Gaze Tracking for Eye-Hand Coordination Training Systems in Virtual Reality

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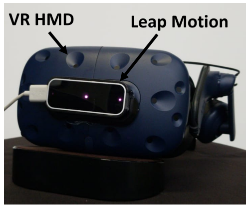
Abstract
Eye-hand coordination training systems are used to improve user performance during fast movements in sports training. In this work, we explored gaze tracking in a Virtual Reality (VR) sports training system with a VR headset. Twelve subjects performed a pointing study with or without passive haptic feedback. Results showed that subjects spent an average of 0.55 s to visually find and another 0.25 s before their finger selected a target. We also identified that, passive haptic feedback did not increase the performance of the user. Moreover, gaze tracker accuracy significantly deteriorated when subjects looked below their eye level. Our results also point out that practitioners/trainers should focus on reducing the time spent on searching for the next target to improve their performance through VR eye-hand coordination training systems. We believe that current VR eye-hand coordination training systems are ready to be evaluated with athletes.

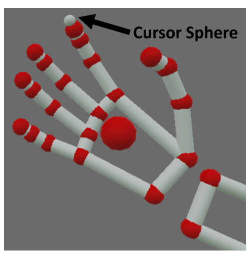
Author Keywords
Eye-Hand Coordination Training System; Virtual Reality; Gaze Tracking; Hand Tracking; Speed and Precision

CCS Concepts
•**Human-centered computing** $\rightarrow$ **Virtual reality;** *Pointing devices; HCI theory, concepts and models;*



(a)

(b)



(c)

Figure 1: (a) VR HMD with Leap Motion, (b) the eye-tracker in the VR HMD, and (c) the virtual hand skeleton with the spherical cursor on the tip of the index finger.

Introduction

Virtual Reality (VR) systems provide a controllable virtual environment (VE), allowing trainers to control and monitor user performance in detail. All aspects of the VE, including the speed and trajectory of an object, can be altered according to user needs. This allows trainers to create virtual scenes where a user can experience the same situation over and over again. Moreover, VR enables users to collect data in a safer environment. Trainees do not have to interact with real world objects (e.g., fast balls, opponents), which also reduces the number of injuries [12].

The eye-hand coordination training (EHCT) task, also called reaction test, is one of the nine psychometric tasks in the Nike SPARQ Sensory Station [24], a tool to enhance athletes' perceptual and visual–motor skills [34]. In this task, trainees have to touch a sequence of randomly activated targets as fast and accurately as possible, improving both their reaction time and accuracy. Previously, this training method was implemented with real world systems (e.g., a wall or buttons) [8, 28] or 2D touchscreens [9, 34],

EHCT systems have been explored for different sports such as American football [12] and hockey [25] and these studies demonstrated that these systems can improve athletic performance. However, none of the studies investigated and assessed gaze performance in such systems.

Here, we extend previous work [5, 6] by using a gaze tracker in our VR EHCT system to understand gaze behaviours during a pointing task. We also ran the experiment with or without (in mid-air) passive haptic feedback to further investigate finger movements in VR training applications.

Previous work

Fitts' Law

Human movement time in pointing is modeled by Fitts' law [10]. Equation 1 shows its Shannon formulation [20]:

$$Movement\ Time = a + b * log_2\left(\frac{A}{W} + 1\right) = a + b * ID \quad (1)$$

In Equation 1, the movement amplitude is A and W is the target size, while a and b are constants, empirically derived via linear regression. The logarithmic term defines the index of difficulty (ID) and indicates the task difficulty.

Passive Haptic Feedback

Passive haptic feedback is a feedback mechanism where user feels a physical surface [19]. Previous research showed that user performance improves with passive haptic feedback since it also increases the sense of presence in VR [14, 16, 29]. On the other hand, previous research on EHCT found that passive haptic feedback does not improve user performance [5, 6].

EHCT in Sports Training

EHCT systems with 2D screens have been studied, for example in American football [12] and hockey [25]. These studies showed that skill transfer is possible with such systems. Krasich et al.'s work [17] revealed that user performance can improve up to 60% with such systems.

