Detecting Disruptions in User Experience using ERPs and Movement Adaptation

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Introduction

Neural interface technology enables low-friction and fast interaction and therefore finds increasing application in virtual and augmented reality (VR/AR). In VR, designing immersion is *the* key challenge; this challenge has driven advancements in displays, rendering and recently, haptics. To increase our sense of physical immersion, for instance, vibrotactile gloves emulate the sense of touching, while electrical muscle stimulation (EMS) provides force feedback. Unfortunately, the established metric to assess the effectiveness of haptic devices relies on the user's subjective interpretation of standardized, yet unspecific questions (Gehrke et al. 2019). Neural interface technology can be leveraged to overcome the problems of discretized sampling of user experience and move towards continuously predicting the sense of physical immersion. However, the neural signal employed for prediction must be reliable. Hence, it is beneficial to directly target the signal's cortical origin, efficiently separating signal from noise (Zander et al. 2016).

In Gehrke et al. (2019), we presented an interactive, cyberphysical VR simulation in which small deviations between expected and actual visuo-haptic feedback, 'glitches', were modulated for each trial, see figure 1a and b. In the current work, we modeled the appearance of visuo-haptic glitches using EEG and movement features. We expected a successful two-class separation (match vs. mismatch trials) using event-related potentials (ERP) with an anterior or midline cingulate EEG signal source origin. Furthermore, we expected behavioral adaptation following visuo-haptic glitches, i.e., post-error slowing.

Results

'Action time', the time between the *start* and *end* of the reaching movement, was on average ~5 ms longer in the trials following a visuo-haptic glitch. Behavioral changes in 'action time' classified mismatch from match trials *just* above chance level ($t_{(1,10)} = 2.4$, $p = .04$) with an average classification accuracy across folds of 55.5% (simulated chance level at 54.3%). However, using ERP windowed mean features, mismatch and match trials were classified with 77% accuracy, exceeding chance ($t_{(1,19)} = 36.6$, $p < .001$). We located midline cingulate and a distributed network of parietal EEG sources to enable the classification success, see figure 1c.

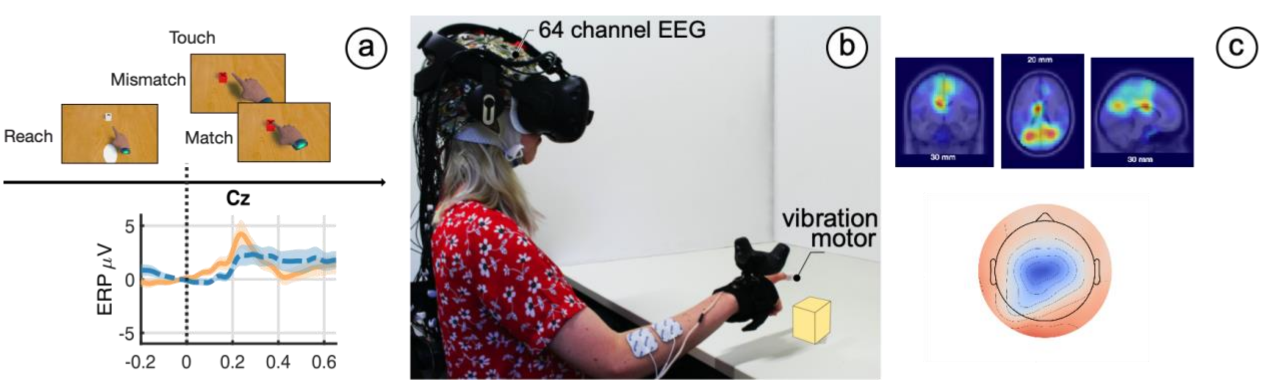

Figure 1. (a) Top: Inside VR task view with example match and glitch, i.e. 'mismatch' trial. Bottom: Grand-average ERP at electrode Cz for mismatch (blue) and match (orange) trials. 0 = collision event. (b) Experimental Setup. (c) Dipole density and scalp map weighted by relevance for classification in the 150-200 ms time window after the collision event.

Conclusions

Especially in immersive environments like VR/AR, continuous assessment of user experience is preferable over discretized assessments, like questionnaires, that interrupt the ongoing user experience. We successfully classified the occurrence of system glitches in a VR reach-to-touch task considering alterations in participants EEG and movement behavior. Especially noteworthy for the future design of predictive models, we localized the EEG source network underlying the classification. EEG features reflecting error computation related to the current action outcome have frequently been localized to midline cingulate sources. Here, cognitive control signals may directly reflect the violations of user's predictions and hence are a robust, targeted, marker for adaptive user interfaces in VR/AR (Zander et al. 2016, Duprez et al. 2020, Cavanagh et al. 2011, Töllner et al. 2017).

Methods

20 participants (12 female, mean age = 26.7, sd = 3.6) performed a 3D reach-to-touch task in VR. After waiting for a cube to appear on a table in three possible positions (center, left, right), sitting participants reached to the cube to touch it with their index finger. The cube indicated contact through a change of color. Then, participants retracted their hand back to the resting position. On 25 % of the trials the change in color occurred prematurely, through an enlargement of the cube collider by a factor of 3.5. Two blocks of 300 trials were completed (please see Gehrke et al. (2019) for further details) with one block rendering vibrotactile feedback under the fingertip.

We computed 'action time' using movement detectors on the hand velocity time series. To assess behavioral adaptation, the 'action time' of each mismatch trial was subtracted from the action time of the subsequent match trial to obtain the *rate of change* as a response to the experimental manipulation (Dutilh et al., 2012). To classify match and mismatch trials using action time, a generalized linear mixed effects model with a 'logit' link function ('mismatch/mismatch ~ difference in action time + 1 | participant ID') was cross validated using 10-folds *across* participants.

For ERP classification, a regularized linear discriminant analysis classifier was trained per participant with all mismatch trials constituting class 1 and a random sample of an equal size of match trials labeled class 2. Using the open-source toolbox BCILAB ver. 1.4 the classifier was trained on band-pass filtered (0.1 to 15 Hz) windowed means as features, i.e., baseline corrected average amplitudes of all channels in eight sequential 50 ms time windows between 50 and 450 ms after the cube was touched. A mean baseline taken in the 0 to 50 ms window post event was subtracted to compensate for the mismatch/match event classes occurring at different stages of the ongoing movement. For robust performance estimation, a 5 x 5 nested cross-validation was used to calculate the classifiers' reliability.

For both prediction schemes, action time and EEG, classification accuracy was statistically evaluated using a two-sample T-test with the mean classifier accuracy per participant across folds for EEG and the mean classifier accuracy across folds for action time compared with the simulated chance level given trial numbers in each class (Müller-Putz et al. 2007).

In order to learn what regions of the brain the classifier specifically relied on, we first transformed the LDA filters at each time window to LDA patterns reflecting a mixture of scalp activations with regards to the discriminative source activity. Subsequently, the relevance for classification can be computed using LDA filter weights per time window and the ICA unmixing matrix (Haufe et al. 2014, Zander et al. 2016). The equivalent current dipole models of independent components were then weighted by their relevance and ultimately visualized via EEGLAB dipoleDensity plots (Krol et al. 2019).

All data processing were performed in Matlab 2019b (MATLAB, The MathWorks Inc., Natick, MA, USA), using EEGLAB toolbox (Delorme and Makeig, 2004) and custom 'BeMoBIL Pipeline' scripts and functions[1].

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[1] https://github.com/BeMoBIL/bemobil-pipeline