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ForceCtrl: Hand-Raycasting with User-Defined Pinch Force for Control-Display Gain Application

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***Abstract*—We present ForceCtrl, a novel 3D hand raycasting technique that enhances pointing precision based on control-display (CD) gain controlled with user-defined pinch force. We introduce a target-agnostic approach for refining raycasting precision, overcoming limitations in human motor accuracy. User-defined pinch force, detected with surface electromyography (sEMG), enables users to easily activate or deactivate CD gain during interaction. We propose three CD gain strategies and compare them through target selection and placement tasks. Our system reduces selection errors, placement jitters, and user workload, especially for distant targets in high-difficulty tasks. These results highlight the effectiveness of applying CD gain to hand raycasting and demonstrate the potential of user-defined pinch force as a robust input modality for precise hand interaction in AR/VR.**

***Index Terms*—Hand Interaction, Force-based Interaction, Virtual and Augmented Realities, Input Accuracy, Raycasting**

I. Introduction

RECENT advances in graphics and display technologies in Augmented Reality (AR) and Virtual Reality (VR) have enabled the visualization of complex 3D environments, often populated with small and densely packed targets. As users increasingly interact with such complicated spatial data, the need for accurate and robust pointing techniques becomes critical for both productivity and user experience. While previous approaches have attempted to reduce interaction complexity by controlling the density or layout of 3D content [1], [2], this strategy is unsuitable in professional domains such as computer-aided design or data visualization, where arbitrary rearrangement hinders interpretation and workflow efficiency.

Raycasting is one of the most widely adopted pointing techniques in AR/VR, particularly effective for selecting out-of-reach targets [3]. Among its variants, hand raycasting is especially valuable in scenarios where seamless transitions between physical and virtual interactions are needed, as it does not rely on a handheld device. However, raycasting is greatly affected by human motor abilities [4] and tracking quality [5], [6], making it less suitable for high-precision tasks. To improve interaction with complex 3D environments, we focus on two key challenges: 1) enhancing raycasting precision and 2) enabling precision control without handheld devices.

Several techniques have been proposed to improve ray-based selection, such as object rating systems [7], [8] and pointing prediction models [9]–[11]. While effective in specific contexts, these methods often depend on specific targets or remain limited by human motor accuracy, reducing their generalizability. To address these issues, we introduce a target-agnostic pointing refinement method by applying control–display (CD) gain to the ray itself, reducing sensitivity to fine motor noise. Drawing from the concept of CD ratio in previous 2D and 3D interaction techniques, we define and compare three strategies for applying CD gain to raycasting.

Although bare-hand interaction offers significant advantages over device-based interactions as it preserves natural hand movement, it faces challenges due to limited input modalities. While gaze-based input is often paired with hand interaction [12], [13], it is less effective for rapid mode switching and small targets [14], [15]. To augment hand raycasting without introducing physical constraints, we leverage a familiar selection trigger such as a pinch gesture and measure its intensity using surface electromyography (sEMG). Unlike prior force-based systems that rely on fixed force thresholds [16], [17], our approach utilizes user-defined force levels based on a subjective scale [18], allowing force-based input that accounts for individual differences in force exertion and perception.

We present ForceCtrl, a novel 3D input technique that enables users to control the CD ratio of hand raycasting through user-defined pinch force. Our goal is to enhance the scalability of hand raycasting to better support the growing diversity of tasks in AR/VR environments. By leveraging pinch force, ForceCtrl provides unobtrusive control of the CD ratio, without requiring disruptive gestures or interrupting ongoing pointing tasks. In the following sections, we introduce user-defined pinch force as a robust input modality for interaction state control (Fig. 1(a)), and propose three CD gain strategies to refine ray precision (Fig. 1(b)). We demonstrate that ForceCtrl improves the pointing performance in high-precision tasks, and reveal the benefits of ray convergence and the drawbacks of visual discontinuity across different CD gain strategies. These findings contribute to advancing 3D interaction techniques for complex AR/VR environments and encouraging its adoption in professional and high-precision use cases.

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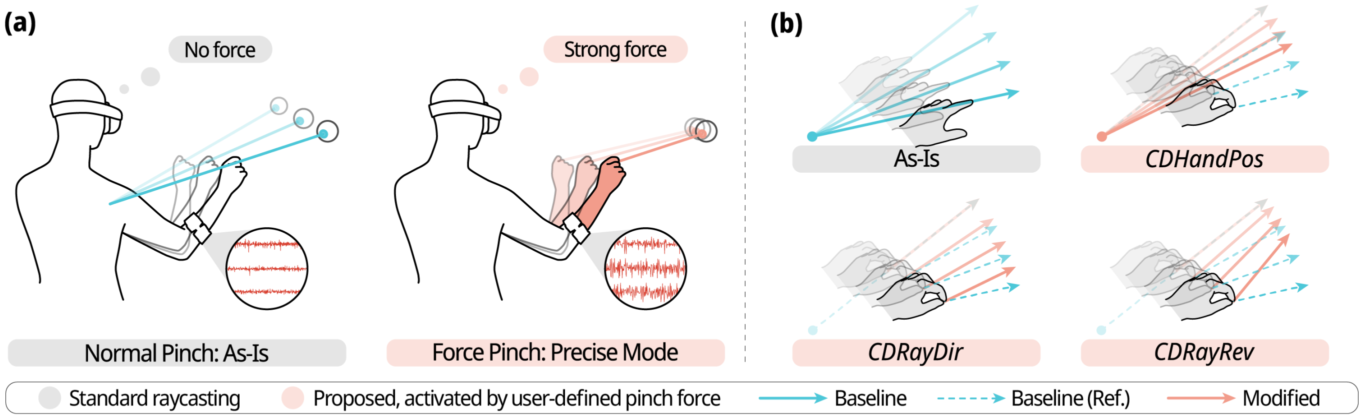

Fig. 1. Overview of ForceCtrl. (a) Users control pointing precision via pinch force detected by an sEMG armband. The ray behaves normally without force and shifts for increased precision when force is applied. (b) We propose and compare three CD gain strategies activated by force: CDHandPos scales hand movement; CDRayDir scales directional change; and CDRayRev applies the scaled directional change in reverse. The strategies are detailed in Section III.C.

II. Related Works

A. Precise Ray Pointing

As one of the most common 3D interaction methods, raycasting allows users to point and select out-of-reach targets [3]. However, the raycasting method is highly dependent on human motor ability [4], [19], and sensitive to even small movements [20], [21]. Also, ironically, raycasting becomes less accurate at greater distances [22]. Various assistive techniques have been proposed, including expanding selection volume [1], [23], [24], hierarchical disambiguation [25]–[28], and object rating systems [4], [7], [8]. While these methods reduce user's burden of accurate pointing, their reliance on specific targets limits their applicability to other tasks, such as target placement. Although computational models can predict the ray's landing pose [9]–[11], pointing resolution is still confined by human motor limitations.

