Predicting the Limits: Tailoring Unnoticeable Hand Redirection Offsets in Virtual Reality to Individuals' Perceptual Boundaries

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Figure 1: We use the psychophysical method of constant stimuli to determine participants' perceptual boundaries for horizontal hand redirection (HR) *Below*, *At* and *Above* their individual detection thresholds (DTs). Next, we collect movement, eye gaze and EEG data, compute features, and analyze them using frequentist and Bayesian statistics. Finally, we train a multimodal classifier using Random Forest to predict if participants are exposed to HR of different magnitudes corresponding to their perceptual boundaries, based on a single movement.

ABSTRACT

Many illusion and interaction techniques in Virtual Reality (VR) rely on Hand Redirection (HR), which has proved to be effective as long as the introduced offsets between the position of the real and virtual hand do not noticeably disturb the user experience. Yet calibrating HR offsets is a tedious and time-consuming process involving psychophysical experimentation, and the resulting thresholds are known to be affected by many variables—limiting HR's practical utility. As a result, there is a clear need for alternative methods that allow tailoring HR to the perceptual boundaries of individual users. We conducted an experiment with 18 participants combining movement, eye gaze and EEG data to detect HR offsets *Below*, *At*, and *Above* individuals' detection thresholds. Our results suggest that we can distinguish HR *At* and *Above* from no HR. Our exploration provides a promising new direction with potentially strong implications for the broad field of VR illusions.

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CCS CONCEPTS

• **Human-centered computing → Virtual reality**; **User studies**.

KEYWORDS

Virtual reality, hand redirection, detection thresholds, VR illusions, EEG, hand movement, eye gaze

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1 INTRODUCTION

Virtual reality (VR) allows humans to enter and interact with immersive virtual environments (IVEs), offering a wide range of potential use cases and applications [41]. In VR, interacting with virtual content is often challenging because users suffer from the absence of haptic feedback. For example, imagine Lisa, a VR user who reaches out to touch a virtual object but only finds "thin air". As a result, she reaches through the virtual object because she expected haptic feedback upon contact. This usually leads to a break in presence [61], which disrupts the immersive nature of a VR experience. VR illusion techniques may help address this issue by manipulating what Lisa feels from what she sees in the virtual environment, "tricking" her perception into, e.g., believing that she experienced haptic feedback. The most common types of illusion rely on offsetting the position of the virtual hand from the position of the real hand, and are often referred to as Hand Redirection (HR) [68]. HR can allow Lisa to interact with objects that are physically out of reach [27, 53], can enhance haptic feedback when touching virtual objects [1, 4, 6, 13, 20, 22, 40, 47], and can even simulate physical properties of virtual objects, such as different weights [55], weight distributions [71], dimensions [10], stiffness [3], or resistance [25], purely based on visual manipulations.

However, HR cannot be scaled up infinitely because if the difference between visual and proprioceptive sensory input becomes too large, it can be noticed by a user—resulting in a break in presence [43]. Therefore, the extent to which illusions may be used without detection has received considerable attention in the HCI/VR research community, where researchers reported detection thresholds (DT) for the extent of unnoticable offsets [1, 7, 10, 14, 19, 22, 22, 23, 26, 32, 33, 37, 51, 63, 66–69]. The authors of these studies describe several limitations with respect to the generalizability and static nature of their results. For example, thresholds can be affected by how people move [7, 14, 23], or the complexity of the task [19] and moreover, seem to differ greatly between individual users [24, 37]. Calibrating DTs for one specific kind of interaction is a long and tedious process, traditionally done by conducting psychophysical experiments that require many repetitive and controlled trials. However, given the dynamic nature of VR, it is unlikely that these methods produce results that can be used throughout an entire VR experience. Thus, the question remains: *how can we seamlessly tailor the magnitude of applied redirection to individual users?*

In this work, we explore the potential of combining movement, eye gaze, and electroencephalogram (EEG) data, i.e., brain-computer interface output, to distinguish whether an applied HR offset is *Below*, *At*, or *Above* a user's individual detection threshold (DT). In our vision, this method allows constant monitoring of a user's tolerance to the exposed VR illusion throughout an entire VR experience, which would allow the VR system to adjust the magnitude of employed HR dynamically, depending on context, interaction, and an individual's sensitivity to visuo-proprioceptive conflicts. Therefore, the goal of this work is to understand if movement, eye gaze, and EEG data can substitute a DT experiment, eventually allowing for continuous adaptation of employed HR offsets. To do so, we conducted a 2-part experiment with 18 participants performing a simple docking task while exposing participants to HR offsets of varying magnitudes. In part 1, we reconstructed each participant's psychophysical function describing the participant's performance in detecting the type of HR used in our study by using the psychophysical method of constant stimuli. On a per-participant basis, we then selected the hand offsets that result in a rate of correct detection of 25%, 50%, and 75%, representing offsets *Below*, *At*, and *Above* the participant's DT. In part 2, participants performed a similar task, but this time, they were only exposed to HR offsets corresponding to their individual perceptual boundaries. This is crucial because the researchers suggested that a personalized threshold is much more useful than a group threshold [22, 24, 37]. We found that movement duration and transition points between ballistic and correction phase can be used to distinguish between HR *Below*, *At* and *Above* the DT. Our analysis of the gaze features suggested that in the absence of HR participants look more frequently and longer to their virtual hand than *Above* their DTs. Our EEG analysis showed promising results in distinguishing between movements under the influence of HR from movements with no redirection applied. By training a machine learning (ML) model, combining the three modalities, we can predict whether a user was exposed to HR significantly above chance level, based on a single trial across all participants.

In this work, we make four main contributions:

1. We outline a novel method to tailor VR systems to perceptual thresholds of different magnitudes.

2. We demonstrate the capability of movement, eye gaze and EEG data to distinguish between HR offsets *Below*, *At* and *Above* an individual's DTs.

3. We train a ML multimodal classifier with movement, eye gaze and EEG features, reaching an overall accuracy of 40.682% with a mean F1 score of 39.359% on single trial prediction.

4. We open-source a data set and the ML model for movement, eye gaze and EEG features to the research community.

2 RELATED WORK

Our work is positioned in the field of VR illusions. We first discuss illusions based on HR in VR, before we outline how EEG, gaze, and movement data have previously been used to detect mismatches.

2.1 Hand Redirection & Illusions in VR

Hand-based illusion techniques have been of central interest to the research community because they promise an inexpensive way to improve VR experiences. For example, the Go-Go interaction technique [53] dynamically scales hand movements, allowing users to interact with virtual objects that are out of reach. To achieve this, the authors visually scaled participants' real-world movements up or down. Although users clearly notice the applied offset, they maintain high control (i.e., agency) over their movements. Such beyond-real interaction techniques [2] are effective, but many VR applications rely on plausible interactions, i.e., the visual manipulation remains unnoticeable. This is possible due to multisensory integration and the visual dominance phenomenon [18, 31, 35]: in the case of two conflicting senses, the most plausible sense dominates over the other. Burns et al. [12] found that vision usually dominates over proprioception during hand movements.

