Detection of Scaled Hand Interactions in Virtual Reality: The Effects of Motion Direction and Task Complexity

Shaghayegh Esmaeili* Brett Benda† Eric D. Ragan‡

University of Florida

ABSTRACT

In virtual reality (VR), natural physical hand interaction allows users to interact with virtual content using physical gestures. While the most straightforward use of tracked hand motion maintains a one-to-one mapping between the physical and virtual world, some cases might benefit from changing this mapping through scaled or redirected interactions that modify the mapping between user's physical movements and the magnitude of corresponding virtual movements. However, large deviations in interaction fidelity may potentially provide distractions or a loss of perceived realism. Therefore, it is important to know the extent to which remapping techniques can be applied to scaled interactions in VR without users detecting the difference. In this paper, we extend prior research on redirected hand techniques by investigating user perception of scaled hand movements and estimating detection thresholds for different types of hand motion in VR. We conducted two experiments with a two-alternative forced-choice (2AFC) design to estimate the detection thresholds of remapped interaction. The first experiment tested the perception of motion scaling for simple hand movements, and the second experiment involved more complex reaching motions in a cognitively demanding game scenario. We present estimated detection thresholds for scale values that can be applied to virtual hand movements without users noticing the difference. Our findings show that detection thresholds differ significantly based on the type of hand movement (horizontal, vertical, and depth).

Index Terms: Human-centered computing—Human computer interaction (HCI)—Interaction paradigms—Virtual reality; Empirical studies in HCI; Information interfaces and presentation—Multimedia Information Systems—Artificial, augmented, and virtual realities

1 INTRODUCTION

Natural physical motions are commonly seen as a fundamental element of virtual reality (VR) systems. By tracking the head, hands, or even the entire body, users are able to interact with virtual environments using familiar movements and gestures. To provide realistic experiences, virtual movements are usually determined by a one-to-one mapping based on physical movements in the real world. However, one-to-one mappings might not always be preferable or possible for all VR applications. Due to reasons such as limited availability of physical space or interacting with distant objects, modified interaction techniques are sometimes used. For example, modified walking techniques allow users to use their physical walking but traverse virtual spaces that are larger than the physical space (e.g., redirected walking [6,34], seven league boots [18], or amplified head turning [33,40]). Changing the scaling for hand movements can also be used to reach far away objects (e.g., the Go-Go technique [32]) or to physically interact with virtual objects via real-world physical props [2, 11, 16].

While modified interactions can be used in VR systems by adjusting the mapping between tracked motion inputs and the corresponding virtual motions, large deviations in interaction fidelity may potentially provide distractions or a loss in perceived realism for users. In some VR applications, system designers aim to preserve the sense of realism while using modified interaction techniques.

Our research focuses on detection of modified hand interaction techniques. Hand-centric controls are commonly used in current VR technology via natural hand movements using tracked hands, controllers, or physical props to enable interactions with virtual objects in order to increase the sense of presence and provide realistic interaction experiences. While previous work [43] has been done on estimating the detection thresholds for the hand redirection using haptic retargeting techniques [2], there is still little knowledge on detection thresholds for scaled hand movements in different types of hand motion in VR. Moreover, more research needs to be done regarding the detection thresholds of the scaled hand movements which involves free hand motion in less controlled scenarios with higher cognitive demands [7].

In this paper, we investigate user perception of scaled hand movements and estimating detection thresholds for different types of hand motion in VR. The primary goal of this paper is to answer our research questions:

- How do detection threshold estimations differ within each single degree of freedom for scaled hand motion?
- How do detection threshold estimations change with respect to task complexity: controlled hand movements compared to complex reaching motions in a cognitively demanding game scenario?

To address our research questions, we conducted two psychophysical experiments with a two-alternative forced-choice (2AFC) design to measure user perception of the scaled hand movements and estimate detection thresholds using psychometric functions. The first experiment tested user perception of motion scaling for simple hand movements in three directions (horizontal, vertical, and depth) while the second experiment involved more complex reaching motions in a cognitively demanding game scenario. In both experiments, hand movements were scaled by multiple scale values (slower, normal, and faster), and participants were asked to indicate whether their virtual hand movement felt normal or not normal. Our results provide estimations of detection thresholds for scaled hand movements and insights on the effects of motion direction and task complexity on the detection thresholds. These detection thresholds are of high value in VR applications that strive to maintain a natural and realistic experience for users, specifically with regards to hand motion.

2 RELATED WORK

Our work extends prior research conducted on modified general interaction techniques, perceptibility of these techniques, and hand remapping techniques. This section provides an overview of prior work in these areas and context for new insights provided by our research.

*e-mail: esmaeili@ufl.edu
†e-mail: brett.benda@ufl.edu
‡e-mail: eragan@ufl.edu

2.1 Modified Interaction Techniques and Detection Thresholds

Many altered modes of interaction have previously been explored, included those for redirected travel [6, 17, 18, 34, 40] and head redirection [36, 39]. These techniques often leverage the ability to manipulate aspects of virtual environments to increase naturalness, comfort, or users' ability to manipulate their environment. When using these types of techniques, it is important to determine the magnitude to which modifications to a user's virtual position can be applied before it is noticeable in order to preserve user immersion. Performance metrics are also important; while a technique may be undetectable, there still may be effects on measures such as task completion times and accuracy.

For example, in order to minimize strain on a user's neck, Sargunam et al. [36] investigated amplified head rotation (physical head turns resulting in larger virtual head turn) and guided head rotation (amplified head rotation with extra rotation added to realign the user's head with a forward direction) in comparison to traditional one-to-one head-tracked viewing in the context of navigation. Semi-natural techniques work for the intended purpose in the virtual environments compared to one-to-one mappings. However, there are side effects, such as sickness and unnatural spatial orientation. Later, Stebbins et al. [39] applied a similar technique to 3D movies where the user must rotate their head to areas of focus in the scene. Rotations were applied in two speeds (avg 3 deg/s and avg 13 deg/s). While the fast speed resulted in less time spent away from the forward direction, it was much more perceptible than the slow speed. However, neither fast, slow, or the control conditions resulted in different comfort or sickness ratings from users.

