DensingQueen: Exploration Methods for Spatial Dense Dynamic Data

Julius von Willich
Technical University of Darmstadt,
Telecooperation Lab
Darmstadt, Germany
willich@tk.tu-darmstadt.de

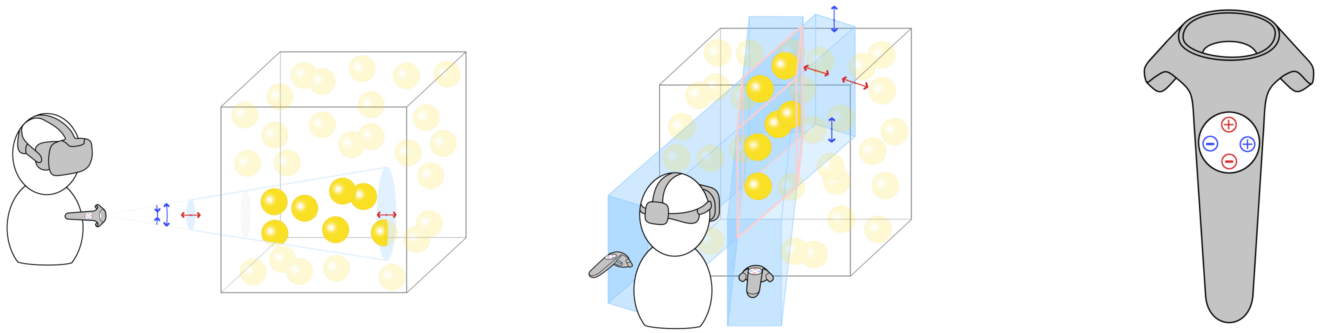
Sebastian Günther
Technical University of Darmstadt,
Telecooperation Lab
Darmstadt, Germany
guenther@tk.tu-darmstadt.de

Andrii Matviienko
KTH Royal Institute of Technology
Stockholm, Sweden
andriim@kth.se

Martin Schmitz
Saarland University,
Saarland Informatics Campus
Saarbrücken, Germany
mschmitz@cs.uni-saarland.de

Florian Müller
LMU Munich
Munich, Germany
f_m@outlook.com

Max Mühlhäuser
Technical University of Darmstadt,
Telecooperation Lab
Darmstadt, Germany
max@tk.tu-darmstadt.de



(a) Illustration of our FLASHLIGHT approach **(b) Illustration of our 3D CUTTING PLANES approach** **(c) Shared control scheme**

Figure 1: We propose two interaction techniques for Dense Dynamic Data to highlight a sub-volume of interest. FLASHLIGHT (a) is suitable for tracking dynamic volumes of interest and 3D CUTTING PLANES (b) – for accurately highlighting stationary volumes.

ABSTRACT

Research has proposed various interaction techniques to manage the occlusion of 3D data in Virtual Reality (VR), e.g., via gradual refinement. However, tracking dynamically moving data in a dense 3D environment poses the challenge of ever-changing occlusion, especially if motion carries relevant information, which is lost in still images. In this paper, we evaluated two interaction modalities for Spatial Dense Dynamic Data (SDDD), adapted from existing interaction methods for static and spatial data. We evaluated these modalities for exploring SDDD in VR, in an experiment with 18 participants. Furthermore, we investigated the influence of our interaction modalities on different levels of data density on the users' performance in a no-knowledge task and a prior-knowledge task. Our results indicated significantly degraded performance for higher levels of density. Further, we found that our flashlight-inspired modality successfully improved tracking in SDDD, while a cutting plane-inspired approach was more suitable for highlighting static volumes of interest, particularly in such high-density environments.

CCS CONCEPTS

• **Human-centered computing** → **Laboratory experiments**; **Virtual reality**; **Empirical studies in interaction design**; Pointing devices; **Laboratory experiments**; **Virtual reality**.

KEYWORDS

Data exploration, Data Interaction, Spatial Data, Dense Data, Dynamic Data, Virtual Reality

ACM Reference Format:
Julius von Willich, Sebastian Günther, Andrii Matviienko, Martin Schmitz, Florian Müller, and Max Mühlhäuser. 2023. DensingQueen: Exploration Methods for Spatial Dense Dynamic Data. In *The 2023 ACM Symposium on Spatial User Interaction (SUI '23), October 13–15, 2023, Sydney, NSW, Australia.* ACM, New York, NY, USA, 12 pages. https://doi.org/10.1145/3607822.3614535

SUI '23, October 13–15, 2023, Sydney, NSW, Australia

ACM ISBN 979-8-4007-0281-5/23/10…$15.00
https://doi.org/10.1145/3607822.3614535

1 INTRODUCTION

From interactive point-cloud labeling [18, 19] to archaeological surveys of 3D landscape data [5] and rescuing [62], Virtual Reality (VR) has proven its effectiveness in facilitating the immersive examination of 3D data. However, when dealing with large sets of 3D data, focusing on specific areas of interest becomes challenging, necessitating the development of methods to hide irrelevant data. For example, existing focus management methods for 3D data in virtual environments typically rely on slicing planes [58], 3D mid-air gestures [15], 2D tactile input [40], or tangible interaction [3]. Although these methods have demonstrated practicality and usefulness, they are primarily designed for low-density, static data, rendering them ineffective for Spatial Dense Dynamic Data (SDDD). As SDDD we define data that takes up more than 25% of the available volume (Section 2).

In recent years, the prevalence of increasingly large and often unlabeled 3D data sets with SDDD has grown, and additional methods that mainly support such data's dynamic and dense nature are required. For example, SDDD can be found from large point clouds, spatio-temporal [54, 63] data analysis [17, 38] or data tagging [18, 19], where the motion of data carries significant information, over to medical imaging [32, 59] where Augmented Reality (AR) and VR have already been employed to support the data exploration [52, 61]. Further, previous research has already proposed supporting tools for selecting [24] and tracking [64] of data objects for managing SDDD in information spaces. However, these approaches rely on knowledge of the object's position changes over time and a specific definition of the object in the data, which are often absent in large unlabeled data sets, to automatically highlight, follow, or select an object [25, 69].

To address these challenges, we extend state-of-the-art interaction techniques for tracking and highlighting data points in sparse and static data to large unlabeled SDDD sets for exploration in virtual environments. Specifically, we adopt two approaches: bubble cursor and cutting planes [50, 58], which resulted in FLASHLIGHT, a flashlight inspired INTERACTION MODALITY and 3D CUTTING PLANES, a cutting plane-inspired INTERACTION MODALITY. We conducted a controlled experiment (N = 18) to assess the performance of these approaches for managing SDDD. Our results indicate that while accuracy, efficiency, and user experience degrade with increased density, the provided tooling support mitigates these effects compared to the absence of such support. Furthermore, both INTERACTION MODALITIES greatly reduced the users' mental load when focusing on objects in SDDD.

In summary, our contribution encompasses a reproducible measure for SDDD within this emerging research field, along with a systematic investigation of two INTERACTION MODALITIES that facilitate focus and identification of objects in SDDD. With FLASHLIGHT being a modification of existing selection methods, adjusted to highlight a volume instead. And 3D CUTTING PLANES presenting a more spatial limited version of a standard cutting plane, allowing for more concise highlighting. Both of these have, to our knowledge, not yet been tested in this form for interaction in SDDD.

2 SPATIAL DENSE DYNAMIC DATA (SDDD)

While related work features multiple papers developing interaction techniques for dense data [25, 39, 60], there is no clear definition of what makes this data dense. Furthermore, dense data in related work is usually less dense than in environments we are interested in [42] or features static data [12, 40]. Thus, we define our reproducible density measure, which also can be defined independently from the surrounding study setup. To achieve this, we relied on the relative proportion D of volume taken up by data d and volume available to display this data v, so $D = \frac{d}{v}$. For example, a value of $D = 0.25$ means that in a display volume of $1m^3$, the presented data has a total volume of $0.25m^3$. High values for D mean that the data features higher levels of inherent occlusion, which we consider to be data with D at least 0.25 or 25%-FILL according to our metric. Considering shape and size, which also influence this measure, these may depend on the specific task. As such, defining them is necessary to ensure reproducibility, but varying it may be unavoidable. In our case, we chose spheres as a volumetric approximation of abstract data points and a radius of 5cm to balance a high number of objects with system performance. This resulted in between 480 and 1450 objects per $1m^3$ in our approach, as illustrated by Figure 2, ensuring constant occlusion throughout the experiment.

3 RELATED WORK

In the following, we provide an overview of existing work in the fields of (1) data representation and interaction in Virtual Environment (VE), (2) selection, and (3) filtering methods for datasets.

3.1 Data Representation and Interaction in Virtual Environments

Spatial data lends itself to spatial representation, which can draw from the user's real-world experience and be easier understood than simplified representations [39]. Digital twins of the data source, for example, can leverage the user's prior knowledge to increase readability and understandability of otherwise complex data [11, 33, 41, 45]. As another approach, utilizing tangible [29] or body-based [44] interaction concepts allows for more immersive and easier-to-understand interaction with data by easing the burden of learning to interact with data. VR offers a platform to explore data in 3D spaces, offering a less abstract representation than 3D projections on a screen. Brunhart et al. [6] have proposed to leverage this additional spatial dimension to better structure and lay out one's thought process, and Kwon et al. [31] have shown how to increase the readability of graphs when embracing the increased layout possibilities of VR. Therefore, VR opens up a promising space for immersive interaction with 3D data. However, the presented approaches are not tailored to the specific requirements of dense and dynamic data, as a high density introduces occlusion, which hinders the exploration of interesting parts hidden by irrelevant data.

