TangibleData: Interactive Data Visualization with Mid-Air Haptics

Ayush Bhardwaj
The University of Texas at Dallas
Richardson, TX, USA
ayush.bhardwaj@utdallas.edu

Junghoon Chae
Oak Ridge National Laboratory
Oak Ridge, TN, USA
chaej@ornl.gov

Richard Noeske
The University of Texas at Dallas
Richardson, TX, USA
richard.noeske@utdallas.edu

Jin Ryong Kim
The University of Texas at Dallas
Richardson, TX, USA
jin.kim@utdallas.edu

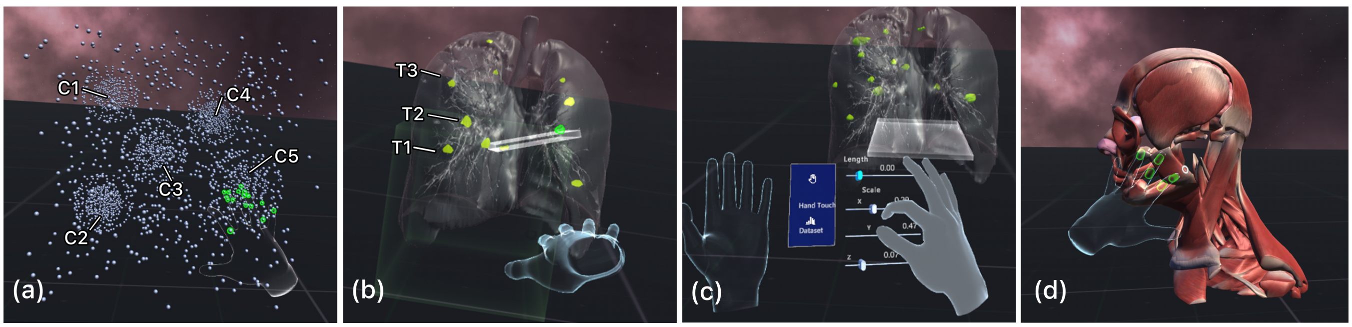


Figure 1: Example scenes. (a) 3D scatterplot with several dense clusters, (b) CT-scan lung dataset with several lung cancer tissues, (c) adjusting values for haptic plane, and (d) human head anatomy volume rendering dataset with muscle layer.

ABSTRACT

In this paper, we investigate the effects of mid-air haptics in interactive 3D data visualization. We build an interactive 3D data visualization tool that adapts hand gestures and mid-air haptics to provide tangible interaction in VR using ultrasound haptic feedback on 3D data visualization. We consider two types of 3D visualization datasets and provide different data encoding methods for haptic representations. Two user experiments are conducted to evaluate the effectiveness of our approach. The first experimental results show that adding a mid-air haptic modality can be beneficial regardless of noise conditions and useful for handling occlusion or discerning density and volume information. The second experiment results further show the strengths and weaknesses of direct touch and indirect touch modes. Our findings can shed light on designing and implementing a tangible interaction on 3D data visualization with mid-air haptic feedback.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

VRST '21, December 8–10, 2021, Osaka, Japan

© 2021 Association for Computing Machinery.

ACM ISBN 978-1-4503-9092-7/21/12...$15.00
https://doi.org/10.1145/3489849.3489890

CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**; **Haptic devices**; **Gestural input**;

KEYWORDS

Data visualization, haptics, immersive analytics, virtual reality

ACM Reference Format:
Ayush Bhardwaj, Junghoon Chae, Richard Noeske, and Jin Ryong Kim. 2021. TangibleData: Interactive Data Visualization with Mid-Air Haptics. In *27th ACM Symposium on Virtual Reality Software and Technology (VRST '21), December 8–10, 2021, Osaka, Japan.* ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3489849.3489890

1 INTRODUCTION

Data visualization has played a vital role in presenting visual representations of information to provide a better understanding of trends and patterns in data. With the emergence of Big Data, visualizing massive data in 3D to allow users to explore multi-axis data interactively becomes even more critical. As 3D data visualization provides the perception of depth, breadth, and height, vast amounts of information should be effectively analyzed from various perspectives to deliver a more comprehensive understanding of data and highlight trends, outliers, and patterns.

