Exploring Embodied Asymmetric Two-Handed Interactions for Immersive Data Exploration

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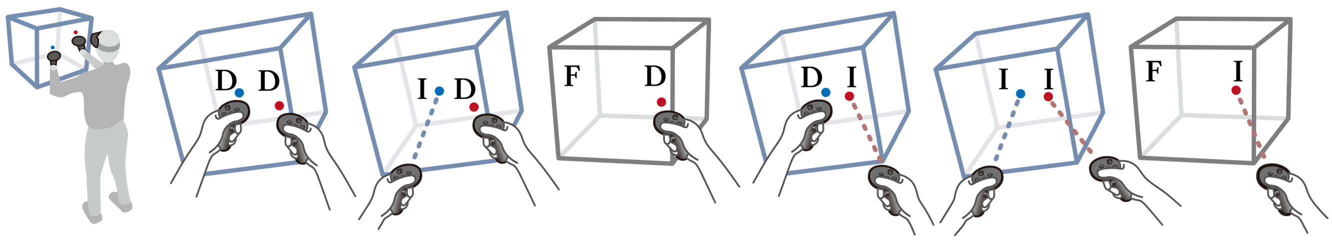

Figure 1: The six conditions for embodied two-handed interactions [dominant, non-dominant] for data exploration in VR: D (Direct): the point of contact is attached directly to the VR controller; I (Indirect): the contacting point has an offset from the VR controller; F (Fixed): the data visualization is shown in a fixed position in VR.

ABSTRACT

Embodied interaction plays a crucial role in facilitating effective data exploration within immersive environments, enhancing user experience, understanding, and exploring complex data presented in the virtual space. While embodied two-handed interaction has demonstrated considerable potential, there remains a gap in understanding how varying levels of embodiment impact asymmetric two-hand interactions for immersive data exploration. In this study, we systematically investigate this aspect by combining three settings (direct, indirect, and fixed) on the visualization control hand and two settings (direct, indirect) on the action hand. This combination results in six conditions that span varying levels of embodiment. We compared these conditions under two fundamental visualization tasks, focusing on curve brushing and object manipulation. Our discussion revolves around the use of techniques related to the specific requirements of the tasks, the characteristics of each condition, and users' experience and expertise in the VR environment. Building upon these discussions, we offer suggestions for designing embodied two-handed interactions for immersive data exploration.

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CHI EA '24, May 11–16, 2024, Honolulu, HI, USA

ACM ISBN 979-8-4007-0331-7/24/05.
https://doi.org/10.1145/3613905.3650777

CCS CONCEPTS

• **Human-centered computing** → **Interaction design**; **Visualization**.

KEYWORDS

Embodied interaction, immersive data exploration, virtual reality

ACM Reference Format:
Haonan Yao, Lixiang Zhao, Hai-Ning Liang, Yu Liu, Yue Li, and Lingyun Yu. 2024. Exploring Embodied Asymmetric Two-Handed Interactions for Immersive Data Exploration. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems (CHI EA '24), May 11–16, 2024, Honolulu, HI, USA.* ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3613905.3650777

1 INTRODUCTION

Virtual Reality (VR) technologies provide a 3D environment for stereo data visualization and spatial interaction. Within such an environment, users can be fully immersed in data exploration tasks [13]. They can walk around/into the data visualization, interact with data intuitively, collaborate, and share insights with others. The embodied interaction [33], which emphasizes the integration of the user's body, movements, and gestures, has been utilized in spatial interaction design for the immersive environment. Previous research indicated that embodiment is effective for data comprehension and accurate 3D manipulation in rotation and panning tasks [5, 14, 17]. Meanwhile, two-handed interaction [37] has been widely recognized as a more natural and intuitive interaction technique in VR [16].

In this paper, we aim to explore the impact of different levels of embodiment in asymmetric two-handed interactions, specifically when both two hands collaborate to complete a single task. An example of such a task is MeTACAST [47], which employs three effective selection techniques for selecting point cloud data in an immersive World in Miniature (WIM). In this scenario, the visualization is attached to the VR controller in the non-dominant hand, while the dominant hand selects data from the WIM. To avoid collisions between the two VR controllers, an offset of 35 cm was introduced by attaching the data to the left controller, and the contacting point of the selection hand was positioned 1 cm above the top of the right controller. Similar issues also arise in other data exploration tasks that require high precision. For example, when domain researchers use Vivern [25] to design and examine DNA origami nanostructures and explore multiple axes for presenting multivariate data with two VR controllers [7].

Therefore, a comprehensive study is necessary to understand the impact of embodied levels on both hands in asymmetric interactions for data exploration tasks. To address this, we established six experimental conditions based on various settings utilizing metaphors for controlling the user's hands. We compared these experimental conditions, focusing on two distinct tasks: 3D curve brushing and 3D object manipulation. Based on the findings, we propose suggestions for designing two-handed interaction techniques for diverse visualization tasks with varying requirements, taking into consideration user experience and expertise in VR.

2 RELATED WORKS

2.1 Embodied Interaction

The concept of "Embodied interaction" was introduced by Dourish [9] and was later expanded into the Human-Computer Interaction (HCI) community [38]. Previous literature has traditionally classified embodiment into distinct dimensions such as self-location [2], agency [29], and body ownership [28]. In recent years, embodied interaction has gained widespread attention for immersive data exploration. Various approaches have been proposed to enhance embodied interaction in data exploration. For instance, tangible agents like tangible globes [34], tangible rings [36], and tangible markers [3] have been utilized to facilitate data manipulation. Another way involves incorporating the human body, where aerial gestures are used to interact with weather data [22], and hands are employed to make embodied choices [6]. In the VR environment, VR controllers are commonly employed to support embodied data exploration [7, 25, 43, 45]. These techniques have demonstrated the advantages of embodied interaction in immersive data exploration, such as natural interaction and effective performance.