Applying a CD gain to a pointing method can mitigate the limitations of human motor ability [19], [29]. While CD gain has been used in direct 3D interaction for target selection [2], [30], placement [22], [31], and manipulation [32], its application in distant 3D interaction remains underexplored. Dual-precision pointing [33], or hybrid pointing [34], [35], improves distal pointing accuracy by separating ballistic and corrective phases. However, most mid-air dual-precision techniques are limited to pointers projected on surfaces [36]–[38]. Prior CD gain applications for raycasting have focused on handheld devices [39], [40]. We aim to define a CD ratio for hand raycasting, which differs from handheld raycasting in terms of ray origin and extrapolation.

B. Hand Interactions

Mid-air hand interaction enables natural and expressive interaction for various tasks such as object retrieval [41]–[43] and mode switching [44], [45], without the need for external devices. It is especially well suited for AR, where seamless transitions between virtual and physical contexts are important. Hand raycasting, in particular, has demonstrated performance comparable to handheld controllers given high-quality hand tracking [6], [46]. Although gaze-based interaction presents a hands-free alternative, its high variability [47], inherent Midas touch problem [48], and limited accuracy for small targets [14], [15] make hand interaction a more reliable choice.

Pinch gestures [20] have been widely studied for their intuitive nature and innate tactile feedback. Often employed as a selection trigger in hand [28], [49], [50] or gaze raycasting [13], [46], [50]–[52], pinch offers fast [53] and temporally precise input [54]. It has also been used for depth control [55], clutching [14], [56], and 3D interaction tasks such as grasping [57], pivoting [58], and bimanual manipulation [12], [59], [60]. However, limiting pinch to binary triggers underutilizes its potential. Recent studies have explored richer input through semi-pinch state [2], [13] or continuous pinch scaling [61]. Building on this, we integrate multiple levels of pinch force, leveraging its natural tactile feedback.

C. Force-based Interactions

Force-based interactions have been widely studied in 2D contexts, particularly in mobile [62] and tabletop settings [63]. These studies have introduced force to enable additional actions [17], [64] or adjust input parameters [16], [65]. In particular, studies that used force or pressure to control input precision [66], [67] suggest its potential to enhance pointing accuracy. In contrast, force-based interactions in 3D has received limited attention. It has mainly focused on mimicking real-world physics [68], [69] and has not been extensively explored as a novel input modality.

The forearm-worn sEMG has long been investigated for hand interactions [70]–[72] due to its non-invasive nature [73]. Although numerous models for sEMG-based finger or pinch force estimation have been proposed, few consider users subjectivity and individual differences. Most models employ direct force regression [69], [74], [75], yielding objective values. Similarly, force level classification typically defines levels based on ground truth force [76] or Maximum Voluntary Contraction (MVC) [77], [78]. Instead, our model classifies user-defined force levels to account for user variability in physical ability and perception.

III. Force Classification Model

The force classification model forms the foundation of our system, enabling reliable recognition of multiple levels of pinch force to provide explicit control over interaction parameters. The model classifies user-defined pinch force leveraging forearm EMG signals, accommodating individual differences in muscle strength and perception. This section first describes a preliminary study to determine feasible force levels for interaction, followed by the design and evaluation of machine learning models for force classification.

A. Preliminary Study on User-Defined Pinch Force

Our aim is to employ subjectively determined pinch force as a robust input, addressing individual differences in muscle ability and perception. We first validated whether users can distinguish multiple levels of pinching force under a subjective scale. From previously observed correlation between the perceived force intensity and objective measures in hand activities [79], [80], we assumed that the correlation would hold the same for the pinch force exertion.

We recruited 12 participants (7 male, 5 female, ages 22–32, $M = 28.5, SD = 3.37$) with the institutional review board's approval. The participants were equipped with a force sensor (CS8-100N, Singletact) on the thumb. The Borg Category Ratio Scale 10 (Borg Scale) [18], which comprises numbers from 0 to 10, has been commonly used to quantify perceived force intensity by assessing muscle fatigue. We measured four in-between force intensities that are noted with verbal anchors, "2:Weak", "3:Moderate", "5:Strong", and "7:Very Strong", as verbal anchors are the key factor of the scale for quantizing user's experience. We excluded the extremities from the scale, as such force levels are either impractical for repeated execution or less suitable for stable sensing in interaction. We collected 4 trials for each level in a balanced order, obtaining 16 measurements in total. We also captured the MVC of each participant for analysis.

We found a cross-user linear relationship between Borg Scale and %MVC with a regression coefficient of 9.72 ($r^2 = .83, F(1,238) = 1189, p < .001$). %MVC value was calculated by dividing the measured force by the MVC of the participant in Newtons. The results suggest a common pinch force exertion behavior among participants under the Borg Scale. We also performed a within-participant linear regression, where the regression coefficient ranged in 9.72 ± 0.97 ($r^2 = 0.88 \pm 0.05$). We confirmed users can consistently exert the same pinch force at a given Borg Scale level.

It was also suggested that force levels should be at least three Borg Scale units away from each other to ensure discernibility. For each participant, we compared the four force levels in %MVC. If the measured force intensities of two paired force levels did not make a significant difference, we assumed that the participant did not clearly distinguish the two levels. The result showed that there were 7 participants who were unable to make a significant difference for the "2:Weak" & "3:Moderate" pair, two participants for the "3:Moderate" & "5:Strong" pair, and another two participants for the "5:Strong" & "7:Very Strong" pair. Accordingly, also considering the stability of sEMG signal, we selected "3:Moderate" & "7:Very Strong" pair as the input to our system.

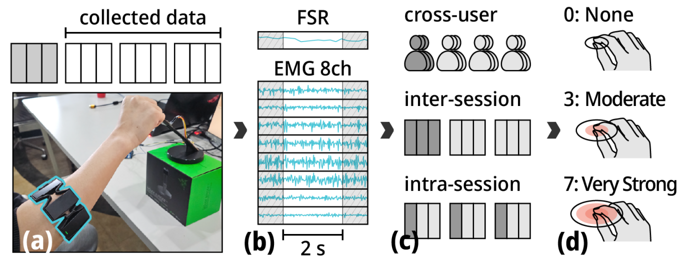

Fig. 2. Force classifier training. (a) Data collection setup and procedure, (b) collected data, (c) training conditions, and (d) classification output.

B. Classification of User-Defined Pinch Force

We explored multiple machine learning models to classify the Borg Scale ratings using forearm EMG signals. We recorded forearm EMG signals using an armband with 8 electrodes[1]. It should be noted beforehand that our methodologies and findings are not confined to a specific device, and could potentially be extended to alternative EMG-based devices. Data were collected from 12 participants (6 male, 6 female, ages 22–37, $M = 28, SD = 4.92$), at three Borg Scale levels ("0:None", "3:Moderate", "7:Very Strong") across four sessions per participant later excluding the first session (Fig. 2(a)). Each trial involved a 4-second pinch and we analyzed the middle 2 seconds (Fig. 2(b)) yielding 10.8 minutes of data.

