Eye-Hand Coordination Training for Sports with Mid-air VR

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ABSTRACT

A relatively recent application area for Virtual Reality (VR) systems is sports training and user performance assessment. One of these applications is eye-hand coordination training systems (EHCTSs). Previous research identified that VR-based training systems have great potential for EHCTSs. While previous work investigated 3D targets on a 2D plane, here we aim to study full 3D movements and extend the application of throughput analysis to EHCTSs. We conducted two user studies to investigate how user performance is affected by different target arrangements, feedback conditions, and handedness in VR-based EHCTSs. In the first study, we explored handedness as well as vertical and horizontal target arrangements, and showed that user performance increases with the dominant hand and a vertical target plane. In the second study, we investigated different combinations of visual and haptic feedback and how they affect user performance with different target and cursor sizes. Results illustrate that haptic feedback did not increase user performance when it is added to visual feedback. Our results inform the creation of better EHCTSs with mid-air VR systems.

CCS CONCEPTS

• **Human-centered computing → Virtual reality**; *Pointing devices*; *HCI theory, concepts and models*; **Human computer interaction (HCI)**; *Haptic devices*; User studies.

KEYWORDS

Virtual Reality, Fitts' task, performance assessment, reaction test, mid-air interaction, haptic feedback

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1 INTRODUCTION

In the last decade, state-of-the art virtual reality (VR) head-mounted displays (HMDs) have not only been used to let users experience imaginary virtual environments (VEs), but also to replicate various real world scenarios. One recent application field for VR are the training environments used to improve the performance of athletes. For this purpose various VR training applications have been presented, including basketball [15], American football [27], skiing, [47] and cycling [45].

Compared to real-world training, one of the main advantages of VR sports training applications is that they enable the creation of controllable environments where the trainer or the athlete can assess all actions as objectively as possible. Also, by changing the environmental conditions in the VE, it is possible to cover diverse training situations. It is relatively easy to create and tune unique VEs and challenge users within them to further improve their performance on relevant tasks, such as asking the user to predict the trajectory of a stopped ball [10].

One example for such sports training systems are eye-hand coordination training systems (EHCTSs), also known as a reaction test, where the athlete needs to select a sequence of randomly activated targets as fast as possible to enhance their perceptual and visual skills [60]. Previous work on such EHCTSs with 2D screens and hard surface setups investigated their effectiveness, skill transfer, and also athlete performance improvements [12, 20, 60]. A previous study demonstrated that HMD-based VR systems have great potential to be used in VR-based EHCTSs [8]. In such systems, user performance can match the level achievable with conventional EHCTSs on 2D screens, in terms of time and error rate [8]. Moreover, Batmaz et al. showed that, compared to 3D mid-air and passive haptic interaction with a bare hand in VR, user performance is better with a VR controller [9]. Since the highest performance was measured with a VR controller in their EHCTS, we decided to further analyze human interaction in mid-air VR-based EHCTS.

However, this previous work on VR EHCTSs assessed only user performance on 3D targets on a 2D plane, i.e., not in full 3D [8, 9, 40].

In this paper, we extend previous work on EHCTSs, e.g., [8, 9, 40], by using a 3D version of Fitts' law, while still using a similar target grid setup as previous work. For this purpose, we conducted two user studies. In the first study, we explored how user performance changes with different experimental setups, to validate if Fitts' law based on 3D distances can indeed be used to consistently assess user performance in VR. In the second study, we further analyzed performance with varying target and cursor sizes and with either haptic and visual feedback in isolation or their combination. With this work, we not only aim to extend the literature on VR-based sports training applications, but also investigate the effect of different forms of feedback according to 3D Fitts' law. The results thus inform both VR research and sports training systems and further deepen our understanding of human performance in VR training systems.

2 PREVIOUS WORK

2.1 Fitts' law

Fitts' law [21] models human movement time in pointing tasks. Here, we use Shannon's formulation [37], see Equation 1:

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

In Equation 1, A and W are the target distance and size, while a and b are empirically derived via linear regression. The logarithmic term in Fitts' law is known as the index of difficulty (ID) and indicates the overall pointing task difficulty.

2.2 Design of the Visual Representation

In VR, the visual representation of the VE itself and how users interact with the virtual objects can both affect user performance [4]. Previous research on 3D Fitts' law has also identified a clear effect of movement direction on time, error rate, and throughput, especially for lateral movements compared to movements that are approaching or moving away from the viewer [2, 3]. In contrast, comparisons of vertical vs. horizontal movements exhibit only small differences [13, 51, 53, 55]. While some of these results are correlated with the display system's properties, they still need to be considered in the design of VR-based training systems to avoid unduly influencing human sensory-motor skills through the VR technology.

Visual feedback plays a key-role in immersive VR. Previous research showed that in 3D pointing tasks user performance is significantly dependent on the visual cues provided [52]. For example, "highlighting" objects, such as changing object color when they are interacted with, significantly increases selection time, while decreasing the error rate [54]. Additionally, other environmental visual cues such as shadows [34], motion parallax [50], and textures [28] can help the user to perceive the environment better and also increase selection performance.