To investigate to what extent vision overrides proprioception in the case of HR, Zenner and Krüger [68] studied how much hand offset can remain unnoticeable for users. The authors report estimates for HR DTs on the horizontal, vertical, and depth axes. Following up on this, researchers looked at variables that may affect the amount of unnoticeable offset, identifying many contributing variables such as movement distance [22], direction [7, 14], trajectory [23, 45], task complexity [19], realism [51], and individual sensitivity [24, 37], and techniques leveraging blinks [69], saccades [66, 67] or tendon stimulation [50] have been introduced to increase unnoticeable HR thresholds. However, the variety of potential factors that may influence detectability and the lack of understanding when to apply these techniques hinder HR from becoming an effective tool in VR design. Moreover, the large number of hand-based illusion techniques [1, 4, 6, 10, 10, 13, 19, 22, 23, 25, 26, 32, 33, 40, 47, 48, 55, 63, 65, 71] that rely on HR and go beyond what can reasonably be discussed within the scope of a paper demonstrate the wide scope of this research problem. Therefore, we propose an alternative method that allows for continuous monitoring of a user's tolerance to HR and dynamically adapts the unnoticeable offset. We were inspired from research looking at detecting perceived mismatches or unexpected events in VR, using quick responding movement, eye gaze and EEG data discussed below.

2.2 Movement, Eye Gaze and EEG Data in VR

Generally, targeted movements have two distinct movement phases, ballistic and (an optional) correction [44]. Feick et al. [24] results suggest that under the influence of strong gain-based HR the transition point between the two phases shifts, both in terms of time and distance. Transition points appear significantly earlier than during movements with no HR, because participants compensate for the unexpected offset. Furthermore, the interaction time is significantly shorter, which is expected given that their applied HR technique uses gain factors, i.e., participants reached the target faster with less physical movement required. Gonzalez and Follmer [34] showed that redirected movements have a variety of distinct properties that differ from normal movements and presented an approach to predict redirected movement trajectories. However, the authors did not incorporate the aspect of noticeability in their investigation. These positive findings informed our decision to include movement data in our experiment to investigate whether **(H1) participants distinctly adjust their movements during HR *Below*, *At* and *Above* their perceptual threshold.**

Eye gaze is commonly used in VR systems to select targets or interact with virtual content [41]. In the context of HR it has been used in haptic retargeting applications. For example, Matthews et al. [47] use gaze fixations for target prediction to seamlessly redirect users' hands between physical proxies. This works because findings from interaction studies showed that during targeted movements, participants predominantly fixate their gaze on objects that are relevant to the task, while devoting minimal attention to their own hand when reaching for an object [42]. We included gaze because we hypothesize that **(H2) participants look at their hand more frequently and for a longer duration if they start to notice the HR offset**, diverting from their "natural" behavior.

Besides eye gaze, other physiological recordings, such as EEG, allow observation of users without needing to disrupt their ongoing experience. As such, EEG has recently become more relevant for VR research and has been leveraged to infer about a variety of user's states. These range from broad applications such as detecting emotional states [38], to more fine-grained descriptives of the user's subjective VR experience of immersion or their readiness to interact [28, 29, 49, 58, 59].

In HR, the most relevant previous work focused on detecting a mismatch between participants' hand motion and the motion of the avatar hand. Here, Padrao et al. [52] designed an experiment to examine the effects of a virtual avatar hand moving in the opposite direction to the movement of a participant's real hand. Their results showed a strong similarity to error-related potentials related to semantic or conceptual prediction violations (captured over central cortical areas). ERPs and their magnitudes can be used to differentiate between no and extreme gain-based HR [24]. However, our work differs substantially from this previous work, because applying HR around the threshold does not result in an immediate noticeable event, which in turn severely disrupts the VR experience. This would be the case with extreme HR and opposite movements, as these become obvious at the start of the interaction. Therefore, we focus on whether **(H3) ERPs of different magnitudes are triggered as a result of exposing participant to HR *Below*, *At* and *Above* their DT.**

To address the specific aspects of unnoticeable HR, we further propose time-frequency decomposed EEG data, which has yet to be explored as a novel direction in characterizing and understanding brain responses to HR. Spectral features may hold significant promise for a continuous metric describing participants' individual perceptual boundaries, as they do not require as precise a temporal anchor for meaningful feature extraction as do ERPs. One metric based on spectral features is the ratio of frontal theta power and parietal alpha power. This ratio has been shown to correlate with a subjective rating of workload, or an increased cognitive load [16, 30]. We explore this metric as a correlate of cognitively processing HR, since predicting the correlation between one's own movements and the HR gain likely increases spatial processing demands. In line with our (**H3**), a higher and therefore more frequently detected HR should result in an increased cognitive load as participants need to elicit a correction movement in order to reach the target.

3 EXPERIMENT

We designed a 2-part experiment, investigating whether gradual horizontal HR around an individual's perceptual boundary can be detected using the 3 modalities: movement, eye gaze and EEG.

In part 1, we used the psychopchysical method of constant stimuli analogous to Steinicke et al. [62] and Zenner and Krüger [68] to model the discrimination performance for each participant for the specific type of HR (i.e., gradual horizontal offsets of the virtual hand to the right; see Figure 1 left). The results were used in part

2 of the experiment, which was tailored to each participant with HR offsets that corresponded to their perceptual boundaries. This way, we ensured that each participant was exposed to the same magnitude of perceived offsets.

In part 1 and 2, we applied a 2-interval-forced-choice method (2IFC) [39], where participants were instructed to perform two consecutive hand movements, hitting a virtual target with their index finger. During the first movement, no HR was applied, whereas in the second movement we either applied HR of different magnitudes or no HR. Participants were asked to compare both movements and report if they felt a difference between them by responding to the 1-alternative-forced-choice (1AFC) question: "Both movements felt the same" [25] (see Figure 1 left). Participants could respond by using the "Yes" or "No" button on a presenter stick in their non-dominant hand [69]. Subsequently, the participants returned their hand to the initial location and continued with the task. The location of the virtual target (a red sphere) always appeared in the same location, 30 *cm* in front of them [24]. Although the task remains the same in part 1 and 2 of the experiment, the underlying methodologies and objectives differ substantially.

Part 1—Determine Perceptual Boundaries. To tailor part 2 to each participant's individual perceptual boundary, we modeled their discrimination performance in distinguishing movements with HR vs. no HR. To do so, we conducted a psychophysical threshold experiment, fitting the psychometric quick function [39] through our collected sample by optimizing the parameters α and β. We define these probabilities as perceptual boundaries, *Below* (25% probability), *At* (50% probability), and *Above* (75% probability), with *At* representing the conservative detection threshold (CDT) or point of subjective equality (PSE) [62]. This means that there is a 50% chance that a participant can detect the presence of HR, respectively, for 25% and 75%. 75% (*Above*) is often used as a less conservative threshold in the literature [24], whereas 25% (*Below*) was chosen to include a sample below the CDT, investigating if participants respond to the offset even without consciously noticing it.