Performance Assessment in Sports Training

While EHCT systems aim to improve both user speed and accuracy, previous studies for 2D screen-based systems used only time to assess user performance (e.g. [12]). Yet, previous research showed that accuracy assessment is as important as time assessment during the learning process [2, 3, 4]. Recent work showed that Fitts' law and the (effective) throughput measure [15] can be used in VR-based EHCT systems [5, 6] for accuracy assessment.

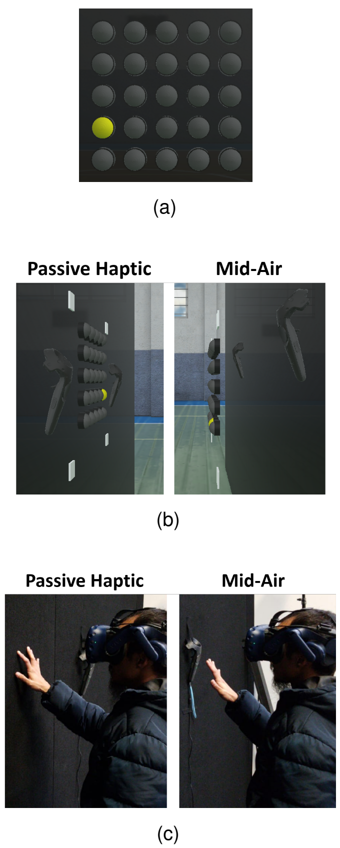


Figure 2: (a) The 5x5 target grid, (b) VE for two feedback conditions, and (c) a participant doing the task in both the conditions.

Eye-tracking in VR for Sports Training
Eye-tracking has been used to analyze and improve perceptual and cognitive skills in different sports [1], including golf [23], basketball [33], and soccer [36], but none of these works used VR systems.

Motivation & Hypothesis

To our knowledge, there is no previous work that explored gaze tracking in VR-based EHCT systems combined with Fitts' law. Since we conducted our study with novices, we expect participants to look at each target and to linger before searching for the next target [18, 22], which should affect their time and thus also throughput performance.

User Study

Participants
12 right-handed subjects (10 male) with an average age of 26.2 $\pm$ 4.15 years were recruited from the local university. The inter-pupillary distance of the headset was adjusted for each subject. Participants who wore glasses were instructed to take them off during the experiment for better eye-tracking. This did not affect their vision as the 5x5 grid (see Figure 2(a)) they interacted with during the task was within their arm's length and thus easily visible.

Apparatus
A computer with i7-4790 processor, 16 GB RAM, and GTX 1060 graphics card was used to run the experiment. The system was developed in Unity3D.

VR headset: We used a HTC Vive Pro headset (see Figure 1(a)) with 2880x1600 pixels, refresh rate of 90 Hz, and 110° (diagonal) FOV.

Eye-tracking: The Pupil Labs VR/AR eye-tracker, designed for the HTC Vive/Vie Pro (see Figure 1(b)) was used to track a subject's gaze at 200 Hz. The *hmd-eyes* API [26] for Unity3D along with Pupil Service [27] was used to capture the gaze data.

Hand tracking: We attached a Leap Motion to the VR HMD to track hand movements (see Figure 1(a)). A virtual skeleton (see Figure 1(c)) of the subject's hand was shown in the VE so that subjects could perceive where exactly their hand was in the virtual space. Also, to allow for accurate selection of objects, a 1 cm diameter spherical virtual cursor (see Figure 1(c)) was added on the tip of the index finger of the virtual hand skeleton. For better tracking, we instructed subjects to keep their hand open (see Figure 2(c)).

We attached two HTC Vive controllers on the real wall to measure its position accurately, which enabled us to replicate it precisely in the VE and thus to give the participants precise passive haptic feedback from the wall. Before running each experimental session, we ensured that the position of the controllers in the real and the virtual world matched. The distance between the two controllers was also used to match virtual and real world distances.

Procedure
We extended our previous EHCT work [5, 6] by adding a gaze tracker to the system to analyze gaze movements. In our current study, we used two **Haptic feedback** levels: passive haptic feedback and mid-air (see Figures 2(b) and 2(c)). A soft surface wall (covered with a thick pile of polypropylene, usually used to dampen sound) was used to provide passive haptic feedback. Participants started the experiment with calibration of the eye-tracker, using Pupil Lab *hmd-eyes'* default calibration scene (see Figure 3), which shows 18 fixation points in a 3D space on a gray background, one after the other for 1.5 s each. Upon successful completion of the calibration, we started a validation phase [7]. Here we showed 13 fixation points again for 1.5 s each, within a 5x5 grid to test how accurate the tracking

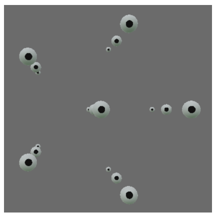


Figure 3: The calibration scene.