We evaluated five distinct models for force classification: logistic regression, a 3-layer neural network, SVM, XGBoost [81], and CNN [69]. We performed tests under three conditions (Fig. 2(c)): cross-user (generalization across users), inter-session (consistency over sessions), and intra-session (performance with session-specific calibration). Participants were split into four groups for cross-user testing, one group for testing and the rest for training, resulting in a 4-fold split. In the inter-session condition, one of three sessions per user was set as test data, forming 36 training-test pairs. For intra-session testing, one of three trials per session was used for testing, creating 108 pairs. The classifier was trained to recognize the three force levels: "0:None", "3:Moderate", "7:Very Strong" (Fig. 2(d)).

In the cross-user condition, the model accuracy ranged from 35.99% to 79.12% with CNN performing best but impractical. In inter-session tests, CNN outperformed logistic regression but showed no significant advantage over SVM and XGBoost in paired t-tests. Pre-training and temporal aggregation improved CNN's median accuracy to 93.35% though still insufficient. In intra-session tests, CNN significantly outperformed all models and reached 99.65% accuracy with pre-training and temporal aggregation. Due to its high intra-session performance, we adopted CNN in our system (Fig. 3(a)).

To address the reliability issues of EMG-based systems from motion noise and equipment problems [73], we added a history accumulator. Our system updates the force level only when

[1] Thalmic Labs Myo armband: https://github.com/thalmiclabs

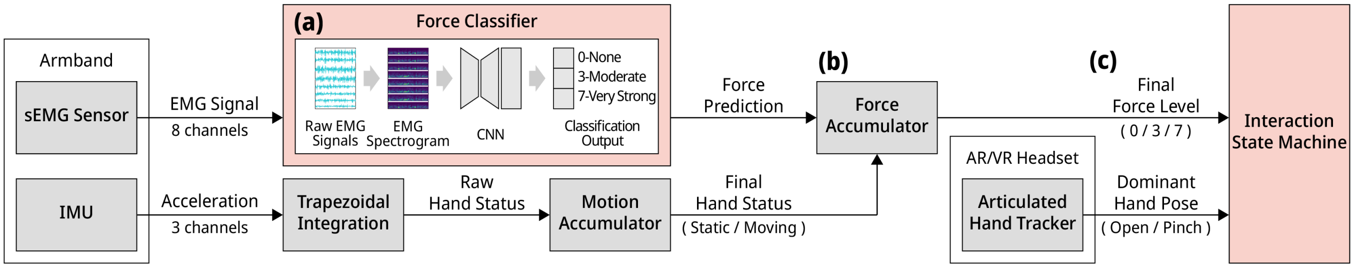

Fig. 3. System architecture of ForceCtrl. (a) A pre-trained CNN processes 8-channel sEMG data and classifies it into three force levels. (b) The output is post-processed with motion data using a history accumulator. (c) The final classification, combined with hand pose, determines the interaction state.

the history accumulator is filled with the same class for 60 frames, for both responsiveness and stability (Fig. 3(b)). We also integrated IMU signals, assuming users would not change pinch force during rapid hand movements. When hand velocity exceeds the threshold, the history accumulator does not update. If the output of the force history accumulator is consistent over 50 ms, we combine it with the hand pose tracked by the headset and alter the system's interaction state (Fig. 3(c)). The interaction state remains unchanged for 0.6 s after a change to ensure stability. By combining EMG and IMU data with temporal aggregation, our system improves force classification reliability.

IV. ForceCtrl System

ForceCtrl is designed to improve the accuracy of hand raycasting in a target-agnostic manner, supporting both precise selection and placement. Built on the force classification model, it enables explicit control of pointing precision: the ray becomes more precise as pinching force increases. The system allows seamless alteration of pointing precision without disrupting users' workflow.

A. Interaction States

Without any force exertion detected by the force classification model, the system operates as usual, in the same way as the standard hand raycasting. When the index finger is open, the pointer is in the coarse pointing state (Fig. 4(a)). When a pinch gesture is recognized, the pointer turns into the coarse dragging state, considered to be clicked (Fig. 4(b)).

When users require grater pointing accuracy, they can activate the precise states by applying the pinching force. A force of "3:Moderate" triggers the precise pointing state (Fig. 4(c)). In this state, the pointer's movement is damped, as detailed later in this section, enabling more sensitive control with the same hand movement. This mapping, where a stronger pinch results in smaller ray movement, may feel intuitive as it resembles the metaphor of drag force.

Then, the force of "7:Very Strong" triggers the precise dragging state (Fig. 4(d)). Pointer movement is also damped in this state. With increased pinching force, users can either select an object with a brief click or grab it by maintaining the force. Although the exertion of "7:Very Strong" can be physically demanding, this state is expected to be held only briefly in typical use.

B. State Transitions

Pinch can activate three different states: coarse dragging, precise pointing, and precise dragging. Upon detecting a pinch gesture, the system awaits the next output from the classification model. If the classified force level is "0:None", coarse dragging state is activated. A force level of "3:Moderate" triggers the precise pointing state. No transition occurs when the force is classified as "7:Very Strong" at the moment of pinch. Notably, the states are not sequential; although the user naturally transition through the intermediate levels, the 50 ms window systematically allows direct activation of the states.

The precise dragging state is only accessible when the pointer is already in either the coarse dragging or precise

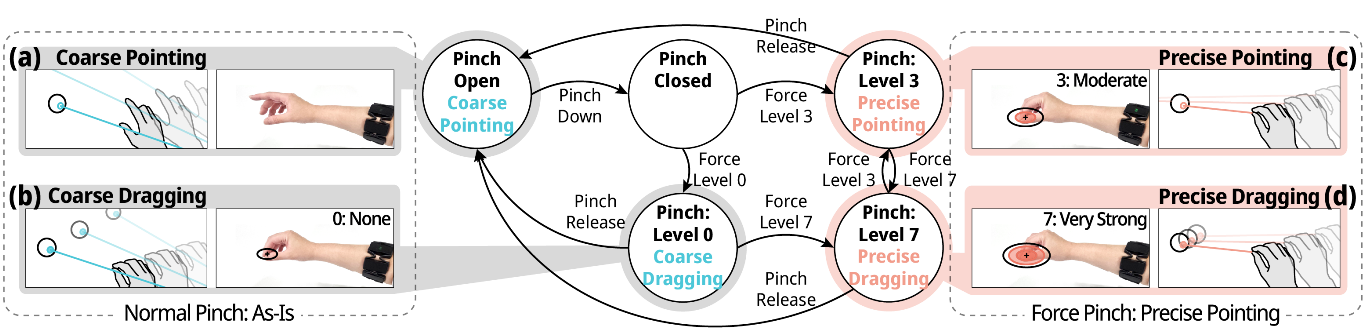

Fig. 4. Interaction state transitions. (a) Coarse pointing, (b) coarse dragging, (c) precise pointing, and (d) precise dragging. Upon a pinch, the system waits for the next force classification and transitions to either coarse dragging or precise pointing. Precise dragging is only reachable from these two. Releasing the pinch returns the system to coarse pointing.