To model the discrimination performance for each individual, a sufficient amount of data is needed. Based on the HR literature and our pilot tests, we arrived at the following configuration for the method of constant stimuli. We tested offsets ranging from 0 *cm* to 7 *cm* in increments of 1 *cm*, resulting in 8 stimuli. Participants experienced each stimulus 8 times (= 64 stimuli; in total 128 hand movements) to improve robustness of the fitting and allow for consistency checks.

Part 2—Collecting Data at Perceptual Boundaries. In the second part, participants performed a total of 8 rounds of the discrimination task while only exposed to HR offsets *Below*, *At*, *Above* as well as no HR (*Base*). Each round consisted of 16 stimuli trials, 4 × *Below*, *At*, *Above* and *Base*, presented in a randomized order, resulting in 32 reaching movements per round. The 2IFC method allowed us to include a sufficient amount of ground truth reaching movements (no HR) on what participants experience to be "normal" [28], which must be captured in VR [17]. In this part of the experiment, the main focus was on collecting movement, eye gaze and EEG data at participants' perceptual boundaries.

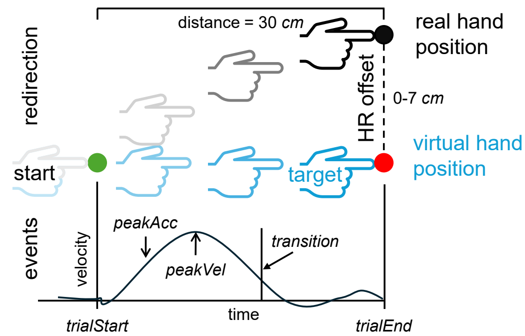

Figure 2: Shows the effect of horizontal HR and our events used during targeted reaching movements in our experiment.

3.1 Participants

We recruited 18 right-handed participants (six females, twelve males), aged 18–31 (mean: 25.05; SD: 3.05) from the general public and the local university. We asked participants not to consume alcohol or caffeine 12 hours before the study. Participants had a range of different educational and professional backgrounds, including media informatics, computer science, education, pharmacy, cybersecurity, entrepreneurship, biomedical engineering, data science, and artificial intelligence. All participants reported normal or corrected-to-normal vision and did not report any known health issues which might impair their perception or proprioception. Nine participants had never used VR before, six had used it a few times (one to five times a year), no one reported using it often (6–10 times a year), and three others used it regularly (more than 10 times a year). Participants not associated with our institution received € 30 as remuneration for participating in the experiment. The study was approved by the University's Ethics Board.

3.2 Apparatus

We used a simple virtual environment consisting of a table, the experimental setup, and an instruction screen, which was implemented in Unity3D (v.2022.2.0). We included an androgynous representation of the virtual hand [57] to prevent unwanted effects such as a drift in DT [51]. The experimental logic was implemented using the Unity Experiment Framework (UXF v.2.4.3) [11], the Unity Staircase Procedure Toolkit [70] and the VRQuestionnaireToolkit [21]. Participants remained seated on a chair throughout the experiment with a table in front of them. They wore an HMD, an EEG headset and a Vive tracker attached to their dominant hand with a finger spline to fixate their index finger. We used the HTC VIVE Pro Eye tracking system (SRanipal SDK) to capture eye movements. The experiment ran on an XMG PRO One offering an Intel® Core i7-10870H CPU, 32 GB RAM and an Nvidia® GeForce RTX 3070.

3.2.1 EEG Setup. EEG data were captured from 32 actively amplified electrodes using BrainAmp DC amplifiers from BrainProducts. Electrodes were placed according to the international 10–20 system, using the nasion/inion as reference points. To establish a connection between the electrodes and the scalp, conductive gel was applied and the impedance of all active electrodes was reduced to 5–10 *kOhm* before the experiment started [28]. The EEG data were sampled at a rate of 500 *Hz*.

3.3 Experimental Protocol

Participants arrived at the location and first received a general introduction to the study, i.e., we showed them the setup and explained the EEG headset to ensure that they were comfortable with it. Next, we gathered participants' consent and asked them to fill in a demographic questionnaire. We then started with the procedure of attaching the EEG electrodes to the heads of our participants. This procedure was carried out with two experimenters, one identified as male and one as female, to improve the comfort of our participants and to reduce the preparation time to about 40 *min*.

Subsequently, participants were placed in the IVE and guided through an open-ended practice round, showing them the effect of horizontal HR. By doing so, we allowed them to familiarize themselves with the system and the task. Once they felt comfortable, we moved to the first part of the experiment, where we modeled their discrimination performance.

Participants were told to sit comfortably and to move their hand to the target position at a consistent and comfortable speed. The system monitored that they stayed within a reasonable time range. Once their virtual index fingers reached the goal position, their finger needed to remain in that position for one second, before the 1AFC question appeared. Participants were required to stay within a 5 *mm* radius for the dwell time indicator to remain active. Participant and experimenters were not allowed to talk to avoid interrupting the continuous docking task or introducing artifacts in the data. This part of the experiment took 40–45 *min*.

Next, participants took a longer break (about 15 *min*), while the experimenters configured part 2 of the experiment. In part 2, participants performed the same task tailored to their perceptual boundaries. After each of the eight rounds, participants took a break to reduce the effects of proprioceptive fatigue [54]. On average, the data collection took 35–40 *min*, during which participants were not allowed to remove the VR headset, to avoid moving the EEG electrodes. In total, the experiment was about 2.5 *h* and we provided complementary snacks and water.

3.4 Data Collection

We collected data from six sources: a pre-study questionnaire for demographic information; EEG, eye tracking and movement data; system logs (including trial times, object position and orientation, and velocity); and we collected participants' responses to the 1AFC question in VR [21]. To synchronize our data streams with VR interactions and the events, we used the lab streaming layer (LSL)[1].

3.5 Events, Pre-Processing & Analysis

Our data from part 2 of the study were split into epochs corresponding to the conditions, the trials and the events within them. We pre-processed, filtered, and analyzed the data using the methods described below. An overview of the events can be seen in Figure 2. The *trialStart* event is triggered after the participants successfully held the start position for 1 *sec* and moved 5 *mm* away from the start, and the *trialEnd* event as soon as they reached the target.

[1]https://github.com/sccn/labstreaminglayer

3.5.1 Gaze and Movement Data. We statistically analyzed our data after verifying the parametric test assumptions at $\alpha = .05$. We performed RM ANOVAs and applied Greenhouse–Geisser corrections when the assumption of sphericity was violated. In the presence of a main effect, we performed post hoc pairwise comparison t-tests adjusted using the Bonferroni-Holm method. In addition, we conducted a Bayesian analysis using JASP following Wagenmakers et al. [64]. We exported the previously used measures *totalTime* [24] and *peakVelocity* [56]. We extracted the transition points between ballistic and correction phases according to Liu et al. [44] in the time (*transitionPointTime*) and spatial domain (*transitionPointDistance*). We statistically analyze the two gaze features, *#handFixations* and *durationHandFixations* previously used by Lavoie et al. [42]. We define *#handFixations* as the number of gaze intersects where the virtual hand is fixated for at least 60 *ms*. *DurationHandFixations* is the total duration of hand fixations that are ≥ 60 *ms*.