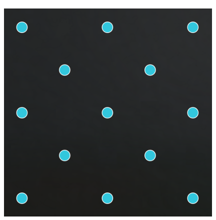


Figure 4: 13 fixation points used for validation.

on the grid, i.e., the region of interest, was (see Figure 4). During this time, the eye-tracker accuracy and precision was calculated following previous work [13]. Since we assumed that it takes about 0.5 s for the subject to move their gaze from one point to another, we ignored the first 0.5 s of gaze data for each target. We moved to the main task of the experiment once the eye-tracking was well calibrated, i.e., we observed an accuracy under 3°. Otherwise, we re-calibrated and re-validated the eye-tracker until we reached the desired accuracy.

The main task for the participants was to select (push) targets (yellow buttons) as quickly and as accurately as possible using their dominant hand's index finger. The buttons were placed 8 cm apart and the targets appeared with three different sizes 3_{TS}: small (1.6 cm), medium (3.2 cm), and large (4.8 cm). When the participants' fingertip (cursor sphere) was in contact with a target, the color of the button was changed to blue. With passive haptic feedback, when the fingertip touched the real wall (whose position in the VE was determined by the VR controllers), or in other words, pushed the buttons far enough that they collided with the virtual wall, a "selection" was detected and the color of the button was changed to green, if the cursor was inside the target, or red, if the cursor was outside the target, when we played an error sound. In the mid-air condition, the target plane was moved 20 cm away from the real wall and the same "selection" technique was used, i.e., subjects had to push into the buttons in mid-air. In the mid-air condition subjects were positioned at an appropriate distance to the target plane to be able to comfortably reach all targets, which means that there was no difference in distance between target plane and subject between both conditions. The first target in the 5x5 grid was selected at random. The ID of Fitts' law was restricted between 1.94 and 4.39 and thus, the Target Distances 4_{TD} of the next randomly selected target were also restricted to 16, 22.6, 24, or 32 cm relative to the previous one. This process continued until no other buttons were available (that met the above requirements) at which point we ended that set. Also, the same target was not selected twice in a single set.

Before the start of the main tasks, participants were given practice trials to familiarize themselves with the setup. During this period, we adjusted the grid height to ensure that the middle row was at the eye level of each participant .

Experimental Design

The 12 participants performed 3 repetitions for two **Haptic Feedback** conditions (2_{HF} = Mid-Air and Passive Haptic). Subject's movement time (s), error rate (%), and effective throughput (bits/s) [15] were measured as dependent variables. Since the number of selected targets was not the same in each trial set and slightly different for each subject, there was no fixed number of data points collected. On average, subjects selected between 21 and 22 targets per trial, which yields approximately 21 x 2_{HF} x 3 repetitions = an average of 126 data points for each subject.

For every data point received from the eye-tracker, we calculated the 2D distance between the projected gaze location and the current center of the target button. The distance between the virtual cursor and the center of the target was calculated in 3D. We made this decision as the gaze was fixed on the grid plane and there was little gaze movement in depth, i.e., along the z-axis. However, the finger does move in depth as the subject hits a target, moves the finger back, and then hits the next target.

To determine how accurate the eye-tracker was, we analyzed the average minimum visual angle between the projected gaze and the targets for each row (the topmost row labelled as 1) and column (the leftmost column labelled as

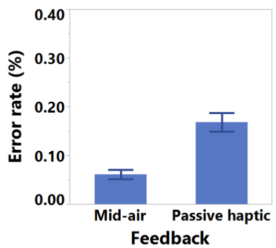


Figure 5: Error rate results for feedback.

