Learning From EEG Error-Related Potentials in Noninvasive Brain-Computer Interfaces

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***Abstract*—We describe error-related potentials generated while a human user monitors the performance of an external agent and discuss their use for a new type of brain–computer interaction. In this approach, single trial detection of error-related electroencephalography (EEG) potentials is used to infer the optimal agent behavior by decreasing the probability of agent decisions that elicited such potentials. Contrasting with traditional approaches, the user acts as a critic of an external autonomous system instead of continuously generating control commands. This sets a cognitive monitoring loop where the human directly provides information about the overall system performance that, in turn, can be used for its improvement. We show that it is possible to recognize erroneous and correct agent decisions from EEG (average recognition rates of 75.8% and 63.2%, respectively), and that the elicited signals are stable over long periods of time (from 50 to $>$ 600 days). Moreover, these performances allow to infer the optimal behavior of a simple agent in a brain–computer interaction paradigm after a few trials.**

***Index Terms*—Brain–computer interface, electroencephalography (EEG), error-related potentials, reinforcement learning.**

I. Introduction

NONINVASIVE brain–computer interfaces (BCIs) and neuroprostheses aim to provide a communication and control channel based on the recognition of the subject intentions from the spatiotemporal neural activity (usually EEG). Typically, user's involvement in current BCI systems is highly demanding in terms of cognitive attention and effort, since he/she needs to continuously deliver mental commands for the brain-actuated device (e.g., a prosthesis, a robotic wheelchair, a computer cursor). In order to surmount this issue, some groups have applied the concept of *shared autonomy* in order to divide the control task between the human user and the device [1], [2], thus reducing the overall load of the human user. Moreover, BCI systems are prone to errors in the recognition of human intentions, increasing the overall difficulty of its use.

Alternatively, we discuss here a new interaction approach where the user monitors the performance of an autonomous *agent* endowed with learning capabilities, and the erroneous behavior of the agent is recognized directly from the analysis of the user's brain signals (i.e., error-related EEG potentials). Furthermore, such potentials can provide the critical information for the agent to learn the optimal behavior according to the user's intention. In this approach, the user acts as a *critic* of the agent's actions providing reinforcement signals that the agent utilizes for improving the overall performance [3].

Our approach is based on the ability of recognizing errors, which is crucial for learning in both humans and animals [4], as well for improving the performance of artificial systems. Recent studies have strongly suggested the existence of a neural system responsible for error processing [5]–[9]. Specifically, a stereotypical electrophysiological signal has been consistently reported to appear as a response to erroneous actions in speed response tasks [7], [10], [11]. This signal—termed *error-related negativity* (ERN)—is characterized by a negative deflection appearing from 50 to 100 ms after the response, followed by a centro-parietal positive peak (Pe). Moreover some studies have pointed out a correlation between trial-by-trial estimates of the ERN and the post-error slowing [12]. Based on these findings, it has been proposed that the ERN signal is the result of an error-detection mechanism, as opposed of being an inhibitory or corrective signal. In addition, it has been proposed that the Pe component of the ERN reflects conscious error processing or post-error adjustment of response strategies [7].

Similarly, and directly related to the framework put forward in this paper, a medial frontal negativity has been found to appear during *observation* of erroneous actions [13]. As in our case, subjects simply monitor someone's actions and the ERN is modulated by the correctness of observed behavior. In particular, there is a negative deflection of the ongoing EEG 250 ms after observing an erroneous response of the operator.

Upon identification of errors, learning of optimal behavior can be achieved by decreasing the likelihood of repeating such decisions in the same context. Specifically, the reinforcement learning theory states that learning—i.e., behavior adjustment—is driven by the difference of observed and expected action outcomes (i.e., reward prediction errors) [3]. Interestingly, several neurophysiological studies have provided evidence of neural correlates of this type of learning [14], [15]. Holroyd and Coles have proposed that the anterior cingulate cortex (ACC), presumed source of the ERN, plays a role on this process by using outcome related signals (i.e., the *feedback-related negativity*, FRN) to adapt reward-seeking behavior [8]. Multiple studies have shown modulations of the FRN signal in decision-making tasks as changes in the amplitude of this potential after losing situations predict decision changes in strategic economic games [16]. Additionally, other experimental results suggest that inter-subject differences of FRN amplitude may indicate whether a person is more sensitive to positive or negative reinforcers [17].