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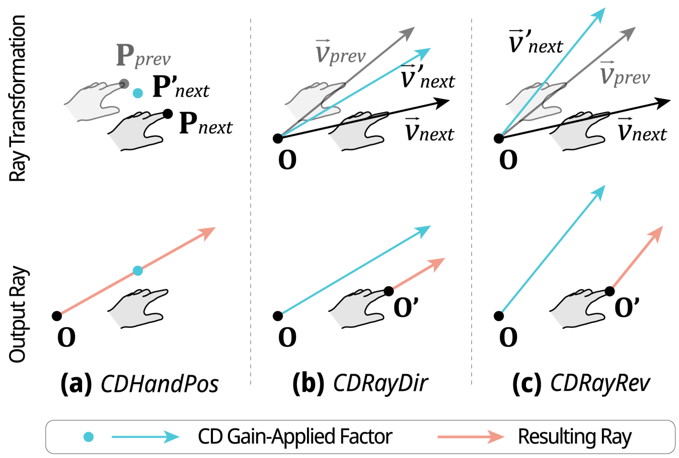

Fig. 5. Three ray shifting strategies. (a) CDHandPos, (b) CDRayDir, (c) CDRayRev. *Top row*: the ray transformation process to apply CD gain; *bottom row*: the resulting output ray. P is the hand's position, P' is the CD gain-applied position. $\vec{v}$ is the vector of the pointing ray, $\vec{v}'$ is the CD gain-applied vector. O and O' are the origins of the pointing ray.

pointing state. This transition logic assumes that users are unlikely to change both precision and selection state simultaneously. The system allows returning from precise dragging to precise pointing, enabling actions such as consecutive clicks. However, transitioning directly from precise dragging to coarse dragging is not permitted, as we assume users would not attempt to "reset" the pointer mid-drag. Users can always exit to the coarse pointing state by releasing the pinch.

C. Ray Shifting

While the CD ratio is well defined in 2D pointing, the concept becomes less clear in 3D ray-based pointing, where the ray extends infinitely and lacks a fixed endpoint. To address this, we propose three approaches, each applied to a different component of the ray. To ensure broader applicability, all approaches are designed to be target-agnostic, making them suitable for both target selection and placement tasks. We implemented the system using discrete force-based states rather than a continuous force-to-gain mapping to support multiple interaction modes and ensure robust interaction. Discrete states allow four functionally distinct phases, whereas continuous scaling would permit only two: pinching and not pinching. Prior work also showed that implicit transition results in significantly lower performance and preference for small targets than using a discrete mode switch [36].

CDHandPos. A straightforward approach is to treat the real hand as the control input and the virtual hand as the display output [2], applying the CD gain to the real hand's translation to determine the virtual hand's position (Fig. 5(a)). Specifically, the 3D displacement of the hand is scaled by the CD gain and added to the virtual hand's previous position: $P'_{next} = P'_{prev} + (P_{next} - P_{prev}) \times g_{CD}$. Likewise, the change in ray direction is scaled and added to the previous ray direction: $\vec{v}'_{next} = \vec{v}'_{prev} + (\vec{v}_{next} - \vec{v}_{prev}) \times g_{CD}$. This effectively extrapolates the ray through the modified hand position. Note that the virtual hand is a conceptual construct and is not rendered to the user. Although simple, this method can cause the ray to visually detach from the user's hand, potentially leading to dissonance in the user experience.

CDRayDir. Inspired by prior work that damped rotational changes in handheld raycasting [39], [40], this second approach scales the directional change of the ray (Fig. 5(b)). In this method, the hand position remains unchanged, while the change in ray direction is scaled by the CD gain and applied to the previous direction: $\vec{v}'_{next} = \vec{v}'_{prev} + (\vec{v}_{next} - \vec{v}_{prev}) \times g_{CD}$. This maintains visual continuity between the ray and the hand, reducing the disconnection introduced in the previous method. In terms of the CD ratio, the control input is the change in ray direction, and the display output is the adjusted ray direction. However, as the ray continues to diverge, pointing resolution still decreases with distance, though to a lesser extent.

CDRayRev. To address not only human motor limitations but also pointing resolution at a distance, we developed a third approach (Fig. 5(c)). Consider a hypothetical target: consistent with the purpose of the CD gain, its movement should follow the user's hand with reduced displacement [22], [31]. To achieve this in a target-agnostic manner, we counteract hand movement by reversing and scaling the directional change of the ray: $\vec{v}'_{next} = \vec{v}'_{prev} - (\vec{v}_{next} - \vec{v}_{prev}) \times g_{CD}$. This causes the ray to gradually converge, reducing the apparent motion of a distant point along the ray. Although the CD gain is applied to the ray direction, this control-display relationship can be interpreted as hand translation (control) resulting in scaled movement of an imaginary target along the ray (display). This results in higher precision as the pointing distance increases.

D. Implementation of CD Gain

We determined different CD gains for each of the three proposed methods. Previous studies have shown that appropriate CD gain values for pointing techniques can be derived from the device characteristics and human factors [29], [33]. Following these frameworks, we calculated CD gains that do not trigger clutching or precision issues.

Device characteristics were based on the technical specifications of the Meta Quest 3[2], used in our implementation, while human factors were drawn from the literature [82], [83]. We assumed optimal performance of vision-based hand tracking, such that input resolution is limited solely by human motor ability. Additionally, the input device's operating range was assumed to match its field of view (FoV), since visual feedback is lost beyond it regardless of tracking.

CD gains were configured to produce an angular resolution between 0.34° to 0.43° at a distance of 2 m with a hand movement of 1.5°. This allows the smallest hand motion to reliably target objects as small as 1° at 2 m, which is considerably small yet clearly visible. The CD gain values for CDHandPos, CDRayDir, and CDRayRev were 0.29, 0.038, and 0.025.

V. User Experiment

We aimed to evaluate the impact of the ForceCtrl system and the three CD-gain-based pointing strategies. To reflect

[2]Meta Quest 3:https://www.meta.com/kr/en/quest/quest-3

real-world AR/VR use cases, we adopted object positioning task [84], following prior work [2], [22]. The task was divided into two parts—a selection task and a placement task—to enable separate analysis of objective performance measures.

The proposed pointing methods were implemented based on the raycasting capabilities of the Meta XR Interactions SDK[3]. The baseline condition (Baseline) used the SDK's default raycasting. Surface EMG data were collected using a Thalmic Labs Myo armband. The interaction system was built on Unity 2021.3.22f1[4] running on Windows 11. All data collection was conducted on a PC equipped with an Nvidia GeForce RTX 3090 GPU and an Intel Core i7-11700K CPU, with a Meta Quest 3 connected via Meta Quest Air Link.