Many studies have also investigated the level of embodiment in interaction techniques. For example, questionnaires have been employed to measure users' sense of embodiment in the VR environment [15, 32]. Yang et al. [42] evaluated the use of embodied navigation methods in abstract data visualization. Huang et al. [23] compared network visualization environments with different levels of embodiment. These investigations effectively explore both the extent of embodiment and the impact of embodied interaction on visualization tasks.

2.2 Asymmetric Two-handed Interaction

Most interactions in human daily life require the simultaneous use of both hands to accomplish [26]. Research related to bimanual movements reveals that two-handed actions can be categorized as symmetric and asymmetric [16, 20, 24]. Two-hand interaction shows the possibility of having better performance than using only the dominant hand in VR [27, 39]. Especially, asymmetric two-handed interaction has great potential in data exploration [19]. A typical example of using asymmetric two-handed interaction for data exploration is WIM [37]. This approach enables support for users to control the exocentric view of 3D data using their non-dominant hand, while using their dominant hand for intuitive and easy-to-use interaction [30, 37, 46]. However, practical challenges arise with the implementation of asymmetric two-handed interaction for data exploration. An example is the need for an offset to the controller to prevent collisions between the two hands during 3D data selection, as discussed in [47]. Therefore, when designing two-handed interaction techniques for data exploration, decisions must be made to balance the advantages of direct interactions with practical considerations. Factors such as users' experience and abilities, task requirements, and other aspects need to be taken into account. Consequently, we conducted a comprehensive user study to explore the extent of embodiment and the impact of embodied interaction in two-handed interactions for visualization tasks.

3 RATIONALE AND CONDITIONS

In this section, we elucidate the six experimental conditions and provide the rationale for their selection. We incorporated the WIM metaphor [30, 37, 46], which leverages the non-dominant hand to hold the target visualization and the dominant hand to perform actions on the visualization. We set the visualization size at 30 cm, striking a balance between hand-sized and table-sized dimensions. For the interaction metaphor, we opted for the virtual hand instead of a virtual pointer to enhance users' engagement and embodiment.

Experimental Conditions. The interaction metaphor for embodiment can be classified as direct input (the point of contact is attached directly to the controller) and indirect input (the contacting point has an offset from the controller). The offset is set at 25 cm in the positive direction of the controller's grip, inspired by GO-GO [31]. We chose 25 cm offset based on a pilot study, which indicated that this distance was the suitable position at which collisions could be mostly avoided while still maintaining a sense of embodiment. We established these two conditions for the dominant hand for actions. For the non-dominant hand on purpose for visualization, we also introduce an additional condition with the data visualization fixed in the space [33]. Thus, combining the three settings (direct, indirect and fixed) on visualization control and the two settings (direct and indirect) on actions, we obtain six experimental conditions, indicated as **[non-dominant, dominant]** in Figure 1 and Figure 2.

4 USER STUDY

We conducted a controlled user study to assess the impact of embodiment level as well as the asymmetric two-handed interaction in two different visualization tasks.

Participants. We recruited 24 unpaid participants (11 females, 13 males) from a local university, aged between 18 and 25 years (M=22.5, SD=1.6), all of whom identified their right hand as dominant. Regarding the expertise of VR, 6 participants reported weekly

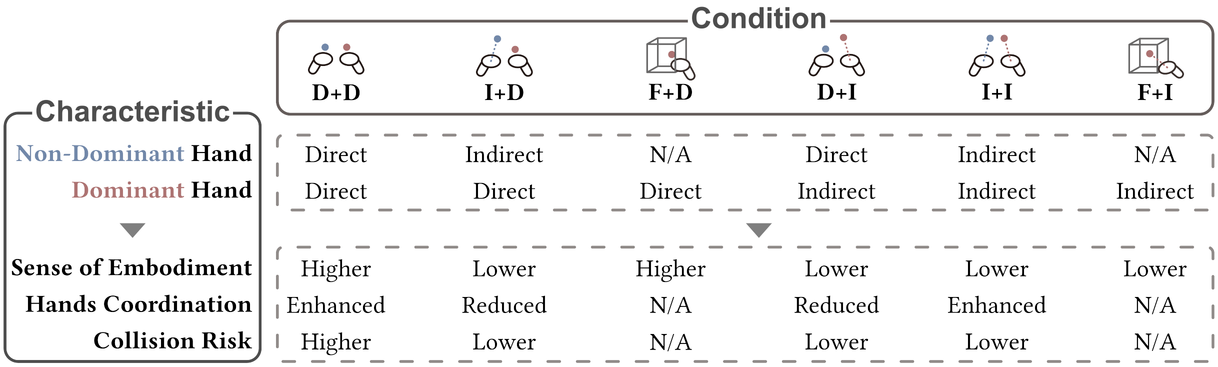

Figure 2: The conditions and characteristics.

experience, 5 reported monthly experience, and 13 reported using VR once a year or never.

Apparatus. The study was conducted in an indoor arena of approximately 3m × 3m with no obstacles. We used an all-in-one VR head-mounted display Meta Quest Pro (1800 × 1920 resolution per eye, 96° field of view, 90Hz refresh rate). We conducted the study by streaming on a Windows 10 PC (Intel Core™ i7 2.21GHz, 32GB RAM, GeForce RTX 3070, 24GB video memory).