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In the frame of brain–computer interaction, Ferrez and Millán have described an error-related EEG potential elicited by errors in the recognition of the user intention when operating a BCI. In their experimental protocol, the human subject tries to move a cursor towards a target location either using a keyboard [18] or mental commands [19]. A consistent evoked potential was found to be generated as a product of errors induced by the interface. This interaction error-related potential (ErrP) is characterized by two fronto-central positive peaks appearing 200 ms and 320 ms after the feedback; a fronto-central negativity near 250 ms and a last, broader fronto-central negative deflection about 450 ms after the feedback. Comparison of experimental measures taken in a period of three months show that these potentials are very similar despite the delay between recordings. In addition, further experiments confirmed that these potentials were mainly related to errors, while being less sensitive to other experimental variables (e.g., frequency of the stimuli appearance, as in *oddball paradigms*).

Although these signals (ERN, FRN, and ErrP) convey valuable information about the user's evaluation of performance, they have seldom been used in the field of noninvasive BCI [19]–[23]. In one of the few related works, Parra *et al.* propose the detection of ERNs to correct user erroneous decisions on speed response tasks [21], while Ferrez *et al.* evaluate the use of ErrPs to improve the information transfer rate of a BCI system [19]. These studies are focused on the correction of errors once the user has emitted a command. Such approach proved to be more efficient that verification procedures previously proposed to improve performance of BCI applications [24]. Nevertheless, they do not include a learning mechanism to prevent that error to be repeated in the future.

In this work, we assess whether similar error-related signals are generated when a human user monitors the performance of an external agent upon which he/she has no control whatsoever. Contrasting to traditional BCI systems, under this approach, the user does not provide commands in a continuous manner, but only monitors the agent's performance. In addition, using a simple BCI paradigm, we show that error-related potentials decoded during human–machine interaction can be used to infer the optimal behavior of the agent, according to the user's intention. This approach puts the human within a *cognitive monitoring loop* with the agent, thus making possible to tailor the agent's behavior to the user's needs and preferences.

Section II of this paper presents the experimental methods and classification techniques used in the study. Section III introduces the idea of using error-related EEG potentials as a learning signal in brain–computer interaction. Experimental results are presented in Section IV, including the description of the EEG signals evoked by monitoring of an external system, single-trial classification, as well as an offline study on the use of ErrP detection to improve the performance of the artificial system. The experimental results and future lines of research are discussed in Section V.

II. Methods

A. Experimental Setup

We have adapted an experimental protocol used previously to study error potentials during brain–computer interaction [19].

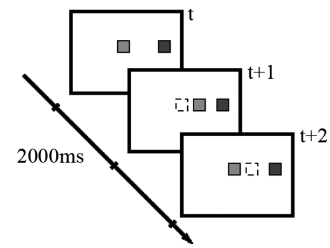


Fig. 1. Experimental protocol. *Green square*, moving cursor. *Red square*, target location. *Dotted square*, cursor location at the previous time step. Correct and erroneous movements are shown at times $t+1$ and $t+2$, respectively.

TABLE I
Time Difference (in Days) Between the two Experimental Recordings

	Subject					
P_{err}	1	2	3	4	5	6
20%	51	50	54	211	628	643
40%	–	–	54	211	628	643

In the current study, humans do not send commands to the autonomous agent and are asked to only assess whether it performs properly. From the recorded EEG signals we extract and analyze event-related potentials elicited after erroneous and correct trials.

Subjects seat in front of a computer screen where a moving cursor (i.e., a green square) is displayed. A colored square at either the left or right of the cursor indicates the target location, as shown in Fig. 1 (targets in the left appear as a blue square, while targets on the right of the cursor are red). At each time step (i.e., thereafter termed a trial) the cursor moves horizontally depending on the location of the target. Trials have an approximate duration of 2000 ms. Once the target is reached, the cursor remains in place and a new target location is drawn at no more than three positions away from the current cursor position. If the new location falls outside of the working area, it is relocated at the center of the screen. The working area consists of 20 locations along the middle horizontal plane of the computer monitor, and subjects are asked to fixate the center of the screen. Therefore, the relative position of the target with respect to the cursor is not necessarily in the same visual hemifield.

During the experiment, the user has no control over the cursor's movement and is asked only to monitor the performance of the agent, knowing that the goal is to reach the target. In order to study signals generated by erroneous actions, at each time step there is a probability of P_{err} for the cursor to move in the wrong direction (i.e., opposite to the target location). For a given error probability, P_{err}, each experimental session consists of 10 blocks of 3 min each (an average of 64 trials per block). Six subjects (1 female, mean age $= 27.83 \pm 2.23$) perform a first recording (Session 1) with two conditions $P_{\mathrm{err}} = 0.20$ and $P_{\mathrm{err}} = 0.40$. A second recording (Session 2) for the same conditions was performed several weeks after the first one. All six subjects perform the second recording with $P_{\mathrm{err}} = 0.20$, and 4 of them (1 female, mean age $= 27.75 \pm 1.50$) took part in a second session with $P_{\mathrm{err}} = 0.40$. Table I shows the number of days between the two recordings for all subjects and conditions.