3.5.2 EEG.. Our analyses focused on the midline eletrodes *FCz*, *Cz* and *Pz* that have previously been successfully used to detect mismatches in VR [24, 28, 29, 58]. Here, we only provide an overview of our EEG analysis. More details can be found in the supplement.

Event-related Potentials (ERPs). We followed Gehrke et al. [28, 29]'s approach to extract single-trial ERPs. After applying a bandpass filter from 0.1 to 15 *Hz*, ERPs were extracted around three event markers coupled to the hand movement: *peakAcceleration*, *peakVelocity*, and *transitionPointTime*. ERPs were baseline corrected by subtracting the average amplitude of the last 100 *ms* preceding the trial start. To ascertain effects the linear mixed-effects, model was fit at each time point. Effects were assessed using likelihood ratio tests for the main effects with Benjamini-Hochberg correction [9]. For post-hoc analyses, we specifically focus on the time window between 150–250 *ms* following salient moments of the movement phase with respect to HR. Specifically in HR, we believe this moment is a good approximation at which the HR offset may be consciously experienced [60].

Event-Related Spectral Perturbation (ERSP). First, we set out to confirm that our experimental task elicited robust spectral brain modulations. Hence, the evoked spectral response was compared to a baseline. To this end, grand-average ERSP were computed using the 'newtimef' function in EEGLAB. In order to account for different trial segment duration and maintain the time-frequency resolution across participants, the spectograms were linearly time-warped to the median times of the movement. Then, a spatio-temporal cluster test (using MNE-python [36]) was conducted in comparison to power values in a −300 to −100 *ms* pre-trial baseline window.

Lastly, we focus our analyses on one specific spectral feature: the ratio of theta band power at electrode *FCz* and alpha band power at *Pz*. This ratio has been shown to correlate with a subjective rating of workload, or an increased cognitive load [16, 30]. Effects were assessed analogous to the ERP analyses.

3.6 Results

3.6.1 Part 1—Determine Perceptual Boundaries. We computed the thresholds at 25%, 50% and 75% detectability based on the fittings of the psychometric function. The results for 75% detectability are depicted in Figure 3, suggesting that the participant provided consistent responses. Plots for 25% and 50% can be found in the supplementary materials. However, for P09 the fitting did not reach convergence and therefore we could not compute the DTs, which means that the participant could not continue part 2 of the experiment. This could have happened for various reasons. For example, the participant perhaps did not really understand the study task, or the HR offsets tested were too small. However, for the remaining 17 participants, we were able to compute DTs shown in Figure 4. The horizontal HR 50% DTs obtained are comparable to those of the existing literature [68]. Furthermore, Figure 4 (left) supports Hartfill et al. [37]'s and Feick et al. [23]'s recommendations towards personalized DTs, because thresholds differ substantially across participants, but are consistently high or low for each individual [22]. This further demonstrates the need for novel approaches to tackle this problem, supporting our overarching research objective.

Threshold experiments can be subject to noise and are very sensitive to their configuration (#repetitions, #steps, etc.). For example, it could be that 25% and 50% result in DT clusters that overlap and are perceived as more or less the same. Therefore, verifying that our HR DTs are perceptually different is a prerequisite for part 2. We statistically analyzed the resulting thresholds and found a main effect ($F(1.036) = 105.7$, $p < .001$, $\eta_p^2 = .869$, $BF_{incl} > 1000$) of condition on the DTs. Post-hoc tests revealed that *Below* has significantly lower thresholds than *At* ($p < .001, d = -1.663, BF_{10} > 1000$) and *Above* ($p < .001, d = -3.524, BF_{10} > 1000$). Similarly, *At* showed lower thresholds than *Above* ($p < .001, d = -1.861, BF_{10} > 1000$) with strong positive correlations ($p < .001, BF_{10} > 280$, with $\rho > .8$) between *Below*, *At*, *Above* based on the DT. **As a result, we can confirm that our obtained HR DTs are perceptually different.**

3.6.2 Part 2—Distinguish Perceptual Boundaries. To ensure that participants did not suffer from fatigue, we first visualized their discrimination performance for the 8 rounds in Figure 5. The graph suggests that there is no notable shift in *Base*, *Below*, *At*, *Above* over the 8 rounds. Bayesian analysis provided strong evidence for the absence of an effect between study round and the four conditions, *Base* ($F(7) = 25.584$, $p = .520$, $\eta_p^2 = .064$, $BF_{excl} = 10.6$), *Below* ($F(7) = 0.664$, $p = .702$, $\eta_p^2 = .049$, $BF_{excl} = 16.5$), *At* ($F(7) = 0.443$, $p = .872$, $\eta_p^2 = .033$, $BF_{excl} = 24.4$) and *Above* ($F(7) = 0.780$, $p = .605$, $\eta_p^2 = .057$, $BF_{excl} = 13.1$). **Thus, we conclude that individuals' thresholds remain consistent throughout part 2 of the experiment, allowing us to link our analysis back to the established perceptual boundaries.**

Movement data. We extracted and analyzed the 4 features, *totalTime*, *peakVelocity*, *transitionPointTime* and *transitionPointDistance*. We found evidence for a main effect on *totalTime* ($F(3) = 25.584$, $p < .001$, $\eta_p^2 = .615$, $BF_{incl} > 1000$), *transitionPointTime* ($F(3) = 15.792$, $p < .001$, $\eta_p^2 = .497$, $BF_{incl} > 1000$) and *transitionPointDistance* ($F(3) = 40.493$, $p < .001$, $\eta_p^2 = .717$, $BF_{incl} > 1000$), but not for *peakVelocity* ($F(3) = 0.336$, $p = .724$, $\eta_p^2 = .021$, $BF_{incl} = 0.111$). Post-hoc tests showed significant differences between movements without HR and any other condition. Transition points from ballistic to correction phase appeared significantly earlier, and hand movements took significantly longer when horizontal HR was applied. The latter effect is in the opposite direction to what Feick et al. [24] reported for gain-based HR. This is an interesting finding that can be explained by the HR direction. Gain-based HR effectively leads to shorter movements because less physical distance is required to reach the virtual target, in contrast to horizontal HR, which increases physical movement distance (see Figure 2), and most likely also task difficulty. Figure 6 reports the test statistics, which are in line with previous findings that investigate the effects of redirected movements [24, 34]—but we extend them to distinct perceptual boundaries around the noticeability threshold. **Thus, our findings support (H1), confirming the potential of movement data to differentiate between HR of magnitudes corresponding to individuals' sensitivity to visuo-proprioceptive offsets.**

Gaze data. Next, we analyze the two features, *#handFixations* and *durationHandFixations* depicted in Figure 7. We found evidence for a main effect for both *#handFixations* ($F(2.322) = 5.616$, $p = .005$, $\eta_p^2 = .260$, $BF_{incl} = 16.141$) and *durationHandFixations* ($F(1.9) = 6.510$, $p = .005$, $\eta_p^2 = .289$, $BF_{incl} = 35.118$), depending on the condition. Post-hoc pairwise comparisons for *#handFixations* showed significant differences between *Base* and *At* ($p = .002, d = .929, BF_{10} = 7.453$) as well as *Below* and *Above* ($p = .018, d = .742, BF_{10} = 3.401$). *DurationHandFixations* showed significant differences between *Base* and *At* ($p = .002, d = .916, BF_{10} = 8.306$) as well as *Base* and *Above* ($p = .002, d = .938, BF_{10} = 5.462$). Bayesian analysis provided evidence for the absence of an effect between *Base* and *Below* for *#handFixations* ($BF_{10} = 0.311$), and between *At* and *Above* for *durationHandFixation* ($BF_{10} = 0.252$).