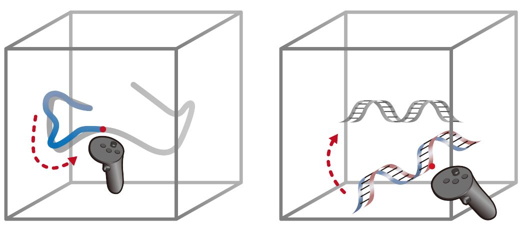

Figure 3: Two tasks: 3D curve brushing task (left) and 3D object manipulation task (right).

Tasks and Data. Our experiment contained two tasks, as shown in Figure 3. In the brushing task, participants were instructed to use a continuous input approach to brush along a 3D curve, aiming to match their input as closely as possible to the target curve. Participants were directed to provide their input in a single pass, starting from the initiation of the controller trigger press to its release. If the input was interrupted in the middle, they were allowed to restart the brushing. A virtual ball served as an indicator, displaying the point of contact. In the manipulation task, participants were tasked with aligning candidate objects to the target object. Participants could make multiple steps, initiating each manipulation from the trigger press to its release. To aid participants in aligning the objects correctly, a purple dot was incorporated into the model to indicate the orientation of both the candidate object and the target object. We rendered tubular Bezier curves and double helix models using mathematical functions and open-source DNA sequences [41]. An example of the Bezier curve and double helix model in the tasks is shown in Figure 4. To minimize the learning effect, the position and orientation of the target were altered across trials within each repetition of the experimental condition.

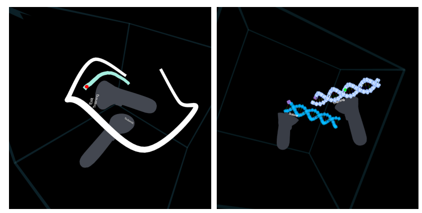

Figure 4: An example of the Bezier curve (left) and double helix model (right) generated from a set of data.

Procedure. The study consisted of a training session and an actual experiment session. The whole study lasted for approximately one hour for each participant. During the training session, we trained participants with additional data for each condition. They were instructed on completing the tasks using VR controllers and were allowed to make as many attempts as necessary to develop suitable strategies. In the actual experiment, they were instructed to carry out the task with both speed and precision without receiving any feedback regarding the outcome of their performance. Participants were allowed to redo the tasks, with the time taken being recorded. Once they believed they had achieved a satisfactory result, they could press a button to finish the trial. For each condition, we asked participants to evaluate their workload and fatigue with NASA's Task Load Index [18], as well as assessments of the sense of embodiment by VEQ [32] and pESQ [15]. Between the conditions, participants were given a five-minute break. After two tasks, participants were asked to rank the six conditions and provide their reasons in a semi-structured interview.

Design. The order of tasks and datasets in the experiment was constant, with the brushing task conducted first followed by the manipulation task. The order of the six experimental conditions was counterbalanced through a balanced Latin square. Each participant was given a specific P_{ID}, where the ID was unique and $\in [0, 23]$. We used "P_{ID} mod 6" to balance the condition order. The study was conducted using an accompanying 3-factor within-subjects design with 3 repetitions of each condition. In total, we had 24 participants × 2 tasks × 6 conditions × 2 datasets × 3 repetitions = 1728 trials.

Measures. To minimize the influence of initial effects on the experimental data, we excluded data from the first repetition of each condition, resulting in a dataset comprising 1440 trials. We recorded task completion time, measured from the trial's initiation to the participant pressing the submit button. Accuracy was assessed by calculating positional distance between the input and the target. For the brushing task, the Modified Hausdorff Distance [12] was employed to quantify errors, while in the manipulation task, the average distance of all model points [21] was computed. Furthermore, we also recorded the number of attempts to complete the task in each trial, which indicates the number of additional repetitions the user needs to complete the task.

Hypotheses. Building upon the literature review and our analysis, we formulated the hypotheses as follows:

- **H1.** Introducing an offset to the dominant action hand reduces the sense of embodiment in task performance, leading to decreased accuracy and longer completion time.
- **H2.** Introducing an offset to the non-dominant visualization control hand would not have a clear impact on accuracy and completion time.
- **H3.** In the Fixed (non-dominant) conditions, the visualization is stable but requires physical body movements for observing 3D data, resulting in reduced accuracy and longer completion time.
- **H4.** Symmetric offsets, applied to both hands or neither, would outperform asymmetric offsets, resulting in increased accuracy and faster completion time.
- **H5.** Conditions emphasizing direct action hand and minimizing hands collision are expected to be preferred.

The rationale for **H1** is that introducing an offset to the dominant hand may disrupt the natural alignment between users' physical hand movements and their virtual representation in the VR environment. This misalignment could result in decreased accuracy and longer completion times, as participants may struggle to accurately translate their intentions into actions within the virtual space. Furthermore, the non-dominant hand, typically more involved in visualization control and navigation tasks, may be less affected by spatial offsets, leading to **H2**. However, in conditions where the position of the visualization is fixed in VR, users may need to physically reposition themselves to achieve optimal views of the data. This additional physical effort could lead to reduced accuracy and longer completion times, as they may spend more time adjusting their position to interact effectively with the data, leading to **H2**. Additionally, **H4** is proposed because symmetric offsets applied to both hands or neither may offer a more consistent and predictable interaction experience. Users may find it easier to adapt to symmetric offsets due to their balanced and uniform nature, potentially resulting in smoother task performance and increased user satisfaction. Lastly, **H5** is proposed because direct interaction methods typically provide more intuitive control, leading to smoother task performance. Minimizing collisions between hands can further enhance the overall user experience by reducing frustration and physical discomfort during interaction.

