A Comparative Pilot Study on ErrPs for Different Usage Conditions of an Exoskeleton with a Mobile EEG Device

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Abstract— **Exoskeletons and prosthetic devices controlled using brain-computer interfaces (BCIs) can be prone to errors due to inconsistent decoding. In recent years, it has been demonstrated that error-related potentials (ErrPs) can be used as a feedback signal in electroencephalography (EEG) based BCIs. However, modern BCIs often take large setup times and are physically restrictive, making them impractical for everyday use. In this paper, we use a mobile and easy-to-setup EEG device to investigate whether an erroneously functioning 1-DOF exoskeleton in different conditions, namely, visually observing and wearing the exoskeleton, elicits a brain response that can be classified. We develop a pipeline that can be applied to these two conditions and observe from our experiments that there is evidence for neural responses from electrodes near regions associated with ErrPs in an environment that resembles the real world. We found that these error-related responses can be classified as ErrPs with accuracies ranging from 60% to 71%, depending on the condition and the subject. Our pipeline could be further extended to detect and correct erroneous exoskeleton behavior in real-world settings.**

I. INTRODUCTION

Research and applications at the intersection of robotics and neuroscience are gaining traction and progressively starting to make positive impacts on healthcare [1]. Brain-computer interface (BCI) development has been an important stepping-stone towards function restoration, and assistive and rehabilitative robotics. Different strategies to control multi-class BCIs have been studied since the 1970s [2] and include, e.g., Steady-State Visually Evoked Potentials (SSVEP) and Motor Imagery (MI) [3]. Electroencephalography (EEG) has been the preferred method to record and decode brain signals, as it is relatively cheap, non-invasive and has a high temporal resolution. Limiting factors such as a low spatial resolution coupled with the non-stationarity of EEG signals constrain the precision with which the user's intent can be decoded, leading to errors. These errors elicit a particular type of response called error-related potentials (ErrPs), which have been shown to occur in the prefrontal region of the brain upon deviations from expected behavior [4], [5]. They have successfully been used to improve BCI decoding performance either by correcting erroneous machine behavior or by error-based adaptation [6]. ErrPs were initially studied in simple cursor-based tasks and then progressed to tasks with robotic devices [7]. Bhattacharyya et al. [8] used a robotic hand setup to elicit visual ErrPs and demonstrated that ErrPs could improve the performance of the robot, thus suggesting the employment of a similar approach for rehabilitative and prosthetic devices. Further, Iturrate et al. [9] showed how a neuroprosthesis could learn optimal motor behaviors using ErrPs elicited from visual observations from a simulated and a real-world device. In addition to this, for the proprioceptive case, it has been shown that event-related potentials (ERPs) are elicited when there is a change in load on the human arm [10]. While these studies point to a path towards intuitive prosthetic and rehabilitative device operation, EEG-based BCIs remain barely used outside laboratories. All the studies cited above were conducted using well-established high-cost wet electrode EEG devices. These setups have higher conductivity at the electrodes and, therefore, a higher signal quality compared to dry electrodes. However, they also require longer setup times and are not well suited for home-based use.

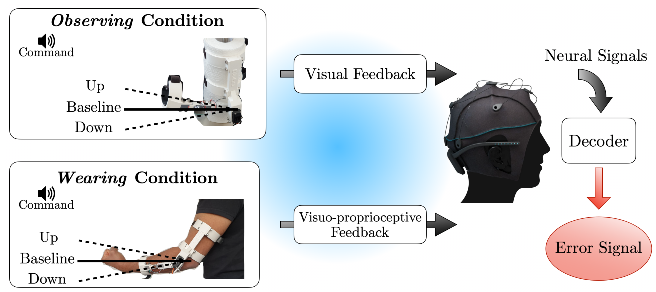

Fig. 1: An overview of our experimental pipeline designed to detect ErrPs for different sensing conditions.

This paper investigates the feasibility of detecting ErrPs with a low-cost, easy-to-setup EEG device in different conditions, namely, *visually observing* and *wearing* the exoskeleton. We used an out-of-lab setup, i.e, the experiments were conducted in environments that mimic daily-life settings. It consisted of a wearable erroneously functioning exoskeleton and easy-to-wear portable dry EEG electrodes. We outline the development of a pipeline with the Unicorn Hybrid Black (Dry Electrode EEG device) and an adapted EduExo exoskeleton (1-DOF exoskeleton).