However, 3D data visualization presents some challenging issues. One major issue is occlusion. Occlusion occurs when data points closer to the viewer obscure the points behind them. One solution to this problem can be adjusting the opacity of data points. However, it does not completely solve the issue and can eventually lead to the misinterpretation and misunderstanding of data. Many techniques have been studied to mitigate the occlusion issue, such as using distortion, filtering, and deformation [11, 21, 34]. While they have shown significant contributions to solving the occlusion problem, each of these techniques focuses on a specific 3D data type and still has limitations. Users generally keep changing their perspective by rotating, zooming, and panning to observe the data. However, when conducted using a mouse and a keyboard, such user interaction can be burdensome and hinder data exploration and examination.

Interactive 3D data visualization in an immersive VR environment provides opportunities to reduce the problems that come with occlusion. Tangible interfaces in VR, for example, can provide better access to the visualized data representations by directly navigating and manipulating them while exploring the 3D data visualization. The approaches utilizing hand gestures and direct touching visualized data can fundamentally change how we interact with data to improve our understanding. As tangible interaction can effectively enhance human cognitive abilities in interpreting data [26, 27], the natural user interface that incorporates hand gestures and touchable interaction in 3D visualization is a promising solution to address perceptual issues like occlusion.

This paper explores the benefits of mid-air haptics to provide tangible interaction in a 3D data visualization. We achieve this by developing an interactive data visualization tool called TangibleData that employs ultrasound haptic feedback seamlessly coupled with 3D representations of data for tangible interaction. We hypothesize that adding tactile modality is beneficial to analyzing and interpreting datasets, especially for handling occlusion or discerning density and volume information. The main contribution of this study is that we show one promising direction towards an effective way to communicate and understand complex data by utilizing tangible interaction with data. We also introduce the TangibleData tool that handles various 3D data visualizations by adopting hand gestures and mid-air haptics, which we believe is another contribution.

2 RELATED WORK

2.1 Interactive 3D Visualization in VR

Various novel approaches for interactive data visualization in AR/VR have been studied. Bach et al. [4] proposed work on tangible user interfaces using physical markers and compared the results across desktop, tablet, and AR environments. The accuracy of AR and desktop was comparable, and tablets gave the most errors. The Microsoft Kinect sensor has been used to track body and hand positions to allow for mid-air gestural interaction with data. Still, it struggles to capture hand orientation accurately, and the use of mid-air hand gestures without arm support was found to cause user arm fatigue upon continuous usage [44]. Another way for providing intuitive interaction in VR is hand tracking. Hand gesture control has the advantage of requiring no additional devices, being highly intuitive, and being free of higher levels of indirection [28]. Many studies showed that hand gesture-controlled VR interactions are more efficient, immersive, and intuitive than standard mouse and keyboard or tangible interface approaches for applications that involve 3D object manipulation [12, 39] and movement control [29]. Immersive analytics has been thoroughly discussed in surveys[15, 16]. Ens et al. [15] discussed 17 different existing challenges. Some of these challenges are difficult to solve, as they are confronted with inherent limitations of digital immersion, human cognition, or immersive technologies. Wearable gesture control devices have also been presented [6], although they are less common and have been connected to user fatigue [43]. However, hand gestures have the disadvantage of not offering tactile feedback [42].

2.2 Occlusion Management in 3D Visualization

Several techniques have been developed for occlusion management, broadly classified into two categories: space-distorting and space-preserving. In space-distorting, data points are moved from their original positions, typically using a distorting function, to clear the path for highlighting certain data points previously obscured by other data elements. Cowperthwaite et al. [11] suggested using a repulsive lens with an access function to focus one or more locations by manipulating the data points around it. Hurter et al. [21] proposed a lens called MoleView that is similar to the repulsive lens but attribute-driven. It consists of a semantic lens that selects a specific spatial and attribute-related data range. The lens keeps the selected data in focus unchanged and continuously deforms the data out of the selection range to maintain the context around the focus. Such techniques, however, are not recommended for the visualization of quantitative data attributes because they change the location of data points and impair understanding [13].