5 RESULTS

Due to limitations of null hypothesis significance testing (NHST) [4, 8, 10, 11], we state results by estimation techniques with effect sizes and confidence intervals recommended by APA [44], as well as p-value statistics. We performed a logarithmic transformation of the completion time to satisfy the normality assumption. Subsequently, we applied linear mixed modeling to independent variables [35] rather than repeated measures ANOVA, since the former is not bound by sphericity and can model more than two independent variables considering both group and individual differences [1]. To be more specific, we modeled the independent variables and their interactions as fixed effects, incorporating random intercepts for individual participants within groups. The significance of these fixed effects was assessed using log-likelihood ratios. We then conducted Tukey's HSD post-hoc tests for least squares pairwise comparisons [35]. For the dependent variables—including error, sense of embodiment, task load, and preference rating—that did not meet the criteria for normal distribution, we employed the Friedman test to assess the influence of the independent variables. Pairwise comparisons were then conducted with the Wilcoxon signed-rank test, adjusting p-values using the Bonferroni method. Effect sizes were computed using means and confidence intervals were determined via the BCa Bootstrap [40].

5.1 Results on offset of Dominant Action Hand

The results have been reported in Figure 5. Three conditions involve offsets on the dominant action hand (D+I, I+I, and F+I). We compare them with the corresponding conditions without offsets.

Accuracy. The results indicated that all indirect action conditions were less accurate in both tasks. In the brushing task, the differences between D+I and D+D (p = .009), between I+I and I+D (p < .001), and between F+I and F+D (p < .001), were statistically significant. In the manipulation task, the differences between I+I and I+D (p < .001), and between F+I and F+D (p = .008) were statistically significant, whereas the difference between D+I and D+D (p = .472) was insignificant.

Speed. Completion times were consistently longer in the indirect action conditions for both brushing and manipulation tasks, although the differences between D+I and D+D (brushing: p = .913, manipulation: p = .957), between I+I and I+D (brushing: p = .657, manipulation: p = .165), and between F+I and F+D (brushing: p = .102, manipulation: p = .758), were found to be insignificant.

Therefore, the introduction of an offset to the dominant action hand resulted in decreased accuracy and longer completion times. **H1** is supported.

5.2 Results on offset of Visualization Control

Four conditions involve visualization control: D+D, I+D, D+I, and I+I. Among them, D+D and D+I do not involve offsets.

Accuracy. In the brushing task, the direct visualization control condition D+D was slightly less accurate than I+D (p = .337). However, D+I was more accurate than I+I (p = .534). In the manipulation task, D+D was slightly less accurate than I+D (p = .589). All these differences were insignificant. However, D+I was significantly more accurate than I+I (p = .049) in the manipulation task.

Speed. In the brushing task, both direct visualization control conditions were faster than the corresponding indirect conditions. The differences, between D+D and I+D (p = .721), between D+I and I+I (p = .943), were insignificant. In the manipulation task, D+D was slower than I+D (p = .69), but the time costs of D+I and I+I were comparable.

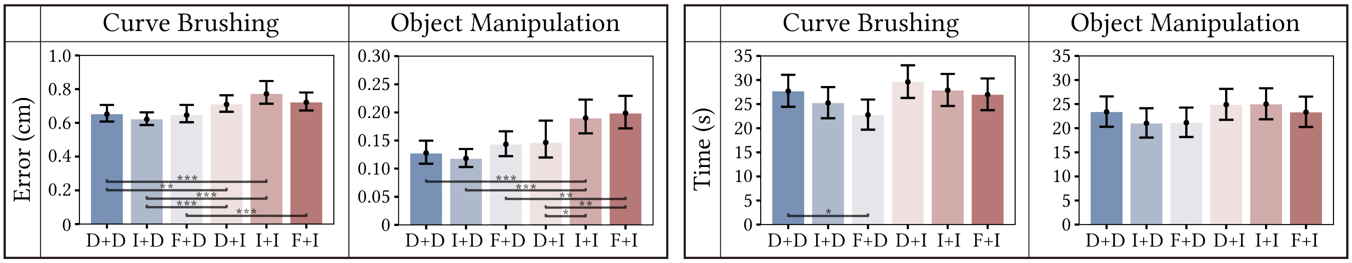

Figure 5: Accuracy (error) and completion time in two tasks. Significance levels: $p < .05$(*), $p < .01$(**), and $p < .001$(***).

Therefore, we did not observe an obvious impact of accuracy and completion time on visualization control with offset. **H2** was supported.

5.3 Results on Fixed Visualization Environment

Two conditions, F+D and F+I, establish a stable visualization environment, facilitating one-hand interaction in the tasks.

Accuracy. In the brushing task, the accuracy of F+D, D+D and I+D was comparable. For the indirect action conditions, F+I was slightly more accurate than I+I but the difference was insignificant. In the manipulation task, the accuracy of F+D was lower than D+D (p = .238) and I+D (p = .19). The differences were insignificant. Among the indirect action conditions, F+I was significantly less accurate than D+I (p = .003).

Speed. In the brushing task, F+D was significantly faster than D+D (p = .035). Although F+I was slightly faster than D+I and I+I, the differences were not statistically significant. In the manipulation task, F+D was slightly faster than D+D. F+I was slightly faster than D+I and I+I. All these differences were insignificant.

Thus, fixed visualization did not result in reduced accuracy or longer completion time in the tasks. **H3** was rejected.