A. Experiment Design

We recruited 16 participants (8 male, 8 female, 22–33, $M = 27.6, SD = 3.6$, all right-handed) through the institute's online community board. All participants self-identified as intermediate to expert users of hand raycasting in AR/VR: 7 reported moderate experience, 7 used it extensively, and 2 used it daily. The experiment was approved by the institutional review board and all participants provided their informed consent. Participants received $20 for 2 hours of participation.

In the selection task, participants were asked to select a designated target from a group of small, identical spheres. Each trial presented one target and 48 obstacle spheres distributed within a 20 cm cube. The target was colored yellow (Fig. 6(a)) and turned blue upon selection (Fig. 6(b)). When pointed at, spheres were highlighted in cyan. The trial began when participants selected a "start" sphere and ended when they released the pinch after correct selection.

The placement task required precisely aligning a spherical target within a cubic goal sized to enclose the sphere. The target-goal pair appeared at an eccentricity of 10° in the FoV, with the target on the non-dominant hand side and the goal on the opposite side. A semi-transparent reference sphere was displayed inside the cube to assist with accurate placement (Fig. 6(c)). The target was highlighted in green upon contact with the goal (Fig. 6(d)). Task completion time was measured from the first collision with the goal, capturing only the fine-tuning phase. The trial ended upon release if the target was in contact with the goal.

Both tasks were conducted using a within-subject design with four **Technique** conditions and two **Depth** conditions. In the Close condition, targets were placed at a distance of 1.0 m, beyond arm's reach. In the Far condition, depths were set to 2.0 m for the selection task and 1.5 m for the placement task, since the latter required higher visual acuity due to its finer spatial demands. To minimize visual confounding, all targets were set to 35 mm in diameter, corresponding to 1° of visual angle at 2 m. While no formal standard exists for the

[3]Meta XR Interactions SDK: https://developer.oculus.com/downloads/package/meta-xr-interaction-sdk/

[4]Unity 2021.3.22f1: https://unity.com/kr/releases/editor/whats-new/2021.3.21

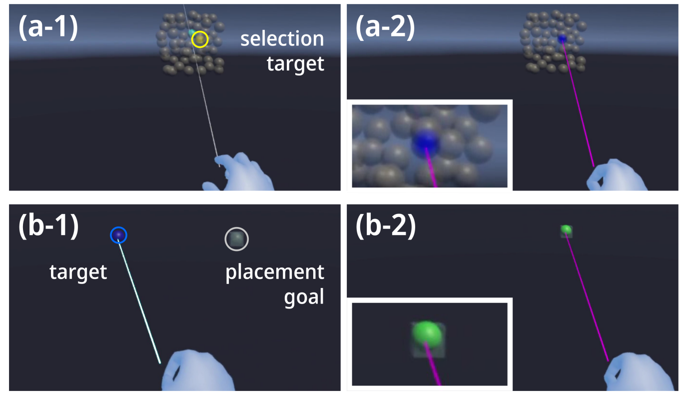

Fig. 6. Experimental tasks. *Selection task*: (a-1) participants select the yellow target; cyan indicates pointing, (a-2) blue indicates correct selection. *Placement task*: (b-1) participants place a target into a cube; (b-2) green indicates successful placement. The colored ray denotes precise states; and thicker ray indicates dragging states.

minimum interactable size of virtual objects, we followed the recommended size of UI buttons in AR[5] to ensure visibility.

We tested four interaction techniques, using standard hand raycasting as the baseline and comparing it with the three proposed methods. With the Baseline, no force-triggered actions were available, and only coarse states were used. We altered line width and color to visualize precision and selection state, with each proposed technique shown in a distinct color (red, green, or blue) during precise states. For experimental control, irrelevant interaction states were deactivated in each task.

In addition to task completion time, we recorded selection errors in the selection task—counting incorrect selections on obstacles or in empty space—and final offset in the placement task. Subjective responses were collected through post-condition questionnaires. Perceived workload was assessed using the NASA Task Load Index (NASA-TLX) [85], with scores ranging from 0 to 100. Participants also responded to two 7-point Likert scale items assessing perceived task performance (Q1: *"I successfully executed the task."*; Q2: *"I successfully controlled the pointer."*). In the post-session questionnaire, participants indicated their most and least preferred techniques, as well as the techniques they perceived as most and least accurate.

The experiment included a total of 240 trials per participant. Each task was performed under two **Depth** conditions, presented in order of distance as the Far condition was more demanding. Four **Technique** conditions were counterbalanced across participants. For each **Depth**×**Technique** combination, participants completed three sets of five trials, with the first set treated as practice and excluded from analysis. Trials were timed out after 20 seconds, and participants rested at least 15 seconds between sets to reduce fatigue. Before the main tasks, participants briefly calibrated the system by exerting each of three force levels—"0:None", "3:Moderate", and "7:Very Strong"—once, based on the Borg Scale. A short verification stage followed in which participants tested a series of force levels. After being introduced to the system, they practiced all

[5]Buttons—Mixed Reality: https://learn.microsoft.com/windows/mixed-reality/design/button

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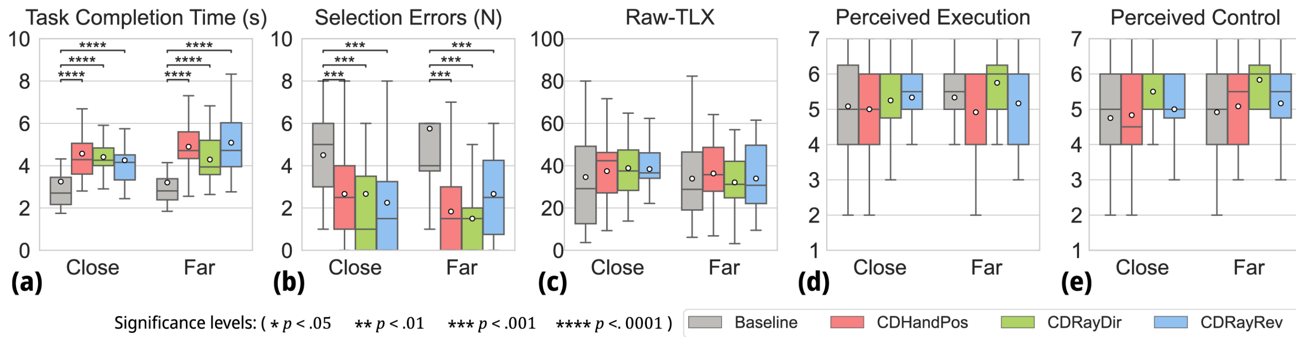

Fig. 7. Selection task results. (a) Task completion time, (b) number of selection errors, (c) Raw-TLX, (d) perceived execution, (e) perceived control.