2.3 Haptic Feedback and Interaction in VR

Since mid-air interaction in VR allows users to interact with the VE without any physical support, many researchers have investigated the addition of haptic feedback. The effects of haptic feedback on user performance have been documented in previous studies, e.g., [46, 56–58, 65]. Other research has shown that haptic feedback improves user performance for 3D pointing in VR over no feedback [35, 42]. Overall, these VR studies yield a broad indication that haptic feedback can increase user performance in VE [11, 42], and further work has proposed to use haptic feedback as an assistance system [29, 42]. In contrast, recent work on EHCTSs identified that passive haptic feedback does not increase the user performance in VR and AR [8, 9].

2.4 Handedness

Previous research on 3D pointing identified that handedness has a significant effect on user performance in time, error rate, and throughput [30]. However, some work identified no major differences for error rate [44]. For instance, previous work on a VR-training system showed that user performance increased with the non-dominant hand for small and complex virtual objects [7].

2.5 Cursor and Target Size Variation

Previous work has identified that cursor size has also a significant effect on user performance [61]. This motivated researchers to also vary the cursor size in VEs, based on the distance between the user and the target, and the density of the environment. The Prince technique [31] and the Bubble cursor [24] are some of the examples for selection methods where the cursor size is varied. In these selection methods, the cursor size changes depending on the position of the pointing device and the nearest object(s) in the VE, i.e., while the size of the cursor is small for close targets, it is bigger when targets are further away.

2.6 Visual and Sensory Performance Assessment

Research on user performance assessment has shown that time alone is not a good approach for assessment, especially when the goal is to train users [4–6]. When other assessment criteria such as precision, accuracy, or error rate are used together with time to evaluate the user, motor skill acquisition and learning can be tracked more effectively. Batmaz et al. previously showed that throughput can be used as training performance assessment criterion [8, 9]. Gathering more information during the learning process also assists trainers towards providing more immediate and accurate feedback to the trainee, which can significantly increase the efficiency of training and improves user performance [16, 17, 62].

2.7 Perception-action and sports training

How users perceive the environment, process it, and react to it, is still one of the biggest research questions in human cognitive science. How information is presented and how we perceive the environment critically affects user performance [22]. Previous research identified that visual skills and sensorimotor abilities can be improved through different vision training systems, e.g., by focusing on aspects such as visual acuity [18], contrast [36], and stroboscopic exposure [1]. Previous work also showed that vision training systems can improve user performance in sports [14, 19].

In the work reported here, we are not aiming to improve user performance for a specific sports task, such as football or soccer. Instead, one of our aims is to provide a *theoretical conceptualization* of how VE dynamics affect user performance for reaction test systems in a specific performance environment in VR [49]. The purpose of EHCTSs is to improve perceptual and visual-motor skills of the athletes, but not to train them for a specific sport. After all, EHCTSs are used in a variety of sports to train users and their effectiveness is already well-established. For instance, recent research on the Nike SPARQ Sensory Station, which is used by athletic teams to train reaction times through EHCT, showed that these systems are useful for the training of professional football [26] and hockey [43] players. Previous work on EHCTSs compared user performance in VR and AR with an industry-standard setup and found that results in VR with mid-air interaction and passive haptic feedback can match conventional systems [8]. Batmaz et al. showed that user performance increases with mid-air interaction compared to passive haptic feedback [9]. Mutasim et al. investigated gaze and finger tracking in VR EHCTSs [40].

3 USER STUDY 1

3.1 Hypotheses

H1.1. User performance in VR-based EHCTS increases with the dominant hand, regardless of target size. 1D pointing experiments revealed that user performance does not change for handedness with large targets [32]. We expect a similar result with EHCTSs since they typically use a simple selection task with large spherical virtual targets

H1.2. User performance increases with a vertical target plane setup. Previous work on conventional and VR-based EHCTSs investigated only targets on a vertical plane [8, 9, 26, 43]. Other studies showed that user performance decreases in VR when subjects move their hands in depth, compared to lateral movements [2, 3] in the horizontal plane. We also expect similar results from this study, i.e., user performance in terms of time (and throughput) will be worse for the horizontal plane in our EHCTS.

3.2 Apparatus

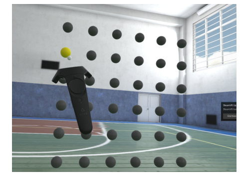
We used a PC with an Intel (R) Core (TM) i7-5890 CPU, 16 GB RAM, and a Nvidia GeForce RTX2080 graphics card. As VR display, we used a HTC Vive Pro HMD and its controllers as input devices.

3.3 Procedure

Here, we use a procedure very similar to the one used in previous work [8, 9, 40]. After a pre-study questionnaire, we demonstrated the VE and sample tasks to the participants. In the VE, they were placed in a virtual gym, facing a plane with targets in 6 rows by 6 columns as shown in Figure 1. All the targets in the grid were 10 cm apart from each other. We set the cursor size to 1 cm and showed the virtual 3D model of the controller to make it easy for the user to orient themselves in the VE. We adjusted the height of the target plane according to each users' height to make sure that they could easily reach all targets. We instructed users to stand (roughly) at the same spot and to mainly just move their arm to perform the tasks. We then gave them a few trials as practice, until they got familiar with the experimental system.