To assess the effects of warped space on redirected touching, Kohli et al. examined task performance [22] and adaptation [23]. Using the Fitt's-law-based ISO 9241-9 multidirectional tapping task, they determined that the task performance in warped space was no worse than an unwarped space [22]. They conducted further work and found that when given time to adapt, warped space and unwarped space performed similarly, though real-world training still outperformed both [23].

Prior work has shown that visual stimuli dominate proprioception in virtual environments, meaning that human's perception in virtual environments is dominated by what they see rather than what they sense regarding the orientation or position of their body and limbs [7]. Burns et al. [7] conducted a user study to investigate whether users are more sensitive to visual interpenetration or the mismatch between visual and proprioceptive cues in virtual environments. They concluded that people are more sensitive to visual interpenetration than the visual-proprioceptive conflict. Furthermore, they investigated the users' detection thresholds for visual and proprioceptive discrepancy by asking the participants to report anything odd in the virtual environment during the study.

Highly relevant to our research is psychometric analysis, a technique used to determine if a proprioceptive difference is perceptible to humans as well as upper and lower magnitudes to which the technique can be applied [13, 19]. Psychometric studies commonly employ a *two-alternative forced-choice* (2AFC) study design where users are repeatedly presented with a stimulus with varying intensity and must classify it as one of two options (e.g., "larger" or "smaller"). 2AFC had been used to analyze human perception when exposed to hand redirection [43], resized grasping [3], travel techniques [6, 8, 15, 17, 40], and haptic sensation [26]. In the realm of hand redirection, Zenner et al. [43] determined detection thresholds for horizontal warping, vertical warping, and gain-based warping. Bergström et al. [3] proposed *resized grasping* to redirect the user's fingers in VR to enable an individual prop to represent virtual objects of different sizes. In their work, they determined detection thresholds for the extent to which we can resize virtual objects from a physical prop. Steinicke et al. [40] utilized a series of 2AFC experiments to determine that walked distances can be up-scaled by 26% or down-scaled by 14% before users perceive proprioceptive discrepancies and that a turning radius of 22m or larger is sufficient to prevent most users from detecting the redirection. Bruder et al. [6] extend this work by analyzing task performance with various magnitudes of redirection and determined an inverse relationship between gain magnitude and task performance.

Bölling et al. [8] found that longer exposure to increased curvature gains can lead to higher detection thresholds in redirected walking. Grechkin et al. [15] also studied detection thresholds for redirected walking when applying two types of perceptual manipulations, curvature and translation gains, simultaneously. Their results found no changes in curvature detection thresholds when combined with translational gains. Moreover, they reported significantly smaller estimates for curvature detection thresholds compared to Steinicke et al. [40]. In a similar vein of research, Hayashi et al. [17] investigated height, rotational, and translation gains applied to users while jumping. Users were more sensitive to larger height gains and smaller rotational/translation gains. Lee et al. [26] utilized a cutaneous haptic device and simulated tracking error to determine thresholds for positional errors in VR. Furthermore, a distinction between *detection* and *immersion* has been proposed by Schmitz et al. [37]. While a stimulus may be detectable by a user, it may not be large enough in magnitude to break their immersion in VR. This suggests that current detection thresholds are not as generous as they could be if the goal of a specific technique is to enhance immersion over undetectability.

2.2 Hand Remapping Techniques

Modified mappings for hand locations have been long explored and utilized as an interaction technique in VR [2, 32]. Prior work has largely focused on the application of these mappings for hand redirection. However, little work has been done to determine the extent and magnitudes to which these mappings can be applied before they are detectable by humans. This section examines prior work on the application and evaluation of hand redirection techniques and outlines areas worthy of further exploration.

Perhaps the earliest instance of virtual hand manipulations, the Go-Go technique proposed by Poupyrev et al. [32] allows the users to extend their arm beyond their normal reach in VR. In this case, it is expected that users are aware of the modified interactions and it is preferred to make certain interactions easier or more convenient rather than natural and unnoticeable interactions [4]. The Go-Go technique uses a smooth curve to control positional gains applied to the virtual hand relative to the chest of the user. The mapping is linear until a threshold distance D (chosen to be 2/3 of the user's reach), after which non-linear gains are applied to the virtual hand. This application of gains has the effect of extending the virtual hand further into the environment as the user fully extends their arm allowing for amplified hand movements. This application of gains, later formalized as a modification of the Control/Display ratio [25], has been shown to significantly alter the perception of movement and mass in VR [12].

Extending the work of Poupryev et al. [32], Azmandian et al. [2] investigated several techniques for hand redirection in VR. The researchers distinguished two primary techniques for achieving hand direction: *body warping* and *world warping*. Body warping manipulates the virtual position of a user's hand in order to align its virtual location with the physical location of a haptic prop by shifting virtual hand's position as the user approaches the target. World warping translates or rotates the scene in order to realign virtual objects with a haptic prop while leaving the user's body unmodified.

Several techniques for passive haptic use in virtual environments rely on hand redirection to map one physical object onto several virtual objects [11, 16, 29]. Han et al. [16] investigated using translational and interpolative methods for mapping a user's virtual hand to a single grabbable prop. Their work indicates that translational hand shifting was generally preferable over interpolation, both in performance and user preference contexts. Similarly, Matthews et al. [29] utilized body warping as well as a new technique *interface warping* to provide users with functionality of several virtual buttons on VR controllers while only using one physical button. A combination of both techniques resulted in fewer errors and produced faster response times. Additionally, Cheng et al. [11] demonstrated hand redirection in combination with physical haptic landmarks used to simulate the geometry of various objects in the scene. To maximize alignment of physical objects in the virtual space, Suhail et al. [41] examined *resetting* (moving virtual objects to match the location of their physical proxy) and *redirected reach* (offsetting the virtual hand to make users grasp a physical object). Both techniques were compared to air grasping using no haptic props, with both haptic techniques yielding higher score for sense of control and realism. Extending this approach, Abtahi et al. [1] haptic retargeting with physical targets mediated through quadcopters by appropriating objects and the environment. To overcome a lack of accuracy in positioning the quadcopter at the target location, haptic retargeting was used to correct for the offset between the quad and the position of the virtual object. Additional factors such as hand size and interaction techniques have also been examined in the context of virtual hand modifications [27], with results showing that motion tracking gloves increased realism and ownership of virtual hands and lend themselves as a more appropriate input device for haptic use in the VR.

