Hz, 14 Hz for Subject I and EEG channels Cz, C4, CP4 and frequencies 12 Hz, 24 Hz, 26 Hz for Subject II.

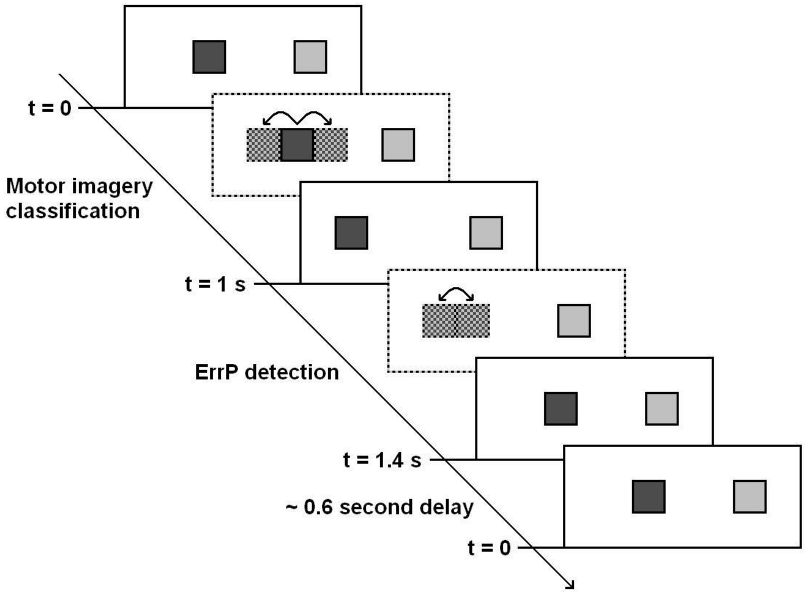

Figure 1: Timing of the protocol. At t=0, the target is 3 steps on the right of the cursor. At t=1 second, the system makes a mistake and moves the cursor to the left while the subject was imagining a movement of his right foot. At t=1.4 second, the system detects ErrP and cancels the wrong movement. After a delay of about 600 ms, the system starts accumulating data for the next motor imagery classification, i.e. for the next single trial.

3 Results

3.1 Performances

For both subjects, Table 1 shows the classification rates for ErrP detection (error and correct) for the four groups of recordings and for the average of them. It also shows the error rates and the rejection rates for motor imagery, with and without ErrP detection. Finally the increase in performance expressed in bits per rials (BpT) is also shown. For both subjects, ErrP detection rate is again around 80% and pretty stable over the different groups. Without the use of ErrP detection, Subject I shows a stable error rate of 34% for motor imagery, whereas for Subject II this rate is just above 30%. These rates are relatively high for a 2 tasks BCI, but keeping in mind that the subjects had very little BCI experience and that these are real-time experiments performed using classifiers built with data from previous sessions recorded several weeks before, they are satisfactory. When integrating ErrP detection, the error rates drop below 10% for both subjects with acceptable rejection rates around 35%. This clearly shows the benefit of using ErrP detection to filter out wrong decisions. This benefit is clear in term of performance, the bit rate is multiplied by more than 3 for both subjects.

Table 1: Classification rates and performance increase. For both subjects, this table presents the classification rates for ErrP detection (error and correct) for the four groups of recordings and for the average of them. It also shows the error rates and the rejection rates for motor imagery, with and without ErrP detection. Finally the increase in performance is also shown. The ErrP detection rate is around 80% and the error rate of the standard BCI is around 30%. When integrating ErrP detection, this error rate is below 10% with an acceptable rejection rate of 30-35%. Finally, for both subjects the bit rate is multiplied by more than 3 when using ErrP detection.

Subject 1 (Cz, C2, C4 and 12 Hz, 14 Hz)

		I	II	III	IV	Average	S.D.
ErrP detection	**Error** [%]	74.8	83.7	76.1	67.5	**75.5**	**6.6**
	Correct [%]	88.3	82.1	91.1	81.6	**85.8**	**4.7**
BCI without ErrP	**Error rate** [%]	33.0	27.5	34.3	39.0	**33.5**	**4.7**
	Rejection rate [%]	0.0	0.0	0.0	0.0	**0.0**	**0.0**
BCI with ErrP	**Error rate** [%]	8.3	4.5	8.2	12.7	**8.4**	**3.4**
	Rejection rate [%]	32.5	36.0	32.0	37.6	**34.5**	**2.7**
Performance	**BpT initial**	0.09	0.15	0.07	0.04	**0.09**	**0.05**
	BpT final	0.31	0.41	0.32	0.17	**0.30**	**0.10**
	Increase [%]	244	173	357	325	**275**	**83**

Subject 2 (Cz, C4, CP4 and 12 Hz, 24 Hz, 26 Hz)