We asked subjects to choose the next target as fast and as precisely as possible. The experimental software randomly selected one of the thirty-six gray spheres as a target and highlighted it in yellow. The cursor was displayed 5 cm above the controller. Whenever the user moved this cursor 'inside' a target sphere or 'touch'ed it, we highlighted this sphere in blue. Users then had to pull the trigger on the VR controller to 'select' the target. When the user pulled the trigger, if the cursor touched or intersected the target sphere, the target sphere would turn green to indicate a 'hit'. Otherwise, the target sphere would turn red and the user would hear a beep sound to inform them that they missed a target.

(a)



(b)

Figure 1: Experimental setup for user study 1. (a) horizontal and (b) vertical target plane.

After such a selection, the software then randomly selected the next target within a set of designated target distances – 20, 28.3 and 30 cm, which corresponds to the distance of 2 or 3 spheres horizontal/vertical or 2 spheres diagonal. This approach allowed us to change A in Equation 1, without exceeding the field of view of the participant. Target positions in the 6x6 grid were fixed, but we varied the next target position by highlighting different targets in yellow. Only spheres in grey were chosen as the next target; previously selected/missed (green/red) spheres were not re-used. When there was no more targets to highlight, e.g., when there was no further target available, such as when the previous target was in the corner and all the potential next targets had already been used, one round of trials was finished. This procedure implicitly also varied the number of targets to select.

Subjects performed the study in two **handedness conditions** – dominant and non-dominant hand. For both handedness conditions, they experienced two different **target plane orientation** – vertical and horizontal. In the horizontal target plane orientation, the target grid was perpendicular to the participant. In the vertical target plane orientation, the target grid was parallel to the participant. The target size varied among 2, 4, and 8 cm after each repetition. We counterbalanced tasks across handedness and target plane conditions through a Latin Square design to compensate for potential learning affects. In total, the experiment took about 30 minutes per participant.

3.4 Participants

We recruited 12 participants from the community. 42% of them were female. 58% of them were 18-24 years old; 42% 25-34 years old. 8% were left handed. We assessed handedness with the Edinburgh Handedness Inventory [41].

3.5 Experimental design

The study used a $2_{Handedness} * 2_{Targetplaneorientations}$ within-subjects design. To vary the ID, we also used three **target size** variations ($3_{Targetsize}$: 2, 4, and 8 cm), and three **target distances** ($3_{Targetdistance}$: 20, 28.8, and 30 cm). Participants performed 5 repetitions for each of three target size condition, where the order of the target sizes also varied with the Latin Square design. For each repetition the target distance was automatically chosen by the software, as mentioned in the procedure section. Participants' time (s), error rate (%) and effective throughput (bits/s) were measured as dependent variables. Handedness, target plane orientation, and ID, which is the combination of target size and target distance, were independent variables. For more detailed analysis based on IDs, we used target size and target distance as independent variables. Based on the 3 different target sizes and 3 different target distances, we evaluated 9 unique ID_9s between 1.94 and 4.39. Since the number of selected targets were not the same in each trial and slightly different for each subject, there was no fixed number of data points collected. On average, subjects selected between 31 and 32 targets per trial, which yielded approximately 32 x $2_{Handedness}$ x $2_{TargetPlaneOrientation}$ x 5 repetitions x 12 subjects = 7680 data points for each dependent variable.

3.6 Data analysis

Before analyzing the data, we verified that (approximately) the same amount of data points had been collected for each experimental condition from each participant. This is shown in Figure 2. We analyzed the data by using SPSS 24.0 with $\alpha = 0.05$. Before the analysis, we deleted "double click" data (0.29% of the data), where the next target was selected without much movement, and instances when the participants were looking for the next target for a long time without moving the input device (1.9% of the data). We accepted normality when Skewness (S) and Kurtosis (K) values were between ±1, as suggested by previous work [25, 38]. We used repeated measures (RM) ANOVA for the log-transformed time variable since the dataset was log-normal (S = 0.6, K = 0.45). We used Mauchly's sphericity test to verify the appropriateness of ANOVA and Huynn-Feldt correction. For dependent variables that were not normally distributed, we transformed the data with an Aligned Rank Transform (ART) [66] before the RM ANOVA. For brevity, we only mention statistically significant results here. There was no significant interaction in the two-way ANOVA results in this study. Significance levels for interactions are shown as * for $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, and 'n.s.' for not significant.

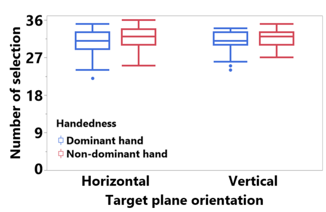


Figure 2: Quantile box-plots showing minimum, 2.5 %, 10%, 25%, median, 75%, 90%, 97.5% and maximum for average number of target selection for each participant for study 1.

3.6.1 *One-Way RM ANOVA Results.*

According to the results in Table 1 and Figure 3(a), subjects were faster with their dominant hand. The results in Table 1 and Figure 3(b) illustrate that subjects were faster in the vertical target plane orientation. Also, according to the results in Table 1 and Figure 3(c), participant's performance in terms of throughput increased with the dominant hand, and the results in Table 1 and Figure 3(d) illustrate that subjects' throughput increased with the vertical target plane.

3.6.2 *Detailed Handedness Analysis.*

In separate analyses for Handedness, Target size, and Target distance, we only found significant

Table 1: RM ANOVA results.