5.4 Results on Symmetric/Asymmetric Offsets

Two conditions, D+D and I+I, establish symmetric settings with respect to the offset level on both the dominant hand (action) and the non-dominant hand (visualization control). In the case of I+I, a 25 cm offset is applied to both hands, ensuring symmetry. On the other hand, D+D provides a direct approach, allowing for both visualization control and action without any applied offset. In contrast, the other two conditions, D+I and I+D, present asymmetric settings, featuring a 25 cm offset applied to only one of the hands.

Accuracy. In the brushing task, D+D was significantly more accurate than D+I (p = .009). However, it was slightly less accurate than I+D but the difference was insignificant. I+I was less accurate than I+D and D+I. The difference between I+I and I+D was significant (p < .001). In the manipulation task, D+D was less accurate than I+D but more accurate than D+I, with insignificant differences. However, I+I was significantly more accurate than I+D (p < .001) and D+I (p = .049). In both tasks, D+D was significantly more accurate than I+I (Brushing: p < .001, manipulation: p < .001).

Speed. In the brushing task, both D+D and I+I were slower than I+D but faster than D+I. All the differences were insignificant. Moreover, D+D and I+I were comparable regarding the speed. In the manipulation task, similar patterns were detected. The only difference was that I+I and D+I had a similar speed.

Therefore, these findings do not provide sufficient evidence to show that symmetric settings regarding offset level on both hands result in increased accuracy or decreased completion time. **H4** is not supported.

5.5 Results on Subjective Ratings

We further report the overall subject ratings regarding user preference (Figure 6). For a more detailed analysis of subject ratings on the sense of embodiment and task load, please refer to Appendix B. In the brushing task, I+D and F+D exhibited similarly high scores. F+D scored significantly higher than D+D (p = .004), D+I (p < .001), I+I (p = .024), and F+I (p = .004). I+D scored significantly higher than D+I (p = .004) and I+I (p = .007), and was higher than D+D, although not significantly. Similarly, in the manipulation task, both I+D and F+D received higher ratings compared to other conditions. Significant differences were observed between I+D and D+I (p < .001), I+D and I+I (p < .001), I+D and F+I (p < .001), F+D and D+I (p = .006), and F+D and F+I (p = .042). However, the difference between I+D and F+D (p = .637) was found to be insignificant. Hence, the conditions I+D and F+D, utilizing direct action and indirect visualization control, were preferred. **H5** was supported. The primary reason may be attributed to the high sense of embodiment, low physical effort, and reduced time pressure they offer compared to other conditions, as analyzed in Appendix B.

5.6 Observation and Qualitative Feedback

Observation. In the study, we noticed a higher incidence of two-handed obstruction in the D+D condition and, to a lesser extent, in the D+I condition. In addition, we also noticed that users have different strategies and behaviors in the two tasks. In the brushing task, participants tended to stabilize the visualization to create a stable environment when using the non-dominant action hand. The number of attempts in the F+D condition was lower than in other conditions, with counts for the remaining conditions being comparable. In the manipulation task, participants attempted to use both two hands to move the object to target positions. Compared to F+I, participants made significantly fewer adjustments with D+D (p = .039), I+D (p = .004), and D+I (p = .002).

Qualitative Feedback. We gathered participants' feedback on their preferences and task experiences through semi-structured interviews. Regarding the dominant hand, the direct setting was praised for providing a more natural and immersive experience (10

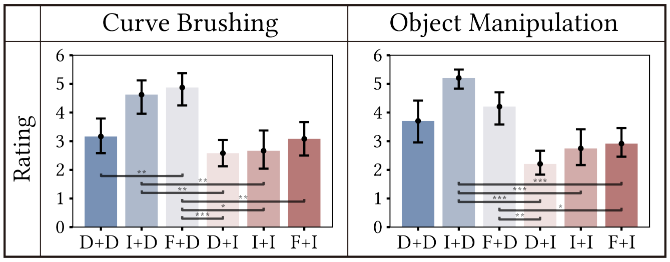

Figure 6: The user preference rating of conditions in two tasks. Significance levels: $p < .05(^{*})$**,** $p < .01(^{**})$**, and** $p < .001(^{***})$**.**

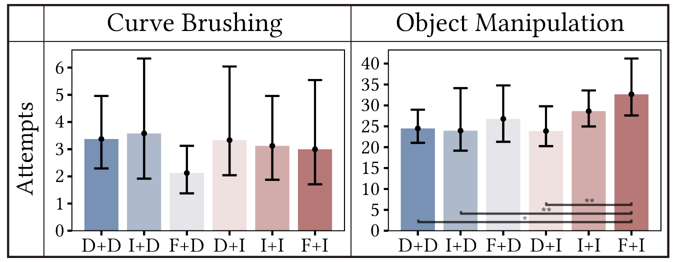

Figure 7: The number of attempts in the two tasks. Significance levels: $p < .05(^{*})$**,** $p < .01(^{**})$**, and** $p < .001(^{***})$**.**

times) and offering better input depth perception (3 times). However, the offset magnified errors were caused by body swaying (15 times), even though it required less body motion (8 times). Regarding the non-dominant hand, participants liked visualization control, benefits such as enhanced observation (4 times in the manipulation task), real-life experiences of holding an object (3 times). Applying an offset to the non-dominant hand had a minimal impact on task completion. However, fixed visualization was reported to require additional body movement in space (14 times), although it aided in understanding the spatial location of the data.Concerning two-handed coordination, two-handed collisions were reported frequently in D+D (25 times) and D+I (3 times). Additionally, symmetric settings for both hands, such as both direct or both with offset, were mentioned 7 times as providing a more coordinated feeling. We further reported our findings considering participants with varying levels of VR experience in Appendix C and Figure 10.