Contrary to (H2), participants looked at their virtual hand more frequently and for longer during hand movements without HR than in any other condition. We believe that this could be the result of the nature of the task, which we further discuss in section 5. Nevertheless, *#handFixations* and *durationHandFixations* clearly separate movements without HR from movements with HR at individuals' 75% DT.

EEG data. First, we examine ERPs by plotting the mean ERP amplitudes for the electrodes *FCz* and *Cz* (available in appendix) located above frontal cortical areas analog to [24, 28, 29, 52]. However, we did not observe the typical ERP amplitude following prediction violations in VR that often exhibit a negative component followed by a strong positive deflection. Given the absence of a distinct event, this is not surprising because semantic violations could, in fact, appear at different points during the interaction given the nature of HR around the noticeability level.

We examined the peak negativity in the 150–250 *ms* window following salient moments of the movement; see Figure 8. We found a main effect of HR for *FCz* at both *peakAcceleration* ($\chi^2 = 15.7, p = .001$) and *peakVelocity* ($\chi^2 = 16.3, p < .001$). Similar main effects were observed at *Cz* for *peakAcceleration* ($\chi^2 = 32.5, p < .001$) and *peakVelocity* ($\chi^2 = 23.1, p < .001$).

Post-hoc tests revealed significant differences between *Base* and *Below* ($p = .005$) as well as *Base* and *Above* ($p = .001$) at electrode *Cz*. There were no other significant differences between conditions after p-adjustments. While some differentiation between the baseline and HR conditions was observed, suggesting a trend towards increasingly larger peak amplitude from modest negativity at *Base*, all the way to the strongest at *Above*, the pattern was inconclusive.

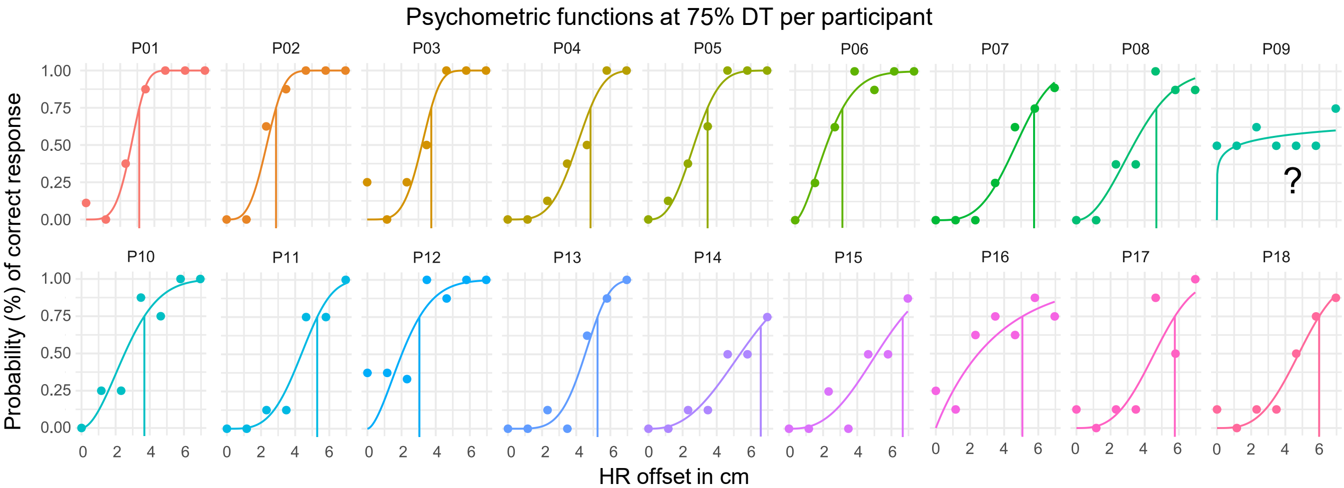

Figure 3: Depicts the plotted psychometric functions with 75% probability of a correct response (i.e., 75% DT) for each participant. The modeled discrimination performance shows an *S*-shaped curve typical for human perception. For P09 marked with a "?", we could not compute DTs, because all stimuli were perceived as equal according to the discrimination performance.

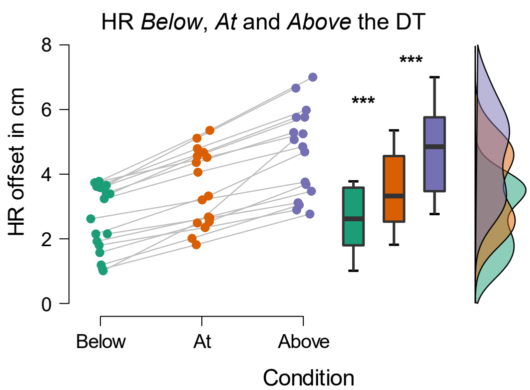

Figure 4: Shows the obtained thresholds corresponding to individuals' perceptual boundaries. *Below* shows significantly lower thresholds than *At* and *Above*. *At* has significantly lower thresholds than *Above*.

The spectral equivalent to ERP is ERSP which provides another view on the effects of HR around the DT. For this type of analysis, we included the *Pz* electrode, because it is located above the parietal lobe of the brain, responsible for movement guidance. Figure 10 shows the grand average ERSP cluster permutation test against the pre-stimulus baseline. The black contours outline the significant activity in the spectral power, differing from the baseline.

At electrode *FCz* an initial burst in theta power occurred with the onset of movement and lasted until the peak velocity was reached. We observed a desynchronization in the beta range between 20–30 *Hz* lasting throughout the movement phase. Interestingly, a synchronization between 35–40 *Hz* first appeared at maximum acceleration, lasting until the end of the trial. At *Pz*, the dominant spectral feature was a desynchronization in the alpha band, appearing at maximum acceleration, lasting until the end of the trial. Peak strength of the desynchronization was between maximum velocity and the onset of the correction phase. Taken together, we consider these findings to be validations of the recorded data, clearly demonstrating task-related spectral dynamics. Post-hoc tests for theta and alpha bands showed significant differences between *Base* and all other conditions; see Figure 9.