	Handedness	Target Plane Orientation	ID
Movement time	F(1, 11) = 43.653 ***, $\eta^2 = 0.799$	F(1, 11) = 46.91 ***, $\eta^2 = 0.810$	F(1.341, 14.751)=111.07 ***, $\eta^2 = 0.91$
Error rate	F(1,11) = 4.49 n.s, $\eta^2 = 0.29$	F(1,11) = 1.56 n.s., $\eta^2 = 0.024$	F(8,88) = 9.884 ***, $\eta^2 = 0.473$
Effective throughput	F(1,11) = 37.123 ***, $\eta^2 = 0.72$	F(1,11) = 57.16 ***, $\eta^2 = 0.84$	F(3.668, 40.349)=11.93 ***, $\eta^2 = 0.52$

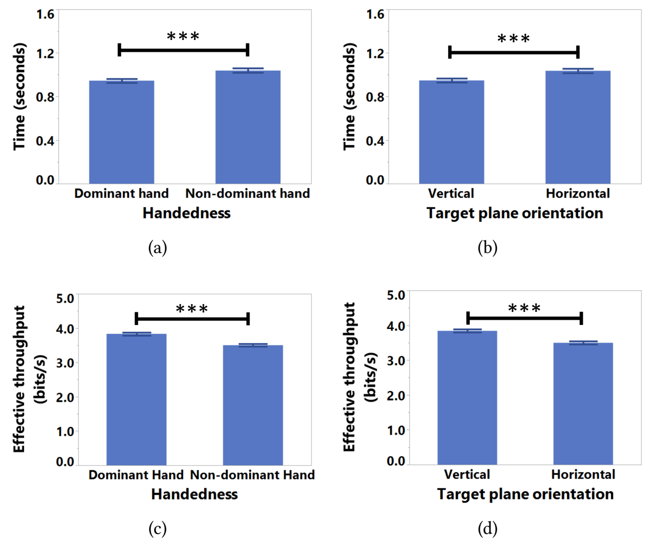


Figure 3: Time results for (a) handedness and (b) target plane orientation condition; effective throughput results for (c) handedness and (d) target plane orientation condition.

interactions between target size and handedness for time (F(2,22) = 9.33, $p < 0.001$, $\eta^2 = 0.459$), and target distance and handedness for time (F(2,22) = 3.755, $p < 0.05$, $\eta^2 = 0.254$). The results in Figure 4 show that subjects were faster with their dominant hand for each target size and target distance.

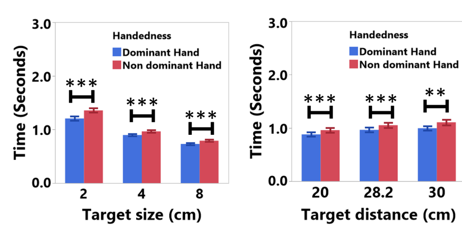


Figure 4: Detailed handedness analysis for (a) target size and (b) target distance for time.

3.6.3 *Subjective measures.*

We used a 7-point Likert scale to evaluate user perceptions for handedness and target plane orientation. None of the participants thought that it was easy to interact with virtual objects with the non-dominant hand (1-easy 7-difficult, the average result was 4.46) nor did they think that it was difficult to interact with virtual objects with the dominant hand (average 2.58). A Mann-Whitney U Test identified a significant difference between preferences (U = 18, $p < 0.05$). For the vertical and horizontal plane, we also asked users about the ease of interaction with the VE. There was no significantly different preference amongst users (U = 80, n.s.), but subjects rated the horizontal plane overall to be slightly easier to interact with (1-easy 7-difficult, the average result was 3.77) than the vertical one (average 3.84). The average task fatigue of 4.23 could be considered normal after participating in an experiment designed to emulate performance assessment in sports.

3.7 Fitts' Law analysis

Using Fitts' law in equation 1, we found that task execution time can be well modeled as 0.11 + 0.30*ID, R^2 = 0.97 for the whole experiment. We also identified that the difference between the dominant and non-dominant hand increases with higher indices of difficulty, as in Figure 5(a). Linear regressions were MT = 0.14 + 0.275 * ID, R^2 = 0.98 for the dominant hand and MT =0.08 + 0.32 * ID, R^2 = 0.95 for the non-dominant one. Furthermore, the results for vertical and horizontal target plane orientation in Figure 5(b) show that the differences in time between the vertical and horizontal plane got smaller with higher indices of difficulty. Linear regression for the horizontal plane was MT = 0.19 + 0.28 * ID, R^2 = 0.97 and for the vertical MT = 0.03 + 0.31 * ID, R^2 = 0.96.

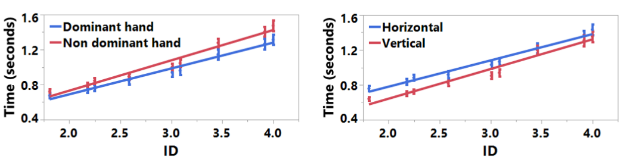


Figure 5: Fitts' law model for (a) handedness and (b) target plane orientation.

3.8 Discussion for User Study 1

In the first study, we analyzed user performance for the vertical and horizontal target plane orientation and the dominant and non-dominant hand. Our results match and extend the findings of previous work and confirm that we can use Fitts' law and throughput to analyze user performance for EHCTSs [8, 9, 40].