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(a) (b)

Fig. 2: (a) The *observing* condition. The user observes the exoskeleton while wearing the EEG headset in the dry-electrode configuration. A visually observed erroneous behavior elicits ErrPs. (b) The *wearing* condition. The exoskeleton supports flexion or extension, and the user perceives an error if the behavior of the exoskeleton does not match their key-press.

II. METHODS

A. The Exoskeleton

The 1-DOF exoskeleton used for all experiments was based on the EduExo. The motor of the off-the-shelf available exoskeleton was upgraded to a motor of higher torque rating (21.5 kg-cm) to provide adequate force to move the arm of the subjects during the *wearing* condition. The control of the exoskeleton is performed using an Arduino microcontroller. Freedom of motion was allowed at the elbow, and we encoded two behaviors that would support flexion and extension of the elbow of the human arm. In behaviors 1 and 2, the exoskeleton moves from a baseline position to a preset extreme position either up (behavior 1) or down (behavior 2) and then returns to the baseline position. The speed of motion is uniform throughout the behavior (see Figure 1).

B. Recording EEG Data

We conducted our experiments on two able-bodied participants (1 female, 1 male) who were internally recruited from the Institute of Cognitive Systems. Both participants are right-handed with normal vision. They were aged 24 and 27 years and had participated in EEG studies before. The subjects were selected for this pilot experiment based on their ability to elicit ErrPs, which we validated in the control condition described in Section II-C.3. This is a pilot experiment for a full study approved by the TU Munich institutional ethics review board under the reference number 254/21 S-EB.

In all parts of this pilot study, EEG data was recorded using the Unicorn Hybrid Black (g.tec medical engineering), equipped with 8 dry electrodes (Fz, Cz, Pz, Oz, C3, C4, PO7, and PO8) arranged according to the international 10-20 system. Data was recorded at a sampling rate of 250 Hz and was transferred via Bluetooth to a separate recording PC. Using the Linux-C API provided by g.tec, the data was further streamed over a wireless network via a Lab Streaming Layer (LSL) stream and recorded using the software *LabRecorder* [11]. The setup is shown in Figure 2. Depending on the condition, participants either sat at a distance of approximately 50 cm to the screen (*cursor* condition) or the moving exoskeleton (condition 1 - *observing* condition) or were seated wearing the exoskeleton on their left arm (condition 2 - *wearing* condition) using the right arm to control the exoskeleton via key-presses.

C. Experimental Conditions

A total of three experimental conditions were tested. The first condition was to simply observe the exoskeleton. To move closer to real-world applications, participants wore the exoskeleton in a second condition. Information processing with the additional sensory modality might potentially be reflected in the EEG signal, thereby enhancing the amount of information available to the classifier. This may influence the classification accuracies positively. It could however also introduce more movement-artifact-based noise, which is unfavorable for single-trial classification. The timing of our conditions was inspired by a a previously-studied cursor condition [12] that had shown to reliably elicit ErrPs. This condition was further performed as a control experiment. This design of conditions takes care that their complexities scale from a toy-problem to real-world use case. All conditions were implemented using the toolbox Psychopy [13].

1) Condition 1 - Observing: To investigate whether observing erroneous, i.e., unintended behavior of the exoskeleton elicits detectable ErrPs in an out-of-lab scenario, participants were instructed through audio commands to control its behavior with key-presses. Audio commands are used to enable participants to only focus their vision onto the exoskeleton. Each trial starts with an audio command that either says ”up” or ”down”, requiring the participant to press the respective arrow key on the keyboard. Upon the key-press, the exoskeleton executes behavior 1 or 2, depending on the command. Analogous to the control experiment (cursor condition, explained below), erroneous behavior is randomly introduced in 30% of the trials, i.e., the exoskeleton moves in the direction opposite to that of the key-press. Errors are only introduced when the participant presses the correct key. At the end of each trial, feedback is presented by playing a short positive sound or a short negative sound, indicating whether the exoskeleton moved in the correct direction. Participants perform this condition a total of 4 blocks with 80 trials each, leading to approximately 96 error and 224 non-error trials.

2) Condition 2 - Wearing: Mimicking real-world applications, e.g, rehabilitative applications, participants wear the exoskeleton in the second condition. Since different studies reported the occurrence of proprioceptively induced Event Related Potentials (ERPs) [10], [14], the objective was to investigate if ERPs, and more specifically ErrPs, can be elicited in a *wearing* condition. For condition 2, we use the same protocol as described for condition 1, with the only difference being that the participant is wearing instead of purely observing the exoskeleton. Participants perform this condition a total of 4 blocks with 80 trials each, leading to approximately 96 error and 224 non-error trials.