Most recently, Zenner et al. [43] used three different techniques of redirecting hands towards a destination, suggested by previous research. They investigated horizontal and vertical warping, as well as gain-based warping. Horizontal and vertical warping displaces the virtual hand along a vector rotated by an angle α around the displacement vector between the physical hand and the warp origin. Gain-based warping scales the position of the virtual hand by a constant value along the displacement vector between the physical hand and the world origin. Their results suggest that hands can be redirected up to 4.5 degrees in any direction using horizontal and vertical warping or scaled up by a factor of 1.07 or scaled down by a factor of 0.88 when using gain-based warping. While they have reported magnitudes at which hand redirection can go unnoticed when reaching for a virtual target under redirection, their work is focused more on the redirected position of the hand, rather than its movement, since they have used targets with a limited distance in front of the user (30-40 cm away from the user, and only in depth direction) and users were asked to touch a point in front of them, therefore their hand movement was limited only to reaching that point. Also related to detection of virtual hand adjustments, Gonzalez et al. [14] examined the effects of rotational gains on bimanual (two-handed) redirection. The researchers examined single hand, bimanual same-direction, and bimanual opposite-direction rotations to hands and determined offsets in the opposite directions yielded lower detection thresholds and offsets in the same direction produced higher detection thresholds indicating the effects of handedness and offset direction on redirection detectability.

Our research examines hand redirection techniques that apply positional gains to a user's hand movement. A multitude of techniques warp and distort or remap hand positioning (e.g., [2, 11, 16, 29]), but few examine the intensity to which these techniques can be applied before they are perceptible to humans. Most prior work [14, 43] has studied detection of scaling with simple controlled motions of reaching away from the body, but prior research has not investigated the effects of scaling over a range of contexts and with different directionality of hand motions. Our work provides a set of detection thresholds for scaled hand movements with (i) simple motions with single independent degrees of freedom, (ii) compound reaching motions, and (iii) varying levels of cognitive load.

3 Experiments

We conducted two psychophysical experiments with a two-alternative forced-choice (2AFC) design to measure user perception of the scaled hand movements and estimate the detection thresholds using psychometric functions. This section includes the study design goals, and detailed explanations of technique and procedure for each of the experiments. Note that although we report two experiments, both use similar methodology and yield comparable outcomes. For this reason, we first describe the experimental designs for each study, and then we present the results from both experiments together.

3.1 Goals

The primary goal of this research is investigating user perception of scaled hand movements in VR and estimating detection thresholds of the scaled values. To measure human perception, *Psychophysical* experiments are commonly used that provide "the analysis of perceptual processes by studying the effect on a subject's experience or behaviour of systematically varying the properties of a stimulus along one or more physical dimensions" [5]. Psychophysical experiments have varieties of procedures, such as *performance-based* procedures, *appearance-based* procedures, and *adaptive* procedures. It is important to consider the advantages and disadvantages of each procedure based on the research questions when designing a psychophysical experiment. Therefore, to address our research question of finding detection thresholds for scaled movement, two-alternative forced-choice (2AFC) methods are commonly used which is one of the methods of the performance-based procedures [19]. Similarly, 2AFC design has been used in previous research for detection thresholds (e.g., [3, 6, 8, 17, 40, 43]). In 2AFC methods, participants are repeatedly exposed to different varieties of a stimulus and forced to choose between two different responses (provided by the researchers) based on their perception of the stimulus. Typically, proportion of correct answers is used to measure the human performance in 2AFC methods [19]. Based on our research question of detection threshold estimation, we adopted a 2AFC method in which participants are exposed to different magnitudes of scaled hand movements in VR while moving their hands and being asked to choose between *normal* and *not normal* based on their perception of the virtual hand movement. The first experiment involves isolated hand movements along each primary axis (horizontal, vertical, and depth). The second experiment investigates complex hand movements under cognitively intense conditions with scaling applied in all three directions.

In each experiment, we used the following scale values:

- fast-scaled values (14 values): $\{1.025, 1.1, 1.175, 1.25, 1.325, 1.4, 1.475, 1.55, 1.625, 1.7, 1.775, 1.85, 1.925, 2.0\}$
- slow-scaled values (14 values): $\{0.5, 0.519, 0.54, 0.563, 0.588, 0.615, 0.645, 0.678, 0.714, 0.755, 0.8, 0.851, 0.909, 0.976\}$

The extreme scaled values (i.e. 2.0, which is the fastest scale, and 0.5, which is the slowest scale) were chosen based on previously reported detection thresholds by [43] and pilot study observations. We wanted to make sure that our slowest and fastest scales are detected by participants as a *not normal* hand movement in VR. Then, based on our study time limitation, we decided to use a step size of 0.075 to cover the scale values between 1.0 and 2.0. Since by using 0.075 steps size, less scale values would have been covered between 0.5 and 1.0, we decided to use $1/value$, the inverse of the fast-scaled values, to create the corresponding slow-scaled values. Using this method, we were able to cover more values in the slow range to get better results for detections thresholds estimation.

3.2 Apparatus

The experiment was run in our lab using an Oculus Rift (consumer version 1) HMD, The default Oculus motion tracking system. The

Oculus Touch right hand controller was used throughout the study, since all participants preferred right hand, or were right-handed. Participants used the right hand controller to move their virtual hand in the study, and no controller buttons were used. The software applications used in both experiments were developed in Unity 5.6.3p1 and run on 64-bit Windows 10 Professional. The computer had a 4.6 Ghz 6-Core processor and a GeForce GTX 1080 8GB GDDR5X. Participants were standing and in a relatively stationary position for both experiments. We provided a line on the floor for participants to stand behind.