According to the handedness results, subjects are faster and their throughput increases with their dominant hand, which matches previous studies [30, 32]. Error rate was not different between the dominant and non-dominant hand, confirming previous work [44]. Compared to previous VR-based studies on handedness [7], our experiment did not require subjects to be more attentive to task constraints. Thus, participants were able to perform rapid, aimed hand movements. Regardless of target size and target distance, subjects were faster with their dominant hand in our experiments, which partially confirms our **H1.1**. Subjects could also have been more careful with their non-dominant hand, to allow them to reach the same level of accuracy as with the dominant hand, but this slowed them down. This could be the reason why we could not identify significant results for error rate for handedness.

Subjects were faster and their throughput increased with the vertical plane, as also shown in previous work [4, 63, 64]. This means that "just" rotating the experimental setup by 90° changes the user performance, especially for small indices of difficulty. This result is also supported by previous work [4, 51] and, thus, supports our **H1.2**. This also means that the design of the VE in an EHCTS can be used to exercise different sensory-motor skills, based on the needs of trainees.

Overall, the handedness and target plane orientation results show that user performance can be increased by using a vertical plane and the dominant hand. Extending previous work [8, 9], this result shows that the scope of VR-based EHCTSs include the vertical target plane and non-dominant hand for performance assessment. In this study, and even though we used only 12 subject, the effect size was large ($\eta^2 > 0.14$), which means that it is likely that we found a replicable result. For practical applications, a vertical target plane and using the dominant hand can be used as a benchmark condition for novice users, e.g., to motivate novices at the beginning of their training. Through the ID term of Fitts' law, the difficulty of the training can be adjusted step by step, simultaneously considering the throughput assessment. This might help athletes to improve their sensory motor skills and even work for different visual training tasks, which can help train other sensorimotor abilities of an athlete.

4 USER STUDY 2

In study 2, we decided to focus on how user performance is affected by cursor and target size variations with different feedback conditions. Our motivation for this study is that previous EHCT studies did not find a significant performance improvement with passive haptic feedback [8, 9]. With this study, we wanted to further explore the effect of active haptic feedback on user performance in VR-based EHCTSs. Thus, we replicated the study by Batmaz et al. [9], where the authors varied the cursor and target size.

As previous work had only investigated the effect of individual forms of feedback on time and error rates [42, 43], we also wanted to investigate how the combination of visual and haptic feedback affects throughput in mid-air VR-based EHCTSs. While conventional systems require a hardware 'hit' or 'click' to select targets and use this 'hit' or 'click' as feedback, VR systems can provide different forms of haptic feedback, such as vibration.

4.1 Hypotheses

H2.1. Active haptic feedback does not increase user performance for EHCTSs. Previous EHCT studies showed that user performance does not increase with passive haptic feedback when subjects hit a wall with their palms [9] or touch a wall with their index fingertips [8]. We thus do not expect to observe an increase in user performance with active haptic feedback.

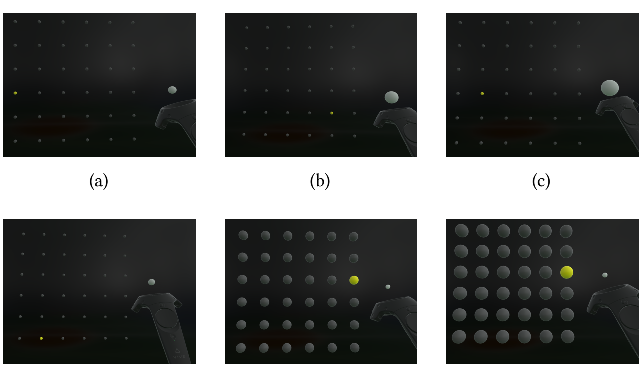
H2.2. User performance decreases with active haptic feedback for small target sizes. Previous VR-Based EHCT work investigated different cursor and target sizes and their effect on user performance, identifying that user performance decreases with passive haptic feedback when subjects interact with a small target [9]. We expect a similar result for active haptic feedback in our EHCTS with mid-air interaction.

4.2 Procedure

We followed the same procedure as in the first study, which also replicates previous EHCT work [9]. Different from Study 1, participants performed Study 2 with three **feedback conditions** - visual, haptic, and the combination of both. In the visual feedback condition, while the cursor was inside or interacted with the target, we changed the color of the target from yellow to blue to give a visual cue to the user. For the active haptic feedback condition, while the cursor was inside or interacted with the target, we vibrated the VR controller as a haptic cue. In the combination of visual and haptic feedback, we changed both the color of the target and vibrated the VR controller as cues.

Also, we varied either the target or the cursor through the **cursor-target size** condition. We chose these target and cursor sizes to be the same as in previous work [9]. With a target size of 1 cm, we explored cursor sizes of 1.6 (Figure 6(a)), 3.2 (Figure 6(b)), and 4.8 cm (Figure 6(c)). Alternatively, with a 1 cm cursor, we varied the target size from 1.6 (Figure 6(d)), 3.2 (Figure 6(e)), to 4.8 cm (Figure 6(f)). We counterbalanced tasks across all different conditions by using a Latin Square design to avoid potential learning effects for feedback and cursor target size conditions.

