

Execution and Omission Errors in Human–Robot Interaction: An EEG Study

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ABSTRACT: Brain-computer interface research has extensively investigated the use of error-related potentials in human-robot interaction. However, while previous research demonstrated the successful decoding of erroneous task execution from the user's electroencephalogram, errors of omission, i.e., the non-execution of an expected activity, remain underexplored. The current work investigates the cortical responses to both execution and omission errors during a robot-assisted task. The grand average event-related potentials ($N = 12$) revealed a significantly attenuated error positivity related to activity omission, likely reflecting reduced confidence in the occurrence of an error. In addition, we could decode both types of errors at a single-trial level with an average balanced accuracy of 80 % in a synchronous classification approach. The results of this work contribute to the development of autonomously corrective systems for human-robot interaction.

INTRODUCTION

Whether to improve, extend, or restore our capabilities, collaborative interaction between humans and robots is increasingly gaining attention from health sciences to industrial settings [1]. Especially for people experiencing limitations in motor function, systems that enable human-robot interaction have considerable potential to provide greater autonomy and thus improved quality of life [2]. However, limitations in the performance of robotic assistance [3], and the intrinsic challenges of adapting such complex systems to changing environments [4], still hinder advancements in the field. To alleviate these shortcomings, human-in-the-loop approaches continue to emerge in which, e.g., robot parameters are adjusted based on the current collaborative performance [5, 6]. However, these approaches require external performance metrics (e.g., ground truth and targets), which are rarely available, particularly in the context of robotic end-effectors designed to restore human capabilities. One approach to circumvent this lack of external metrics for improving performance relies on the users themselves. Specifically, previous studies in the field of brain-

computer interfaces (BCIs) [7, 8] directly leveraged human error-monitoring capabilities to automatically correct errors committed by the robot and to adapt the system itself based on user-derived feedback [9]. To this end, the sequence of error-related negativity (ERN) and error positivity (Pe) — two prominent markers of unconscious and conscious error processing in error-related potentials (ErrPs) [10] arising 100 ms and 300-500 ms after an erroneous event, respectively [11] — can be decoded non-invasively using electroencephalography (EEG). For example, a study by Salazar-Gomez and colleagues employed ErrPs to automatically correct erroneous robot movement during a binary object selection task [12]. In contrast, other work used ErrPs as reward signals in reinforcement-learning to adapt the behavior of a robotic arm or learn to navigate a mobile robot in a foreign environment, both in virtual and real-world settings [13, 14].

Overall, a considerable body of research has investigated ErrPs in the context of human-robot interaction. Nevertheless, these reports almost exclusively document ErrP decoding in relation to erroneous *execution* of an intended task [12, 15–19]. In contrast, reports on *omission* errors — errors relating to the *absence* of a reaction altogether rather than the illegitimate execution of a task [20] — remain scarce [21]. In BCI contexts, however, such aborted responses hold specific relevance for spelling devices [22], motor decoding tasks [23, 24], and other applications. Detailed investigations of neurophysiology and applicability of the different error types in human-robot-interaction remain, to the best of our knowledge, to be demonstrated.

The current study aims to close this gap by exploring cortical responses to errors in execution and errors by omission during human-robot interaction. Specifically, we aim to answer two research questions: (1) Are there differences in the ErrPs elicited by erroneous task execution and omission? (2) Can these error types be distinguished from correct task execution in BCIs? The results of this work should expand the current scope of EEG-based error detection for human-robot interaction and advance the development of adaptive and corrective systems.

MATERIALS AND METHODS

Participants: Twelve volunteers (6 male, 6 female, 28 ± 2 years (mean (M) $\pm$ standard deviation (SD)) participated in this study. All participants were right-handed and 6 were naïve to BCIs. The study was approved by the University of Melbourne Human Research Ethics Committee (Project ID: 20853). Written consent was obtained from all participants before the experiment. All participants received a \$20 AUD voucher after completion.