3.2 Selection

Multiple approaches exist to compensate for inherent occlusion for dense or dynamic data interaction scenarios. Rosa et al. developed selection methods providing additional depth cues for more accurate selection [50]. Argelaguet et al. studied the impact of the mismatch between what a user sees and what they can point at with their hand, proposing a combined technique, compensating for this mismatch [1]. Object selection techniques (e.g., [24, 51]) and more recent approaches exploring bare-hand mid-air interaction [55] highlight objects of interest and work well when looking for known objects, but were not tested with constantly changing regions. Previous research has proposed techniques to approach occlusion in dense data scenarios, such as selection via cone select [60] or depth rays [25]. For distinguishable, partially occluded objects in VR, approaches using a pre-selection and disambiguation workflow such as ClockRac [66] show promising results but rely on a definition for individual objects. For distinguishable, fully occluded objects in VR by Yu et al. [67] also relies on the disambiguation of possible targets on a per-object basis. However, information about what constitutes an object is not always available.

3.3 Filtering

X-ray vision is a straightforward approach to solving occlusion, which provides the user with information otherwise occluded by geometry. Approaches range from seeing through walls [34], into rooms [4], and overlaying details in-situ [36] to seeing subterranean infrastructure [22, 51, 70]. However, current approaches rely on a thorough semantic understanding of the surrounding world, which includes, for instance, determining where an obstacle should be erased [8, 28], giving context about what the user is looking through [2], or keeping information about both, the occluding and the occluded object [21]. However, these approaches only account for real-world objects occluding data, not data-inherent occlusion, such as a digital engine cover occluding the individual digital pistons.

Prouzeau et al. present a toolset to explore 3D-scatter-plots in VR, communicating the results of a kernel density estimation to the user via haptic feedback and providing a lens to enhance interesting areas found [47]. However, such approaches are often cumbersome to use [40, 58], require the user to previously know exactly what they want to view [48], or rely on semantic meta-information about the data set being explored [47, 57]. The immersive CT colonoscopy system developed by Lopes et al. provides a high level of control over the visualization but still assumes prior knowledge from domain experts [35]. Another promising group of occlusion management approaches is based on gradual refinement via context-aware [68, 69] or context-agnostic [20, 27, 53] methods. However, these approaches rely on either knowledge about what constitutes an object to pre-select and track them [9] or only work on static data as otherwise, and the selection is quickly outdated [3, 40].

Data agnostic approaches, such as cutting planes [46], only filter along one dimension, thus making it challenging to create a limited enough, therefore comprehensible subvolume. Approaches implementing a more fine-grained subvolume selection [12, 43, 51] enable the definition of more precise and thus comprehensible subvolumes in dense environments. Such approaches can be further refined if the extent of the 3D data is known and limited, as shown by the CT data viewer VRRRRoom [58] and can even visualize changes over time, such as the space-time hypercube [23]. Further, the specialized 3D axis controller by Cordeil et al. [14, 16], is geared towards interacting with data in a limited box volume. However, they are unsuitable for dynamic environments since their advanced adjustments take time, during which the region of interest might have shifted, or their limited input accuracy due to fixed-length analog sliders. Head mounted [4] and hand-held [70] X-ray vision, on the other hand, relies on knowledge about the data and surroundings, such as interesting objects or room boundaries, to present comprehensible data to the user. Cashion et al. have presented a promising approach [9], relying on gradual refinement to solve occlusion problems in dense, dynamic scenarios. However, this approach rearranges possible objects of interest from a preselection, which would disrupt the context of the object's position and motion which is often relevant information itself and should be conserved. Furthermore, the approach relies on knowing what constitutes an object, information not always available.

To overcome the limitation explained above, namely the need for meta-data, slow and iterative adjustment, and reliance on specialized hardware, we designed two data-agnostic, dynamic INTERACTION MODALITIES, based on promising approaches from related work, which we explain below.

4 INTERACTION MODALITIES

VR has become a viable medium for data exploration, as it allows for intuitive representation and navigation. However, existing techniques for tracking and analyzing moving objects within three-dimensional datasets often lack a specific approach tailored to unlabeled Spatial Dense Dynamic Data. They mostly rely on either meta-data or static data or focus on selecting and highlighting a single point instead of an area. Therefore, we have identified the following requirements for our proposed INTERACTION MODALITIES. First, they need to be data-agnostic, not relying on metadata so that users can track arbitrary data in SDDD environments. Second, they also need to be agile, so users can follow interesting data as it moves through the data space, which is often not covered by approaches relying on gradual refinement. Following these requirements, we propose two interaction techniques based on common related work and adapted them for the special needs of SDDD. (1) FLASHLIGHT that facilitates one-handed interaction and mimics a flashlight's light cone to highlight a subvolume, similar to the *cone select* method by Vanackena et al. [60]. And (2) 3D CUTTING PLANES that employ two hands to control two cutting planes with limited, adjustable extend, similar to the methods proposed by Sousa et al. [58]. In both cases, the highlighted volume is rendered fully opaque, and the rest is rendered semi-transparent.

4.1 Flashlight

The FLASHLIGHT method is based on the metaphor of a flashlight illuminating data the user is interested in, mimicking real tool use, which has been employed in various previous work [10, 49, 56]. Namely, using a virtual 'light cone' to determine which volume and information is important to the user, making the affected volume visible and the rest semi-transparent. A user can adjust the radius of the visible volume and its distance to the controller (see Figures 1a and 1c). By pressing left and right on the controller's touchpad, the user can decrease and increase the cone's radius, respectively by 1cm per 1 second if the button is held. The distance to the controller can be increased and decreased by pressing up and down on the controller's touchpad, by 5cm per 1 second the button is held, polled every 0.02sec. The controller can move the lamp around freely in space to enable dynamic and continuous exploration of SDDD. Unless changed via the touchpad, the distance between the 'beginning' of the light cone and the controller remains constant, enabling the user to look past occluders. We chose this method to mimic the real-life concept of handling a flashlight in darkness or fog, allowing users to draw from their experience and expectations of regular flashlights.

4.2 3D Cutting Planes

The 3D CUTTING PLANES technique draws inspiration from similar methodologies commonly employed in domains such as medicine [65], geology [30], or engineering [37]. This technique facilitates the slicing of spatial datasets, allowing for precise adjustment of the contextual focus by manipulating a plane that selectively displays data on one of its sides. In our work, we extended this concept by introducing a two-plane configuration controlled by both hands. The orientation of the 3D CUTTING PLANES is aligned with the controllers, ensuring that the planes' normals face forward, aligning with the Z-axis of the controllers. The plane's extent is limited along the X and Y-Axis, which can be adjusted using the controller's touchpads (see Figure 1b). The adjustment was possible 1cm per 1sec held, polled every 0.02sec. We added a second plane and limited the plane's extension after a pre-study that revealed the need for more concise occlusion management. The visible subvolume is defined by the intersection of the volumes in front of the planes, as depicted in Figure 1b. To enhance the precision of highlighting, users can dynamically modify the size and position of the visible subvolume by altering the angle between the two planes.

5 METHODOLOGY

In our study, we evaluated the impact of DATA SET DENSITY and INTERACTION MODALITY on the participants' performance for the exploration of Spatial Dense Dynamic Data. The primary objective was to comprehend the effects of DATA SET DENSITY and identify effective strategies for supporting users in navigating and comprehending SDDD environments. To structure our evaluation, we established the following research questions:

- **RQ1** How does the DATA SET DENSITY affect the accuracy, efficiency, mental and physical demand of extracting relevant information from SDDD in VR?
- **RQ2** How does the INTERACTION MODALITY affect the accuracy, efficiency, mental and physical demand of extracting relevant information from SDDD in VR?

5.1 Study Design

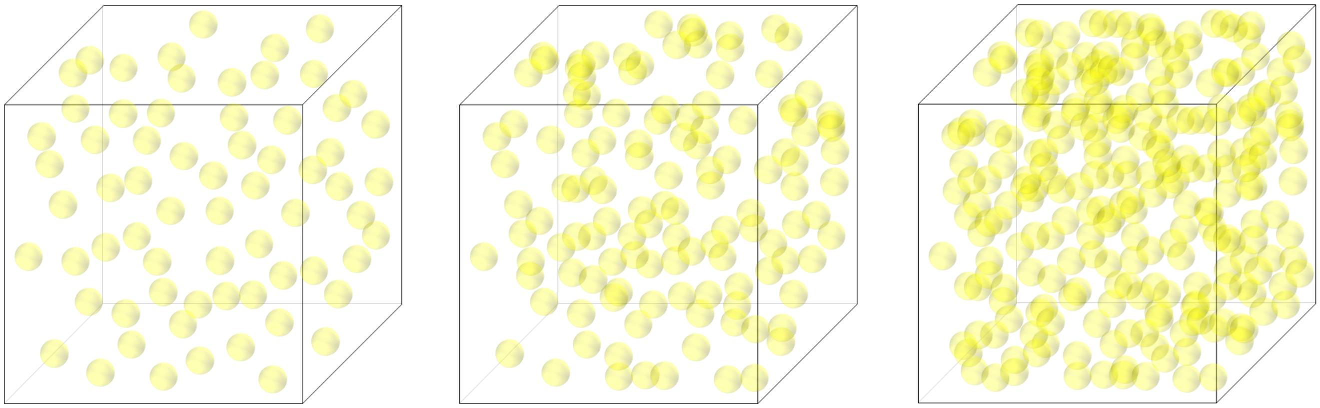
We conducted a controlled experiment with a within-subjects design in which participants explored a dense and dynamic data set in VR and defined two independent variables: (1) DATA SET DENSITY and (2) INTERACTION MODALITY of the data set. Adhering to this measure defined above, we defined three levels of DATA SET DENSITY, 25%-FILL: $D = 0.25$, 50%-FILL: $D = 0.5$, 75%-FILL: $D = 0.75$, resulting in one trial per DATA SET DENSITY to INTERACTION MODALITY combination. As the task already lasted for around 50 minutes and proved mentally draining, we chose not to vary the shape and size of the object as an additional dependent variable. In our case, this results in roughly 480, 950, and 1450 spheres for 25%-FILL, 50%-FILL, and 75%-FILL, respectively. With INTERACTION MODALITY being either FLASHLIGHT or 3D CUTTING PLANES and a NO SUPPORT baseline. We varied both independent variables in a repeated measures design with three levels each, resulting in a 2-factorial experiment design with a total of $3 \times 3 = 9$ conditions. We counterbalanced the order of the conditions using a Balanced Latin Square design. For each condition, the system randomized the series of targets while assuring that each target was repeated two times.