EEG potentials were recorded at a sampling rate of 512 Hz for all subjects using a Biosemi ActiveTwo system. We use 64 electrodes according to the standard 10/20 international system. Data was spatially filtered using common average reference (CAR) and then a 1–10 Hz band-pass filter was applied. Epochs corresponding to erroneous and correct cursor movements were extracted for further analysis and classification. EEG preprocessing was done using the EEGLAB Matlab toolbox [25].

Since the nature of the experiments may induce lateral eye movements, we compute the horizontal electrooculogram (HEOG) as the difference between two lateral frontal electrodes (F7 and F8), and analyze the signals to discard the possibility of ocular artifacts that could have contaminated the recordings or biased one condition over the other. In principle, however, horizontal eye movements due to gaze shifts to the new position of cursor after errors should not contaminate the medial electrodes Fz and FCz used for the recognition of the ERP.

B. Single-Trial Classification

The use of error-related potentials in practical BCI applications requires their accurate recognition on a single-trial basis. Following previous studies, we classify the signals using a Gaussian classifier, as described in [18]. This statistical classifier estimates the posterior probability of a single trial corresponding to one of the two classes "*error*," and " *correct*."

In this study, each class is assigned the same prior probability. The class-conditional probability density function C_k, for class $k \in \{error, correct\}$, is a superposition of N_k Gaussian prototypes; the number of prototypes is equal for both classes $(N_k = N_p, \forall k)$. All prototypes having equal weight $(1/N_p)$, the activity a_k^i of the ith prototype of class C_k for a sample x is

$$a_k^i(x) = |\Sigma_k|^{-1/2} \exp\left(\frac{-1}{2}(x-\mu_k^i)^T \Sigma_k^{-1}(x-\mu_k^i)\right) \quad (1)$$

where μ_k^i is the center of the ith prototype of class C_k and Σ_k^i is the covariance matrix for that class and $|\Sigma_k^i|$ is the determinant of that matrix. Here, a common diagonal matrix Σ_k^i was used for all classes. The posterior probability, y_k of a sample x corresponding to the class C_k is

$$y_k = p(x|C_k) = \frac{a_k(x)}{A(x)} = \frac{\sum_{i=1}^{N_p} a_k^i(x)}{\sum_{k'=1}^{2}\sum_{j=1}^{N_p} a_{k'}^j(x)} \quad (2)$$

where a_k^i is the activity of class C_k, and A is the total activity of the network. The response of the classifier for the input sample x is the class with highest probability.

Following previous studies in our laboratory the electrical activity on the FCz and Cz electrodes, downsampled to 64 Hz, was used as input to the classifier (for details of the electrode selection process, see [26]). The same learning rates and number of prototypes were used in all cases. Classifier parameters are then tuned using a stochastic gradient descent on the mean square error [18]. Learning rates were 10^{-2} and 10^{-4} for the center and covariances of the Gaussian prototypes, and a total of 6 prototypes were used for each class. Electrodes (FCz, Cz, or both) and time windows used for classification were selected independently per subject based on the classification performance in the training set. Sessions on the first recording day were used as training set, and session 2 was used for testing the classification performance.

III. Error-Based Learning in Brain–Computer Interaction

Given the possibility of detecting error-related potentials in single trial, we want to explore next whether this information can be exploited to infer the optimal behavior of the agent. The rationale of this approach is that, given the system decisions and the user's evaluation of such decisions—indicated by the presence or not of ErrPs—it is possible to infer what strategy is considered as correct by the human user [27].

The agent's optimal strategy is to move the cursor towards the target location. Let $T_t, A_t \in [L, R]$ be the target location and the cursor's direction of movement at time t, respectively, with $[L, R]$ standing for left and right, respectively. We define $P_{A,T}$, the probability of taking action A given the target location T under the strategy Π, as

$$P_{A_t,T_t} = P(\text{Action} = A_t \mid \text{Target} = T_t, \Pi). \quad (3)$$

The optimal strategy Π^* is $P_{L,L} = P_{R,R} = 1$ and $P_{L,R} = P_{R,L} = 0$.