Data acquisition: We recorded EEG signals with 32 electrodes positioned according to the 10-10 system at AF3, AF4, F7, F3, Fz, F4, F8, FC5, FC1, FCz, FC2, FC6, C3, C1, Cz, C2, C4, CP5, CP1, CPz, CP2, CP6, P7, P3, Pz, P4, P8, PO7, PO3, PO4, PO8, and Oz. Ground and reference electrodes were placed at AFz and on the right ear lobe, respectively. In addition, we acquired 4-channel electroocular (EOG) signals (outer canthi of both eyes, above and below the right eye) and 4-channel electromyographic (EMG) signals (flexor digitorum profundus, referenced to the respective elbow on each arm). All signals were recorded with active electrodes (g.USBamp amplifier with g.Scarabeo electrodes, g.tec medical engineering, Austria) and synchronized with the experimental markers using Simulink (Matlab 2015a, MathWorks Inc., USA). Data were recorded at a sampling rate of 512 Hz.

Experimental setup and design: The experimental task resembled a whack-a-mole game in which participants used a robotic arm (Reachy, Pollen Robotics, France) to press a button indicated to them. The participants sat comfortably in a chair facing a two-button setup, holding a tennis ball in each hand (Fig. 1). Upon illumination of one of the buttons, they were instructed to squeeze the ball in the corresponding hand. The increase in EMG activity (see *EMG data processing*) triggered the robot to start a predefined sequence of movements (i.e., *movement initiated*) to press the button. First, the robot moved toward the selected button and stopped momentarily at the via point above the button (i.e., *above button*). Next, the robot moved downward to press the button (400 ms), which turned off the light and finally returned to the home position (*correct* task execution). In *error* trials, the robot would either move to the wrong button (erroneous task execution; **ErrMov**) or hover above the correct button for 500 ms without pressing the button (omitted task execution; **NoMov**) before returning to the home position. The experimental protocol encompassed 10 blocks of 40 trials (12 *error*: 6 **ErrMov** and 6 **NoMov**, 28 *correct*), with left and right trials balanced and a randomized trial sequence. The participants were not instructed regarding erroneous robot behavior and hence expected a correctly functioning system.

EMG data processing: EMG signals were decoded online using Matlab 2015a with Simulink to initiate actions of the robotic arm. Specifically, the root mean square (RMS) of the EMG signal was continuously computed using a 250 ms sliding window shifted one sample at a

time. When the RMS exceeded a predefined threshold for either arm, the corresponding robotic movement was triggered. Thresholds were manually tuned for each participant prior to the experiment.

EEG data processing: Offline data processing and analysis were performed in Matlab 2015a and Python using the EEGLAB toolbox [25] and MNE-Python [26], respectively. First, power-line noise was removed using a notch filter at 50 Hz (Butterworth, 2nd order, non-causal). Next, data were band-pass filtered between 1 and 30 Hz (Butterworth, 4th order, non-causal) and downsampled to 128 Hz. Bad channels were identified based on kurtosis and joint probability (both ± 5 SDs) [27] and spherically interpolated. We filtered the data in the 1-10 Hz range (MNE-Python default filter settings) to focus on low frequencies relevant to error processing [9]. Subsequently, we performed independent component analysis using the FastICA algorithm [28] to remove ocular artifacts based on visual inspection. Then, we segmented the data into epochs of 4 s (i.e., [-1, 3] s relative to *movement initiated*). Epochs with residual contamination were removed based on amplitude (exceeding $\pm 100 \mu\text{V}$), kurtosis, and joint probability (both ± 5 SDs). Finally, we extracted segments of 1.75 s, i.e., [-0.5, 1.25] s around both *movement initiated* and *above button*, related to **ErrMov** and **NoMov**, respectively. Epochs of each error type were corrected with the corresponding [-0.25, 0] s baselines.

After data preprocessing, a total of 258 ± 13 *correct* trials, as well as 54 ± 5 (**ErrMov**) and 57 ± 3 (**NoMov**) *error* trials remained per participant (all M $\pm$ SD). On average, we rejected 8% of the recorded trials.