3.3 Experiment 1: Simple Hand Movements

Experiment 1 was a within-subjects user study, designed to investigate the perception of scaled movements during simple, axis-isolated movements.

3.3.1 Experimental Design

Experiment 1 followed a within-subjects design and each participant completed all the conditions and trials. We tested 14 different values for faster hand movements, 14 different values for slower hand movements, and 14 *normal* hand movements (scale = 1.0). We had 42 (3×14) scale values, consisting of slow, fast, and *normal* scale values, and repeated each scale value twice to strengthen our data analysis results. Since in this experiment we aim to compare detection thresholds for simple, axis-isolated movements, we repeated all of the scales in three different axis: horizontal (x), vertical (y), and depth (z). Overall, each participant completed 252 trials (3 directions $\times$ 42 scale values $\times$ 2 repeats). The order of directions were counterbalanced with all order combinations. The ordering of scale values within each direction block was randomized for each participant. For each trial, we logged participant's answers (either *normal* or *not normal*), and their response time (from the time the participant started moving their hand to the time they said their answer). We used each participant's answers and response time as the measures for our data analysis.

3.3.2 Technique

The primary goal of this experiment was to determine the estimations of detection thresholds for scaled hand movements in simple, axis-isolated movements. It was necessary to develop a technique to isolate scaled movements to one axis at a time. To achieve this, we used the following formula to calculate an offset to be applied to the user's hand per frame based on the current scale value:

$$O_a = s * D_a$$

- O: offset added to virtual hand
- D: displacement of real (tracked) hand between the previous and current frame
- s: current scale value
- a: axis currently being scaled (x, y, z)

3.3.3 Procedure

The study was approved by our university's Institutional Review Board (IRB). Participation was voluntary, and extra credit was offered as a compensation for approved courses. We conducted an in-lab study, with one participant completing the study procedure at a time. Upon participant's arrival, informed consent was obtained from participant prior to beginning the study. Afterwards the participant was randomly assigned to a group dictating the order of axis-isolated movements that they were going to perform during the study. Participants were instructed on how to wear the HMD and were advised to make sure it was comfortable on their head and the display was clear. Then, the experimenter introduced the concept of VR briefly and asked the participant to use the controllers to get familiar with virtual hand movement, as well as turning their head around to explore Oculus Rift's default virtual environment. This step was mainly done to reduce the novelty of VR [31], i.e., the *'Wow' factor*, and prevent further distractions during the actual study.

A practice session (using the procedure stated below) was permitted using 1.0, 0.5, and 2.0 scale factors respectively, in order to (a) practice the study procedure, and (b) allow participants to gain an understanding of *normal* and *not normal* hand movements.

Participants proceeded to begin the first block of movements which consisted of all the scale factors for the initial axis, determined by the counterbalanced group at the start of the study. Participants were allowed to move their hand until an answer was determined. When a response was given, it was logged by a researcher in the system and the scale factor was updated automatically. The participant was then notified to begin moving their hand again for the next trial. This process was repeated until all scale factors were tested for that specific axis. The participant completed all the scale factors for the second block of movements, for the second axis, followed by completion of the third block of movements. Breaks were provided as needed and the participants were reminded every 4-5 minutes to take a break to minimize the risk of motion sickness. In one of the breaks, the participant was given a brief demographic questionnaire to fill. At the end of the study session, they completed a final questionnaire and answered several free response questions about their VR experience and preferences. Each participant took approximately 60 minutes to complete the study.

3.3.4 Participants

In Experiment 1, 46 university students of graduate and undergraduate level participated, consisting of 32 males and 14 females. Their age ranged from 18 to 34 with a median of 21 years old. 18 participants reported spending at least one hour a week playing 3D video games. When asked to rate their experience with VR on a scale from 1 to 5 (1 being with no prior experience and 5 being expert), 16 participants rated themselves 1 (No prior experience), 25 participants rated themselves 2-3 (Beginner and Average), and five participants rated themselves 4-5 (Advanced and Expert). 20 participants reported that they have never used a VR headset before. 4 participants reported they were comfortable with using both hands, and others reported being right-handed. All participants completed the experiment with their right hand.

3.4 Experiment 2: Complexity in a Game Context

Continuing the work from Experiment 1, we conducted a within-subjects user study exploring the effects of perception of scaled hand movements in more complex scenarios, involving compound motions (rather than simple movements in a single degree of freedom, as in Experiment 1). In Experiment 2, participants played two variations of a game with different degrees of difficulty to study the effects of greater cognitive load.

3.4.1 Technique

This experiment utilized the gain-warping technique to scale the virtual hand motion. The addition of a calibration step before starting each game was necessary, since participants are moving their hand continuously in the game version. Therefore an origin for the hand scaling is needed to provide a seamless experience while changing the scale values during the study. In our experiments, participants were asked to hold the controller in a neutral position in front of them (see Figure 1b). Its position was logged and used as the origin of scaling for their hand while playing each game.

$$V = O + s * (P - O)$$

- V: displayed position of virtual hand
- P: position of real (tracked) hand

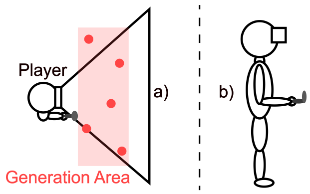

Figure 1: a) A top-down view of the setup for both games. b) A side view of the pose used to calibrate the scaling position. The controller position from this pose was used as the origin for scaling in 3D space.

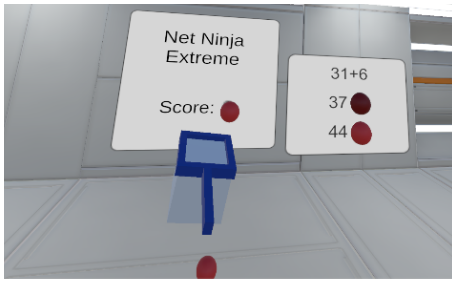

Figure 2: Player's view during the complex game. Target balls fall vertically, and the player must catch the ball indicated by a dynamically updating math problem on the right. Distinguishing between two colors requires additional focus to distinguish targets.