At any time step, the current strategy can be improved upon recognition of ErrP by decreasing the likelihood of performing actions considered as erroneous and, in the opposite case, to encourage correct actions. Let define $\Pi^t = \{P_{L,L}^t, P_{L,R}^t, P_{R,L}^t, P_{R,R}^t\}$ the strategy at time t. Then, if an ErrP is detected, the probability of repeating the action A_t given the target location T_t must be decreased

$$P_{A_t,T_t}^{t+1} = P_{A_t,T_t}^t - \Delta P_{A_t,T_t}^t. \quad (4)$$

Conversely, if the trial is considered as correct, P_{A_t,T_t}^t is increased by Δ. The probabilities of other actions given T_t are updated so that $\sum_i P_{A_i,T_t} = 1$. Note that we keep separate models for each possible target location.

We choose a variable learning rate Δ such that probabilities close to chance level are penalized (i.e., $P_{A_t,T_t}^t = 0.5$ for two-action problems). In the current implementation

$$\Delta P_{A_t,T_t}^t = \eta H(P_{A_t,T_t}^t) \quad (5)$$

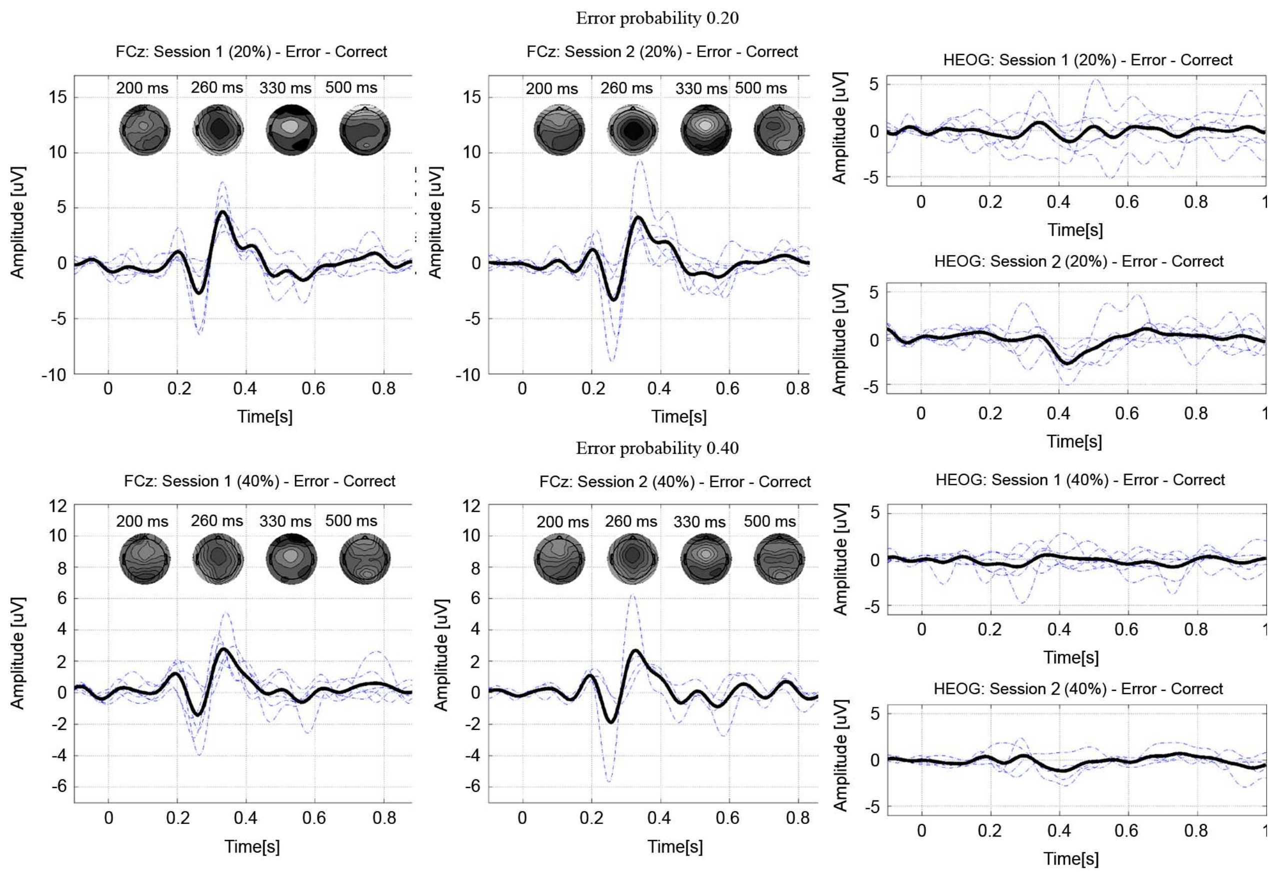
where η is a constant scaling factor and $H(x)$ is the binary entropy function

$$H(x) = -\sum_i^n P(x_i)\log_2 P(x_i). \quad (6)$$

IV. Experimental Results

A. Event-Related Potentials

Consistently with previous studies EEG error-related activity appears in fronto-central areas, as illustrated by the topographical maps of scalp activity in Fig. 2. This figure also shows the