5.2 Tasks

We designed two tasks with a common setting, a volume (1m × 1 m × 1m) filled with dynamically moving yellow spheres of varying densities, simulating auxiliary data that distracts the participant. When reaching the outer edges of the volume, the spheres bounced off the invisible border and continued to move linearly within the volume. To achieve a random behavior, we randomized the direction of each sphere setting their velocity to 0.5m/s. To focus on the specific influence of the two independent variables, we aimed to minimize the external influences in the experiment. Therefore, we deliberately chose a very abstract setting in which both tasks took place to reduce the effect of participants' prior knowledge of a domain on performance. Blue and yellow were chosen to avoid problems for color-blind participants and in accordance with the setup by Vanacken et al. [60]. We intentionally chose two tasks requiring the participant to track a distinct sphere in the volume. However, they differ in the prior knowledge available: While there is no knowledge about the chaotic structure of the volume in task 1, the participant is equipped with prior knowledge in task 2 in the form of visualized checkpoints (that the sphere to be tracked will pass in any case). We explain the two tasks in detail in the following:

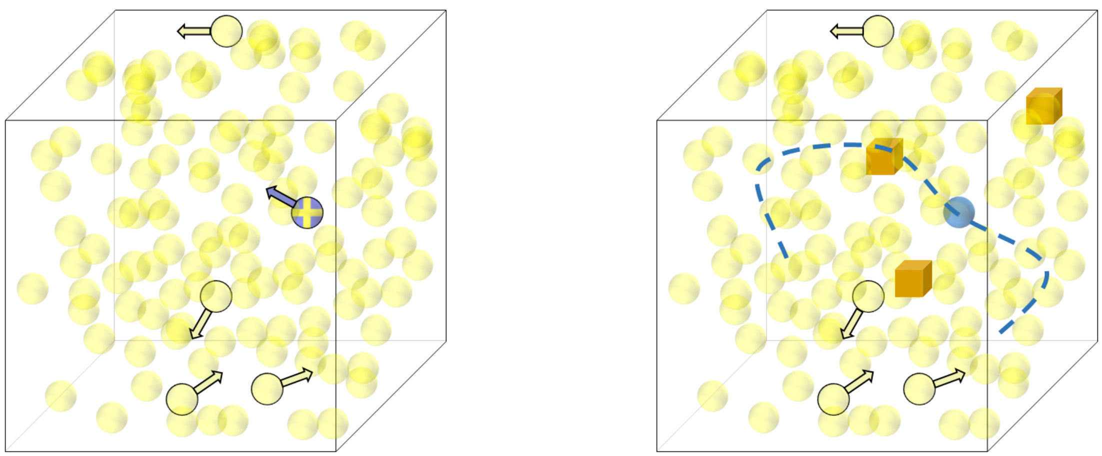
5.2.1 Task 1: NO-knowledge task. For this task, we introduced a blue colored sphere into the volume, representing data the participant is interested in. This sphere was set on a physically correct path, similar to the distractor object. In regular, semi-random intervals, the sphere featured yellow crosses, visible for four seconds and from every angle (Figure 3a). The participants were instructed to press a button as soon as this change appeared. This task was aimed to test the ease with which the INTERACTION MODALITIES can be used to keep a specific, dynamically changing sub-volume in focus.

5.2.2 Task 2: PRIOR-knowledge task. For this task, we introduced a blue colored sphere into the volume, representing data the participant is interested in. The object of interest was set on an invisible path, creating a dynamic tracking task. The path consisted of five segments, at the start of every segment, we introduced three checkpoints, two decoys, and one situated on the path, past checkpoints were deleted (Figure 3b). These checkpoints presented a controlled, uncertain prior knowledge for the participants, intended to simulate domain knowledge. The participants were instructed to press a



(a) 25%-fill scenario **(b) 50%-fill scenario** **(c) 75%-fill scenario**

Figure 2: Illustration of the three density settings, equidistantly spread between filling 0% and 100% of the available volume. Mock-up is used as differences are not perceivable on screenshots of the actual study setup. They were, however, clearly perceivable in motion using a VR headset.



(a) Visual representation of the *no-knowledge task* used, without any support tool present.

(b) Visual representation of the *prior-knowledge task* used, without any support tool present.

Figure 3: Visualization of the two different tasks the participants were asked to complete.

button when the object of interest entered a checkpoint. The object of interest took four seconds to pass through the checkpoint, limiting the participants' time to correctly react. This task was aimed to test the usability of the interaction modalities when exploring unfamiliar data sets but with a prior understanding of its subject matter.

5.3 Apparatus

The study setups consisted of a 3m × 3m SteamVR tracking space allowing users to walk freely around the 1m × 1m data volume, so no artificial locomotion was needed. We used two Vive Wand controllers for the 3D cutting planes method and one for the flashlight. The application was written in Unity3D, and the source files of the project are available online [1].

5.4 Procedure

We welcomed the participants and introduced them to our concepts and study. Therefore, we provided a brief overview of the procedures, which included explanations of interaction modalities and the dimensions of the data volumes. After obtaining informed consent, we asked participants for demographic data. We then initialized the distractor orbs and placed the blue target orb at its starting position, allowing participants to familiarize themselves with the current task and interaction technique. To familiarize

[1] https://github.com/LOEWE-emergenCITY/DensingQueen

themselves with the INTERACTION MODALITIES, participants could interact with the scene before the object of interest started moving. We started the task once they located the object of interest and felt ready. At the end of the study, we briefly interviewed each participant about their preferences for INTERACTION MODALITIES and any changes they would make. Each density condition took an average of 5 minutes per task and the entire study, including the introduction and questionnaires, lasted about 50 minutes per participant.

5.4.1 Adherence to Health Guidelines. For this study, we adhered to our institute's health department's guidelines for user studies during the COVID-19 pandemic. All testing equipment was disinfected and the room used was aired out for a minimum of half an hour between participants. When possible, the participant and examiner kept a minimum distance of at least 1,5m. During the greeting and explanation, the participant and examiner wore a mask to reduce the probability of infection.

5.5 Measures

For each condition, we measured the following dependent variables:

Wrong Click Error Rate The percentage of clicks made by the participant while the target object did not change color or was not in the area of the checkpoint.

Missed Changes Error Rate The number of color changes not confirmed by the participant.

Missed Checkpoints Error Rate The percentage of checkpoints that were not confirmed by a click of participants.

Reaction Time The reaction time between the target object changing color or entering the checkpoint area and the participant's confirmation click.

Total Movement The accumulated distance the participant moved during the condition (measured as the position of the participant's head).

Time in Volume The accumulated time the object of interest was in the highlight-area of the respective INTERACTION MODALITY.

After each condition, we asked the participant to fill out a NASA TLX questionnaire for further data collection.

5.6 Analysis

We analyzed the recorded data using two-way repeated measures (RM) ANOVAs with DATA SET DENSITY and INTERACTION MODALITY as two factors to reveal significant effects. Before the analysis, we tested the data for normality using Shapiro-Wilk's test without any significant deviations. When Mauchly's test indicated a violation of the assumption of sphericity, we corrected the tests using the Greenhouse-Geisser method and report the corresponding ϵ. When the RM ANOVA revealed significant effects, we used Bonferroni-corrected pairwise t-tests for post-hoc analysis. Further, we report the eta-squared η^2 as an estimate of the effect size and classify the effect size as small, medium or large according to Cohen's suggestions [13]. For the analysis of the NASA TLX questionnaires, we used the raw method, indicating an overall workload as described by Hart [26].

5.7 Participants

We recruited 18 participants (12 identified as male, four as female, one as non-binary, and one as gender Variant/non-Conforming) aged between 21 and 33 (M = 26.4, SD = 3.2) years using word-of-mouth and a snowball sampling. Four participants identified themselves as experienced virtual reality users, four considered their experience above average, six as average, two as below average, and two used VR for the first time. Besides snacks and drinks, no compensation was provided.

6 RESULTS

The following section reports the results of our controlled experiment investigating the research questions presented in section 5.

6.1 Accuracy

We analyzed the accuracy of participants as two different error measures as presented in section 5.5.

6.1.1 Wrong Clicks - PRIOR-knowledge task. The analysis revealed a significant ($F_{2,34} = 3.42$, $p < .05$, $\eta^2 = .03$) main effect of the DATA SET DENSITY on the wrong click error rate with a small effect size for the *PRIOR-knowledge task*. Post-hoc tests confirmed significant ($p < .05$) lower wrong click error rates for the 25%-FILL ($\mu = .03$, $\sigma = .08$) conditions compared to the 75%-FILL ($\mu = .09$, $\sigma = .14$) conditions. The differences to the 50%-FILL ($\mu = .07$, $\sigma = .14$) conditions were not significant. The analysis did not indicate a significant ($F_{2,34} = 3.03$, $p > .05$) main effect of the INTERACTION MODALITY on the wrong click error rate. The recorded mean values ranged from $\mu = .03$, $\sigma = .10$ for the FLASHLIGHT conditions over $\mu = .07$, $\sigma = .15$ for the 3D CUTTING PLANES conditions to $\mu = .10$, $\sigma = .13$ for the NO SUPPORT conditions. The analysis did not show a significant ($F_{2.57,43.66} = 1.34$, $p < .05$, $\epsilon = 0.642$) interaction effect between the two factors.