- O: position of origin
- s: current scale value

3.4.2 Experimental Design

Similar to Experiment 1, Experiment 2 also followed a within-subjects design with a new set of participants. Each participant completed all the conditions and trials. The same set of 42 *normal*, fast, and slow scales from Experiment 1 were used in Experiment 2, each with two repetitions. In total, we had 42 (3×14) scale values, consisting of *slow*, *fast*, and *normal* scale values, and we decided to have two repeats per each scale value to strengthen our data analysis results. Since in this experiment, we aimed to compare detection thresholds of scaled hand movements for two variations of a game with different degrees of difficulty, we repeated all of the scales in two different game version: basic and complex. Overall, each participant completed 168 trials (2 game versions $\times$ 42 scale values $\times$ 2 repeats). The order of game versions were counterbalanced to reduce the ordering-effect on the data analysis results. Similar to Experiment 1, the ordering of scale values within each version block was randomized for each participant. For each trial, we logged participant's answers (either *normal* or *not normal*), and their response time (from the time that the scale value changes to the time that they say their answer). We used participant's answers and response time as the measures for our data analysis.

3.4.3 Task and Game Context

For a more complex application involving additional attention attentional requirements and freedom of motion, we developed a simple game for users to play while experiencing different scaled movements. In the game, the player's hand is replaced with a net, which the player uses to catch target objects (spheres/balls) that fall from above. This gaming scenario was used to add a dual-task basis for the study of detection of motion scaling. While Experiment 1 allowed participants to solely focus on the motion and detecting scaling effects, Experiment 2 requires attention to the game task while they are also queried about scaling detection.

The player would score points during the game by catching the targets. Objects are generated randomly in an area located above and in front of the player, thus requiring a variety of hand reaching motions for optimal performance. The generation area is sufficiently large enough to require players to move their arm when attempting to catch an object, rather than using small movements like wrist rotation. All objects are identical except for their starting location in the generation area.

To study differences in the amount of cognitive load, Experiment 2 tested two versions of the game, which we refer to as the *basic* version and the *complex* version. In the *basic* game, the falling target objects all had the same color (dark red), size, and speed. A new falling target was generated every second.

The *complex* game followed the same basis of catching falling target spheres, but the game had a few key modifications to increase difficulty and mental workload. Rather than all targets being the same color, the complex game had targets in two colors—two shades of red. Similar colors were chosen to make it more difficult to quickly distinguish colors. At any point in the game, catching objects of one color will allow the player to earn one point while catching the other will make the player lose three points. The correct target color changed throughout the game, as indicated by a code on a virtual sign in front of the participant (see Figure 2). The sign shows a simple arithmetic problem participants need to solve to determine which color is currently correct. Once the correct value is determined, the player was instructed to verbally repeat the correct number to earn double points until the sign changes. The sign and arithmetic updated whenever participant responded *normal* or *not normal* question during the game, so players needed to continually pay attention to changes and then compute the new target color while the game continued.

Several game parameters were additionally modified in the *complex* version of the game to increase difficulty. The fall speed and generation rate of targets was increased by a factor of 3. One target per second was generated in *basic*, while 3 targets per second were generated in *complex* while their size was decreased as falling closer to the ground. The added complexity required players to split attention between playing the game (i.e., solving the addition problem, distinguishing different shades of red, and carefully planning hand movements to avoid accidentally catching targets of the wrong color) and also providing intermittent responses for the detection of motion scaling. The participants were prompted to respond seven seconds after the change of scale value. A virtual sign would appear after that seven seconds in front of the participant asking if their hand movement at that moment was *normal* or *not normal*.

3.4.4 Procedure

Informed consent was obtained from participants prior to beginning the study. Participants were randomly assigned to one of two groups dictating which game version to play first. The experimenter helped participants to wear and adjust the headset. Participants were given instructions for the first game well as an overview of the procedure.

Participants were told they would play each game continuously for several minutes at a time. While they were playing, the speed of their hand would be modified. After a delay, a sign would appear asking if their hand movement at that moment was *normal* or *not normal* and that they should verbally respond as soon as they could make a judgement about the movement. Participants were also instructed to respond as quickly as they detected whether the hand movement was normal, even before the sign appeared. Participants were then told to enter the calibration pose while the experimenter logged the position of the controller. Participants were allowed to play the game and practice the procedure using 1.0, 0.5, and 2.0 scale factors prior to starting the study.

Each participant was given seven seconds to play the game with each hand speed. Modifications to the speed of the hand were only made after a response about the previous speed was collected. Upon their response being collected, the speed of the hand was linearly interpolated to the next scale value over the course of 0.25 seconds to remove instantaneous hand warping. In the case of the complex game, a correct sum response was also recorded if provided by participants. However, this was not a necessary condition to move to the next scale value.

Throughout the study, breaks were provided as needed to minimize risk of sickness. Between games, participants were given a brief demographic questionnaire, and then, were provided instructions for the second game. The above process was repeated for the second game. After completing the second game, participants completed a final questionnaire and answered several free response questions about their experience.

3.4.5 Participants

Twenty university students, consisting of 13 males and 7 females, took part in Experiment 2. Their ages ranged from 19 to 28 with a median of 22 years old. Participants were undergraduate and graduate students. Sixteen participants reported spending at least one hour a week playing 3D video games. When asked to rate their experience with VR on a scale from 1 to 5 (1 being *no prior experience* and 5 being *expert*), 3 participants rated themselves 1 (No prior experience), 4 participants rated themselves 2 (Beginner), 10 participants rated themselves 3 (Average), and 3 participants rated themselves 4 (Advanced). Five participants reported that they have never used a VR headset before. 1 participant reported being comfortable with using both hands, and all others reported being right-handed. All participants completed the experiment with the right controller.

4 Results

We present the results for the scaled hand movements detection threshold, and response time analysis.