(a) (b) (c)

Fig. 2. Grand average event related potentials, error-minus-correct condition (*thick line*); *thin dashed lines* indicate individual subject averages. *Top*: Error probability 0.20, *Bottom*: Error probability 0.40. The first two columns show the ERP on the FCz electrode for the two recording sessions. Topographical maps of scalp activity appear in the insets (nose up); activity is color coded fom black to white in the range $[-5\ 5]\ \mu\mathrm{V}$. Right-most column shows the horizontal EOG (F7-F8). Time $t = 0$ corresponds to the feedback onset (a) Session 1, (b) Session 2, (c) Horizontal EOG.

grand average ERP for the error minus correct condition in the FCz electrode for $P_{\mathrm{err}} = 0.20$ ($N = 6$ subjects in both sessions) and $P_{\mathrm{err}} = 0.40$ ($N = 6$ and $N = 4$ subjects in sessions 1 and 2, respectively). In all cases the waveform is characterized by a small positive peak near 200 ms after delivery of feedback, followed by a negative deflection around 260 ms. A second, larger positive peak appears around 330 ms. Statistically significant differences between error and correct trials were found for the three peaks in all the experiments ($p < 0.001$; except for the negative peak in the first session with err probability 0.40 with $p = 0.135$). These signals, elicited during user monitoring of the system performance, are similar to other error-related signals, in particular interaction error potential [18]. Moreover, the probability of errors does not change significantly the signal waveform, although the peak amplitude appears to decrease with higher error probabilities, as reported in previous studies [19]. Quantitatively, the waveforms of the two grand-average ERPs have an almost perfect correlation (Pearson's correlation coefficient $r = 0.96$).

The stability of these signals is a key issue for their use in practical applications. Comparison of the ERPs for the two different recording days shows that the signal remains stable over several weeks (cf. Fig. 2). In particular, the first three ERP components—i.e., negative peak at 260 ms and two positive peaks at 200 ms and 330 ms—are quite stable between the two recording sessions. No significant difference was found between sessions in any of the three components for error probability 0.20 ($p > 0.29$). In the case of error probability 0.40, no significant difference was found between sessions in the signals elicited by correct trials at $t = 260$ and $t = 330$ ms ($p > 0.05$). However, we did find significant differences in the case of signals generated at error trials ($p < 0.05$) for two of the subjects. Nevertheless, a high correlation was again found between the grand-average ERPs (Pearson's coefficient $r = 0.97$ and $r = 0.91$ for error probability 0.2 and 0.4, respectively).

Fig. 2 also shows the horizontal EOG for the error-minus-correct condition. It seems that eye movements are not contaminating the ERP. The only peak with a relatively large amplitude appears slightly after 400 ms in just one experiment, which is used as testing test. Furthermore, the correlation between the signal at the FCz electrode and HEOG is very low (average of single-trial correlation is -0.008 ± 0.26, -0.03 ± 0.27, -0.02 ± 0.24, and -0.04 ± 0.26 for the four experiments, respectively). Also, a previous study with the same protocol showed no influence of gaze shifts on the ERP when the analysis is done with respect to the side where the target appears [19].

TABLE II
SINGLE TRIAL RECOGNITION RATES (%) FOR ALL SUBJECTS ON THE TEST SET (I.E., SESSION 2), ERROR PROBABILITY 0.20. LAST COLUMN SHOWS THE AVERAGE RECOGNITION RATE OVER THE 6 SUBJECTS

$P_{err} = 0.20$

	S1	S2	S3	S4	S5	S6	Avg
Electrodes	FCz,Cz	Cz	FCz,Cz	FCz	FCz,Cz	FCz,Cz	
Time window (ms)	200-450	150-600	200-450	0-600	150-600	150-600	
Correct	85.84	73.71	82.18	70.73	74.31	68.06	**75.81±6.84**
Error	76.07	65.89	69.66	58.33	58.20	51.09	**63.21±9.06**

TABLE III
SINGLE TRIAL RECOGNITION RATES (%) FOR ALL SUBJECTS ON THE TEST SET (I.E., SESSION 2), ERROR PROBABILITY 0.40. LAST COLUMN SHOWS THE AVERAGE RECOGNITION RATE OVER THE 4 SUBJECTS