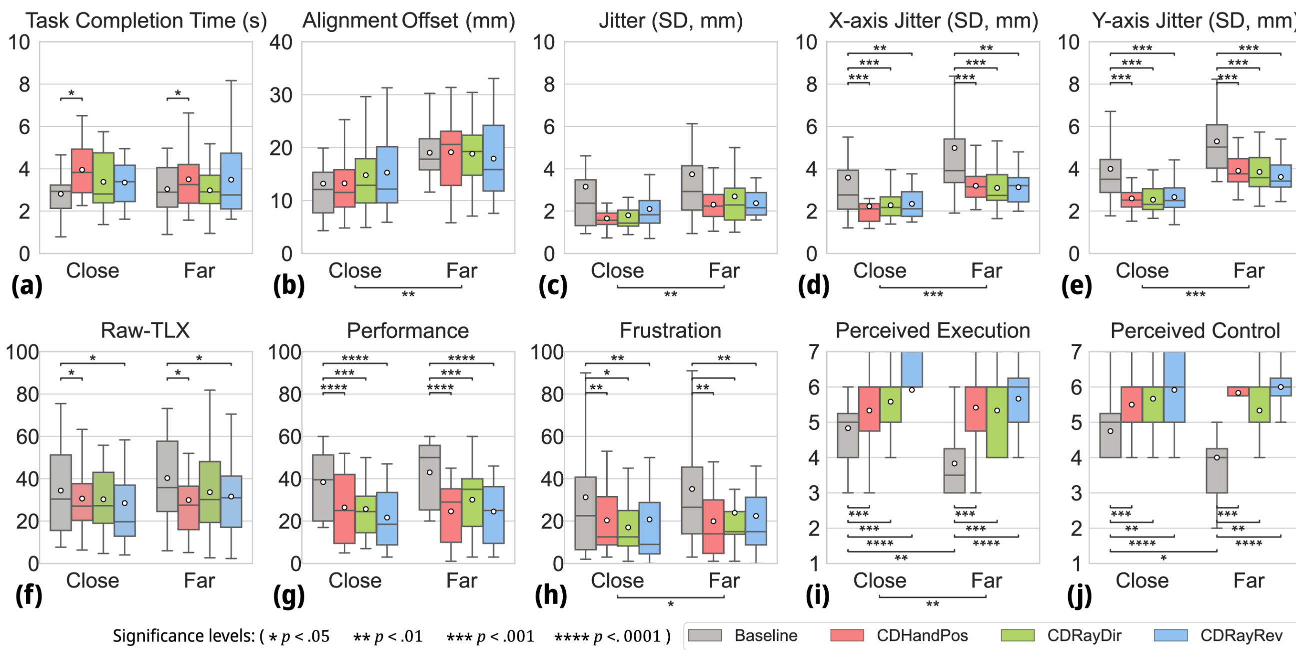

Fig. 8. Placement task results. *Top row*: objective results. (a) Task completion time, (b) final offset between target and goal, (c) jitter standard deviation, (d) jitter along X-axis, (e) jitter along Y-axis. *Bottom row*: subjective results. (f) Raw-TLX, (g) performance subscale, (h) frustration subscale, (i) perceived execution, (j) perceived control.

four interaction states. During the experiment, participants responded to the NASA-TLX and a post-condition questionnaire every 15 trials. After the selection task, participants completed a post-session questionnaire. The same procedure was repeated for the placement task.

B. Quantitative Results

For objective measures, we used a two-way repeated measures ANOVA ($\alpha = .05$) after verifying normality with the Shapiro-Wilk test and sphericity with the Mauchly's test. When assumptions were violated, we applied a two-way repeated measures ANOVA using Aligned Rank Transform (ART) [86] for non-parametric factorial analysis. All post-hoc pairwise comparisons were corrected using the Benjamini-Hochberg procedure. Subjective measures were analyzed using ART as well. Participants with an extreme number of timed-out trials or selection errors were excluded from the analysis.

1) Selection task: **Technique** had a significant main effect on task completion time ($F(3,33) = 23.898, p < .001, \eta_p^2 = .685$). All ForceCtrl techniques increased completion time compared to the Baseline (all $p < .001$; Fig. 7(a)). **Technique** also significantly affected the number of selection errors ($F(3,33) = 9.715, p < .001, \eta_p^2 = .469$), with Baseline resulting in more frequent incorrect selections than all three ForceCtrl techniques (all $p < .001$; Fig. 7(b)). No significant differences were observed in subjective workload among techniques (Fig. 7(c)–(e)).

2) Placement task: **Technique** had a significant effect on task completion time ($F(3,33) = 3.370, p = .030, \eta_p^2 = .235$), with CDHandPos requiring more time than Baseline ($p = .023$; Fig. 8(a)). For placement accuracy, measured as the offset between the target and goal, only **Depth** showed a significant main effect ($F(1,11) = 17.674, p = .001, \eta_p^2 = .616$; Fig. 8(b)).

We additionally analyzed the target's jitter during the alignment using the standard deviation of the target's position. Although only **Depth** had a significant effect

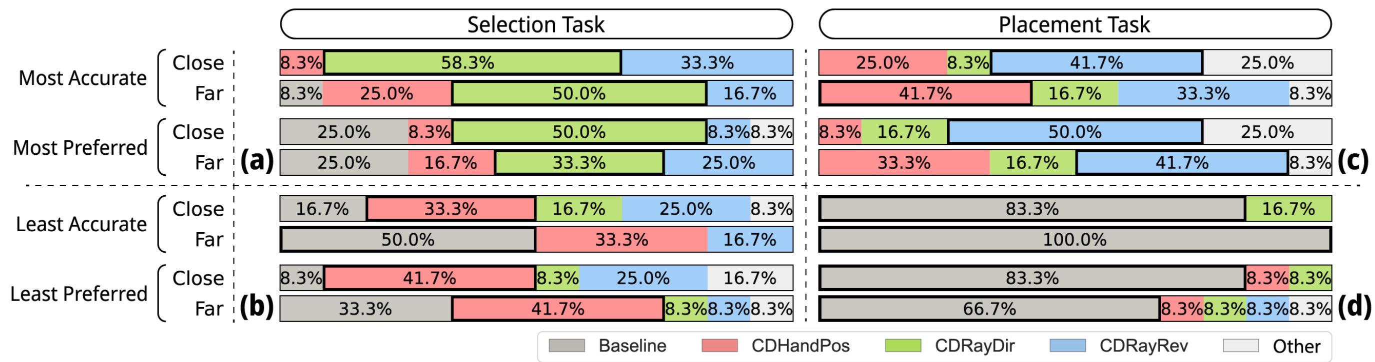

Fig. 9. Qualitative ratings. (a) Positive and (b) negative ratings in the selection task, and (c) positive and (d) negative ratings in the placement task.

on overall jitter ($F(1,11) = 18.965, p = .001, \eta_p^2 = .633$; Fig. 8(c)), **Technique** significantly affected jitter along the X-axis ($F(3,33) = 8.694, p < .001, \eta_p^2 = .441$; Fig. 8(d)) and Y-axis ($F(3,33) = 10.823, p < .001, \eta_p^2 = .496$; Fig. 8(e)). Baseline resulted in greater fluctuations than CDHandPos ($p < .001$), CDRayDir ($p < .001$), and CDRayRev ($p = .001$) on the X-axis, all three techniques (all $p < .001$) in Y-axis. **Depth** also significantly increased jitter along X-axis ($F(1,11) = 70.515, p < .001, \eta_p^2 = .865$) and Y-axis ($F(1,11) = 112.773, p < .001, \eta_p^2 = .911$).