6 DISCUSSION

Impact of Level of Embodiment in Asymmetric Interactions. On the one hand, direct action provides a higher sense of embodiment in WIM-based asymmetric tasks, highlighting its importance in task completion. In contrast, the offset of visualization did not affect task performance. We assume the main reason is that the visualization control hand functions as supplementary support, primarily aiding users in observing data from various directions. Although, to some extent, the introduction of an offset would cause users to feel it was an indirect manipulation, the advantages are also clear. The offset reduces the chance of two hands collisions. Moreover, the requirement for users' arm movements is not as much as in the direct manipulation. On the other hand, we also noticed that frequent two-handed collisions would significantly affect performance. Although D+D provides a high sense of embodiment, it did not show better accuracy but took a longer time compared to other direct action conditions. We assume the reason was because of the frequent collisions, users would need to restart their interactions. Thus, even though its advantage of embodiment was noticed, only 8.3% of participants selected it as the most preferred condition in the brushing task. Considering all these aspects, the asymmetric setting I+D seems to be an appropriate choice since it provides direct action and avoids collisions in two-handed interactions.

Another appropriate choice is F+D. F+D achieved comparable accuracy compared to direct action conditions and higher accuracy compared to all other indirect action conditions, but it was noticed as the fastest method in both tasks. We assume the reason is that this condition provides direct action in the stable visualization environment. While users move around the fixed visualization, it also enhances their engagement in the data exploration. This dynamic interaction allows users to explore the data from various perspectives, fostering deeper engagement and understanding. As a result, it was scored by participants as a noticeably preferred condition in the brushing task.

Two-handed Interaction. Two-handed coordination stands out as a significant aspect deserving thorough discussion. The two tasks in the study impose distinct requirements on the collaboration between the two hands. In the brushing task, the non-dominant hand plays a pivotal role in supporting users by stabilizing data visualization, necessitating the establishment of a stable environment. This setup allows users to employ the dominant hand for precisely brushing data in the correct positions. Given that users also need to verify if the input aligns with the target curve, a fixed position for the data visualization appears to be optimal. Conversely, in the manipulation task, users needed to manipulate data with six degrees of freedom (6 DOF) to obtain the optimal view of the target location. Here, the non-dominant hand not only aids users in observing data but also assists the dominant hand in aligning the object to the target position. Consequently, for tasks demanding high precision, we recommend creating a stable environment—such as fixing the visualization in a specific position—which not only facilitates users' spatial awareness during data exploration but also supports precise interaction through direct engagement and explicit indication of the point of contact.

For tasks requiring users to observe data from various viewpoints, it is advantageous to empower them to manipulate the data effectively with 6 DOF. Thus, WIM design proves to be user-friendly, with data visualization held in the non-dominant hand. Particularly in data exploration, where many visualization tasks demand multitasking from both hands, WIM design enables users to manipulate, for instance, a clipping plane for observing data features on a 2D slice. In such cases, both hands can be utilized to find the optimal position or orientation of the 2D slice—one hand holding the data visualization while the other manipulates the cutting plane.

However, it is also crucial to consider the VR experience concerning two-handed coordination. While experienced VR users adeptly navigate two-hand settings, novices tend to prefer fixed visualization instead.

7 CONCLUSION

This study focuses on a controlled user study that compared six experimental conditions for two visualization tasks: curve brushing and object manipulation. These tasks showcase distinct requirements in terms of precision, object observation, and two-handed coordination. We presented our key findings and offered recommendations for the design of two-handed interaction techniques in the context of data visualizations. However, our study did not examine users' ability of two-handed coordination, as well as behavioral and ergonomic metrics for embodied interaction, which could be further studied. Moreover, currently, we interact with data using VR controllers and virtual hands as the visual metaphor. For a more embodied approach, we plan to investigate the impact of embodiment and two-handed coordination when employing mid-air gestures for data exploration.

ACKNOWLEDGMENTS

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Exploring Embodied Asymmetric Two-Handed Interactions for Immersive Data Exploration

Appendix

In this appendix, we offer additional tables, graphs, and charts. In the graphs, significance levels are denoted as $p < .05$(*), $p < .01$(**), and $p < .001$(***) with corresponding stars.

A TASK PERFORMANCE AND PREFERENCE RATING

Condition	Curve Brushing		Object Manipulation	
	Effect Size	CI	Effect Size	CI
D+D	.652cm	[.608, .706]	.127cm	[.109, .150]
I+D	.622cm	[.587, .662]	.118cm	[.103, .135]
F+D	.647cm	[.604, .707]	.143cm	[.122, .166]
D+I	.710cm	[.666, .764]	.146cm	[.120, .185]
I+I	.772cm	[.714, .848]	.189cm	[.163, .223]
F+I	.722cm	[.674, .780]	.198cm	[.172, .229]

Condition	Curve Brushing		Object Manipulation	
	Effect Size	CI	Effect Size	CI
D+D	.595cm	[.545, .656]	.111cm	[.091, .135]
I+D	.550cm	[.518, .590]	.098cm	[.079, .126]
F+D	.556cm	[.520, .599]	.148cm	[.119, .185]
D+I	.624cm	[.588, .665]	.116cm	[.092, .152]
I+I	.723cm	[.655, .839]	.175cm	[.146, .207]
F+I	.638cm	[.594, .684]	.191cm	[.157, .234]

Condition	Curve Brushing		Object Manipulation	
	Effect Size	CI	Effect Size	CI
D+D	.700cm	[.635, .790]	.141cm	[.112, .176]
I+D	.682cm	[.630, .743]	.134cm	[.114, .158]
F+D	.723cm	[.650, .811]	.138cm	[.111, .173]
D+I	.782cm	[.711, .868]	.171cm	[.130, .239]
I+I	.814cm	[.737, .932]	.202cm	[.158, .256]
F+I	.792cm	[.713, .887]	.205cm	[.168, .252]

Table 1: Mean task error and 95% confidence intervals for overall (top), VR users (middle), and novices (bottom).