	Feedback	ID
Time	F(1,11)=0.207 Not Significant	F(4.97, 54.64)= 23.675 $p<0.001$ $\eta^2 = 0.68$
Error rate	F(1,11)=42.47 $p<0.001$ $\eta^2 = 0.79$	F(9,99)= 33.767 $p<0.001$ η^2=0.754
Throughput	F(1,11)=0.879 Not Significant	F(9,99)=4.699 $p<0.001$ η^2=0.29

Table 1: RM ANOVA results for time, error rate, and throughput.

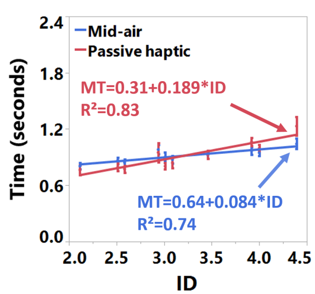


Figure 6: Fitts' law analysis results for mid-air (blue) and passive haptic feedback (red) conditions.

1) of the 5x5 grid. The minimum visual angle is the closest point to the target that the gaze could achieve for a particular click, i.e., the gaze location during selection.

Data Analysis

In this section, we only report significant results and focus on the results that contribute to our work on EHCT systems. For data analysis, we used Repeated Measures (RM) ANOVA in SPSS 24.0 with $\alpha < 0.05$. We considered the data as normal when Skewness and Kurtosis values were within $\pm$ 1 [6, 11, 21]. We applied Huynh-Feldt correction when the ϵ was less than 0.75.

Time, Error Rate, and Throughput Analysis

The time independent variable was normal after log-transform (Skewness=0.44, Kurtosis=0.67). ID violated sphericity χ^2(44)=71.79, p<0.05, ϵ=0.522. Error rate was not normal even after log-transform, thus, we applied ART [35] before RM ANOVA. According to the results in Figure 5, subjects made more errors with the passive haptic feedback condition. Throughput had a normal distribution (Skewness=0.49, Kurtosis=0.25) and ID did not violate the sphericity assumption, χ^2(44)=54.29, *not significant*. Results of the RM ANOVA are shown in Table 1. Fitts' law results are shown in Figure 6.

Gaze Tracking and Finger Tip Position Analysis

Averaging across the two **Haptic Feedback** conditions, subjects' took about 0.25 s before they started visually searching for the next target (reaction time: RT), 0.3 s to locate the target (search time: ST), 0.25 s waiting for the finger to hit the target (wait time: WT), and the rest as fixation time (FT), as shown in Figure 7. The finger lagged behind the gaze with the average reaction time (RT_F) of about 0.35 s. The time taken to reach the target (corresponding to the search time for gaze; ST_F) was about 0.45 s, with the rest being fixation (FT_F). When separating the two **Haptic Feedback** conditions, there was no major difference for the gaze distance from target in terms of RT, ST, WT, and FT. However, for the cursor distance from the target, a lag of about 0.06 s was observed for both reaction ($RT_F^M - RT_F^H$) and search time ($ST_F^M - ST_F^H$) in the mid-air condition (see Figure 8).

Gaze Tracking Accuracy for EHCT System in VR

The average minimum visual angle between gaze and target rows was normal after log-transform (Skewness=-0.04, Kurtosis=-0.52). Row data violated sphericity, χ^2(9)=47.46, *p*<0.001, ϵ=0.340. One-way RM ANOVA revealed rows had a significant effect on the average minimum visual angle (*F*(1.36, 14.955)=32.06, *p*<0.001, η^2=0.745). Post-hoc analysis with the Sidak method revealed that the average minimum visual angle for the bottom row (Row 5) was significantly higher than Rows 1-4. Similar results were found for the second-last row (Row 4) where the average minimum visual angle was significantly higher than all rows above (Rows 1-3; see Figure 9). No significant differences were found between Rows 1-3. Average minimum visual angle between gaze and target columns was not significant.

Discussion

In this paper, we investigated gaze behaviours in a VR-based eye-hand coordination training (EHCT) system with or without passive haptic feedback. The results for time, error rate, and throughput on haptic feedback support the results of previous work on EHCT in VR [5, 6]. Passive haptic feedback did *not* improve user performance and increased the error rate of the subjects. We hypothesize that since the subjects were not able to see the real wall, they might not have trusted the passive haptic feedback, which might have decreased their performance.