3) Control Condition - Cursor: To rule out individuals who couldn't generate feasible ErrPs, participants performed a control condition that had shown to reliably elicit ErrPs [12]. The cursor condition requires participants to move a small square into a bigger square placed either above, right or to the left of the small square with respective key-presses. Erroneous behavior was introduced by randomized wrong cursor responses in 30% of the trials.

III. Signal Processing and Single-Trial Decoding

A. Preprocessing

For visual inspection of the data as presented in Figure 3, recordings were processed using the MATLAB package EEGLAB [15]. EEG signals were first high and then low pass filtered using the integrated FIR filter, leading to remaining frequencies between 1 Hz and 20 Hz. Afterwards, bad channels were detected and interpolated. The data was then epoched into error trials and non-error trials starting from 200 ms before the key-press to 1000 ms after. The epoched data of all channels were single-trial normalized by subtracting the mean of the signal in each epoch for each channel after the key-press. Additionally, bad epochs were excluded when they contained amplitudes +- 100 μV (less than 5% of all epochs in all conditions). All error trials and all non-error trials were averaged over time to visualize ERPs and identify condition differences.

B. Single-Trial Decoding

To discriminate error and non-error trials, we followed the approach employed by Ehrlich et al. [7]. We trained a Linear Discriminant Analysis (LDA) per subject and condition on the preprocessed data after balancing our data by random downsampling. We considered all 8 channels available in the recording device to construct our features. Differences between the error and the non-error trials were observable within 600 ms after the key-press (see Figures 3). Thus, a total of sixteen sliding windows with a length of 100 ms and a stride of 50 ms were selected starting from after the key-press and averaged for every channel, leading to one hundred twenty-eight features per trial. We performed 10-fold cross-validation to validate the accuracy of our classifier trained for each subject.

IV. Results

A. Evidence from Visual Inspection

After the occurrence of the error (stimulus), the typical choice-reaction ErrP signal shows an error related negativity followed by a positivity which occurs 100-400 ms later [4]. In this regard, we inspect our results after preprocessing the raw signal and averaging them over the trials. Comparisons of error-trials and non-error trials are presented in Figure 3(left for the *observing* condition and right for the *wearing* condition). For subject 1, a negativity is observable for error trials compared to non-error trials at Cz at around 200 ms. It is followed by a positivity at around 500 ms. For this subject, the topoplots reveal a positivity at Cz at around 400 ms that evolves into a stronger positivity over the entire head at 500 ms. Looking at subject 2's topoplot a similar pattern is observable. A positivity at Cz is observable at around 400 ms that evolves into a stronger positivity that extends over all electrodes at around 500 ms. Results are less conclusive for the *wearing* condition. No characteristic ErrP trace is observable for neither of the subjects. However, in line with findings for the *observing* condition, the biggest difference between error and non-error trials was found at around 500 ms for both subjects (see topoplots in Figure 3).

B. Results on Single-Trial Decoding of ErrPs

The results of the LDA based classifier for the ErrPs in the *wearing* and *observing* conditions are shown in Table I. Single-trial decoding accuracies of up to 71% were obtained for the *observing* condition, which is another evidence in support of ErrPs. For the *wearing* condition, the single-trial decoding performed less accurately (60%), which is plausible considering the visual inspection in Figures 3.

TABLE I: ErrP classification accuracy in the *observing* and *wearing* conditions.

Observing condition			
Participant	Overall Accuracy	True Positive Rate	True Negative Rate
Subject 1	70.9%	71.0%	70.9%
Subject 2	66.8%	67.4%	66.4%
Wearing condition			
Participant	Overall Accuracy	True Positive Rate	True Negative Rate
Subject 1	61.3%	61.1%	61.4%
Subject 2	61.0%	60.1%	61.5%

V. Discussion

With our low-cost setup, we saw evidence for the occurrence of ErrPs in the *observing* condition that was further supported by single-trial decoding accuracies of up to 71%. For the *wearing* condition, our findings are less conclusive. While we achieved single-trial classification accuracies of around 60%, a visual comparison of averaged error and non-error trials did not reveal systematic differences. This is in line with findings reported by Lopez et al. [16] who investigated visual, auditory and vibratory feedback-related negativity, reporting the highest single-trial decoding accuracies for the visual and the lowest accuracies for the vibratory condition. Even though different studies reported the occurrence of proprioceptively induced ERPs [10], [14], to the best of our knowledge, no indications for the occurrence of proprioceptively induced ErrPs have been reported so far. A full study is needed to explore whether there are circumstances under which ErrPs can be elicited proprioceptively. Our setup consisted of only 8 electrodes. Increasing the number of electrodes could result in increased classification accuracies and decrease inter-subject variability.