6.1.2 Wrong Clicks - NO-knowledge task. The analysis did not indicate a significant ($F_{2,34} = 2.454$, $p > .05$) main effect of the DATA SET DENSITY on the wrong click error rate. The recorded mean values ranged from $\mu = .11$, $\sigma = .11$ for the 25%-FILL conditions over $\mu = .17$, $\sigma = .5$ for the 50%-FILL conditions to $\mu = .22$, $\sigma = .28$ for the 75%-FILL conditions. The analysis did not indicate a significant ($F_{2,34} = 1.426$, $p > .05$) main effect of the INTERACTION MODALITY on the wrong click error rate. The recorded mean values ranged from $\mu = .11$, $\sigma = .22$ for the FLASHLIGHT conditions over $\mu = .11$, $\sigma = .28$ for the 3D CUTTING PLANES conditions to $\mu = .11$, $\sigma = .5$ for the NO SUPPORT conditions. The analysis did not show a significant ($F_{4,68} = 0.7$, $p > .05$) interaction effect between the two factors. Figure 4 (left) depicts the measured wrong click error rates for all conditions in the experiment.

6.1.3 Missed Checkpoints - PRIOR-knowledge task. The analysis indicated a significant ($F_{2,34} = 27.44$, $p < .001$, $\eta^2 = .17$) main effect of the DATA SET DENSITY on the missed checkpoint rate with a large effect size. Post-hoc tests confirmed significantly higher missed checkpoint error rates for higher densities between all levels ($p < .01$ for 25%-FILL - 50%-FILL, $p < .001$ otherwise). We found mean

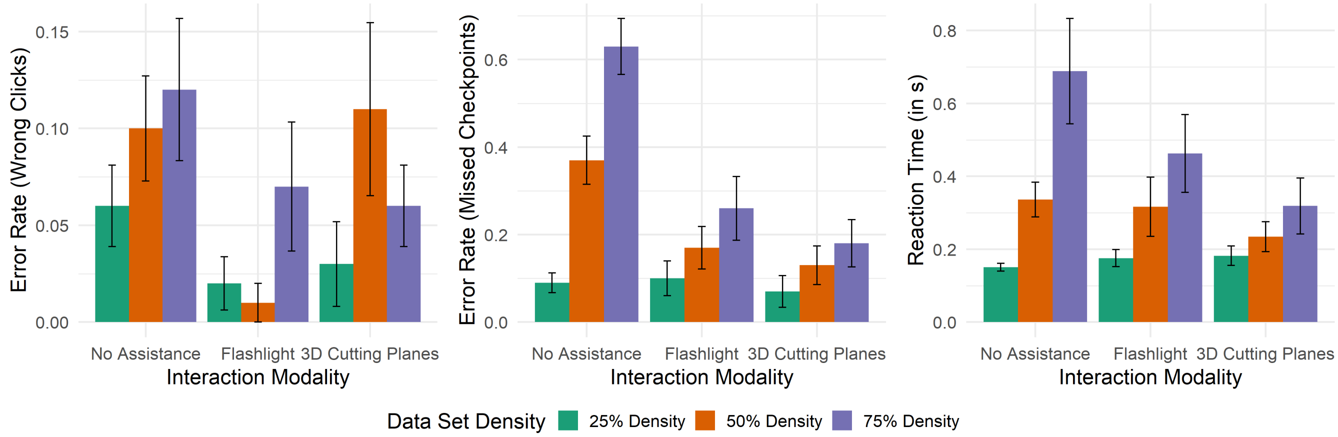


Figure 4: *Wrong clicks* (PRIOR*-knowledge task*), *missed checkpoints* (PRIOR*-knowledge task*) and *reaction time* (NO*-knowledge task*). All error bars depict the standard error.

missed checkpoint error rates ranging from $\mu = .09$, $\sigma = .15$ (25%-FILL) over $\mu = .22$, $\sigma = .25$ (50%-FILL) to $\mu = .38$, $\sigma = .34$ (75%-FILL). Further, the analysis indicated a significant ($F_{1.39,23.60} = 13.40$, $p < .001$, $\epsilon = .69$, $\eta^2 = .129$) main effect of the INTERACTION MODALITY on the missed checkpoint error rate with a medium effect size. Post-hoc tests confirmed significant lower missed checkpoints error rates for 3D CUTTING PLANES ($\mu = .13$, $\sigma = .21$) and FLASHLIGHT ($\mu = .18$, $\sigma = .26$) compared to NO SUPPORT ($\mu = .37$, $\sigma = .32$, both $p < .001$). Finally, the analysis indicated a significant ($F_{2.91,49.51} = 8.51$, $p < .001$, $\epsilon = .73$, $\eta^2 = .08$) interaction effect between DATA SET DENSITY and INTERACTION MODALITY with a medium effect size. While the differences between NO SUPPORT and both other levels of the INTERACTION MODALITY are not significant for the 25%-FILL level, the differences become larger for higher levels of the DATA SET DENSITY. This results in higher missed checkpoint error rates for NO SUPPORT compared to both other levels of INTERACTION MODALITY, for 50%-FILL (NO SUPPORT - 3D CUTTING PLANES: $p < .01$) and 75%-FILL (both $p < .001$). Figure 4 (middle) depicts the measured missed checkpoints error rates for all conditions in the experiment.

6.1.4 Missed Changes - NO-knowledge task. The analysis indicated a significant ($F_{1.48,25.24} = 25.92$, $p < .001$, $\epsilon = .742$, $\eta^2 = 0.294$) main effect of the DATA SET DENSITY on the missed changes rate with a large effect size. Post-hoc tests confirmed significantly higher missed changes error rates for higher densities between all levels ($p < .001$ for 25%-FILL - 75%-FILL, $p < .01$ otherwise). We found mean missed changes error rates ranging from $\mu = .06$, $\sigma = .28$ (25%-FILL) over $\mu = .5$, $\sigma = 1.17$ (50%-FILL) to $\mu = 1.56$, $\sigma = 2.67$ (75%-FILL). Further, the analysis indicated a significant ($F_{2,34} = 4.75$, $p < .05$, $\eta^2 = .027$) main effect of the INTERACTION MODALITY on the missed changes error rate with a small effect size. Post-hoc tests confirmed significant lower missed changes error rates for FLASHLIGHT ($\mu = .75$, $\sigma = 1.26$) compared to NO SUPPORT ($\mu = 1.22$, $\sigma = 1.5$, $p < .05$) but not for 3D CUTTING PLANES ($\mu = .88$, $\sigma = 1.19$). Finally, the analysis did not indicated a significant ($F_{2.76,46.87} = 2.82$, $p > .05$, $\epsilon = .689$) interaction effect between DATA SET DENSITY and INTERACTION MODALITY.

6.2 Efficiency

We analyzed the efficiency as the reaction time of indicating when the target to follow reached a checkpoint.

6.2.1 Reaction time - PRIOR-knowledge task. We found a significant ($F_{2,22} = 4.52$, $p < .05$, $\eta^2 = .104$) main effect of the DATA SET DENSITY on the efficiency of participants with a medium effect size. Post-hoc tests showed significantly lower reaction times for the 25%-FILL ($\mu = 0.69$ s, $\sigma = 0.25$ s) compared to the 75%-FILL ($\mu = 0.76$ s, $\sigma = 0.27$ s) conditions ($p < .05$). We could not find significant differences to the 50%-FILL conditions ($\mu = 0.75$ s, $\sigma = 0.29$ s). The analysis could not show a significant ($F_{1.41,15.48} = 1.078$, $p > .05$, $\epsilon = .704$) main effect of the INTERACTION MODALITY on the efficiency of participants. We found reaction times ranging from $\mu = 0.74$ s, $\sigma = 0.26$ s (3D CUTTING PLANES) over $\mu = 0.73$ s, $\sigma = 0.26$ s (FLASHLIGHT) to $\mu = 0.71$ s, $\sigma = 0.31$ s (NO SUPPORT). The analysis did not indicate significant ($F_{1.94,21.38} = 0.35$, $p > .05$, $\epsilon = .486$) interaction effects between the two factors.

6.2.2 Reaction time - NO-knowledge task. We found a significant ($F_{1.44,20.18} = 11.76$, $p < .001$, $\epsilon = .721$, $\eta^2 = .17$) main effect of the DATA SET DENSITY on the efficiency of participants with a large effect size. Post-hoc tests showed significantly lower reaction times for the 25%-FILL ($\mu = 0.77$ s, $\sigma = 0.59$ s) compared to the 75%-FILL ($\mu = 1.16$ s, $\sigma = 0.99$ s) conditions ($p < .01$). We could not find significant differences to the 50%-FILL conditions ($\mu = 1.1$ s, $\sigma = 0.97$ s). The analysis could not show a significant ($F_{2,22} = 3.16$, $p > .05$) main effect of the INTERACTION MODALITY on the efficiency of participants. We found reaction times ranging from $\mu = 0.8$ s, $\sigma = 0.55$ s (3D CUTTING PLANES) over $\mu = 0.98$ s, $\sigma = 0.90$ s (FLASHLIGHT) to $\mu = 1.18$ s, $\sigma = 1.05$ s (NO SUPPORT). The analysis did not indicate significant ($F_{2.04,28.58} = 2.24$, $p > .05$, $\epsilon = .510$ interaction effects between the two factors. Figure 4 (right) depicts the measured reaction times for all conditions in the experiment.