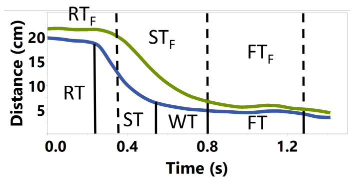


Figure 7: Average distance of gaze (blue) and cursor (green) from target over time.

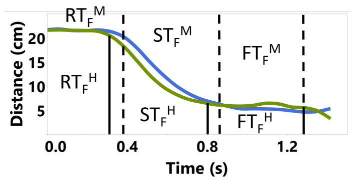


Figure 8: Average distance of cursor from target over time for mid-air (blue; superscript ^{M}) and passive haptic feedback (green; superscript ^{H}) conditions.

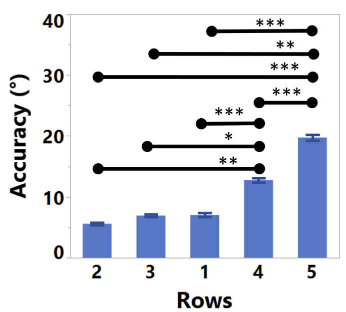


Figure 9: Average minimum visual angle between the gaze and the target for each row of the 5x5 grid.

According to the gaze tracking results, we found the reaction time lag of the fingertip relative to the gaze to be approximately 0.1 s ($RT_F - RT = 0.1$). However, the gaze finds the target in ($RT + ST$) 0.55 s, about 0.25 s (WT) before the finger, which supports our hypothesis. Nonetheless, a long fixation at the end for both gaze (FT) and cursor (FT_F) can be seen at the right of Figures 7 and 8. We believe this is the result of trials where the subject could not properly select the target at their first attempt and thus, had to try once more. As mentioned before, the distance between target plane and subject was same in both **Haptic Feedback** conditions. Results showed that this did not affect results for the gaze distance from target over time. The same is true for cursor distance from target over time, with a 0.06 s time shift for mid-air in Figure 8, which is very small and thus, negligible.

In Figures 7, 8, and 9, the results never reach zero. Potential explanations for this could be that: 1. subjects do not always hit the target and/or do not always look at the center of the button; 2. we considered the system to be well calibrated when the eye-tracker accuracy was less than 3°; 3. according to the results, eye-tracker accuracy was bad for the buttons at the bottom two rows; and 4. trials where the subject missed/selected the wrong target were also included in the analysis. Also, for Figures 7 and 8, since the targets are 3D buttons and get pushed in when selected, there is always a non-zero difference in depth between the center of the cursor and the button.

Potential explanations for the gaze data being less accurate for rows below the user's eye level (Row 4 and 5) include limitations of the eye-tracker. Yet, although a human neck can be tilted more downwards (flexion) than it can be tilted upwards (extension) [31], we noticed that subjects were more reluctant to flex down than to extend their neck up while doing the experiment. This is related to the vertical FOV of human vision being 50° upwards and 70° downwards [30]. Thus, they mostly only moved their eyes down to see the buttons at the bottom of the grid but extended their neck as well as moved their eyes for buttons on or above their eye level, which positioned their pupil at the center of the eye, yielding better eye-tracking accuracy.

Unlike Clay et al. [7], we found gaze accuracy to be better in the center than in the periphery during pilot studies. For this reason, we reduced the grid size to 5x5 (relative to 6x6 in our previous work [5, 6]). As previous work [7], we also noticed deteriorating eye-tracker precision over time, which led these authors to repeat the calibration and validation of the eye-tracker every 5 to 10 minutes. As our experimental task was only ~10 minutes, we only performed these two steps just once at the beginning of the experiment.

Conclusion & Future Work

In this study, we explored gaze movements in a eye-hand coordination training (EHCT) system. Our results revealed significant deterioration of gaze accuracy below eye level. Also, subjects spent 0.55 s to find a target in the VE and waited another 0.25 s before the finger caught up. The only difference between passive haptics and mid-air conditions was in terms of error rate. In the future, we plan to work on improving user performance in terms of gaze times with the "quiet eye" method [32]. Moreover, we want to replicate our study with bi-manual hand interaction to investigate how peripheral vision affects user performance in EHCT systems. Finally, the number of repetitions in this study was not enough to assess the training aspect of the EHCT system, similar to previous work [5, 6]. Thus we also plan to apply our gaze tracking system to athletes and analyze their long-term learning curves.

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