		I	II	III	IV	Average	S.D.
ErrP detection	**Error** [%]	94.8	76.6	76.5	80.2	**82.0**	**8.7**
	Correct [%]	68.0	88.5	86.1	91.4	**83.5**	**10.6**
BCI without ErrP	**Error rate** [%]	31.3	30.2	31.1	29.2	**30.5**	**1.0**
	Rejection rate [%]	0.0	0.0	0.0	0.0	**0.0**	**0.0**
BCI with ErrP	**Error rate** [%]	1.6	7.6	7.6	5.8	**5.7**	**2.8**
	Rejection rate [%]	51.6	32.5	33.1	29.5	**36.7**	**10.1**
Performance	**BpT initial**	0.10	0.12	0.11	0.13	**0.12**	**0.01**
	BpT final	0.38	0.36	0.33	0.42	**0.37**	**0.04**
	Increase [%]	280	200	200	223	**226**	**38**

3.2 Motor imagery

Subject were asked to imagine a movement of their left hand when the left target was proposed and to imagine a movement of their right foot when the right target was proposed. The most relevant EEG channels and frequencies were selected by a simple feature selection algorithm based on the overlap of the distributions of the different classes. The data recorded during the off-line study [6] mentioned in Section 1 and 2 was used to select the relevant features (EEG electrodes and frequencies) for motor imagery classification as well as to build the initial statistical classifier used for these real-time experiments. For Subject I the relevant features are EEG channels Cz, C2, C4 and frequencies 12 Hz, 14 Hz whereas for Subject II we used EEG channels Cz, C4, CP4 and frequencies 12 Hz, 24 Hz, 26 Hz. Previous studies confirm these results. Indeed, alpha and beta rhythm over left and/or right sensorimotor cortex have been successfully used for BCI control [8]. Event-related de-synchronization (ERD) and synchronization (ERS) refer to large-scale changes in neural processing. During periods of inactivity, brain areas are in a kind of idling state with large populations of neurons firing in synchrony resulting in an increase of amplitude of specific alpha (8-12 Hz) and beta (12-26 Hz) bands. During activity, populations of neurons work at their own pace and the power of this idling state is reduced, the cortex has become de-synchronized [9]-[10]. In our case, the most relevant electrodes for both subjects are in the C4 and Cz area. These locations confirm previous studies since C3 and C4 areas usually show ERD/ERS during hands movement or imagination whereas foot movement or imagination are focused in the Cz area [9]-[10].

Figure 2 shows the discriminant power (DP) of frequencies (top) and electrodes (bottom) for both subject. The DP was calculated off-line after the real-time recordings to check the stability of

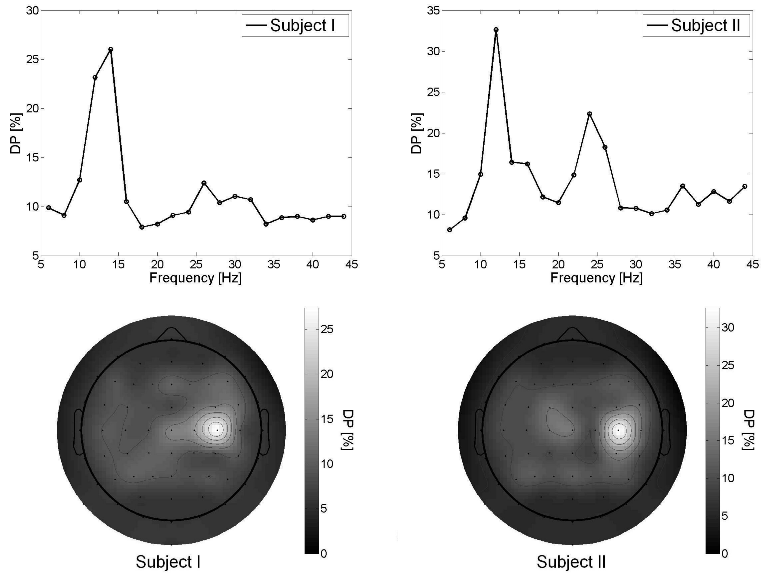

Figure 2: (*Top*) Discriminant power (DP) of frequencies. Sensory motor rhythm (12-16 Hz) and some beta components are discriminant. (*Bottom*) Discriminant power (DP) of electrodes. The most relevant electrodes are in the central area (C4 and Cz) according to the ERD/ERD location for hand and foot movement or imagination.

the selected features. For Subject I, the best frequencies are 12 Hz and 14 Hz, whereas for Subject II the best ones are 12 Hz, 24 Hz and 26 Hz. This matches exactly the selected frequencies. For both subjects, the best EEG electrodes are located around C4, matching relatively well the selected ones. These results indicates that the relevant features are stable over time.

3.3 Error-related potentials

Figure 3 shows the averages of error trials, of correct trials and the difference error-minus-correct for channel FCz for both subjects). A first small positive peak shows up about ∼200 ms after the feedback (t=0). A negative peak clearly appears ∼270 ms after the feedback. This negative peak is followed by a positive peak ∼330 ms after the feedback. Finally, a second negative peak appears ∼430 ms after the feedback. Both subjects show very similar ErrP time courses whose amplitudes slightly differ from one subject to the other. These experiments seem to confirm the existence of a new kind of error-related potentials [7].