For subjective measures in the placement task, **Technique** had a significant effect on Raw-TLX scores ($F(3,33) = 3.814, p = .019, \eta_p^2 = .257$), with CDHandPos ($p = .034$) and CDRayRev ($p = .022$) reducing perceived workload compared to Baseline (Fig. 8(f)). **Technique** also affected the NASA-TLX performance subscale ($F(3,33) = 16.701, p < .001, \eta_p^2 = .603$) and frustration subscale ($F(3,33) = 5.977, p = .002, \eta_p^2 = .352$). All ForceCtrl techniques were rated as significantly better in performance than Baseline (all $p < .001$; Fig. 8(g)). Baseline resulted higher frustration than CDHandPos ($p = .005$), CDRayDir ($p = .011$), and CDRayRev ($p = .004$). In terms of **Depth**, frustration was significantly higher in the Far condition compared to the Close condition($F(1,11) = 6.204, p = .030, \eta_p^2 = .361$; Fig. 8(h)).

Perceived task execution, measured on a 7-point Likert scale, was significantly affected by both **Technique** ($F(3,33) = 12.587, p < .001, \eta_p^2 = .534$) and **Depth** ($F(1,11) = 14.533, p = .003, \eta_p^2 = .569$). Participants rated their execution with Baseline significantly lower than with all three ForceCtrl techniques (all $p < .001$). Execution ratings also declined in the Far condition compared to Close. Additionally, a significant interaction between **Technique** and **Depth** was observed ($F(3,33) = 3.704, p = .021, \eta_p^2 = .252$). Perceived execution decreased with depth when using the Baseline technique ($p = .006$; Fig. 8(i)). **Technique** also significantly affected perceived control ($F(3,33) = 12.139, p < .001, \eta_p^2 = .525$), with participants reporting better control with three ForceCtrl techniques than with Baseline (all $p < .001$). A significant interaction between **Technique** and **Depth** ($F(3,33) = 3.245, p = .034, \eta_p^2 = .228$) indicated that perceived control declined with increased depth in the Baseline condition ($p = .036$; Fig. 8(j)).

C. Qualitative Feedback

1) Selection task: Participants most frequently rated CDRayDir as the most accurate technique in both Close (58.3%) and Far (50.0%) conditions, followed by CDRayRev in Close condition (33.3%) and CDHandPos in Far condition (25.0%). Regarding preference, CDRayDir was also the most preferred technique in both Close (50.0%) and Far (33.3%) conditions (Fig. 9(a)). For the least accurate ratings, CDHandPos was most frequently selected in the Close condition (33.3%), while Baseline received the highest proportion in the Far condition (50.0%). CDHandPos was again selected most often as least preferred technique (41.7% in both depth conditions), followed by CDRayRev in Close condition (25.0%) and Baseline in Far condition (33.3%) (Fig. 9(b)).

2) Placement task: CDRayRev was rated as the most accurate technique in Close (41.7%) condition, while CDHandPos was most often selected in Far condition (41.7%) followed by CDRayRev (33.3%). In terms of preference, CDRayRev was selected most frequently in both Close (50.0%) and Far (41.7%) conditions (Fig. 9(c)). For least accurate, Baseline was most frequently chosen in both Close (83.3%) and Far (100.0%) conditions. CDRayDir was selected as the least accurate in Close condition (16.7%), and the remaining techniques received no votes in either condition. For least preferred, Baseline was selected by the majority of participants in both Close (83.3%) and Far (66.7%) conditions (Fig. 9(d)).

VI. Discussion

The experimental results demonstrate that ForceCtrl enables users to stabilize the pointer for precise interaction with small and distant targets, while maintaining a comparable level of perceived workload. Although the ForceCtrl techniques resulted in slower task completion times, this was expected, as the technique inherently involves an additional step for adjusting the pointer. Importantly, the ForceCtrl techniques reduced frustration and perceived performance difficulty, particularly in high-precision tasks. Based on these results, we discuss three key areas in this section: *1)* the feasibility of using user-defined force as an input modality, *2)* the implications of applying CD gain to raycasting, and *3)* limitations and future directions. Our goal is to provide a comprehensive interpretation of the findings and outline the potential for further development of precise pointing techniques in 3D environments.

1) User-Defined Force as Input: The results suggest that the performance benefits from our method outweigh the required efforts to perform force-based input. As we used the user-defined values corresponding to "3:Moderate" and "7:Very Strong" as input levels, we anticipated higher physical load in compare to the standard raycasting due to additional force exertion. However, no significant increase in physical demand was observed in either the Raw TLX or its physical demand subscale. At the same time, participants reported reduced frustration and perceived performance difficulty with ForceCtrl techniques. These findings indicate that when users perceive substantial benefits—such as improved pointing accuracy in demanding tasks—they are more willing to accept the physical effort involved.

Our findings also show that user-defined force can be generalized across individuals and used as a robust input approach. All 16 participants were able to successfully control the system with only a minimal calibration process, requiring a one-time measurement of three force levels. The system reliably classified users' subjective force input, demonstrating both the robustness of the model and a common pattern in how users apply force. Moreover, participants were able to exert force consistently throughout the experiment, without noticeable fluctuation or decline over time. These results support the feasibility of user-defined force as a reliable input method for both the user and the system.

2) CD Gain for Hand Raycasting: While the application of CD gain showed clear advantages over the Baseline technique, among the three proposed methods, CDRayRev with convergence was most preferred in high-difficulty tasks, whereas the visual detachment in CDHandPos negatively impacted user experience. In general, techniques rated highly in accuracy were also commonly rated as the most preferred. As task difficulty increased in the Far condition, differences in perceived performance became more pronounced. Despite all three proposed techniques requiring the same amount of force and offering comparable pointing resolution at the tested depths, participants' subjective impressions varied considerably between techniques.

Aligned with the quantitative results, the Baseline technique showed a clear drop in subjective performance as task difficulty increased. While only 16.67% of participants rated Baseline as the least accurate in Close condition of the selection task, 100.00% of participants reported that Baseline was the least accurate in Far condition of the placement task. This disparity highlights its unsuitability for spatially demanding tasks. Participants pointed out that Baseline was *"hard to control in high-difficulty tasks"* (P16). Specifically, many responded that they had to *"put both mental and physical effort to keep my arm steady"* and some even *"found myself holding my breath"* (P14) and *"felt frustration"* (P16) with Baseline technique.

CDRayDir was consistently rated as the most accurate and preferred technique in the selection task, and reported to be *"intuitive"* (P3) and *"natural"* (P9). However, in the placement task, where higher spatial accuracy is required, both the perceived accuracy and preference of CDRayDir decreased. Participants reported that they were *"able to control accuracy without having to move my arm much"* (P1), but *"had the lowest precision"* (P1) at the same time. This indicates that CDRayDir has a relatively subtle effect on precision, making it suitable for moderate-difficulty tasks, but not sufficient for high-difficulty tasks. Consequently, participants did not prefer CDRayDir in the placement task reporting that *"it didn't really feel effective while I still had to apply force"* (P15).