Classification: We implemented the same trial-wise and stimulus-locked classification strategy (*error* vs. *correct*) for **ErrMov** and **NoMov**. Classification features were derived from the time domain signals in the [0.2, 1] s segment after *movement initiated* or *above button*, respectively. Specifically, we computed the average amplitude of overlapping windows with a window length of 100 ms and an overlap of 50 ms (i.e., [0.2, 0.3] s, [0.25, 0.35] s, etc.) [29]. For each participant, we iteratively trained and tested personalized shrinkage linear discriminant analysis (sLDA) classifiers [30] using a stratified 10 times 5-fold cross-validation (CV) scheme with random sampling. The classification threshold was adjusted to the prior probability of the minority class (i.e., *error*) to account for the class imbalance and fixed at 0.15 [31]. To summarize the decoding performance, we computed the true positive rate (TPR; proportion of errors correctly classified), the true negative rate (TNR; proportion of non-errors correctly classified), and the balanced accuracy (BA; the average of TPR and TNR). The reported metrics are the averages of the 50 held-out sets.

Statistics: We performed sample-wise Wilcoxon signed-rank tests (two-sided, $\alpha = 0.05$) to compare event-related potentials (ERPs) of *correct* and *error* events at Cz and controlled the false discovery rate (FDR) with the Benjamini-Hochberg procedure [32]. Similarly, we used Wilcoxon signed-rank tests and subsequent FDR correc-

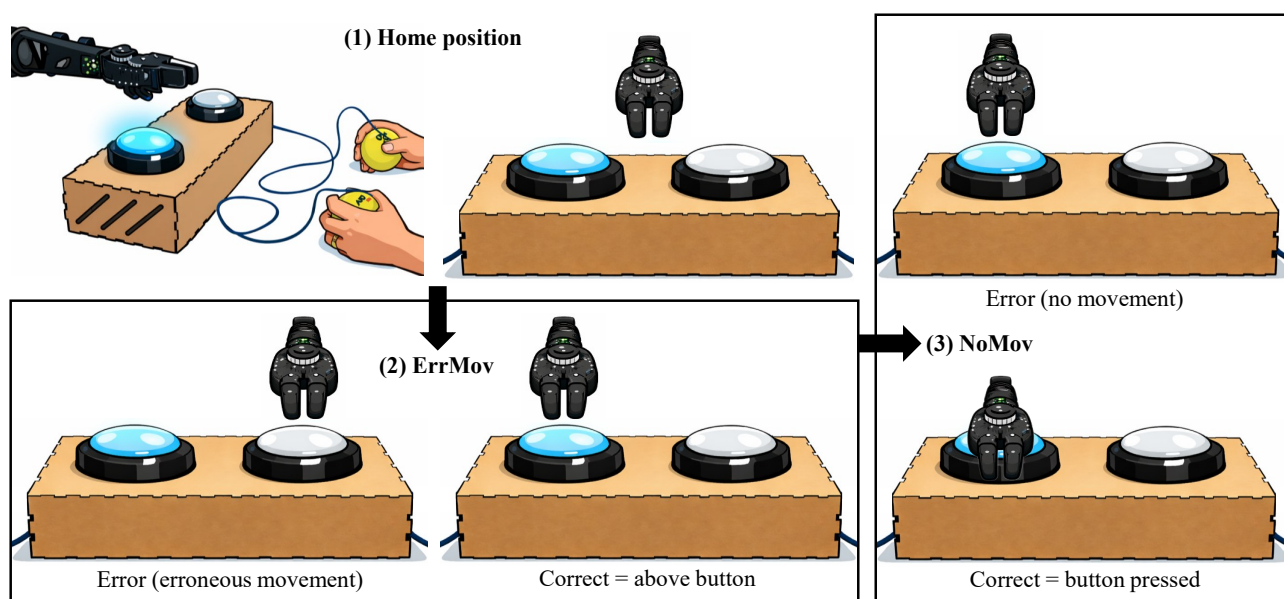


Figure 1: **Experimental setup and paradigm.** (1) The robot rests in the home position and a light instructs the participant to squeeze the left ball. (2) After squeezing (*movement initiated*), the robot moves toward the corresponding button (*above button*). In *error* trials, it instead moves toward the wrong button (**ErrMov**). (3) From the *correct* position (*above button*), the robot either presses the button (*correct*) or omits any movement (*error*; **NoMov**). At the end of the trial, the robot returns to the home position.