4.1 Estimations of Detection Thresholds

Due to our 2AFC task design, we used a psychometric function to show the relationship between proportion of correct responses and the different scale values, and to measure the detection thresholds [19]. We follow accepted analysis methodology used by similar 2AFC psychophysical studies (e.g., [9,10,38]) and used the *quickpsy* package in *R* [28] which fits curves to data observations by direct maximization of the likelihood (see [19,21]) using psychometric functions of the form:

$$\varphi(x) = \gamma + (1-\gamma-\lambda) * f(x)$$

where γ is the guess rate, λ is the lapse rate and f is a sigmoidal-shape function with asymptotes at 0 and 1. The *quickpsy* package fits the psychometric functions to each of the conditions in Experiment 1: Simple Hand Movements, i.e., horizontal, vertical, and depth, as well as the conditions of the Experiment 2: Complexity in a Game Context, i.e., basic and complex, separately for the slow and fast scale values. Figure 3 shows the plots for the probability of a *normal* response against the fast and slow scale values in Experiment 1. Figure 5 shows the probability of a *normal* response against the fast and slow scale values in Experiment 2. The solid lines show the fitted psychometric data with the *Cumulative Normal* distribution of the form:

$$F_N(x;\alpha,\beta) = \frac{\beta}{\sqrt{2\pi}} \int_{-\infty}^{x} exp(-\frac{\beta^2(x-\alpha)^2}{2})$$

with 2 free parameters, assuming 0 for guess rate (γ) and lapse rate (λ), and with the probability to calculate the threshold set to 0.5. A probability level of 50% is often used to find the absolute threshold which is the level of intensity of a stimulus (i.e., scale value in our experiment) at which the participant is able to detect the presence of the stimulus 50% of the time [24].

		α [CI]	β [CI]
slow	*horizontal*	0.809 [0.800, 0.819]	0.125 [0.117, 0.132]
	vertical	0.669 [0.059, 0.879]	0.167 [0.156, 0.178]
	depth	0.779 [0.768, 0.790]	0.162 [0.152, 0.171]
fast	*horizontal*	1.310 [1.300, 1.330]	0.216 [0.201, 0.228]
	vertical	1.520 [1.480, 1.550]	0.561 [0.510, 0.606]
	depth	1.380 [1.360, 1.400]	0.294 [0.277, 0.310]

Table 1: Table of thresholds (α) and standard deviations (β) for slow and fast scales in each direction tested in Experiment 1. Confidence intervals (CI) estimate 95% of the population.

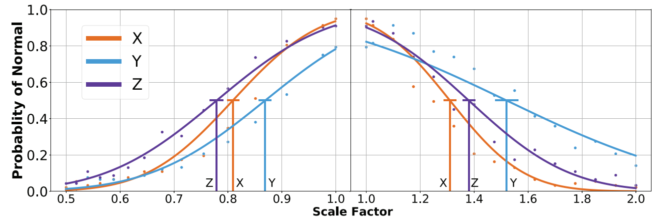

Figure 3: Fit psychometric functions for slow (left) and fast (right) scales from Experiment 1. Dropdown lines represent detection thresholds based on 50% detection probability. Error bars show a 95% confidence interval.

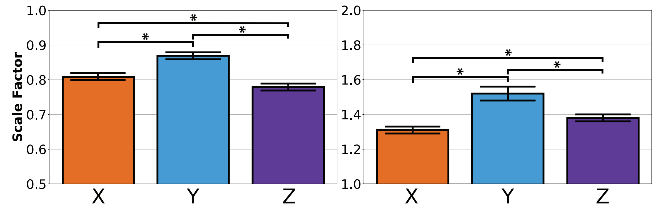

Figure 4: Thresholds for slow (left) and fast (right) scales from Experiment 1. Statistical significance at p < 0.05 is denoted by (*). Error bars show 95% confidence interval.

We report the values for the fitted psychometric functions for each of the experiments.

4.1.1 Detection from Simple Motions

Fast Scales: Figure 3 shows $\varphi_N(x;\alpha,\beta)$, where F is modeled by *Cumulative Normal* function $F_N(x;\alpha,\beta)$ for **fast** scales in horizontal, vertical, and depth directions. Values for α, i.e., threshold, and β, i.e., standard deviation, can be found in Table 1.

Comparison of Thresholds for Fast Scales: Figure 4 shows the comparison of thresholds for each of the axis in simple motions experiment. We used the *thresholdcomparisons* function of the *quickpsy* to test if there is any significant difference between the thresholds for different motions or not. The *thresholdcomparisons* function conducts paired comparisons between groups for all possible pairs of groups using the parametric bootstrap test. This function compares two given groups by calculating the difference between the bootstrap estimations of the threshold for all samples and from the distribution of differences, given the 0.95 significance level. Then the percentile confidence intervals are calculated as $P(\alpha \in CI) \geq 1-a$ where P is a probability and a is chosen as 0.05 in *quickpsy* (See [28]). The confidence intervals for the other parameters are obtained similarly.

We found a significant difference between thresholds for all the paired directions using fast scales in the simple motion experiment:

- *horizontal* vs *vertical*: $dif = -0.204$, $p < 0.05$

		α [CI]	β [CI]
slow	*basic*	0.797 [0.778, 0.817]	0.234 [0.210, 0.261]
	complex	0.758 [0.729, 0.783]	0.282 [0.247, 0.318]
fast	*basic*	1.390 [1.360, 1.430]	0.449 [0.402, 0.504]
	complex	1.430 [1.380, 1.480]	0.501 [0.446, 0.570]

Table 2: Table of thresholds (α) and standard deviations (β) for slow and fast scales for each game tested in Experiment 2. Confidence intervals (CI) estimate 95% of the population.

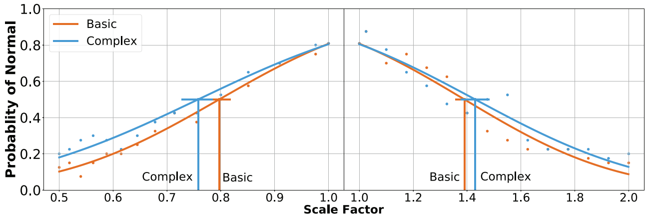

Figure 5: Fit psychometric functions for slow (left) and fast (right) scales during Experiment 2. Dropdown lines represent detection thresholds. Error bars represent a 95% confidence interval.