Condition	Curve Brushing		Object Manipulation	
	Effect Size	CI	Effect Size	CI
D+D	27.661s	[24.933, 30.688]	23.354s	[21.222, 25.700]
I+D	25.206s	[23.125, 27.474]	20.993s	[18.954, 23.251]
F+D	22.724s	[20.601, 25.067]	21.114s	[18.870, 23.624]
D+I	29.578s	[27.094, 32.291]	24.853s	[22.402, 27.571]
I+I	27.848s	[25.337, 30.607]	24.974s	[22.690, 27.488]
F+I	26.953s	[24.794, 29.300]	23.295s	[20.997, 25.845]

Condition	Curve Brushing		Object Manipulation	
	Effect Size	CI	Effect Size	CI
D+D	27.488s	[23.811, 31.733]	24.379s	[20.950, 28.370]
I+D	25.362s	[22.849, 28.152]	22.874s	[19.583, 26.717]
F+D	23.755s	[21.063, 26.792]	21.922s	[18.449, 26.048]
D+I	29.373s	[26.128, 33.022]	23.308s	[19.736, 27.526]
I+I	29.413s	[26.389, 32.783]	27.125s	[23.538, 31.258]
F+I	26.677s	[23.901, 29.775]	22.740s	[19.059, 27.132]

Condition	Curve Brushing		Object Manipulation	
	Effect Size	CI	Effect Size	CI
D+D	27.808s	[23.869, 32.398]	22.520s	[19.864, 25.530]
I+D	25.074s	[21.894, 28.717]	19.523s	[17.025, 22.388]
F+D	21.887s	[18.783, 25.503]	20.453s	[17.565, 23.816]
D+I	29.753s	[26.080, 33.945]	26.240s	[22.961, 29.988]
I+I	26.589s	[22.870, 30.913]	23.288s	[20.419, 26.559]
F+I	27.188s	[23.961, 30.850]	23.775s	[20.964, 26.963]

Table 2: Mean task time and 95% confidence intervals for overall (top), VR users (middle), and novices (bottom).

Condition	Curve Brushing		Object Manipulation	
	Effect Size	CI	Effect Size	CI
D+D	3.167	[2.583, 3.792]	3.708	[2.958, 4.417]
I+D	4.625	[3.958, 5.125]	5.208	[4.833, 5.500]
F+D	4.875	[4.250, 5.375]	4.208	[3.583, 4.708]
D+I	2.583	[2.125, 3.042]	2.208	[1.833, 2.667]
I+I	2.667	[2.042, 3.375]	2.750	[2.167, 3.417]
F+I	3.083	[2.500, 3.667]	2.917	[2.458, 3.458]

Condition	Curve Brushing		Object Manipulation	
	Effect Size	CI	Effect Size	CI
D+D	3.364	[2.545, 4.364]	3.818	[2.636, 4.818]
I+D	4.909	[4.091, 5.545]	5.455	[5.000, 5.818]
F+D	4.636	[3.727, 5.364]	3.909	[3.182, 4.727]
D+I	2.364	[1.636, 3.273]	2.364	[1.727, 3.182]
I+I	2.909	[2.182, 3.727]	2.818	[2.000, 3.727]
F+I	2.818	[1.909, 3.727]	2.636	[1.909, 3.364]

Condition	Curve Brushing		Object Manipulation	
	Effect Size	CI	Effect Size	CI
D+D	3.000	[2.231, 3.769]	3.615	[2.538, 4.615]
I+D	4.385	[3.385, 5.077]	5.000	[4.385, 5.462]
F+D	5.077	[4.154, 5.692]	4.462	[3.385, 5.077]
D+I	2.769	[2.231, 3.231]	2.077	[1.615, 2.615]
I+I	2.462	[1.615, 3.615]	2.692	[1.846, 3.692]
F+I	3.308	[2.538, 4.000]	3.154	[2.615, 3.846]

Table 3: Mean preference rating and 95% confidence intervals for overall (top), VR users (middle), and novices (bottom).

B SUBJECTIVE RATINGS ON SENSE OF EMBODIMENT AND TASK LOAD

Sense of Embodiment. In both tasks, the direct action conditions scored higher for self-location, agency, and body ownership than the indirect action conditions (Figure 8). I+D had higher agency (brushing: $p = .01$) and body ownership (brushing: $p = .035$, manipulation: $p = .014$) scores than I+I, and D+D had higher agency (brushing: $p = .009$) scores than D+I. F+D was significantly higher than F+I on self-location (brushing: $p = .016$, manipulation: $p = .04$), agency (brushing: $p = .013$, manipulation: $p = .017$), and body ownership (brushing: $p = .043$, manipulation: $p = .03$) scores in two tasks.