tion to compare participant-level ERN and Pe amplitudes. To assess the significance of the classification results, we computed significance levels (SLs) using a shuffling approach. Specifically, we repeated the same 10 times 5-fold CV procedure described in *Classification* 100 times while randomly permuting the class labels in each iteration. The individual SLs were defined as the 95th percentile of the resulting test BA distributions. Additionally, we compared the BAs of **ErrMov** and **NoMov** using a two-sided Wilcoxon signed-rank test ($\alpha = 0.05$).

RESULTS

EEG results: The grand average ERPs ($N = 12$) for both error conditions are shown in Fig. 2. The ErrP for **ErrMov** exhibits the strongest response in Cz and features an initial negative peak 0.45 s ($-4.5 \mu\text{V}$) after *movement initiated*, followed by a positive peak at 0.64 s ($4.5 \mu\text{V}$). Significant differences between erroneous and correct robot movements were observed in the respective segments [0.41, 0.47] s and [0.61, 0.72] s (see Fig. 2a). Similarly, the ErrP to **NoMov** errors comprised negative and a positive components peaking at 0.52 s ($-4.2 \mu\text{V}$) and 0.6 s ($2.8 \mu\text{V}$) after *above button*, with significant activity in the segments [0.5, 0.53] s and [0.59, 0.65] s (all $p < 0.05$). The topographical distributions of the ERPs reveal error-related activity in frontocentral and centroparietal areas of the brain.

Moreover, significant difference arose in participant-level Pe amplitudes in central channels relevant for error processing, i.e., FCz ($p = 0.003$), Cz ($p = 0.005$), and CPz ($p = 0.003$) (see Fig. 3). ERN amplitudes did not significantly differ between error types (FCz: $p = 0.08$; Cz: $p = 0.16$; CPz: $p = 0.2$).

Classification results: The single-trial classification results are summarized in Tab. 1. All participants achieved above-chance decoding performance, irrespective of the error type. Specifically, the grand average BAs ($N = 12$) of 80.6 % in **ErrMov** (TNR = 90.4 %, TPR = 70.8 %) and 79.8 % in **NoMov** (TNR = 89.6 %, TPR = 70.1 %) exceeded the respective SLs (approximately 56%) considerably. No significant BA differences were observed between the two error types ($p = 0.62$).

DISCUSSION

The present work investigated passive BCIs for human-robot interaction. In a game-inspired paradigm, participants initiated a sequence of goal-directed robot movements (i.e., to whack a mole) while experiencing abnormal system behavior typical of real-world robotic applications. Extending prior work on unexpected robot actions [12, 15], we studied neurophysiological responses to erroneous (**ErrMov**) and omitted (**NoMov**) movements, including their use in BCIs.

The responses to both **ErrMov** and **NoMov** comprise a uniform sequence of ERP components in frontocentral and centroparietal brain areas (i.e., ERN and Pe), characteristic of error processing [11]. The latencies observed for both error types were slightly longer than typically reported in related studies (i.e., 200 to 300 ms) [9]. This discrepancy likely resulted from a combination of factors, including hardware limitations, such as delays between user commands and robot activity. Further, contrary to most studies, participants were not confronted with distinct error events (**ErrMov**) but rather with a gradually solidifying error perception, arguably contributing to increased ERP latencies. Indeed, similar findings have been