$P_{err} = 0.40$

	S3	S4	S5	S6	Avg
Electrodes	FCz,Cz	FCz,Cz	FCz,Cz	FCz	
Time window (ms)	200-450	0-600	150-600	150-600	
Correct	75.85	57.78	62.68	53.38	**62.42±9.72**
Error	67.84	50.67	61.54	57.39	**59.36±7.21**

B. Single-Trial Classification

We assess single trial classification of error-related potentials using the second session as testing set. This allows us to evaluate the feasibility of recognizing such signals using classifiers built on data recorded several weeks before. Table II shows the recognition rates for the condition $P_{\text{err}} = 0.20$. Successful single-trial classification is achieved for both classes with higher detection of correct trials (mean classification accuracy of 75.81% and 63.21% for correct and error trials, respectively). Subject differences are also observed with better performance for subjects 1–3, for whom the recordings were about seven weeks apart. In addition, it must be noticed that reasonably good performances are also achieved for subjects 4 and 5, whose recordings were around 200 and 600 days apart.

Regarding the experiment with 40% of errors, classification performance is lower than in the previous condition, with mean accuracies of 64.42% and 59.36% for correct and error trials, respectively (cf. Table III). As previously noted in Section IV-A, the amplitude of the ERP appears to be inversely modulated by the error rate. Nevertheless, subjects 3 and 5 achieve performances around 70% and 60% for both correct and error conditions, respectively.

No variation was found in the within-session performance with respect to time. This suggests that fatigue or changes in the attentional level did not affect the classification. We assess this by dividing the test session in 10 consecutive intervals and computing the performance for each interval. The variance in performance across intervals is lower than 0.08 for all subjects and conditions.

Additionally, to assess whether performance variations are due to the time difference between the two recording sessions, we compute the within-session classification performance using a 10-fold cross-validation for both error probabilities keeping the same parameters (electrodes and time windows) as above. We found similar performances for cross-validation than those obtained using session II as testing set for all subjects and conditions (Fig. 3). The difference in performance is within the standard deviation (SD) for all cases, except three of them where

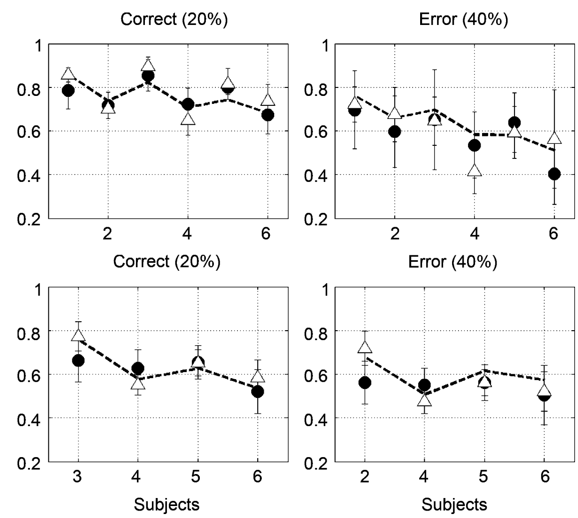


Fig. 3. Within-session 10-fold cross validation $(\mathrm{mean} \pm \mathrm{SD})$. *Top*: Error probability 0.20. *Bottom*: Error probability 0.40. *Dotted line*: test performance on session II. *Dots* (●): CV test performance on session I. *Triangles* ($\triangle$): CV test performance on session II.

was below 1.8 times the SD. This suggests that, since trial variability within—and across—sessions is not significantly different, inter-subject differences have stronger influence on performance than the time elapsed between sessions.

C. Error-Based Learning

We test the error-based learning approach using the classified data on the second session ($P_{\text{err}} = 0.20$) for all subjects. Starting from a random policy, $\Pi^{t=0} = \{P^t_{L,L} = P^t_{L,R} = P^t_{R,L} = P^t_{R,R} = 0.5\}$, each trial is classified as corresponding to an erroneous or correct trial using the EEG activity. Based on this classification, the policy Π^t is updated using the (4) (scaling factor $\eta = 0.1$). Fig. 4 depicts how the policy changes with time, until it converges to the optimal strategy Π^*. For all subjects, the recognition of error and correct trials increases the probability of performing the correct action for both possible target locations. The optimal strategy is acquired in much less than 50 trials for all subjects, except subject 6 who requires a few more.