Task Load. The scores of direct action conditions are higher than the indirect action conditions in both two tasks (Figure 9). In the brushing task, I+D and F+D provided better experiences. However, there were no significant differences except between F+D and F+I ($p = .022$), and between I+D and I+I ($p = .018$) in time pressure. In the manipulation task, differently, I+D demonstrated better experiences. Specifically, the I+D condition was significantly better than I+I in terms of mental ($p = .002$), physical ($p = .012$), temporal ($p = .02$), and effort ($p = .02$).

C RESULTS ON USERS WITH DIFFERENT VR EXPERIENCES

The comprehensive results are presented in Appendix A. Overall, VR users exhibited higher accuracy compared to novices in both tasks. Notably, participants utilized less time in the F+D condition compared to other conditions, while maintaining comparable accuracy.

In the brushing task, the performance patterns across the six conditions were consistent for both novices and VR users. However, in the manipulation task, there were slight variations in performance patterns between novice and VR users. Specifically, for VR users, F+D was less accurate than D+I, whereas for novice users, F+D was more accurate.

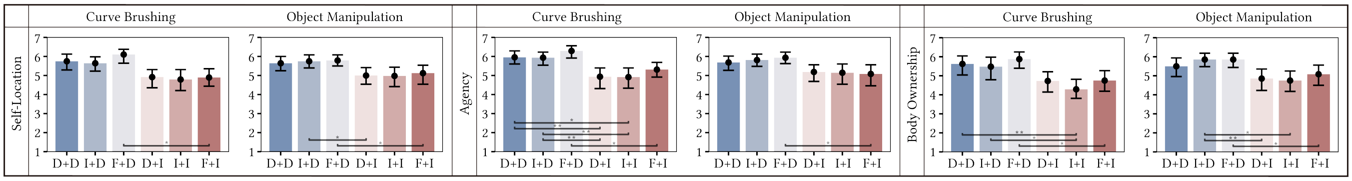

Figure 8: The sense of embodiment in two tasks. Significance levels: $p < .05(^*)$, $p < .01(^{**})$, and $p < .001(^{***})$.

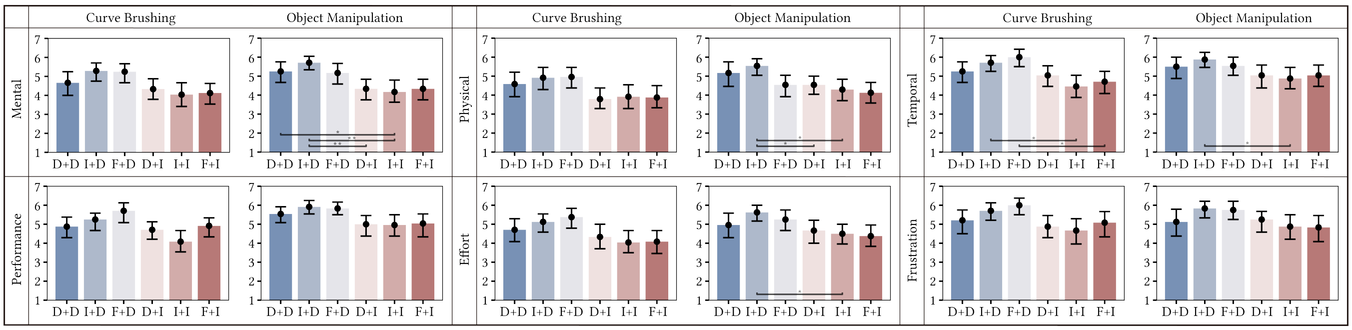

Figure 9: The task load in two tasks. Significance levels: $p < .05(^*)$, $p < .01(^{**})$, and $p < .001(^{***})$.

Although differences in time and accuracy were not prominently observed, we did notice some findings from users' experiences. In general, I+D and F+D were more preferred in both tasks. VR users consistently rated I+D the highest in both tasks, while novice users rated F+D the highest in the curve brushing task.

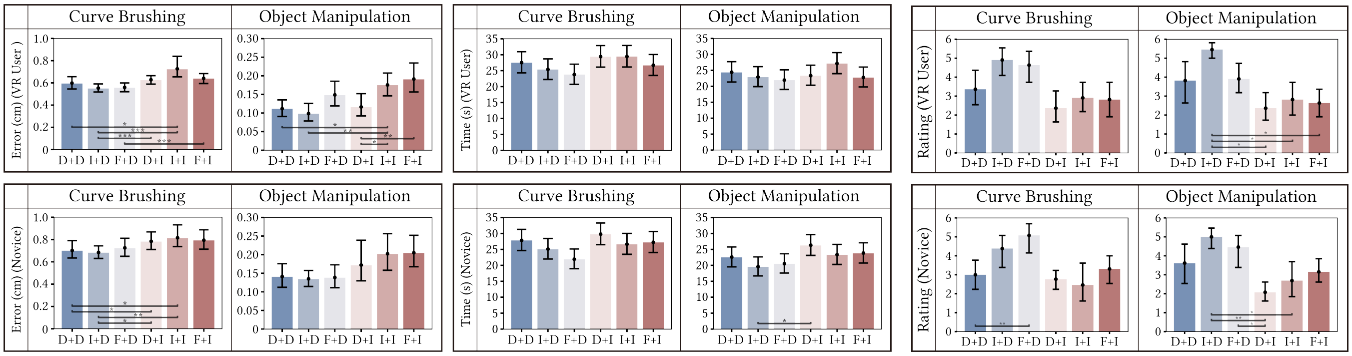

Figure 10: Accuracy (error) (left), completion time (center), and user preference rating (right) of VR users (top) and novices (bottom) in two tasks. Significance levels: $p < .05$(*), $p < .01$(**), and $p < .001$(***).