Finally, we calculated the ratio of theta *FCz* and alpha *Pz*, which is commonly used to measure cognitive load [16, 30]. Similarly, we found a main effect and a post-hoc test showed a significant difference between *Base* and any other condition.

Nevertheless, we can only partially confirm (H3), because contrary to previous studies [28, 58], we did not observe the same distinct ERP signatures. However, our analysis of the peak error negativity showed promising results at the *peakAcceleration* event, especially at *Cz*. As a result, *peakAcceleration* is an interesting marker for further exploration. Our ERSP analysis allowed us to distinguish between movements under the influence of HR from movements with no redirection applied. However, we did not find evidence that would suggest that, based on the presented features, we can easily differentiate between HR of different magnitudes.

3.6.3 Summary. In part 1 of the experiment, we established participants' perceptual boundaries *Below*, *At* and *Above* their personal DTs using the method of constant stimuli. We verified that the thresholds obtained are perceptually different from each other and that the participants did not suffer from proprioceptive drift or fatigue in part 2 of the experiment. Our analysis showed that movement time and the transition points from ballistic to correction phase can be used to distinguish between all three perceptually different HR offsets **(H1)**. Furthermore, participants looked significantly more often and longer at their virtual hand when no HR was applied than *Above* the DT **(H2)**. Finally, ERP peak error negativity and the ERSP results showed great potential to detect the presence of HR, even at the unnoticeable *Below* level **(H3)**.

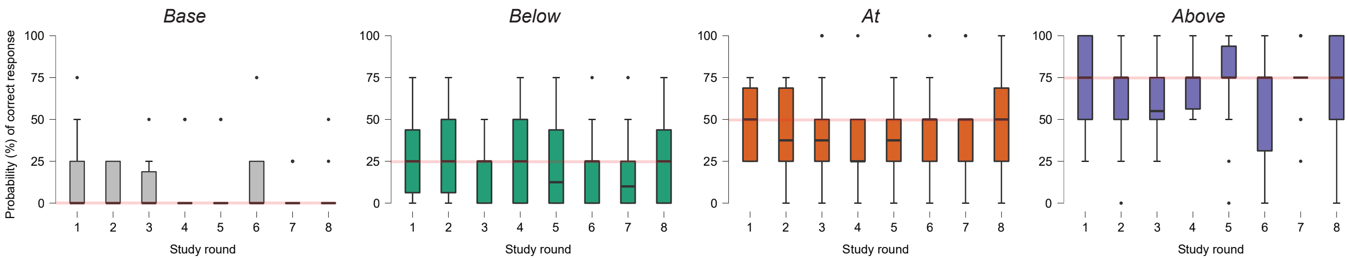

Figure 5: Shows the participants' discrimination performance at *Base*, *Below*, *At* and *Above* their individual DTs over the 8 study rounds. The horizontal red line shows the expected probability of a correct response for *Base* = 0%, *Below* = 25%, *At* = 50% and *Above* = 75%. The boxplots display participants' responses throughout part 2 of the experiment. Visual inspection and Bayesian analysis suggest that there is no noticeable difference in discrimination performance, e.g., caused by fatigue.

time \ peakVelo	*Base*	*Below*	*At*	*Above*
Base	-	$p = 1.0$; $B_{10} = 0.403$	$p = 1.0$; $B_{10} = .279$	$p = 1.0$; $B_{10} = .305$
Below	$p = .028$; $B_{10} = 3.6$	-	$p = 1.0$; $B_{10} = .270$	$p = 1.0$; $B_{10} = .260$
At	$p = .001$; $B_{10} = 106.7$	$p = .208$; $B_{10} = .481$	-	$p = 1.0$; $B_{10} = .259$
Above	$p < .001$; $B_{10} > 1000$	$p < .001$; $B_{10} = 263.2$	$p < .001$; $B_{10} = 311.7$	-

transitT \ transitD	*Base*	*Below*	*At*	*Above*
Base	-	$p < .001$; $B_{10} = 183.2$	$p < .001$; $B_{10} > 1000$	$p < .001$; $B_{10} > 1000$
Below	$p = .437$; $B_{10} = .745$	-	$p = .005$; $B_{10} = 17.3$	$p < .001$; $B_{10} > 1000$
At	$p = .116$; $B_{10} = 1.4$	$p = .437$; $B_{10} = .433$	-	$p = .008$; $B_{10} = 6.2$
Above	$p < .001$; $B_{10} = 311.5$	$p < .001$; $B_{10} = 185.4$	$p < .001$; $B_{10} = 193.4$	-

Figure 6: Shows p-values and Bayesian factors for the 4 movement features *totalTime*, *peakVelocity*, *transitionPointTime* and *transitionPointDistance*.

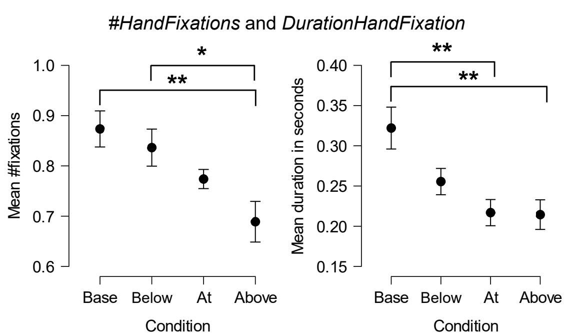

Figure 7: *#HandFixations* occurred significantly more frequently in the *Base* condition and *Below* the threshold than *Above* it. Besides looking more frequently to the hand, participants also spent more time looking at the hand in the *Base* condition than *At* and *Above* the threshold.

4 PREDICTING PERCEPTUAL BOUNDARIES USING A MULTIMODAL CLASSIFIER

To better understand the potential of our proposed method, we combine the three modalities: movement, gaze and EEG by training a multimodal classifier. Here, our goal was to predict whether users were exposed to no HR vs. HR *Below*, *At* or *Above* their detection thresholds based on a single trial. Unlike Si-Mohammed et al. [58], we did not perform a per-participant analysis, but aggregated our collected samples into one data set, which we make publicly available to the community in the supplementary materials. This way, researchers can train their own models or formulate new research hypotheses. The data set contains 4352×77 data points.

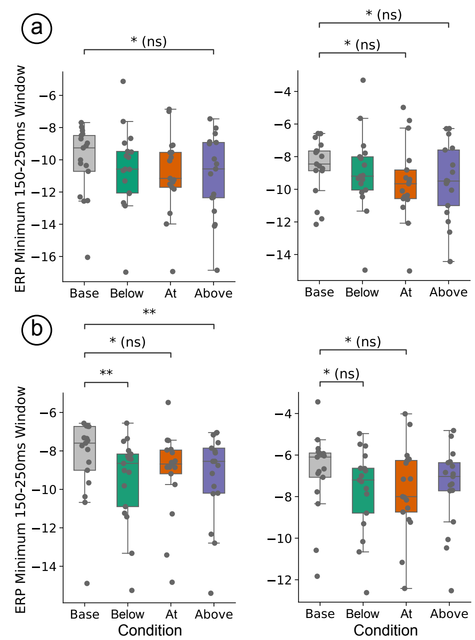

Figure 8: Amplitude minima in the 150–250 *ms* time window at electrode *FCz* (a) and *Cz* (b) following peak acceleration (left column) and peak velocity (right column).