6.2.3 Total Head Movement - PRIOR-knowledge task. To evaluate the influence of the two factors on the physical movement of participants, we analyzed the sum of movements of the head-mounted

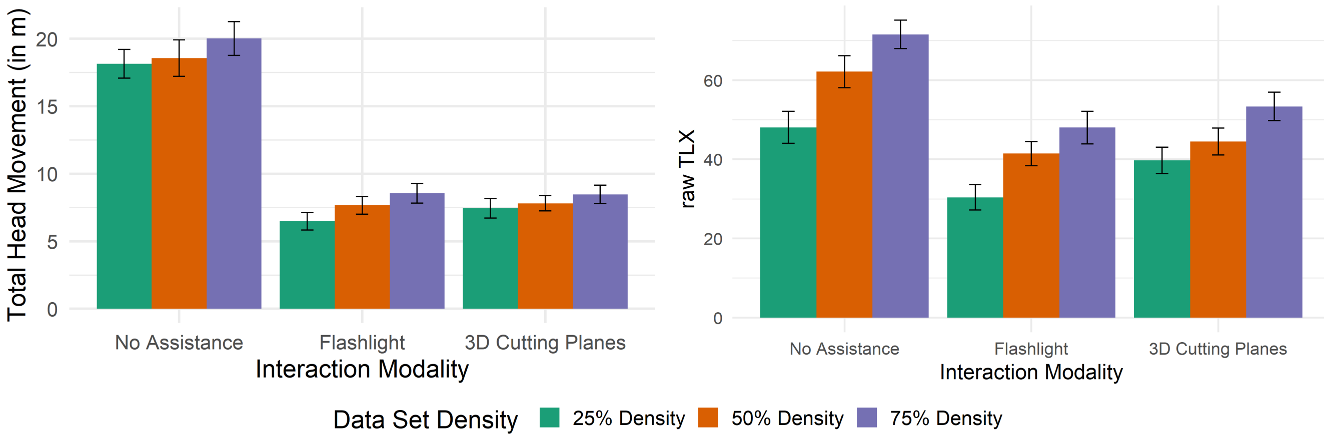


Figure 5: *Total head movement* (PRIOR*-knowledge task*) and *raw TLX* (overall). All error bars depict the standard error.

display (HMD) as the total movement. The analysis revealed a significant ($F_{2,34} = 6.07$, $p < .001$, $\eta^2 = .016$) main effect of the DATA SET DENSITY on the total movement of participants with a small effect size. Post-hoc tests showed significant differences between the 25%-FILL ($\mu = 10.29$ m, $\sigma = 6.4$ m) and 75%-FILL ($\mu = 12.39$ m, $\sigma = 6.94$ m) conditions ($p < .01$). We could not find significant differences to the 50%-FILL ($\mu = 11.24$ m, $\sigma = 6.82$ m) conditions. Further, we found a significant ($F_{1.41,23.98} = 90.92$, $p < .001$, $\epsilon = .71$, $\eta^2 = .64$) main effect of the INTERACTION MODALITY on the total movement of participants with a large effect size. Post-hoc tests confirmed significantly lower total movements for both, the FLASHLIGHT ($\mu = 7.26$ m, $\sigma = 3.02$ m) and 3D CUTTING PLANES ($\mu = 7.79$ m, $\sigma = 3.06$ m) compared to NO SUPPORT ($\mu = 18.87$ m, $\sigma = 5.64$ m) conditions (both $p < .001$). We could not find significant ($F_{4,68} = .28$, $p > .05$ interaction effects between both factors. Figure 5 (left) depicts the measured total movement distances for all conditions in the experiment.

6.2.4 Total Head Movement - NO-knowledge task. The analysis revealed a significant ($F_{2,34} = 4.6$, $p < .05$, $\eta^2 = .016$) main effect of the DATA SET DENSITY on the total movement of participants with a small effect size. Post-hoc tests showed significant differences between the 25%-FILL ($\mu = 11.5$ m, $\sigma = 7.11$ m) and 75%-FILL ($\mu = 13.91$ m, $\sigma = 8.24$ m) conditions ($p < .01$). We could not find significant differences to the 50%-FILL ($\mu = 13.17$ m, $\sigma = 8.0$ m) conditions. Further, we found a significant ($F_{1.35,22.88} = 63.87$, $p < .001$, $\epsilon = .67$, $\eta^2 = .55$) main effect of the INTERACTION MODALITY on the total movement of participants with a large effect size. Post-hoc tests confirmed significantly lower total movements for both, the FLASHLIGHT ($\mu = 8.31$ m, $\sigma = 3.9$ m) and 3D CUTTING PLANES ($\mu = 9.1$ m, $\sigma = 4.05$ m) compared to NO SUPPORT ($\mu = 21.17$ m, $\sigma = 6.96$ m) conditions (both $p < .001$). We found significant ($F_{4,68} = 33.7$, $p < .05$, $\eta^2 = .014$) interaction effects between both factors when NO SUPPORT was involved.

6.2.5 Time in Volume - NO-knowledge task. We found a significant ($F_{2,34} = 17.68$, $p < .001$, $\eta^2 = .034$ main effect of the DATA SET DENSITY on the efficiency of participants with a small effect size. Post-hoc tests showed significantly higher time in volume for the 25%-FILL ($\mu = 52.15$ s, $\sigma = 15.06$ s) compared to the 75%-FILL ($\mu = 35.29$ s, $\sigma = 17.53$ s) conditions ($p < .01$), and between 25%-FILL and 50%-FILL ($p < .05$) ($\mu = 44.53$ s, $\sigma = 16.57$ s). The analysis of the INTERACTION MODALITY is omitted, due to no data being measured for NO SUPPORT. The analysis did indicate significant ($F_{2,34} = 5.17$, $p .001$, $\eta^2 = .022$) interaction effects between the two factors, with a low effect size. Additionally, post-hoc tests revealed significant interaction effects between 25%-FILL - 3D CUTTING PLANES and 75%-FILL - 3D CUTTING PLANES, 25%-FILL - 3D CUTTING PLANES and 75%-FILL - FLASHLIGHT, 25%-FILL - FLASHLIGHT and 75%-FILL - 3D CUTTING PLANES but not 25%-FILL - FLASHLIGHT and 75%-FILL - FLASHLIGHT.

6.3 Mental Load - both

We measured the mental load of participants using the NASA TLX questionnaire. Combined measure was chosen, as sub-scales did not yield different results. The analysis revealed a signification ($F_{2,34} = 49.85$, $p < .001$, $\eta^2 = .16$) main effect of the DATA SET DENSITY on the raw TLX with a large effect size. Post-hoc tests showed significantly higher raw TLX values for higher densities between all groups (all $p < .001$) with measurements ranging from $\mu = 39.38$, $\sigma = 17.18$ (25%-FILL) over $\mu = 49.35$, $\sigma = 17.99$ (50%-FILL) to $\mu = 57.63$, $\sigma = 19.38$ (75%-FILL). Further, the analysis showed a significant ($F_{2,34} = 23.83$, $p < .001$, $\eta^2 = .19$) main effect of the INTERACTION MODALITY on the raw TLX with a large effect size. Post-hoc tests confirmed significantly lower raw TLX values for both, FLASHLIGHT ($\mu = 39.93$, $\sigma = 16.96$) and 3D CUTTING PLANES ($\mu = 45.85$, $\sigma = 16.11$) compared to NO SUPPORT ($\mu = 60.57$, $\sigma = 19.67$, both $p < .001$). The analysis did not indicate significant interaction effects ($F_{4,68} = 2.45$, $p > .05$) between both factors. Figure 5 (right) depicts the measured raw TLX for all conditions in the experiment.

6.4 Qualitative Results

Most participants (12) preferred the FLASHLIGHT approach over the 3D CUTTING PLANES approach. Those preferring the FLASHLIGHT commented on how "[...] it is easier to judge where I [the visible volume] am in the volume [...]" (P2) and how it was "[...] easier to find the [object of interest] once I lose it." (P5). Others described the 3D CUTTING PLANES tool as "[...] like the [FLASHLIGHT] with an unnecessary second lamp." (P18). However, multiple participants commented on the easier distance adjustment with the 3D CUTTING PLANES. To adjust the distance of the visible portion, participants simply adjusted the intersection point as desired, whereas the FLASHLIGHT approach relied on button presses to achieve this. Multiple participants expressed their desire to adjust the FLASHLIGHT's volume's depth to further limit the visible data. The was originally discarded in favor of an easier control scheme and including the ability to adjust the volume's distance to the FLASHLIGHT. However, participants also noted they would "[...] rather adjust the size [depth] than the distance from the [FLASHLIGHT] [...]" (P12) We could also observe the participants neglecting the button input during the condition, most participants only adjusted the INTERACTION MODALITIES' dimensions to their liking before starting the condition. This behavior makes a more complex, in-depth adjust-ability of the FLASHLIGHT's volume a feasible approach for future iterations. Multiple participants expressed their discomfort to have objects pass through their head, participant 8 even asked "Do I really have to go in there?" when faced with the 75%-FILL, NO SUPPORT task. Presenting the participants with the 75%-FILL condition without INTERACTION MODALITIES often prompted profanities on their part, leading us to the conclusion that unsupported interaction with 75%-FILL data was undesirable.

7 DISCUSSION

In this section, we discuss the findings and implications of the conducted study, in particular, detailing the role of the INTERACTION MODALITY and DATA SET DENSITY.

7.1 Effects of Interaction Modality and Density on Performance

The results of the study confirm the significant impact of density on participants' performance in exploring SDDD. Since our low-density setting was already on a comparable level of high-density settings as defined in related work, we found that our high-density scenarios pose even greater challenges compared to such low-density settings, as indicated by mental demand, focus on the object of interest, and reaction time. In both tasks, INTERACTION MODALITIES proved beneficial in improving participants' performance. Interestingly, however, the importance of support via INTERACTION MODALITIES was less pronounced in 25%-FILL settings, suggesting that participants were able to manage lower density effectively even without additional assistance. In contrast, INTERACTION MODALITIES greatly improved **head movement** for high DATA SET DENSITY. This was particularly evident during the *NO-knowledge task*, where no fallback to checkpoints was possible and participants needed to maintain constant visual contact with the target to avoid missing any changes.In such cases, the interaction effect became more pronounced, highlighting the crucial role of the INTERACTION MODALITIES. Combined with the **TLX-scores** this shows that both INTERACTION MODALITIES make exploring SDDD less tiresome compared to NO SUPPORT, especially in 75%-FILL scenarios.