In contrast, CDRayRev was rated highest in the placement task in both perceived accuracy and preference. Four participants perceived CDRayRev to be *"most accurate"* (P2–5), and P4 reported that *"it showed significantly less jitter when stationary"*. As the placement task required finer control, the convergence of CDRayRev may have helped participants stabilize their movements during precise object alignment. While this technique deviates most from the standard raycasting, the technique aligned most closely with participants' mental model, explicitly supported by six participants. CDRayRev was reported to be *"most natural"* (P2), *"matched my expectation"* (P6), and *"intuitive"* (P4). Since CD gain is intended to reduce pointer movement relative to user input, the converging behavior of CDRayRev may have affected participants' perception of the technique as intuitive.

Although CDHandPos received high accuracy ratings especially in the Far condition of the placement task, it was not preferred in general. Some participants highlighted this contrast: *"it had the highest precision, but required the most arm movement"* (P1), even though the pointing resolutions of three tools at the presented depth were considerably similar. This disparity suggests that while users may have recognized the functional effectiveness, aspects such as comfort or mental load may have negatively influenced their preference. Many participants perceived CDHandPos was *"too heavy"* (P15), *"much slower than my actual hand motion"* (P3), and *"wasn't really following my arm"* (P1). The disconnection between the ray and the hand may have significantly affected participants' perception of control.

CDRayRev proved to be the most effective technique for high-precision tasks, offering strong perceived accuracy, preference, and stability. Despite its departure from conventional raycasting, its converging behavior contributed to a strong sense of intuitiveness. CDRayDir was better suited for moderate-precision tasks where speed and ease of control were prioritized. In contrast, CDHandPos revealed a trade-off between perceived accuracy and user comfort, caused by a disconnect between hand motion and pointer response. These findings emphasize the importance of aligning interaction techniques to task demands. Overall, CDRayRev appears most appropriate for fine manipulation, while CDRayDir may be beneficial for general-purpose contexts.

3) Limitations & Future Works: Although ForceCtrl demonstrated clear benefits in both objective performance and subjective responses, there remains room for refinement. In our implementation, higher force levels (e.g., "3:Moderate" and "7:Very Strong") were chosen to ensure stable sensing, but repeatedly exerting strong force may be physically demanding. While users would likely activate high-precision states less frequently in practice, increasing force detection sensitivity could improve responsiveness and user experience. Likewise, enhancing force classification accuracy and speed would help reduce latency in state transitions. Although this study focused on experienced hand-raycasting users, the system is scalable to broader populations due to its controller-free design, familiar gestures, and minimal cognitive effort. In addition, we focused on user-defined force input rather than gesture recognition, but the wristband's potential for out-of-sight interaction could be further explored in future work.

While we adopted a discrete state approach to balance usability and interaction clarity, future work may explore hybrid strategies that combine continuous control of CD gain with discrete state transitions. Such an approach could offer finer-grained precision while preserving distinct interaction phases, potentially enhancing user performance in complex spatial tasks. Incorporating real-time visualization of force classification could also assist users in maintaining more consistent control. A proper visual feedback will reduce cognitive effort [68] and improve performance especially during high-precision tasks. Finally, exploring use cases could further demonstrate the system's practical utility. We anticipate our system to support high-precision tasks in dense 3D environments, such as those found in advanced AR/VR applications.

VII. Conclusion

We introduced ForceCtrl, a novel 3D hand raycasting technique that enables users to control pointing precision through user-defined pinch force. By applying CD gain directly to the ray, the system offers a target-agnostic, bare-hand method for refining pointing accuracy. Our evaluation demonstrated that ForceCtrl significantly improves pointing performance, particularly for small and distant targets. We also proposed and compared three CD gain strategies, highlighting the benefits of ray convergence in high-difficulty tasks. These findings underscore the potential of personalized, force-based input as a scalable and effective modality for precise 3D interaction. Future work may explore more stable sensing, broader task generalization, and integration with multimodal feedback to further expand the utility of ForceCtrl. We believe this research contributes to advancing 3D interface design for professional and immersive contexts that involve complex visual data and demand high pointing precision.

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VIII. Biography Section

Seo Young Oh is currently pursuing a Ph.D. degree with the Graduate School of Culture Technology (GSCT), Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Korea. She investigates 3D hand interactions for augmented reality as part of the Ubiquitous Virtual Reality (UVR) Lab under Prof. Woontack Woo. She is focusing on enhancing the accuracy of 3D interactions for professional scenarios in augmented reality. She received her M.S. from GSCT, KAIST (2020) and B.S. in Mechanical Engineering from KAIST (2014).

Junghoon Seo is currently pursuing a Master's degree at GSCT, KAIST, Daejeon, Korea, where he is a member of the Human-centered Interactive Technologies Lab (HCI Tech Lab) under the supervision of Prof. Sang Ho Yoon. His research interests include intellectual user interface, computer vision, machine learning, and remote sensing. He received his B.S. degree in Electrical Engineering and Computer Science from Gwangju Institute of Science and Technology (GIST), Gwangju, Korea, in 2021.

Juyoung Lee is pursuing his Ph.D. at GSCT, KAIST, Daejeon, Korea. As a member of the UVR Lab under Prof. Woontack Woo, he explores novel interaction techniques for AR. His research interests include smartglasses interaction, gestural and subtle interaction, wearable computing, and augmented reality. Mr. Lee received his M.S. from GSCT, KAIST (2017) and B.S. in Electrical & Electronic Engineering from Yonsei University (2014).

Boram Yoon is a senior researcher at the KI-ITC Augmented Reality Research Center (ARRC), KAIST, Daejeon, Korea. Her research focuses on virtual avatar embodiment and user experience for XR remote collaboration and Metaverse. She received her Ph.D. and M.S. degrees from GSCT, KAIST, and B.S. in Computer Science and Engineering from Ewha Womans University, Seoul, Korea.

Sang Ho Yoon is an associate professor in GSCT, KAIST. He leads the HCI Tech Lab. His research focuses on developing natural user interactions that address physical, mental, and social barriers with novel haptic interfaces and sensing techniques. He was a principal engineer at Samsung Research and a research engineer at Microsoft Applied Sciences Lab. He received Ph.D. from Purdue University, and M.S. and B.S. from Carnegie Mellon University.

Woontack Woo is a professor of GSCT, KAIST, Daejeon, Korea. He is also the director of both the CT Research Institute and the KI-ITC ARRC, KAIST. In 2001, he coined the term 'Ubiquitous Virtual Reality (UVR)' and started the UVR Lab, GIST, Gwangju, Korea. The main theme of his research is to realize augmented humans, augmented cities, and even augmented societies by implementing Ubiquitous VR in smart spaces.