4.0.1 Features. Following our statistical analysis, we used the features *totalTime*, *transitionPointTime*, *transitionPointDistance*, *#handFixations*, *durationHandFixations*, *Cz_amplitude_min*, *FCz_amplitude_min* and *FCz theta/Pz alpha ratio*. Then, we normalized all features using z-scoring. Since *FCz theta/Pz alpha ratio* is a continuous high-dimensional feature, we computed skewness, median, interquartile range (*iqr*), kurtosis, cumulated frequency ($cumfreq\_3$), the 10th and the 90th quantile ($quantile\_10$ and $quantile\_90$).

4.0.2 Training. We performed a 10-fold cross-validation by shuffling the data and splitting them in a stratified way, preserving the

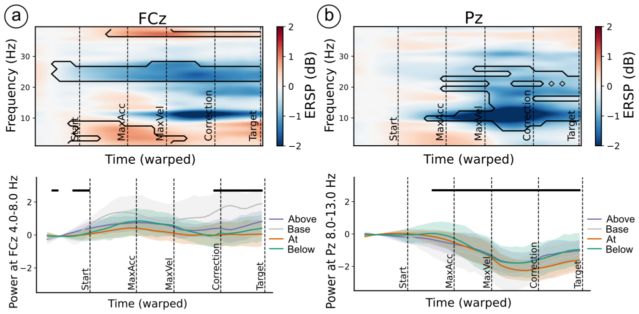

Figure 9: Top: Event-related spectral perturbations at electrodes FCz (a) and Pz (b). Changes in power from a -300 to -100 ms pre-stimulus baseline are marked by a black contour for significance. Bottom: Band power in theta (4–8 Hz) frequency range for electrode FCz (a) and alpha (8–13 Hz) for electrode Pz. Significant time points for the main effect *condition* are marked by black bars.

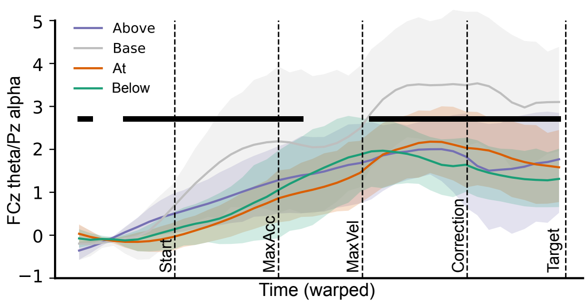

Figure 10: Ratio of power in theta (4–8 Hz) frequency range at electrode FCz divided by power in alpha (8–13 Hz) frequency range at electrode Pz. Significant time points for the main effect *condition* are marked by black bars.

relative imbalance in the data set. Samples of each class in the train and the test set are removed until the data set is balanced. Then we trained a classifier using Random Forest. We provide our model and code base in the supplementary materials.

4.0.3 Results. Our results show that without any optimization, we can achieve an overall accuracy of 40.682% and a mean F1 score of 39.359% at a theoretical probability of 25%, with a confusion matrix shown in Figure 11. We computed Combrisson and Jerbi [15]'s adjusted chance level of 36.184% at $p < .001$. This method takes the number of classes and samples into account, where if the accuracy is higher than the adjusted chance level, the result is statistically significant by a p-value. Since our classifier exceeds this probability, we can conclude that we can predict the correct class with an accuracy significantly higher than chance level. In particular, movements without HR can be correctly predicted with an accuracy of 63.2%. It appears that there is ambiguity between movements *Below*, *At* and *Above* the DT. Here, the classifier performance seems rather weak under the influences of HR *At* (28.0%) and *Below* (29.2%) the DT, while *Above* can be predicted with an accuracy of 40.4%.

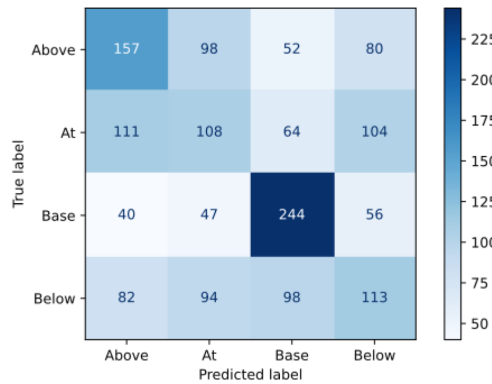

Figure 11: Confusion matrix for 10-fold cross-validation of our multimodal classifier. The classifier can distinguish *Base* from any other condition. It appears that between movements under the influences of HR *At* and *Below* the DT are challenging to predict.

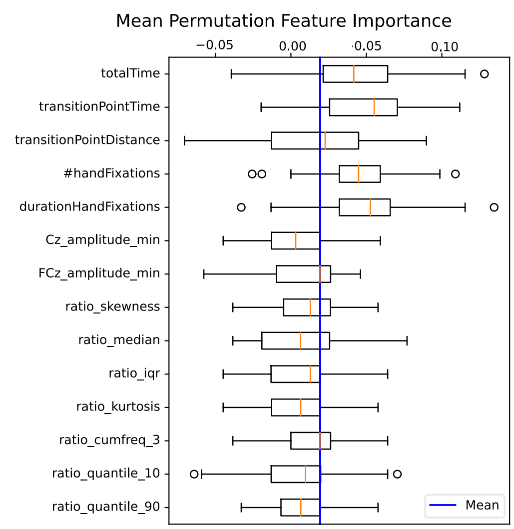

Figure 12: Shows mean permutation feature importance, suggesting that the most relevant features are *totalTime, #handFixations, transitionPointDistance* and *durationHandFixations*, because their predictive power is above average.

The permutation feature importance depicted in Figure 12 suggests that no single feature dominated the prediction, but highlights that *totalTime*, *#handFixations*, *transitionPointDistance* and *durationHandFixations* are above average in terms of prediction power.

4.0.4 Summary. We trained a multimodal classifier using Random Forest and performed a 10-fold cross-validation, achieving an overall classification accuracy of about 40%. This is significantly higher than the adjusted chance level and demonstrates that movement, gaze and EEG data collected *Below*, *At* or *Above* participants' individual detection thresholds can be used to distinguish no HR from any other condition. However, for movements under the influence of HR *Below*, *At* and *Above* the DT, it is challenging to separate them from one another. All features contributed to the prediction of the perceptual limits, with *totalTime*, *transitionPointDistance*, *#handFixations* and *durationHandFixations* contributing most significantly. This marks a substantial step forward in tailoring illusions to individuals' perceptual boundaries.