7.2 Flashlight for Dynamic Tracking

The FLASHLIGHT INTERACTION MODALITY demonstrated better performance for *PRIOR-knowledge task*, as evidenced by the significantly lower **Missed Changes** compared to NO SUPPORT, which was not significant for 3D CUTTING PLANES. During the *NO-knowledge task*, participants were unable to rely on checkpoints to find the target after losing sight of it, a scenario where FLASHLIGHT likely performed better due to its simpler interaction. As such, FLASHLIGHT offers a more direct interaction experience, with hand motion directly following the target, which may not hold true for tracking using 3D CUTTING PLANES, and might facilitate following a constant trajectory more easily. Considering **Time in Volume**, every combination of 25%-FILL and 75%-FILL with FLASHLIGHT and 3D CUTTING PLANES exhibited significant improvement, with the exception of 25%-FILL-FLASHLIGHT to 75%-FILL-FLASHLIGHT, which further suggests that FLASHLIGHT consistently delivers better performance across different scenarios compared to 3D CUTTING PLANES. In conclusion, the FLASHLIGHT INTERACTION MODALITY proved to be a suitable tool for tracking continuous motion, as it offered the advantage of directly following an object with a controller rather than relying on an imaginary intersection point of two controllers, as in the case of 3D CUTTING PLANES.

7.3 Planes for Static Targets

Looking at the *PRIOR-knowledge task*, performance was significantly better compared to NO SUPPORT for 75%-FILL, considering both INTERACTION MODALITIES. However, for 50%-FILL only 3D CUTTING PLANES showed a significant improvement. This suggests that 3D CUTTING PLANES performs better when focusing on a fixed point. This is further supported by behaviors we observed, where participants waited at one particular checkpoint or cycled through all of them while waiting for the target to appear. Looking into **wrong clicks** in the *PRIOR-knowledge task* revealed that participants predominantly clicked late, directly after a target had exited the checkpoint. This behavior can be attributed to two factors. Firstly, participants often cycled through the checkpoints, occasionally missing the precise moment to click. Secondly, participants tended to click multiple times when they identified the correct checkpoint at the last moment, leading to a sharp spike in the **wrong click error rate**. Conversely, the **error rate** remained relatively stable during other instances, indicating a more typical pattern of performance. These findings, combined with the worse results in *NO-knowledge task* compared to FLASHLIGHT suggest that the 3D CUTTING PLANES is better suited for highlighting a specific, stationary point, rather than moving targets.

7.4 Adjustment UI

In terms of interaction, it is worth noting that adjustments during a task were mainly done with hand motions. Button input was mainly used to adjust the volumes to a comfortable size before a task was started. Only with 3D CUTTING PLANES the participants adjusted the volume size during a task by increasing and decreasing the intersection of both beams. Overall we could see distinct benefits of both INTERACTION MODALITY, with FLASHLIGHT for dynamic tracking and 3D CUTTING PLANES for fixation of static targets. We could also see a clear preference for motion-based interaction when it came to adjustments.

8 LIMITATIONS AND FUTURE WORK

We are confident that the results presented provide valuable insights into tracking in SDDD sets. However, the experiment design, the experiment results, and the non-representative participant population impose some limitations and directions for future work. With the existing sampling bias toward young, male-identifying participants, additional evaluation is needed to verify the findings as applicable to the general population. However, the current results may be used to inform the scope of future experiments.

8.1 Ecological Validity

We presented an experiment that deliberately investigated tracking in an abstract task. We chose this approach to reveal the isolated effects of the DATA SET DENSITY and INTERACTION MODALITY without the influence of external factors. While we are convinced that our work can make an important contribution to the future tracking in SDDD using VR, we also acknowledge that real-world systems pose further questions, such as the influence of different data types and sizes of the displayed volume. Future work is necessary to conclude these challenges, and an interesting approach would be investigating the INTERACTION MODALITIES in real-world use cases. This would enable better judgment regarding the INTERACTION MODALITIES' validity for real-world, practical tasks.

8.2 Varying Dynamics and Size of the Base Volume

We have not investigated different dynamics of the occluder data nor different sizes of the base volume that contains both occluders and regions of interest. We regard the characteristics of these factors as strongly dependent on the type of data to be displayed, which strongly depends on the respective use case. Our results can provide a valuable baseline for future work in different application domains.

8.3 Focus On Motion-Based Input

We could also see that the additional fine-tuning option provided via controller input was largely ignored by participants, who primarily relied on hand movement for adjustment, especially for 3D CUTTING PLANES. This observation suggests that participants could have perceived the buttons as valuable or impactful in addressing the challenges posed by density. However, participants also expressed a desire to adjust the length of the FLASHLIGHT's "light" beam, which was the only dimension that was not adjustable. This observation is interesting, as participants mostly disregarded other adjustment capabilities, indicating a need for improved input modalities for these adjustments rather than a specific missing adjustment. Future research could explore alternative methods or interfaces for fine-tuning in high-density scenarios to enhance user experience and performance even more.

8.4 Focus+Context

The two techniques presented in this work allow users to split a 3D data set into two subsets: The set to focus on and the auxiliary context set. This split into two subsets allows a Focus+Context [7] approach in which the user can focus on a specific property while retaining the rest of the data set as context to understand how the property is nested in the overall data set. While we provide first insights into dynamically adjusting the focus set, understanding the benefits of these two subsets in exploring SDDD is beyond the scope of this work. It is an interesting starting point for future work.

9 CONCLUSION

We have investigated the effects of different INTERACTION MODALITIES for exploration of SDDD in VR, gaining insights on challenges and possible solutions for managing occlusion in these environments. We used a comparable, easy-to-replicate measure for density, and offered considerations for creating SDDD exploration tools. While both approaches presented in this paper showed promising improvements for exploring SDDD, we found FLASHLIGHT to be more suitable for dynamic motion and 3D CUTTING PLANES to be more suitable for static target acquisition. The data gathered, combined with the users' feedback, shows that navigating SDDD is a very challenging task in need of simple, easy-to-use tool support, sparing the user's already taxed mental and physical resources. With the presented applications in mind and the considerations provided, we hope to see suitable interaction techniques emerge, empowering users to explore and learn complex data at their own pace and on their own terms.

ACKNOWLEDGMENTS

This work has been funded by the LOEWE initiative (Hesse, Germany) within the emergenCITY centre.

REFERENCES

[1] Ferran Argelaguet and Carlos Andujar. 2009. Efficient 3D pointing selection in cluttered virtual environments. *IEEE Computer Graphics and Applications* 29, 6 (2009), 34–43.

[2] Benjamin Avery, Christian Sandor, and Bruce H. Thomas. 2009. Improving Spatial Perception for Augmented Reality X-Ray Vision. In *2009 IEEE Virtual Reality Conference*. Institute of Electrical and Electronics Engineers (IEEE), 79–82. https://doi.org/10.1109/vr.2009.4811002

[3] Benjamin Bach, Ronell Sicat, Johanna Beyer, Maxime Cordeil, and Hanspeter Pfister. 2018. The Hologram in My Hand: How Effective is Interactive Exploration of 3D Visualizations in Immersive Tangible Augmented Reality? *IEEE Transactions on Visualization and Computer Graphics* 24, 1 (jan 2018), 457–467. https://doi.org/10.1109/TVCG.2017.2745941

[4] Ryan Bane and Tobias Höllerer. 2004. Interactive tools for virtual X-ray vision in mobile augmented reality. In *ISMAR 2004: Proceedings of the Third IEEE and ACM International Symposium on Mixed and Augmented Reality*. 231–239. https://doi.org/10.1109/ISMAR.2004.36

[5] Rebecca Bennett, David J. Zielinski, and Regis Kopper. 2014. Comparison of interactive environments for the archaeological exploration of 3D landscape data. In *2014 IEEE VIS International Workshop on 3DVis (3DVis)*. 67–71. https://doi.org/10.1109/3DVis.2014.7160103

[6] Nicholas Brunhart-Lupo, Brian W. Bush, Kenny Gruchalla, and Steve Smith. 2017. Simulation exploration through immersive parallel planes. In *2016 Workshop on Immersive Analytics, IA 2016*. Institute of Electrical and Electronics Engineers Inc., 19–24. https://doi.org/10.1109/IMMERSIVE.2016.7932377

[7] Stuart K. Card, Jock D. Mackinlay, and Ben Shneiderman. 1999. *Readings in information visualization: using vision to think*. Morgan Kaufmann Publishers. 686 pages. https://dl.acm.org/citation.cfm?id=300679

[8] Robert Carnecky, Raphael Fuchs, Stephanie Mehl, Yun Jang, and Ronald Peikert. 2013. Smart transparency for illustrative visualization of complex flow surfaces. *IEEE Transactions on Visualization and Computer Graphics* 19, 5 (2013), 838–851. https://doi.org/10.1109/TVCG.2012.159