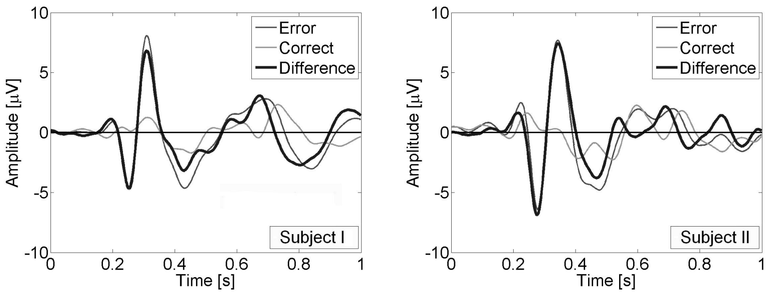

Figure 3: Averages of error trials, of correct trials and the difference error-minus-correct for channel FCz for both subjects. Both subjects show similar ErrP time courses whose amplitudes slightly differ from one subject to the other.

4 Discussion

In this study we have closed the loop using a previously described protocol [6] for real-time experimentations, i.e. with statistical classifiers for motor imagery and ErrP detection running in real-time and simultaneously. Two subjects were able to control the cursor using motor imagery with an average accuracy just below 70%. In parallel, the system was able to detect the presence of ErrP with an accuracy above 80% to improve the quality of the brain-computer interaction. Indeed, in terms of bit rate, the integration of ErrP detection multiplies the performance by a factor 3. The features used for classification were those selected in [6]. They show a relatively good stability, in particular the potentials used for ErrP detection.

More generally, the ErrP potentials described in this study are relatively similar for all subjects. We could therefore maybe build a general ErrP classifier that we would use for all subjects. This would simplify the training sessions, since no preliminary ErrP recordings to build classifiers would be needed anymore. The duration of the window used for motor imagery classification was 1 second. This could probably be shortened to 0.5 second or maybe even less without decreasing performances, so that if we reduce the delay after ErrP detection, we could be able to deliver a feedback almost every second. In this study, ErrP detection was used to filter out erroneous responses of the system. ErrP could also be used as learning signals for an unsupervised online adaptation of the BCI classifier. Finally, the work described in this paper suggests that it could be possible to recognize in real-time high-level cognitive and emotional states from EEG (as opposed, and in addition, to motor commands) such as alarm, fatigue, frustration, confusion, or attention that are crucial for an effective and purposeful interaction. Indeed, the rapid recognition of these states will lead to truly adaptive interfaces that customize dynamically in response to changes of the cognitive and emotional/affective states of the user.

References

[1] J.R. Wolpaw, N. Birbaumer, D.J. McFarland, G. Pfurtscheller, and T.M. Vaughan. Brain-computer interfaces for communication and control. *Clinical Neurophysiology*, 113:767–791, 2002.

[2] J. del R. Millán, F. Renkens, J. Mouriño, and W. Gerstner. Non-invasive brain-actuated control of a mobile robot by human EEG. *IEEE Transactions on Biomedical Engineering*, 51:1026–1033, 2004.

[3] G. Schalk, J.R. Wolpaw, D.J. McFarland, and G. Pfurtscheller. EEG-based communication: Presence of and error potential. *Clinical Neurophysiology*, 111:2138–2144, 2000.

[4] B. Blankertz, G. Dornhege, C. Schäfer, R. Krepki, J. Kohlmorgen, K.-R. Müller, V. Kunzmann, F. Losch, and G. Curio. Boosting bit rates and error detection for the classification of fast-paced motor commands based on single-trial EEG analysis. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 11:127–131, 2003.

[5] L.C. Parra, C.D. Spence, A.D. Gerson, and P. Sajda. Response error correction—a demonstration of improved human-machine performance using real-time EEG monitoring. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 11:173–177, 2003.

[6] P.W. Ferrez and J. del R. Millán. EEG-based brain-computer interaction: Improved accuracy by automatic single-trial error detection. *21st Annual Conference on Neural Information Processing Systems (NIPS)*, 2007.

[7] P.W. Ferrez and J. del R. Millán. Error-related EEG potentials generated during simulated brain-computer interaction. *IEEE Transactions on Biomedical Engineering*, 55:923–929, 2008.

[8] D. McFarland and J.R. Wolpow. Sensorimotor rhythm-based brain-computer interface (BCI): Feature selection by regression improves performance. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 13(3):372–379, 2005.

[9] G. Pfurtscheller and F.H. Lopes da Silva. Event-related EEG/MEG synchronization and desynchronization: Basic principles. *Clinical Neurophysiology*, 110:1842–1857, 1999.

[10] G. Pfurtscheller and C. Neuper. Motor imagery and direct brain-computer communication. *Proceedings of the IEEE*, 89:1123–1134, 2001.