5 DISCUSSION & FUTURE WORK

5.0.1 Predicting Perceptual Boundaries of HR. Considering all results, we provide evidence for being able to distinguish between hand movements with (*At* and *Above*) from without HR. Focusing on this binary classification problem would yield more impressive prediction accuracy, but it is insufficient to address our vision of predicting the perceptual boundaries of users. While we can differentiate *At* and *Above* from no HR, we acknowledge that our current model performs rather poorly between HR offsets of different magnitudes. Our results still support our research goal, because offsets *Below* can be safely used (practically not crucial to detect), and appear to be indistinguishable from no HR, following our Bayesian features analysis. The effects start to occur when reaching *At*, but seem to be more prominent at *Above*.

We envision that users would start the VR experience with no offset and the system would increase it (*Below*) until it detects the unnoticeable limit (*At*, *Above*). Theoretically, it could dynamically adjust offsets within that range (*Below*) and detect potential shifts (*At* = no HR). However, based on our data, we cannot yet differentiate if HR offsets corresponds to *At* or *Above* DT.

Given the ambiguity in the *Below* condition, we would argue that achieving an overall accuracy of 40% for a 4-stage classifier on this type of data, without a sophisticated learning model and any hyperparameter tuning, is promising for a novel approach. We want to emphasize that the participants experienced horizontal HR offsets of different magnitudes in part 2 of the experiment and that our analysis was performed across all participants. Therefore, we can confidently say that our method is tailored to individuals' perception rather than fixed offset magnitudes. Most likely, better prediction accuracy can be achieved when training and evaluating on a per-participant level similar to [58]; however, obtaining the necessary per-user data through a controlled psychophysical experiment in advance defeats the purpose of our method.

It is important to note that the perceptual boundaries *Below*, *At* or *Above* of the individual detection thresholds should not be considered as distinct effects. For example, the average horizontal 25% threshold corresponds to an offset of 2.58 *cm*, while the 50% threshold was 3.56 *cm* at the target location of the hand, 30 *cm* in front of the participants. Thus, the type of effect always remains the same (i.e., virtual hand offset to the right), and only its magnitude changes. In light of this, achieving an overall accuracy of about 40% in single-trial classification, given the limited amount of data that can reasonably be collected in a psychophysical experiment, demonstrates the impressive potential of our approach. We expect that with more data the robustness and prediction accuracy will improve further. Therefore, we recommend future work to build on our foundation and the data set provided, adding other types of redirection [67, 68] and interaction [4, 5, 33, 40], or without informing participants [8]. Hence, researchers can simply retrain our multimodal classifier using our resources, extending beyond our current setup to test its validity in diverse and more applied VR settings. To this end, there also seems to be a tendency towards movement and gaze features being most effective. This opens up exciting opportunities, because these are much easier to monitor than EEG data. However, it remains to be explored how these modalities perform in more complex VR scenarios and interactions.

5.0.2 Generalizability & Limitations of the Method. As with any novel method, the main question remains whether our results are directly related to the effects of HR. To the best of our knowledge, we controlled for as many variables as possible to isolate potential effects by (1) calibrating individuals' detection thresholds [24, 37] and (2) verifying that the threshold did not drift over the course of the experiment [54]. In the next iteration of this research, we aim to investigate the robustness of the method in more realistic and complex IVEs. For example, to ensure that we operate at participants' perceptual boundaries, we used an established methodology [62, 68] and informed the participants about the presence of HR. As a result, some effects may be related to the procedure itself, rather than the interaction under the influence of HR. For example, participants may have spent more time looking at their virtual hand when no HR was applied because they observed their hand closely to detect a potential offset, in contrast to the 75% *Above* threshold condition, where participants noticed the offset relatively early and therefore returned to their natural behavior, i.e., looking at the target [42]. Additionally, we used a specific type of HR (i.e., horizontal offsets to the right) [68], a fixed virtual distance [22] and only looked at hand movements performed by participant's dominant hand. Thus, the generalizability of the method to bi-manual interactions [33], other HR algorithms [46, 50, 67, 69, 72], or greater visuo-haptic integration [18, 40] remains to be explored.

Furthermore, by informing the participants about the procedure and designing the task around HR detection, we used a very conservative approach. For our first exploration, this was needed to ensure comparability between participants, but it is far from any real VR experience. For example, Benda et al. [8] found that the detectability of HR differs greatly when participants are informed of its presence. The application of HR techniques without informing users is more realistic and practically relevant for VR design. As a result, much larger HR offsets can be used without disrupting the VR experience, which may help to improve the power of our method. Finally, understanding how other variables and VR interactions affect movement, gaze and EEG features is crucial to assess the potential of the method for constant monitoring in immersive VR experiences, going beyond substituting a threshold experiment. Ultimately, we rely on further research to validate our method.

5.0.3 Practicality and Utility of the Method. Our method relies on tracking hand movements, gaze and participants' EEG. The first two measures can be monitored with most modern HMDs and do not require additional trackers, such as the one we used in our experiment. The bottleneck of the method is the acquisition of EEG data, because it is a time-consuming, tedious, and uncomfortable procedure for users. Calibrating a DT for one type of interaction takes about 10 minutes using a state-of-the-art DT experiment which is equivalent to $\frac{1}{4}$ of the time it took 2 experiments to position gel-based EEG electrodes. However, this is only a hardware limitation because companies such as Galea[2] offer HMDs with integrated physiological sensing capabilities for not just EEG, but also ECG, EDA and face EMG. Ultimately, this would allow ubiquitous data collection inside IVEs, and in contrast to calibrating just a single DT for one type of interaction, it enables us to constantly monitor participants' perceptual sensitivity and adapt if necessary. In this way, the system could collect more data in varying environments, improving the robustness and overall accuracy. With this promising potential on the horizon, our investigation marks a significant step forward with serious implications for the broad spectrum of perceptual VR illusion techniques, pushing toward immersive sensory experiences that feel indistinguishable from reality.

6 CONCLUSION

In this work, we introduced a novel method using movement, gaze and EEG data with the goal to distinguish between HR offsets corresponding to participants' individual perceptual boundaries *Below*, *At* and *Above* their DTs. We conducted a 2-part experiment with 18 participants to investigate the potential of our proposed method. First, we established participants' distinct perceptual boundaries using the method constant stimuli, and verified that participants did not suffer from fatigue. Our analysis showed that movement data, especially movement duration and transition points from ballistic to correction phase, can be used to distinguish between HR *Below*, *At* and *Above* the DT. The number of gaze intersects with the virtual hand and their duration was significantly lower in the presence of HR than without HR. HR at the perceptual boundaries did not trigger distinct ERP signatures, but peak error negativity at the *peakAcceleration* event was significantly lower *Above* the DT. Our ERSP analysis allowed us to distinguish movements under the influence of HR from movements with no redirection applied. However, we did not find evidence that would suggest that we can differentiate between HR of different magnitudes solely based on using ERPs or ERSP. When combining the modalities through training a multimodal classifier, we achieved an overall prediction accuracy of about 40% for all four HR magnitudes. Overall, we can differentiate *At* and *Above* from no HR, but our current prediction model struggles to separate HR offsets of different magnitudes, which needs to be improved. Our work marks the first step towards achieving our long-term goal of dynamically tailoring VR illusions to individuals' perceptual boundaries.

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