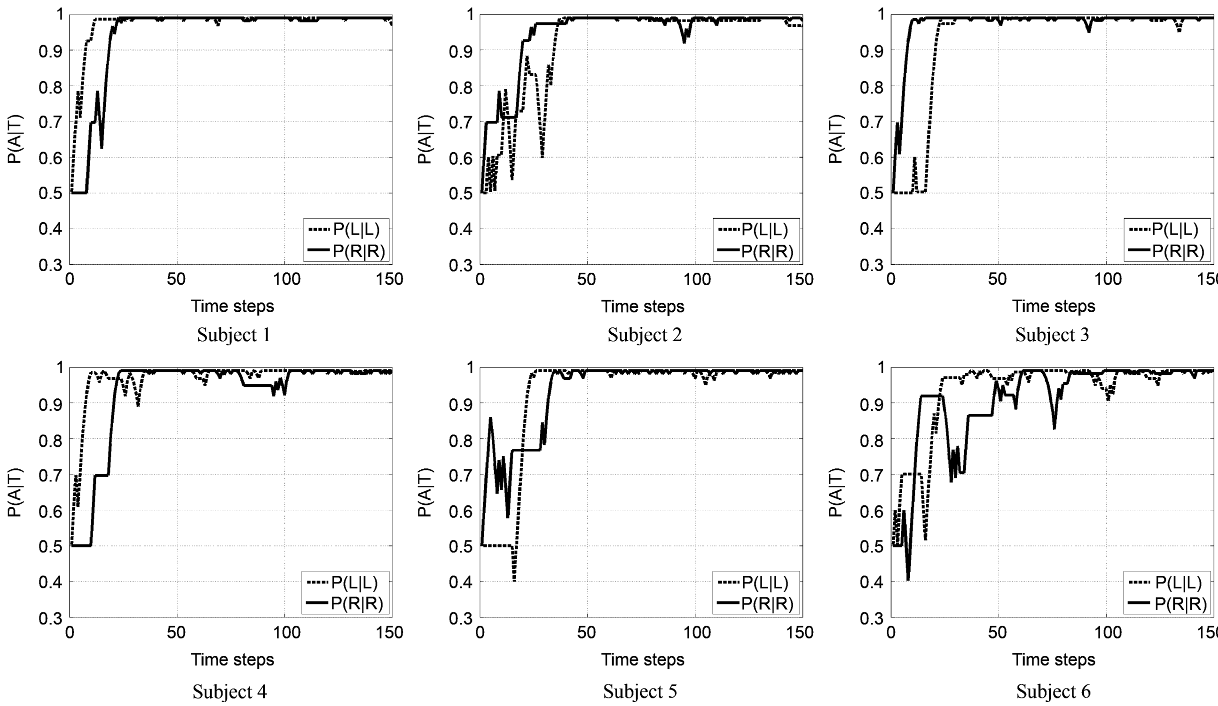


Fig. 4. ErrP-based learning of the user's intended strategy for all subjects. The X-axis represents the time steps and the Y-axis represents the probability of performing the correct action given the current strategy (i.e., $\Pi^t = \{P^t_{L,L}, P^t_{R,R}\}$).

Notice that the update rule based on the entropy function yields a small step size when $P(A|T)$ is close to one or zero, making such conditions very stable.

These results show that single-trial recognition of correct and error trials can be achieved and provides critical information for an autonomous agent to learn the user's intended strategy, thus improving its performance. In the present experiment we show that it is possible to infer in just a few interaction trials the optimal policy from the user's EEG signals evoked by the agent's decisions.

V. Discussion

This study extends previous works on error-related potentials during the operation of brain–computer interfaces to a new scenario, namely the human monitoring of the performance of an external autonomous device. We report EEG signals elicited when the user perceives an erroneous decision taken by a system upon which he/she has no control. Moreover, we show that optimal control strategies can be inferred by using the ErrPs as negative reinforcers of the actions that elicit such signals.

Grand average ERPs show error-related potentials similar to those previously reported during the operation of BCI systems [19]. Furthermore, these ERPs exhibit a medial-frontal negative peak around 260 ms, in agreement with a previous study on observation of erroneous actions [13].

Consistently with reported findings, peak amplitudes are inversely modulated by the frequency of errors. Nevertheless, waveforms reported in this and similar studies remain similar independently of the error probability. This suggests that, although we cannot exclude contributions from oddball-related EEG components (i.e., P300 components), these signals cannot be entirely attributed to them.