Since the target sizes were smaller in the second study, it was not trivial to perceive the next target position. In pilot trials, we had observed that subjects had a hard time to reliably see some of the smallest targets, which led to instances where participants had to spend extra time to visually search for the next target, which artificially raised the time measured for a single trial. Thus, and to make it easier to find the next target, we decreased the distance between targets to 8 cm. Also, to increase the contrast, we placed a dark transparent plane behind the targets to make it easier for users to see small targets and/or cursors, as in previous VR-based EHCTSs [8, 9]. Based on the results of the first study, we let participants use only their dominant hand with a vertical target plane orientation in this experiment.



(a) (b) (c)

(d) (e) (f)

Figure 6: Experimental environment for (a) 1.6, (b) 3.2, and (c) 4.8 cm cursor size. Similarly, experimental environment for (d) 1.6, (e) 3.2, and (f) 4.8 cm target size.

4.3 Participants

We recruited 12 participants from the community. 67% of them were female. All of them were between 18 and 24 years old.

4.4 Experimental Design

The study used a $3_{Feedback} * 2_{Cursor-TargetSize}$ within-subject design. The participants performed 5 repetitions for each of the 6 experimental conditions: three **feedback** conditions $3_{Feedback}$: visual, haptic, and visual+haptic and two **Cursor-Target Size** conditions, where we varied either the cursor or target size. To change the task difficulty, we used three different **sphere sizes**: 1.6, 3.2, and 4.8 cm, which we applied to either the cursor or the target (depending on the **Cursor-Target Size** condition), and three **target distances**: 16, 22.6, and 24 cm. Subject's time (ms), error rate (%), and effective throughput (bits/s) were measured as dependent variables. Feedback, cursor-target size, and ID, which is the combination of target size and target distance, were independent variables. For more detailed analyses, we used target size and target distance as our independent variables. Based on the 3 different target sizes and 3 different target distances, we evaluated 8 unique ID_8s between 2.12 and 4.0. Based on Equation 1, our chosen target sizes and distances lead to the same ID for target size = 3.8, 4.8 cm and target distance = 16, 24 cm, respectively. Since the number of selected targets was not the same in each trial and slightly different for each subject, there was no fixed number of data points collected. On average, subjects selected between 31 and 32 targets per trial, which yields approximately 32 x $3_{Feedback} * 2_{Cursor-TargetSize} * 3_{SphereSize}$ x 5 repetitions, i.e., an average of 2880 data points for each subject. All participants did the experiment with all cursor and target sizes.

4.5 Data Analysis

As in the previous experiment, we first analyzed the number of selections. Since the average was 31.87 per subject, which is similar to study 1, we did not investigate this further here. We again removed outliers from our data, such as double-clicks (0.3% of the data) and points when the participants spent substantial time to look for the next target without moving the input device (1.4% of the data). As above, we only report significant results in this section. The throughput data was normal (S = -0.02, K = -0.25). Still, even after a log-transformation, time and error rate data were not normal. Thus, we used ART [66] before ANOVA for those variables. When a significant interaction was found, we used the Holm-Sidak method to illustrate statistically significant differences between groups at each level of each factor in figures.

4.5.1 One-Way ANOVA Results. According to the results in Table 2 and Figure 7 only the error rate dependent variable was significantly different for the **feedback** and **cursor-target size** variables. Subjects made more errors when they experienced only haptic feedback (Figure 7(a)) and when the cursor size was fixed and target size varied (Figure 7(b)).

4.5.2 Two-Way ANOVA Results. In the two-way ANOVA results, we found a significant interaction between **feedback** and **target-cursor size** conditions F(2,22) = 13.602, $p < 0.01$, $\eta^2 = 0.553$, as shown in Figure 8(a). According to these results, subjects made

Table 2: One-Way RM ANOVA results

	Feedback	Cursor-Target Size	ID
Movement time	F(2,22) = 0.41 n.s. , η^2 = 0.036	F(1,11) = 1.574 n.s., η^2 = 0.125	F(7,77) = 175.77 ***, η^2 = 0.941
Error rate	F(2,22) = 10.336 *, η^2 = 0.48	F(1,11) = 99.58 ***, η^2 = 0.90	F(7,77) = 28.52 ***, η^2 = 0.72
Effective throughput	F(2,22) = 0.562 n.s., η^2 = 0.05	F(1,11) = 0.514 n.s., η^2 = 0.05	F(2.04, 22.42) = 72.29 ***, η^2 = 0.87

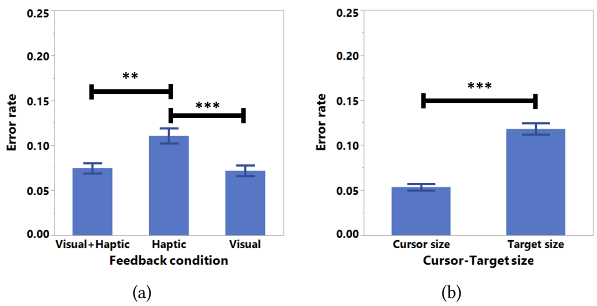


Figure 7: Error rate results for (a) feedback and (b) cursor-target size.

more errors with haptic feedback when the cursor size was fixed and the target size varied.