[9] Jeffrey Cashion, Chadwick Wingrave, and Joseph J. Laviola. 2012. Dense and dynamic 3D selection for game-based virtual environments. *IEEE Transactions*

on Visualization and Computer Graphics 18, 4 (apr 2012), 634–642. https://doi.org/10.1109/TVCG.2012.40
[10] Arpan Chakraborty, Kyung Wha Hong, Ryan Gross, Jae Yeol Lee, Shea McIntee, and Robert St. Amant. 2014. CAPTIVE: A cube with augmented physical tools. In *Conference on Human Factors in Computing Systems - Proceedings*. 1315–1320. https://doi.org/10.1145/2559206.2581340
[11] Zhutian Chen, Yifang Wang, Tianchen Sun, Xiang Gao, Wei Chen, Zhigeng Pan, Huamin Qu, and Yingcai Wu. 2017. Exploring the design space of immersive urban analytics. *Visual Informatics* 1, 2 (jun 2017), 132–142. https://doi.org/10.1016/j.visinf.2017.11.002
[12] Zhutian Chen, Wei Zeng, Zhiguang Yang, Lingyun Yu, Chi Wing Fu, and Huamin Qu. 2020. LassoNet: Deep Lasso-Selection of 3D Point Clouds. *IEEE Transactions on Visualization and Computer Graphics* 26, 1 (2020), 195–204. https://doi.org/10.1109/TVCG.2019.2934332 arXiv:1907.13538
[13] Jacob Cohen. 1988. *Statistical Power Analysis for the Behavioral Sciences*. Routledge. https://doi.org/10.4324/9780203771587
[14] Maxime Cordeil, Benjamin Bach, Andrew Cunningham, Bastian Montoya, Ross T. Smith, Bruce H. Thomas, and Tim Dwyer. 2020. Embodied Axes: Tangible, Actuated Interaction for 3D Augmented Reality Data Spaces. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, Vol. 20. 1–12. https://doi.org/10.1145/3313831.3376613
[15] Maxime Cordeil, Benjamin Bach, Yongchao Li, Elliott Wilson, and Tim Dwyer. 2017. Design space for spatio-data coordination: Tangible interaction devices for immersive information visualisation. In *IEEE Pacific Visualization Symposium*. IEEE Computer Society, 46–50. https://doi.org/10.1109/PACIFICVIS.2017.8031578
[16] Maxime Cordeil, Andrew Cunningham, Tim Dwyer, Bruce H Thomas, and Kim Marriott. 2017. ImAxes: Immersive axes as embodied affordances for interactive multivariate data visualisation. In *UIST 2017 - Proceedings of the 30th Annual ACM Symposium on User Interface Software and Technology*. 71–83. https://doi.org/10.1145/3126594.3126613
[17] Ciro Donalek, S. G. Djorgovski, Alex Cioc, Anwell Wang, Jerry Zhang, Elizabeth Lawler, Stacy Yeh, Ashish Mahabal, Matthew Graham, Andrew Drake, Scott Davidoff, Jeffrey S. Norris, and Giuseppe Longo. 2015. Immersive and collaborative data visualization using virtual reality platforms. *Proceedings - 2014 IEEE International Conference on Big Data, IEEE Big Data 2014* (jan 2015), 609–614. https://doi.org/10.1109/BIGDATA.2014.7004282
[18] Achref Doula, Tobias Güdelhöfer, Andrii Matviienko, Max Mühlhäuser, and Alejandro Sanchez Guinea. 2022. Immersive-Labeler: Immersive Annotation of Large-Scale 3D Point Clouds in Virtual Reality. In *ACM SIGGRAPH 2022 Posters*. 1–2.
[19] Achref Doula, Tobias Güdelhöfer, Andrii Matviienko, Max Mühlhäuser, and Alejandro Sanchez Guinea. 2023. PointCloudLab: An Environment for 3D Point Cloud Annotation with Adapted Visual Aids and Levels of Immersion. In *2023 IEEE International Conference on Robotics and Automation (ICRA)*. 11640–11646. https://doi.org/10.1109/ICRA48891.2023.10160225
[20] Emmanuel Dubois and Adrien Hamelin. 2017. Worm Selector: Volume Selection in a 3D Point Cloud Through Adaptive Modelling. *International Journal of Virtual Reality* 17, 1 (jan 2017), 1–20. https://doi.org/10.20870/ijvr.2017.17.1.2884
[21] Niklas Elmqvist, Ulf Assarsson, and Philippas Tsigas. 2007. Employing dynamic transparency for 3D occlusion management: Design issues and evaluation. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, Vol. 4662 LNCS. Springer Verlag, 532–545. https://doi.org/10.1007/978-3-540-74796-3_54
[22] Mustafa Tolga Eren and Selim Balcisoy. 2018. Evaluation of X-ray visualization techniques for vertical depth judgments in underground exploration. *Visual Computer* 34, 3 (mar 2018), 405–416. https://doi.org/10.1007/s00371-016-1346-5
[23] Gwendal Fouché, Ferran Argelaguet, Emmanuel Faure, and Charles Kervrann. 2023. Immersive and interactive visualization of 3D spatio-temporal data using a space time hypercube: Application to cell division and morphogenesis analysis. *Frontiers in Bioinformatics* 3 (2023), 998991.
[24] Tovi Grossman and Ravin Balakrishnan. 2005. The bubble cursor: enhancing target acquisition by dynamic resizing of the cursor's activation area. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 281–290.
[25] Tovi Grossman and Ravin Balakrishnan. 2008. The design and evaluation of selection techniques for 3D volumetric displays. In *UIST 2006: Proceedings of the 19th Annual ACM Symposium on User Interface Software and Technology*. ACM Press, New York, New York, USA, 3–12. https://doi.org/10.1145/1166253.1166257
[26] Sandra G. Hart. 2006. Nasa-Task Load Index (NASA-TLX); 20 Years Later. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 50, 9 (oct 2006), 904–908. https://doi.org/10.1177/154193120605000909
[27] Bret Jackson, Brighten Jelke, and Gabriel Brown. 2018. Yea Big, Yea High: A 3D User Interface for Surface Selection by Progressive Refinement in Virtual Environments. In *25th IEEE Conference on Virtual Reality and 3D User Interfaces, VR 2018 - Proceedings*. 320–326. https://doi.org/10.1109/VR.2018.8447559
[28] Denis Kalkofen, Erick Mendez, and Dieter Schmalstieg. 2009. Comprehensible visualization for augmented reality. In *IEEE Transactions on Visualization and Computer Graphics*, Vol. 15. 193–204. https://doi.org/10.1109/TVCG.2008.96
[29] H. Kato, K. Tachibana, M. Tanabe, T. Nakajima, and Y. Fukuda. 2003. MagicCup: A tangible interface for virtual objects manipulation in table-top augmented reality. In *ART 2003 - IEEE International Augmented Reality Toolkit Workshop*. Institute of Electrical and Electronics Engineers Inc., 75–76. https://doi.org/10.1109/ART.2003.1320434
[30] Richard A. Ketcham. 2005. Computational methods for quantitative analysis of three-dimensional features in geological specimens. *Geosphere* 1, 1 (aug 2005), 32–41. https://doi.org/10.1130/GES00001.1
[31] Oh-Hyun Kwon, Chris Muelder, Kyungwon Lee, and Kwan-Liu Ma. 2016. A Study of Layout, Rendering, and Interaction Methods for Immersive Graph Visualization. *IEEE Transactions on Visualization and Computer Graphics* 22, 7 (jul 2016), 1802–1815. https://doi.org/10.1109/TVCG.2016.2520921
[32] Andras Lasso, Hannah H. Nam, Patrick V. Dinh, Csaba Pinter, Jean Christophe Fillion-Robin, Steve Pieper, Sankhesh Jhaveri, Jean Baptiste Vimort, Ken Martin, Mark Asselin, Francis X. McGowan, Ron Kikinis, Gabor Fichtinger, and Matthew A. Jolley. 2018. Interaction with Volume-Rendered Three-Dimensional Echocardiographic Images in Virtual Reality. *Journal of the American Society of Echocardiography* 31, 10 (oct 2018), 1158–1160. https://doi.org/10.1016/J.ECHO.2018.06.011/ATTACHMENT/B318E870-25B8-40CF-BD15-D0FBD762F2DD/MMC1.MP4
[33] Benjamin Lee, Dave Brown, Bongshin Lee, Christophe Hurter, Steven Drucker, and Tim Dwyer. 2021. Data Visceralization: Enabling Deeper Understanding of Data Using Virtual Reality. *IEEE Transactions on Visualization and Computer Graphics* 27, 2 (2021), 1095–1105. https://doi.org/10.1109/TVCG.2020.3030435
[34] Klemen Lilija, Henning Pohl, Sebastian Boring, and Kasper Hornbæk. 2019. Augmented reality views for occluded interaction. In *Conference on Human Factors in Computing Systems - Proceedings*. ACM, 12. https://doi.org/10.1145/3290605.3300676
[35] Daniel Simões Lopes, Daniel Medeiros, Soraia Figueiredo Paulo, Pedro Brasil Borges, Vitor Nunes, Vasco Mascarenhas, Marcos Veiga, and Joaquim Armando Jorge. 2018. Interaction techniques for immersive CT colonography: A Professional assessment. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, Vol. 11071 LNCS. Springer Verlag, 629–637. https://doi.org/10.1007/978-3-030-00934-2_70
[36] Ursula Luna, Pilar Rivero, and Naiara Vicent. 2019. Augmented reality in heritage apps: Current trends in Europe. *Applied Sciences* 9, 13 (2019), 2756.
[37] Tom Meyer and Al Globus. 1993. Direct manipulation of isosurfaces and cutting planes in virtual environments. *Department of Computer Science, Brown University* (1993).
[38] Patrick Millais, Simon L. Jones, and Ryan Kelly. 2018. Exploring data in virtual reality: Comparisons with 2d data visualizations. *Conference on Human Factors in Computing Systems - Proceedings* 2018-April (apr 2018). https://doi.org/10.1145/3170427.3188537
[39] Jules Moloney, Branka Spehar, Anastasia Globa, and Rui Wang. 2018. The affordance of virtual reality to enable the sensory representation of multi-dimensional data for immersive analytics: from experience to insight. *Journal of Big Data* 5, 1 (dec 2018). https://doi.org/10.1186/s40537-018-0158-z
[40] Roberto A. Montano-Murillo, Cuong Nguyen, Rubaiat Habib Kazi, Sriram Subramanian, Stephen DiVerdi, and Diego Martinez-Plasencia. 2020. Slicing-Volume: Hybrid 3D/2D Multi-target Selection Technique for Dense Virtual Environments. In *2020 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*. Institute of Electrical and Electronics Engineers (IEEE), 53–62. https://doi.org/10.1109/vr46266.2020.00023
[41] Andrew Moran, Vijay Gadepally, Matthew Hubbell, and Jeremy Kepner. 2015. Improving Big Data visual analytics with interactive virtual reality. In *2015 IEEE High Performance Extreme Computing Conference (HPEC)*. IEEE, 1–6. https://doi.org/10.1109/HPEC.2015.7322473
[42] Annette Mossel and Christian Koessler. 2016. Large Scale Cut Plane: An Occlusion Management Technique for Immersive Dense 3D Reconstructions. In *Proceedings of the ACM Symposium on Virtual Reality Software and Technology, VRST*, Vol. 02-04-Nove. Association for Computing Machinery, 201–210. https://doi.org/10.1145/2993369.2993384
[43] Annette Mossel and Christian Koessler. 2016. Large scale cut plane: An occlusion management technique for immersive dense 3D reconstructions. In *Proceedings of the ACM Symposium on Virtual Reality Software and Technology, VRST*, Vol. 02-04-Nove. Association for Computing Machinery, 201–210. https://doi.org/10.1145/2993369.2993384
[44] Florian Müller, Niloofar Dezfuli, Max Mühlhäuser, Martin Schmitz, and Mohammadreza Khalilbeigi. 2015. Palm-Based Interaction with Head-mounted Displays. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct (MobileHCI '15)*. ACM, Copenhagen Denmark, 963–965. https://doi.org/10.1145/2786567.2794314
[45] Kaya Okada, Mitsuo Yoshida, Takayuki Itoh, Tobias Czauderna, and Kingsley Stephens. 2019. VR system for spatio-temporal visualization of tweet data and support of map exploration. *Multimedia Tools and Applications* (aug 2019). https://doi.org/10.1007/s11042-019-08016-y
[46] Krzysztof Pietroszek, James R. Wallace, and Edward Lank. 2015. Tiltcasting: 3D interaction on large displays using a mobile device. In *UIST 2015 - Proceedings of the 28th Annual ACM Symposium on User Interface Software and Technology*.