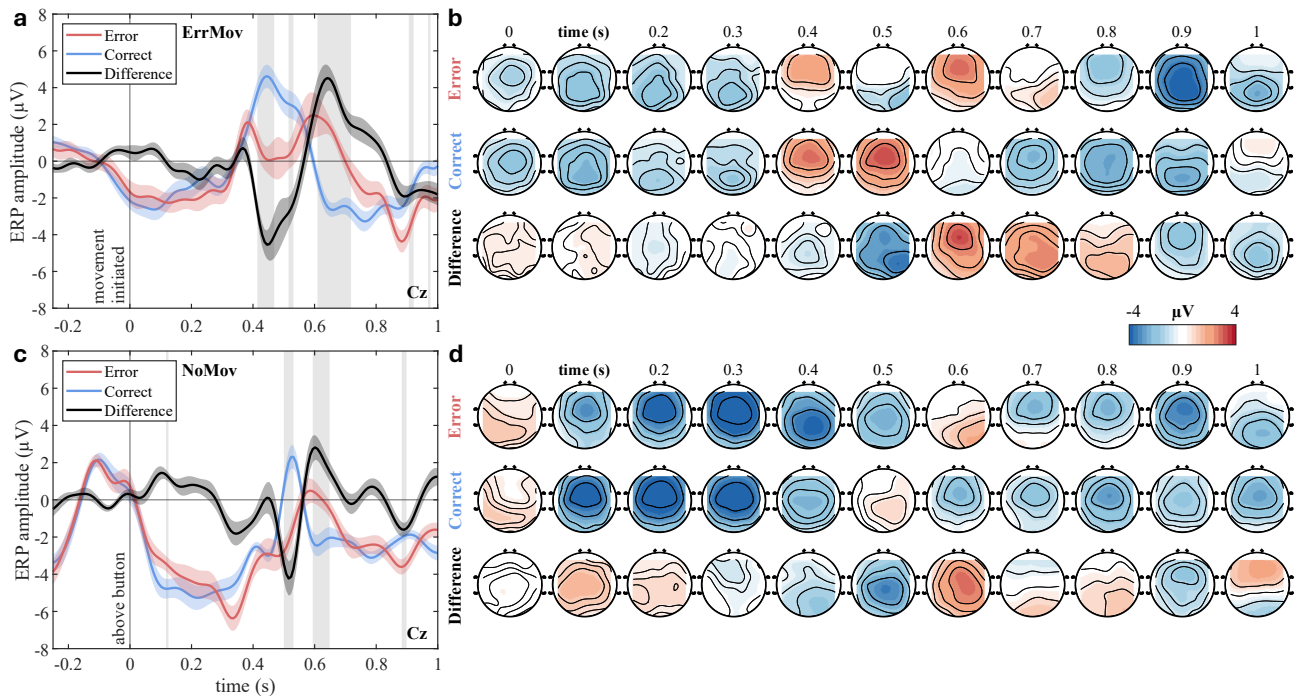


Figure 2: **Grand average ERP results ($N = 12$).** (a) ERPs at Cz for *error* (red), *correct* (blue), and their difference *error minus correct* (black) for **ErrMov**. Shaded areas indicate $\pm$ SE. Gray boxes show significant differences between *error* and *correct* ($p < 0.05$, two-sided Wilcoxon signed-rank, FDR-corrected). Timings are relative to *movement initiated* at time = 0 s. (b) Topographical distribution of the ERPs at the given time points for *error* (top row), *correct* (middle), and *difference* (bottom). (c, d) as in (a, b) for **NoMov**. Timings are relative to *above button* at time = 0 s.

Table 1: **Classification results.** Participant-level results for **ErrMov** and **NoMov**, including TNR, TPR, BA, the significance level (SL), and the corresponding grand average metrics ($M \pm SD$).