4.5.3 Detailed Cursor-Target Size Variation Analysis. Apart from the two-way ANOVA results, we found significant interactions between **target-cursor size** and **ID** conditions for time F(7,77) = 10.835, $p < 0.001$, $\eta^2 = 0.496$, error rate F(7,77) = 3.04, $p < 0.01$, $\eta^2 = 0.217$, and throughput with F(1.63,17.97) = 8.359, $p < 0.001$, $\eta^2 = 0.432$. Moreover, we found significant interactions between **feedback** and **ID** for the error rate dependent variable F(14,154) = 6.222, $p < 0.001$, $\eta^2 = 0.361$ and between the **feedback**, **target-cursor size**, and **ID** variables for time F(14,154) = 1.861, $p < 0.05$, η^2=0.145 and error rate F(14,154) = 3.165, $p < 0.001$, $\eta^2 = 0.223$. Since the **ID** variable includes different object sizes and we varied object sizes in the different **target-cursor size** conditions, we decided to analyze cursor-target size variation in more detail.

To separate the effects for the **feedback** conditions, we performed individual analysis for **target size** and **cursor size**. At this point, we present and additional (derived) independent variable called **sphere size**, $3_{spheresize}$, which is either: 1.6, 3.2, or 4.8 cm. We used a $3_{feedback}{}^{*}3_{spheresize}$ analysis to analyze the data for all three dependent variables. Analysis results are shown in Table 3.

Table 3: Detailed Cursor-Target Size Analysis

	Target Size		Cursor Size	
	Feedback	Sphere Size	Feedback	Sphere Size
Movement time	F(2,22) = 1.08 n.s. η^2 = 0.09	F(2, 22) = 93.36 ***, η^2 = 0.90	F(2,22) = 2.29 n.s. , η^2 = 0.026	F(2,22) = 90.92 *** , η^2 = 0.88
Error rate	F(2.22) = 8.33 ** , η^2 = 0.43	F(2,22) =23.49 ***, η^2 = 0.68	F(2,22) = 1.40 n.s. , η^2 = 0.113	F(2,22) = 65.96 *** , η^2 = 0.86
Effective throughput	F(2,22) = 0.167 n.s. , η^2 = 0.01	F(2,22) =19.27 *** , η^2 = 0.636	F(2,22) =1.22 n.s. , η^2 = 0.1	F(2,22) =41.77 *** , η^2 = 0.792

The results shown in Table 3 exhibit similarity with the information shown in Tables 2 and Figure 7. The error rate results are significant for both **feedback** and **cursor-target size** conditions. When the **sphere size** factor varied, we found significant results for all dependent variables.

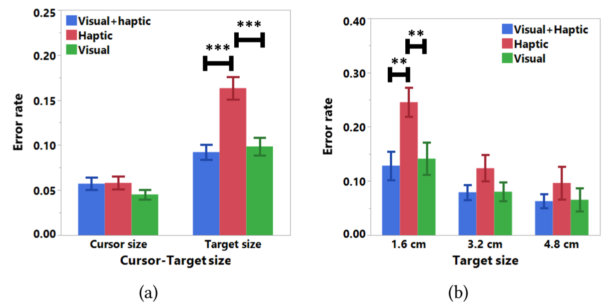


Figure 8: Two-way interaction for (a) feedback and cursor-target size and (b) target size conditions.

However, we were only able to identify a significant interaction between feedback and sphere size conditions for target size, F(4,44) = 11.10. $p < 0.001$, $\eta^2 = 0.502$, but not for cursor size. This result is illustrated in Figure 8(b). According to the results in Figure 8(b), subjects made more errors with the 1.6 cm targets when they only had haptic feedback, compared to visual feedback and the combined haptic and visual conditions.

4.5.4 Subjective Measures. We used a 7-point Likert scale to evaluate user perceptions of the various forms of feedback. 11 out of 12 participants felt that it was easy to interact with virtual objects with visual feedback (1-easy 7-difficult, the average result was 1.50) and 10 out of 12 with haptic feedback (average 1.42). All participants felt that it was easy to interact with virtual objects with the combination of visual and haptic feedback (average 2.08), however we could not identify a significant difference for ease of interaction between conditions through Kruskal-Wallis analysis, H(2) = 1.811, p = 0.39. 3 participants preferred to have visual feedback, 9 participants preferred both forms of feedback simultaneously, and none preferred only haptic feedback, but there was no significant difference, $p = 0.364$. As for the sphere size, 8 participants preferred a small target with a large cursor, and 4 preferred a large target with a small cursor, but the difference was not significant, $p = 0.248$. The average task fatigue of 5.08 could be considered normal after participating in an experiment designed to emulate performance assessment in sports.

4.5.5 Fitts' Law Analysis for Study 2. When we applied Fitts' law, Equation 1, we found that time can be overall modeled as: 0.135 + 0.287*ID, R^2 = 0.94. A linear regression for the visual feedback condition yields MT = 0.125 + 0.282 * ID, R^2 = 0.93, for haptics MT = 0.099 + 0.301 * ID, R^2 = 0.91, and for the combined feedback MT = 0.180 + 0.279 * ID, R^2 = 0.96, as in Figure 9(a). A linear regression for cursor size yields MT = 0.29 + 0.232 * ID, R^2 = 0.94 and for target size variation MT = -0.01639 + 0.34 * ID, R^2 = 0.93, as in Figure 9(b) .