Association for Computing Machinery, Inc, 57–62. https://doi.org/10.1145/2807442.2807471

[47] Arnaud Prouzeau, Maxime Cordeil, Clement Robin, Barrett Ens, Bruce H Thomas, and Tim Dwyer. 2019. Scaptics and Highlight-Planes: Immersive Interaction Techniques for Finding Occluded Features in 3D Scatterplots. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. ACM, 12. https://doi.org/10.1145/3290605.3300555

[48] Hannah K Ricketts, Alexa M Salsbury, David R Bevan, and Anne M Brown. [n.d.]. Using Immersive Visualization Environments to Engage Students in Hands-On Learning. ([n. d.]). https://doi.org/10.1145/3219104.3229274

[49] Brett Ridel, Patrick Reuter, Jeremy Laviole, Nicolas Mellado, Nadine Couture, and Xavier Granier. 2014. The Revealing Flashlight: Interactive Spatial Augmented Reality for Detail Exploration of Cultural Heritage Artifacts. *J. Comput. Cult. Herit.* 7, 2, Article 6 (jun 2014), 18 pages. https://doi.org/10.1145/2611376

[50] Daniel Alejandro Winkler Rosa and Hubert Hoffmann Nagel. 2010. Selection techniques for dense and occluded virtual 3D environments, supported by depth feedback. Double, bound and depth bubble cursors. In *Proceedings - International Conference of the Chilean Computer Science Society, SCCC*. IEEE Computer Society, 218–225. https://doi.org/10.1109/SCCC.2010.51

[51] Gerhard Schall, Erick Mendez, Ernst Kruijff, Eduardo Veas, Sebastian Junghanns, Bernhard Reitinger, and Dieter Schmalstieg. 2009. Handheld Augmented Reality for underground infrastructure visualization. *Personal and Ubiquitous Computing* 13, 4 (jun 2009), 281–291. https://doi.org/10.1007/s00779-008-0204-5

[52] Ramiro Serrano-Vergel, Pedro Morillo, Sergio Casas-Yrurzum, and Carolina Cruz-Neira. 2023. Exploring the Suitability of Using Virtual Reality and Augmented Reality for Anatomy Training. *IEEE Transactions on Human-Machine Systems* (2023).

[53] Guihua Shan, Maojin Xie, An Li, Yang Gao, and Xuebin Chi. 2014. Interactive visual exploration of halos in large-scale cosmology simulation. *Journal of Visualization* (2014). https://doi.org/10.1007/s12650-014-0206-5

[54] Shashi Shekhar, Zhe Jiang, Reem Y Ali, Emre Eftelioglu, Xun Tang, Venkata MV Gunturi, and Xun Zhou. 2015. Spatiotemporal data mining: A computational perspective. *ISPRS International Journal of Geo-Information* 4, 4 (2015), 2306–2338.

[55] Rongkai Shi, Jialin Zhang, Yong Yue, Lingyun Yu, and Hai-Ning Liang. 2023. Exploration of Bare-Hand Mid-Air Pointing Selection Techniques for Dense Virtual Reality Environments. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–7.

[56] Alireza Sahami Shirazi, Christian Winkler, and Albrecht Schmidt. 2009. Flashlight Interaction: A Study on Mobile Phone Interaction Techniques with Large Displays. In *Proceedings of the 11th International Conference on Human-Computer Interaction with Mobile Devices and Services* (Bonn, Germany) *(MobileHCI '09)*. Association for Computing Machinery, New York, NY, USA, Article 93, 2 pages. https://doi.org/10.1145/1613858.1613965

[57] Jonathan C. Silverstein and Fred Dech. 2005. Precisely Exploring Medical Models and Volumes in Collaborative Virtual Reality. *Presence: Teleoperators and Virtual Environments* 14, 1 (Feb. 2005), 47–59. https://doi.org/10.1162/1054746053890233

[58] Maurício Sousa, Daniel Mendes, Soraia Paulo, Nuno Matela, Joaquim Jorge, and Daniel Simões Lopes. 2017. Vrrrroom: Virtual reality for radiologists in the reading room. In *Proceedings of the 2017 CHI conference on human factors in computing systems*. 4057–4062.

[59] Margot van Deursen, Laura Reuvers, Jacobus Dylan Duits, Guido de Jong, Marianne van den Hurk, and Dylan Henssen. 2021. Virtual reality and annotated radiological data as effective and motivating tools to help Social Sciences students learn neuroanatomy. *Scientific Reports 2021 11:1* 11, 1 (jun 2021), 1–10. https://doi.org/10.1038/s41598-021-92109-y

[60] Lode Vanacken, Tovi Grossman, and Karin Coninx. 2007. Exploring the effects of environment density and target visibility on object selection in 3D virtual environments. In *IEEE Symposium on 3D User Interfaces 2007 - Proceedings, 3DUI 2007*. 115–122. https://doi.org/10.1109/3DUI.2007.340783

[61] Ramiro Serrano Vergel, Pedro Morillo Tena, Sergio Casas Yrurzum, and Carolina Cruz-Neira. 2020. A comparative evaluation of a virtual reality table and a HoloLens-based augmented reality system for anatomy training. *IEEE Transactions on Human-Machine Systems* 50, 4 (2020), 337–348.

[62] Julius Von Willich, Andrii Matviienko, Sebastian Günther, and Max Mühlhäuser. 2022. Comparing VR Exploration Support for Ground-Based Rescue Robots. In *Adjunct Publication of the 24th International Conference on Human-Computer Interaction with Mobile Devices and Services* (Vancouver, BC, Canada) *(MobileHCI '22)*. Association for Computing Machinery, New York, NY, USA, Article 26, 6 pages. https://doi.org/10.1145/3528575.3551440

[63] Senzhang Wang, Jiannong Cao, and S Yu Philip. 2020. Deep learning for spatio-temporal data mining: A survey. *IEEE transactions on knowledge and data engineering* 34, 8 (2020), 3681–3700.

[64] Yang Wang, Mohit Gupta, Song Zhang, Sen Wang, Xianfeng Gu, Dimitris Samaras, and Peisen Huang. 2008. High resolution tracking of non-rigid motion of densely sampled 3D data using harmonic maps. *International Journal of Computer Vision* 76, 3 (2008), 283–300.

[65] Ivo Wolf, Marcus Vetter, Ingmar Wegner, Thomas Böttger, Marco Nolden, Max Schöbinger, Mark Hastenteufel, Tobias Kunert, and Hans Peter Meinzer. 2005. The medical imaging interaction toolkit. *Medical Image Analysis* 9, 6 (dec 2005), 594–604. https://doi.org/10.1016/j.media.2005.04.005

[66] Huiyue Wu, Xiaoxuan Sun, Huawei Tu, and Xiaolong Zhang. 2023. ClockRay: A Wrist-Rotation based Technique for Occluded-Target Selection in Virtual Reality. *IEEE Transactions on Visualization and Computer Graphics* (2023).

[67] Difeng Yu, Qiushi Zhou, Joshua Newn, Tilman Dingler, Eduardo Velloso, and Jorge Goncalves. 2020. Fully-occluded target selection in virtual reality. *IEEE transactions on visualization and computer graphics* 26, 12 (2020), 3402–3413.

[68] Lingyun Yu, Konstantinos Efstathiou, Petra Isenberg, and Tobias Isenberg. 2012. Efficient structure-aware selection techniques for 3D point cloud visualizations with 2DOF input. *IEEE Transactions on Visualization and Computer Graphics* 18, 12 (2012), 2245–2254. https://doi.org/10.1109/TVCG.2012.217

[69] Lingyun Yu, Konstantinos Efstathiou, Petra Isenberg, and Tobias Isenberg. 2016. CAST: Effective and Efficient User Interaction for Context-Aware Selection in 3D Particle Clouds. *IEEE Transactions on Visualization and Computer Graphics* 22, 1 (jan 2016), 886–895. https://doi.org/10.1109/TVCG.2015.2467202

[70] Stefanie Zollmann, Raphael Grasset, Gerhard Reitmayr, and Tobias Langlotz. 2014. Image-based X-ray visualization techniques for spatial understanding in outdoor augmented reality. In *Proceedings of the 26th Australian Computer-Human Interaction Conference, OzCHI 2014*. 194–203. https://doi.org/10.1145/2686612.2686642