Participant	ErrMov				NoMov			
	TNR (%)	TPR (%)	BA (%)	SL (%)	TNR (%)	TPR (%)	BA (%)	SL (%)
P01	91.6	77.2	84.4	54.9	85.3	64.0	74.7	55.8
P02	86.0	58.6	72.3	55.5	85.9	48.0	67.0	56.4
P03	94.8	80.0	87.4	55.6	91.6	79.6	85.6	55.0
P04	87.2	54.5	70.8	55.9	87.5	62.1	74.8	54.5
P05	94.7	76.5	85.6	55.4	89.8	70.7	80.2	55.2
P06	86.7	63.7	75.2	55.6	89.0	71.6	80.3	56.0
P07	89.8	75.9	82.8	55.2	94.3	80.8	87.6	55.6
P08	89.7	66.3	78.0	53.8	93.7	84.8	89.2	55.1
P09	93.2	78.4	85.8	56.6	90.4	66.2	78.3	54.8
P10	87.4	70.8	79.1	55.9	85.4	66.0	75.7	56.7
P11	94.1	82.3	88.2	54.7	91.0	71.6	81.3	55.4
P12	89.8	65.3	77.6	55.3	91.2	75.5	83.3	55.4
$M \pm SD$	90.4 ± 3.2	70.8 ± 9.0	80.6 ± 5.9	55.4 ± 0.7	89.6 ± 3.1	70.1 ± 9.9	79.8 ± 6.3	55.5 ± 0.6

reported for errors in continuous cursor movements [33]. Interestingly, we additionally observed a reduction in peak Pe amplitude in **NoMov** compared to **ErrMov**, while the ERN remained unaffected by the error type. This finding is in line with prior literature that has linked Pe to error awareness [11, 34]. For instance, in studies that explicitly asked participants to signal their committed errors, Pe (but not ERN) amplitudes were attenuated after unreported errors [35]. Similarly, Pe has been associated with the accumulation of evidence that an error has occurred [34]. Consequently, our results suggest that participants were uncertain about the system status when

an action was omitted, whereas movements toward the wrong button constituted an obvious malfunction. The absence of instructions regarding the robot's erroneous behavior may have contributed to these results. Additionally, differences in the physiology might be partially attributed to a smearing effect in the grand average ERPs, resulting from the inherent variability in the onset of the **NoMov** error (*When did participants realize the error, i.e., that the button press would not happen?*). Similar effects have been described earlier [36, 37].

The discrepancy in ERP amplitudes did not translate into a significant difference in classification performance. The

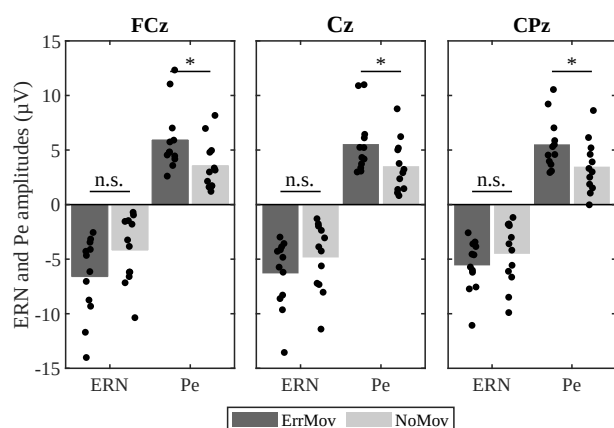


Figure 3: **Comparison of ERN and Pe components.** Dots show the participant-level ERN and Pe amplitudes at FCz (left), Cz (middle), and CPz (right) for **ErrMov** (dark) and **NoMov** (light) and the corresponding group-level averages (bars). Results of the significance tests are indicated (two-sided Wilcoxon signed-rank, FDR-corrected, $\alpha = 0.05$, $*p < 0.01$).

single-trial BAs for both **ErrMov** and **NoMov** scaled at approximately 80 % and were well within the range of typically reported accuracies (i.e., 70 to 80 % for time-locked ErrP classification [9]). This provides evidence that a variety of errors in human-robot interactions, both in unexpected and omitted actions, can be identified through passive BCIs.

CONCLUSION

This work extends the current scope of BCI applications in human-robot interaction by characterizing and decoding EEG responses to erroneously omitted robot activity. We found that both erroneously executed and omitted tasks elicit ErrPs of comparable morphology exhibiting frontocentral and centroparietal activity. Notably, Pe components associated with task omission were significantly attenuated, likely linked to increased uncertainty about the occurrence of an error. Additionally, both error types could be classified on a single-trial level with 80 % BA. This provides evidence that decoding previously underexplored omission errors via EEG can advance autonomously corrective systems in human-robot interaction.

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