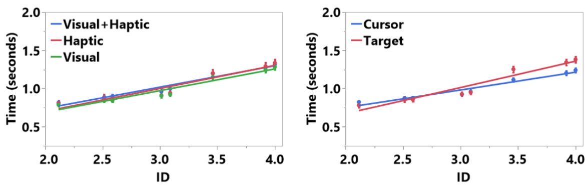


Figure 9: Fitts' law model for (a) different interaction modes and (b) target and cursor sizes.

4.6 Discussion for User Study 2

In the second study, we analyzed user performance with visual, haptic, and the combination of visual and haptic feedback, and also with different cursor and target sizes. Results for the feedback conditions showed that visual feedback and the combination of visual and haptic feedback exhibit no significant difference for time, error rate, and throughput. Yet, haptic feedback alone does not seem to improve user performance, which confirms the results of previous research on haptic feedback, such as [48, 59] and EHCT in VR [8, 9]. Results also confirm that 'highlighting' objects in VR improves user performance [53]. It is important to mention that we only changed the color of the target sphere for visual feedback. For haptic feedback, we only provided vibration through the VR controller. Even though we did not provide any visual cue for the haptic feedback condition, subjects were still able to recognize if the cursor position was inside the target. Still, changing the color of the whole target sphere proved to be more efficient than only providing haptic feedback. One explanation of this effect is that instead of waiting to feel the haptic vibration, subjects decided to make a decision based on their visual feedback, which seems to have been the faster method. This results partially supports our hypothesis **H2.1**, since haptic feedback did not exhibit any improvement in user performance.

Another result of this study is that subjects made fewer errors when the cursor size is varied. In most Fitts' law studies, target size is varied. However, Wang and MacKenzie showed that 2D cursor size also plays a critical role for Fitts' law tasks [61]. Our results show that, similar to 2D systems, it is possible to affect user performance by varying the cursor size in VR-based systems. A potential explanation is that this effect could be caused by the visual representation of the VR controller and cursor size. When the user aims at a target in VE, the virtual controller could obstruct the view, which could increase the error rate. And indeed, the detailed analysis showed that subjects made more errors with haptic feedback for the smallest target size (1.6 cm), which supports our **H2.2**. As in previous work on passive haptic feedback [9], user performance also decreased with active feedback in this study. This shows that for small target sizes, it is better to change target colors in the VE. Since we did not observe this significant difference in error rate for a small cursor size, this result was either caused by the technical limitations of the VR system, such as the tracking of the VR controller, or by limitations of the human perceptual system. We believe that the small target size was not large enough for users to accurately position the cursor to select targets with haptic feedback. Thus, the tracking of the system might not be accurate enough for small targets to enable users to perceive the position of the cursor. Also, the haptic feedback was an insufficient stimulus relative to other target size for EHCTSs. In our study, we did not alter the vibration of the controller. Thus, we hypothesize that a large cursor sphere might be more beneficial, even for small targets. As long as the density of targets in the VE is sufficiently low, this approach could be used in EHCTSs.

5 GENERAL DISCUSSION

Previous work on EHCTSs had identified that user performance increases with mid-air interaction [9] and passive haptic feedback does not increase user performance [8]. The results of our first study presented here showed that user performance increases when using a vertical target plane and the dominant-hand for EHCTSs with mid-air interaction. In the second study, we found that haptic feedback alone has no advantage over visual feedback and that the error rate increases for the smallest target size (1.6 cm) when only active haptic feedback was provided. This result also matches the work on passive haptic feedback of Batmaz et al. [8, 9], where user performance did not increase when hitting a physical object. Moreover, the results of the work presented here were calculated based on 3D measures. Thus, the results of this study not only extend previous work but also support that Fitts' law and throughput can be used to assess human performance in VR-based EHCTSs in 3D with different target plane arrangements and handedness.

While skill transfer from traditional EHCTSs to sports has been demonstrated [26, 33, 43], this is still not established for VR-based EHCTSs. Previous work in this area had identified that the effect of different forms of sensory feedback needs to be well understood to achieve successful skill transfer [23, 39, 67]. Thus, there is a need to first understand how the properties of 3D VR-based training systems influence user performance, before fully investigating and validating them with athletes. We believe that, before performing long-term studies with VR-based EHCTSs, the steps we report here are crucial to identify the components of an optimal VE setup with effective feedback mechanisms.

Even though we used only 12 subjects in both studies, we found significant differences with high effect sizes. The minimum effect size we observed here is 0.254, i.e., a large effect, commonly defined through a criterion of $\eta^2 > 0.14$. Based on these large effect sizes, we believe our findings to be robust.

After the experiments, we did not observe substantial physical fatigue, and participants also did not exhibit or report mental fatigue. We believe that the manual height adjustment of the virtual targets decreased the potential task fatigue. Moreover, since users were not moving their head in the virtual and physical space much, subjects did not report any simulator or motion sickness.

6 CONCLUSION AND FUTURE WORK

In this work, we investigated a mid-air VR version of an eye-hand coordination training system for mid-air interaction with different target setups. We identified that a vertical target plane used with the dominant hand delivers the highest user performance. Moreover, based on our results we can recommend using visual feedback, and not to rely solely on haptic feedback.

While this paper focused on regular users, our system could be directly used for training of professional athletes. In the future we are planning to focus on training of athletes to show that our system is beneficial for sports training. Furthermore, another use of mid-air VR eye-hand coordination training systems is for the rehabilitation of patients, e.g., after surgery.

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