Similar deflections in fronto-central areas have been reported in visual attention tasks [28]. In an experimental protocol studying selective attention to color, location or the conjunction of both, authors reported the same three components observed in our protocol (i.e., positive deflections around 200 and 350 ms and a negative deflection around 250 ms). The first positive component appeared to be modulated by color selection. In contrast, the negative component—referred to as N2b—was modulated by the appearance of attended stimuli in the three conditions, thus probably related to feature independent attention processes. Specifically, Lange *et al.* suggest this component to reflect the activity of a system (located in the ACC) able to evaluate the presented stimulus and select responses accordingly.

In the current experiment, erroneous feedback is correlated to the cursor direction of movement (i.e., opposite to target location) thus spatial location could influence the reported EEGs. Nevertheless, we have found similar ERP waveforms in a study where visual feedback was always displayed at the same location during teleoperation of a mobile robot [29], [30]. This suggests that these signals are mainly related to the cognitive monitoring process rather than spatial visual attention, although is not yet clear whether these waveform generalize to other modalities of feedback.

Moreover, several studies point out that novelty related ERP components have a predominant posterior scalp distribution, whereas components related to cognitive control (e.g., ERN, FRN) are located in anterior sites [31], as are the ERPs reported in this work. Thus, the presented signals are consistent with previously reported "N2-P3" signals and are mainly modulated by the erroneous behavior of the agent and to a lesser extent by the frequency of errors.

To summarize, the observed ERPs are similar to previously reported waveforms correlated to error-processing, novelty and attentional processes. Moreover, such signals appear to be generated in the same brain area (i.e., anterior cingulate cortex, ACC). The question of whether these signals correspond to different cognitive processes is yet to be elucidated [32]. Nevertheless, we claim that these processes are consistent to the cognitive monitoring process proposed by our approach; as well as with the reinforcement learning theory of ERN [8]. Further studies are required to fully characterize the cognitive phenomena that originate this signal, and to assess how the different components of the waveforms are modulated by factors like attention, error processing and stimulus frequency.

We assess single trial recognition for both error and correct conditions, achieving higher performance for lower error probabilities. Remarkably, the waveforms remain stable after long periods of time (from 50 to >600 days) and our results show the feasibility of recognizing these signals without need for retraining. Moreover, comparison of the classification performance within- and across-sessions suggests that the observed differences across subjects is not due to differences in the time between the two recording sessions, and that for a given subject the inter-trial variability does not change with time.

Previous studies have proposed the use of error potentials to correct mistakes in motor responses during human–machine interaction. Parra *et al.* implemented a system where EEG signal is acquired while a human user executes a forced two-choice visual discrimination task [21]. EEG classification using linear discriminant analysis (LDA) yields a 21% increase of performance with respect to the human performance without ERN-based correction. Alternatively, Ferrez and Millán successfully use statistical classifiers to achieve single-trial recognition of error-potentials during interaction, either using a keyboard or a BCI, yielding a theoretical increase in the information transfer rate of a BCI up to 70% [18], [19].

Complementing these studies, and based upon successful single-trial classification of the ERP, we put forward the use of such signals in a cognitive monitoring loop where the user provides corrective signals that the external agent can exploit to modify its behavior taking into account the user's intentions and preferences. In a simple paradigm we applied a ErrP-based learning mechanism that decreases the likelihood of actions eliciting these potentials (i.e., actions perceived as erroneous by the human). Although the performance of ErrP detection is far from perfect, this approach converges towards the optimal behavior in a short number of steps, even for those subjects with low classification rates. The reason for such a steady convergence despite the relatively low error recognition rates is that, contrarily to previous approaches coupling ERP and BCI where error detection corrects the *current* BCI output, in our framework error detection changes the *future* behavior of the agent.

Like other interaction schemes, performance is modulated by the level of attention of the user. This may have particular effects in systems with low performance or protocols that fail to engage the subject's interest. In order to further study these issues, as well as the applicability of the approach, we are extending it to more realistic experimental conditions (i.e., navigation in virtual environments) where preliminary results show that it is also possible to recognize error-related signals above chance level [33]. Moreover, coupling the current approach with the estimation of the user's attentional level—using EEG and other physiological signals [34]—can allow to study how error-related signals are dependent on attention. Other future research avenues to explore are the scalability of our approach, in terms of the number of states and actions, as well as its online application.

The approach presented in this work relies on the detection of a particular cognitive state, i.e., the user's recognition of the agent's errors. This allows a type of brain–machine interaction that relieves the user of the burden of providing control commands in a continuous manner. Moreover, it takes advantage of a unique characteristic of the brain channel that carries information about cognitive states of the user. Future developments along this line may take further advantage of this characteristic to improve human–machine interaction by exploiting other cognitive states or processes such as image processing [35], anticipation of future events [36], fatigue [34], or mental workload [37].

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