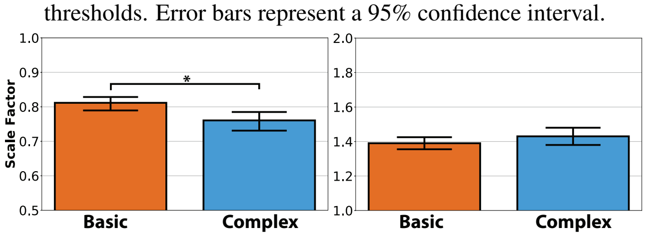

Figure 6: Thresholds for slow (left) and fast (right) scales during Experiment 2. Statistical significance at p < 0.05 is denoted by (*). Error bars represent a 95% confidence interval.

- *horizontal* vs *depth*: $dif = -0.067$, $p < 0.05$
- *vertical* vs *depth*: $dif = -0.138$, $p < 0.05$

Slow Scales: Figure 3 shows $\varphi_N(x;\alpha,\beta)$, where F is modeled by *Cumulative Normal* function $F_N(x;\alpha,\beta)$ for **slow** scales in horizontal, vertical, and depth directions. α and β values are found in Table 1.

Comparison of Thresholds for Slow Scales: Figure 4 show the comparison of thresholds for each of the axis in simple motions experiment. Similar to fast scales, we used the *thresholdcomparisons* to test for significance. We found a significant difference between thresholds for all the paired directions using slow scales in the simple motion experiment as well.

- *horizontal* vs *vertical*: $dif = -0.060$, $p < 0.05$
- *horizontal* vs *depth*: $dif = 0.30$, $p < 0.05$
- *vertical* vs *depth*: $dif = 0.090$, $p < 0.05$

4.1.2 Detection from Compound Motions

Fast Scales: Figure 5 shows $\varphi_N(x;\alpha,\beta)$, where F is modeled by *Cumulative Normal* function $F_N(x;\alpha,\beta)$ for **fast** scales in *basic* and *complex* game versions. α and β values are found in Table 2.

Comparison of Thresholds for Fast Scales: Figure 6 shows the comparison of thresholds for each of the game versions in Experiment 2: Complexity in a Game Context. Similar to Experiment 1 comparisons, we used the *thresholdcomparisons* to test for significance. We did not find a significant difference of the detection thresholds between two versions of game for fast scales.

Slow Scales: Figure 5 shows $\varphi_N(x;\alpha,\beta)$, where F is modeled by *Cumulative Normal* function $F_N(x;\alpha,\beta)$ for **slow** scales in *basic* and *complex* game versions. α and β values are found in Table 2.

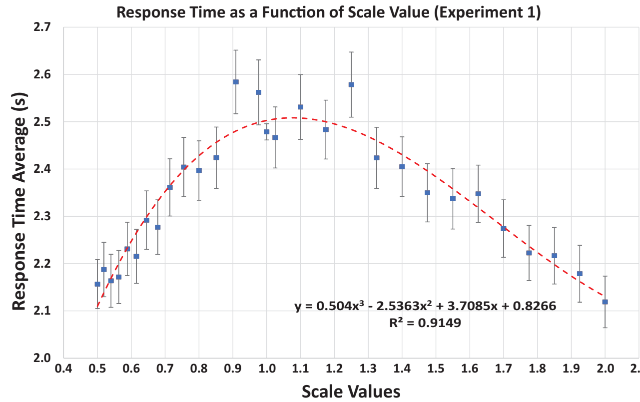

Figure 7: Response time as a function of scale value during Experiment 1. Error bars show standard error.

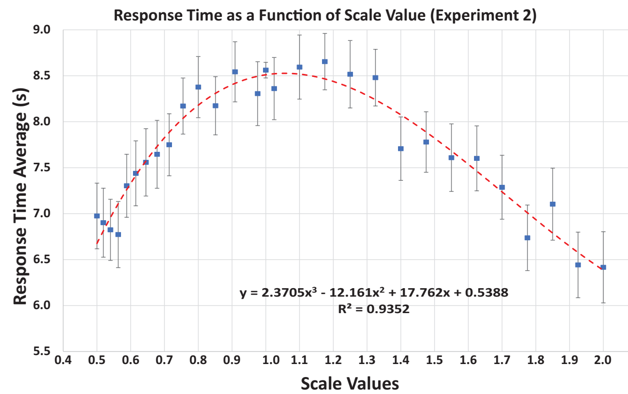

Figure 8: Response time as a function of scale value during Experiment 2. Error bars show standard error.

Comparison of Thresholds for Slow Scales: Figure 6 show the comparison of thresholds for each of the game versions in in Experiment 2: Complexity in a Game Context. We used the *thresholdcomparisons* to test for significance. We found a significant difference between thresholds of the different game versions for slow scales: $dif = -0.039, p < 0.05$

4.2 Correlation between Response Time and Scaling

We measured response time for each trial. In Experiment 1, response time indicates the time between when the participant starts moving their hand to when they provide their response. Since participants may behave inconsistently during the study in regards to answering the *normal* and *not normal* question (e.g., some participants might wait longer to say their answer or forget to say it as soon as they reached their decisions), the response time data may vary. Therefore, we need to detect and remove outliers before continuing the correlation analysis. For both of the experiments, we removed outliers for response times based on the 1.5xIQR rule (data points more than 1.5 times the interquartile range beyond the first or third quartiles). Then, we combined all trials from different directions in Experiment 1, and different game versions in Experiment 2, and calculated the average of response time per scale value. Figures 7 and 8 show the fitted curves and their equations for response time averages of different scale values for Experiment 1 and 2, respectively. We also ran an AIC (Akaike's Information Criterion) test [35] for the best fitting curve; the results of the AIC function with a polynomial with degree of 3 was the best fit. The fitted curves and their formulas have been shown in Figure 7 and 8.