VI. Conclusion

In this pilot study, we investigated the feasibility of detecting ErrPs during exoskeleton usage in a low-cost, out-of-lab setup. We found indications for the occurrence of ErrPs

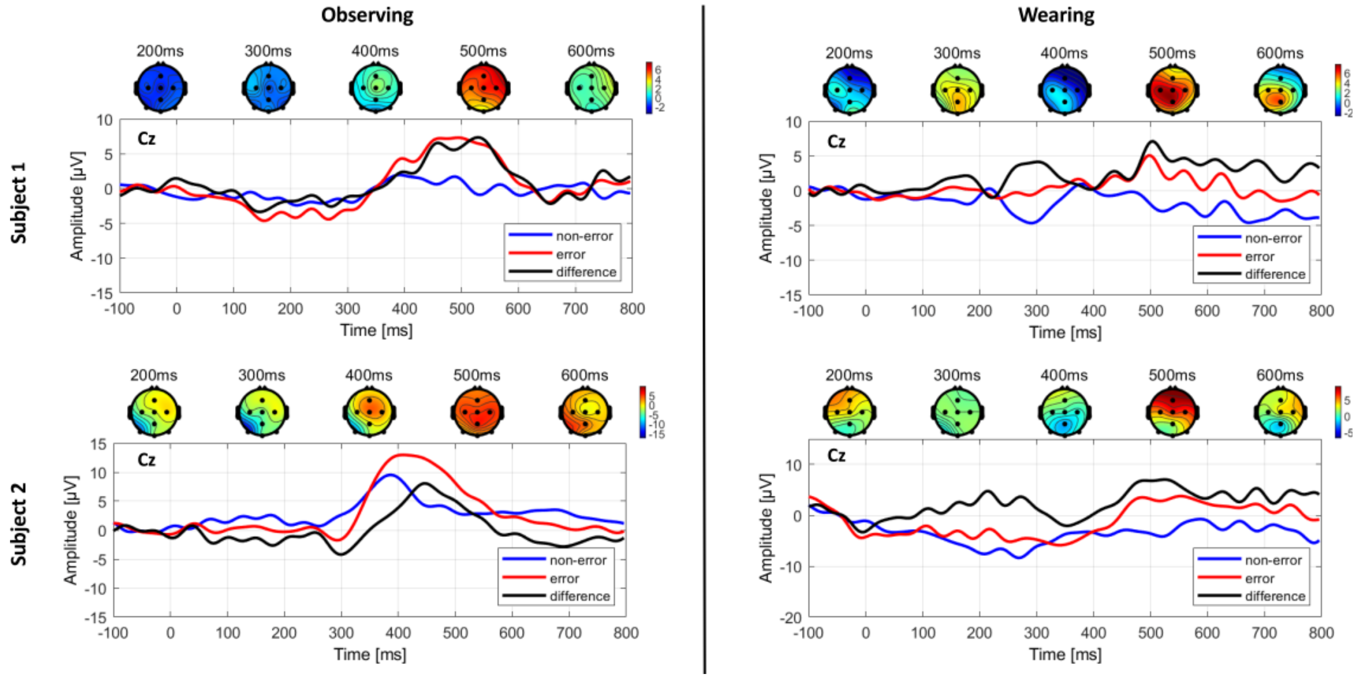

Fig. 3: The averaged response over all error and non-error trials of the channel Cz for the two conditions. The left panel shows the response of the two subjects for the *observing* condition. The corresponding topoplots show how the frontocentral regions are activated during the interval of 400-500 ms after the keyboard press. The right panel shows the response of the two subjects in the *wearing* condition. While the averaged error trials' modulations are smaller compared to their visual-observation counterparts, the relative activations of the frontocentral regions follow a similar trend.

when participants were observing the exoskeleton, leading to single-trial decoding accuracies of up to 71%. To mimic real-world applications even closer, we investigated whether ErrPs would be elicited while wearing the exoskeleton. In this condition, results remained inconclusive and require further investigation with additional subjects. Nevertheless, extending this setup to an online system that corrects the erroneous behavior of a rehabilitative device would be a major step towards making a closed-loop rehabilitative device for real-world use cases.

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