5 Discussion

We present the range of scales that can be applied to the motion of virtual hand while the difference between the physical hand movement and the virtual one is undetectable to users. We estimate thresholds for each of the directions separately, as well as the compound hand movements in the *complex* scenario:

- *horizontal* plane: **(0.809, 1.310)**, scales in the range of 0.809 (slow) to 1.310 (fast)
- *vertical* plane: **(0.869, 1.520)**, scales in the range of 0.869 (slow) to 1.520 (fast)
- *depth* plane: **(0.779, 1.380)**, scales in the range of 0.779 (slow) to 1.380 (fast)
- *compound (3-dimensional)*: **(0.758, 1.430)**, scales in the range of 0.758 (slow) to 1.430 (fast)

These scale ranges are valuable for the design of future VR applications that use scaled hand movements as a modified interaction technique while aiming to provide a realistic, natural, and immersive experience for users in VR. These values are estimations of detection thresholds that can be applied to either increase or decrease the speed of the virtual hand. Slow-scaled hand movements can be beneficial in situations where accuracy of an interaction in VR is important (e.g., using VR for hand rehabilitation training [10], or medical training VR applications [30]). Therefore, they can be used in such applications to provide more controlled hand movements in VR. By applying scales within the proposed thresholds, it can be expected that discrepancies between VR and real world would not distract users. Fast-scaled hand movements, on the other hand, can be useful in VR applications aiming to provide a higher range of hand reach, or faster hand interactions (e.g., VR game applications). Using fast-scaled hand movements, VR users can move their physical hands less while their virtual hands are moving faster and can be used to reach far distant objects.

The results of our research also provide new insights on human perception of scaled hand movements in different motion directions in VR. We detected significant differences between detection thresholds in different directions both for slow and fast scales. The range was narrower for detection of modified motion scaling in the horizontal plane. This may be due to the visual field of view of horizontal plane covering a larger range than vertical [42]. Many common object motions make use of horizontal and depth motions (e.g., moving objects on a table or desk; opening doors; reaching for objects), but motion in the horizontal direction allows clear visual perception of positional changes, whereas depth changes also make use of somewhat less precise depth cues (e.g., vergence, relative size). Our interview subjective responses show people may be more familiar with hand motions in the horizontal plane and therefore can detect the abnormality better. On the other hand, our results show that we can have the highest range of detection thresholds in the vertical plane. This is probably due to the more limited degrees of FOV in vertical plane. Additionally, our participants' reports during the interview section suggests less use of vertical motion in day to day interactions, which may be related to a larger range in detection thresholds for scaled vertical hand movements.

Overall, the contributed knowledge of detection thresholds for different directions is relevant when considering application of scaled or remapped hand movements in VR applications. For example, in applications that require use of vertical motions (e.g., lifting objects or making climbing gestures) hand movements can be scaled higher using the estimation of detection thresholds and therefore provide higher reach for users while preserving realism. Similarly, estimation of detection thresholds for depth interactions can be useful in applications with back-and-forth hand movements such as reaching for virtual objects, or opening/closing actions. The results from our response time analysis is aligned with the detection thresholds of the scale values. As scale value becomes closer to 1.0, i.e., *normal* motion, users have a higher response time, which shows that they probably have a harder time in choosing *normal* or *not normal*. Additionally, compared to the scale thresholds suggested by [43], we report a broader range of scale values. This difference is likely due to our differences in study design. Similarly to previous work focused on very limited hand motion, we also conducted a controlled experiment. However, our study design focuses more on hand movements which are closer to the real world use cases.

5.1 Limitations and Future Work

We found no significant results between the *basic* and *complex* versions of our tested game scenarios which can be attributed to our study design limitations. It may be that detection ability is not greatly affected by cognitive load differences, as Zenner et al. [43] also did not find significant differences. Though we designed the complex game to be more cognitively demanding than the tasks in this study compared to the previous work, it might be that even more complex tasks would be needed to observe differences. Additionally, in more controlled or limited movements detection of compound motion may have differing sensitivity. The thresholds we propose for compound scaling are likely more intense due to the cognitively demanding tasks given to participants. We suggest further research into detection using simple motions to determine more conservative thresholds for compound motion, as well determining acceptable scales after continuous use or training.

Moreover, we point out that psychophysical methods have inherent limitations and are accompanied by different perspectives for analysis [20]. We note that while we present the results with an analysis based on standard 2AFC methods similar to other researchers studying similar detection thresholds in VR [3, 6, 8, 15, 17, 26, 40, 43], alternative analysis considerations may also be applicable based on yes/no variations of 2AFC methods [20]. We acknowledge the possibility of response bias in our study based on answering *normal* and *not normal*. The meaning of *normal* and *not normal* may vary between users, unlike other work which determine thresholds using less subjective means (i.e. "right" or "left"). Users may default to one option if they are unsure. Therefore, the reported detection thresholds of scaled values should be considered estimations based on the psychometric methodology used, i.e., proportion correct. To reduce the effects of bias, future work can also consider alternative d' *methods*, which uses a measure derived from signal detection theory.

6 Conclusion

We investigated user perception of scaled hand movements and estimating detection thresholds for different types of hand motion in VR. We conducted two psychophysical experiments with a two-alternative forced-choice (2AFC) design to measure user perception of scaled hand movements and estimate detection thresholds using psychometric functions. The first experiment involved isolated hand movements along each primary axis (horizontal, vertical, and depth). The second experiment investigated complex hand movements under cognitively intense gaming conditions with scaling applied in all three directions. We analyzed the data using a psychometric function methodology and found estimations of thresholds of scaled values that can be applied to hand movements. Our results showed that scales in the range of (0.758, 1.430) can be applied to virtual hand movements without the user detecting any difference. We also found significant differences between thresholds of the scaled values between horizontal, vertical, and depth directions. Our results are of value for the design of future VR applications. The scale ranges can be used to modify the hand movements in VR (either slower or faster than normal) based on the purpose of applications, while maintaining a natural and realistic experience for users.

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