On the other hand, the space-preserving technique is a method to improve understanding of the data without altering the location of data points by using different perspectives and viewing angles. Besancon et al. [5] suggested a cutting plane method utilizing a tangible tablet to investigate fluid dynamics visualization and found the maximum accuracy in a hybrid mode of supporting tangible and tactile. Jackson et al. [25] suggested a low-cost tabletop arrangement made of paper props that used a depth-sensing camera as a tactile interface for the 3D interactive display of thin fibers. Issartel et al. [23] suggested a tangible slicing tool for AR, comparing three ways (i.e., mouse, tablet, and stylus), with the stylus proving to be the most efficient. Space-preserving approaches primarily consist of cutting plane methods that extract a 2D cross-section of the data, avoiding occlusion [20]. This cross-section can be visualized in a separate view [5, 31]. A separate view diverts attention away from the user; thus, perception towards the data decreases. However, the space-preserving approach for encoding density with visual cues has been identified as inefficient [37] as in the case of large clustered datasets, simply using visual cues or shape outlines for data points does not result in significant improvements in data perception for users.

2.3 Haptics in 3D Visualization

Haptics has been utilized in 2D and 3D visualization to improve users' perception and better understand data. Volume haptization [24] is a collection of methods for mapping force to volume data. In this work, the authors discovered that force input from a pantograph device outperformed the visual feedback with significantly lower error rates than the pure visual scenario. A phantom arm is a visuo-haptic device that provides force feedback to users during the exploration of a volume rendering dataset [3, 14]. Their work demonstrated how data exploration could benefit from adding haptic representations in the visualization workflow. This work not only enhances the augmented visual images but also adds new modes of exploration. Menelas et al. [35] found that vibrotactile feedback, when combined with visual feedback, was favored by users and allowed them to pinpoint an area of interest [36]. Ammi and Katz [1] demonstrated that vibrotactile feedback combined with audio was more efficient than vibrotactile feedback alone for a similar task. Prouzeau et al. [38] investigated how vibrotactile haptic feedback can help find dense and hollow regions in a 3D scatterplot. They employed vibrotactile feedback from the VR controllers to convey density information about the clusters. They discovered that haptics outperforms the pure visual situation in both accuracy and time. However, they lacked an interface and visual cues for the datasets for rotation and scaling. Thus users in the pure visual scenarios had to rely only on stereoscopic vision to interpret the density of clusters.

Mid-air haptics using ultrasound display has been actively investigated in many research fields and applications [10, 17–19, 22, 30, 32, 40, 46, 49, 51]. Mid-air haptics is based on the algorithm that creates a focused pressure point in 3D space using multiple ultrasound speakers. It has a great benefit that it can create tactile sensations on bare hands in mid-air without wearing any devices. Despite its advantages, the efficiency of using mid-air haptics in 3D visualization has not been investigated yet.

3 IMPLEMENTATION

3.1 Design Consideration

The goal of TangibleData is to develop a tool kit that handles various 3D data visualizations by utilizing hand gestures and mid-air haptics for natural data interaction in VR. We consider several design factors for intuitive and seamless user interfaces to enhance user performance and experience.

Multimodal Interaction. The main objective of providing multiple sensory feedback is to improve human cognition for understanding data through multiple sensory channels. Thus, designing hand gestures and tangible interaction with sensory feedback is the key to delivering comprehensive data analysis in a massive dataset. As each modality complements one another for multimodal interaction, visual and haptic feedback should be carefully designed. For example, when exploring and examining clusters in a noise mixture on a 3D scatter plot, combining visual cues and hand gestures with haptic feedback should support users in distinguishing clusters and help them measure the level of clusters' density. In addition, the multiple modalities can assist analyzing 3D volume rendering data. For example, a distinct haptic sensation corresponding to specific rendered objects can help differentiate the objects in a complicated mixture of 3D volumes.

3D Data Interaction. One of the goals in designing TangibleData is to provide a simple and intuitive user interface for both novice and expert users. Because we utilize hand gestures for natural interaction, data exploration should be direct and consistent across all datasets. Still, some constraints should be imposed to avoid any complicated circumstances. For example, a scatter plot with massive dataset may require an interaction technique to interact with the data when the data points become too small to grasp. For another example, a mechanism to switch between different layers in the volume rendering datasets to highlight desired areas should be considered for a smooth transition between layers without interfering with the users' experience.

In sum, the framework needs to support a simple and intuitive user interface for both novice and expert users. The framework should also have a mechanism to map multimodal representations to the datasets. Interaction techniques should be defined with proper constraints for a better user experience.

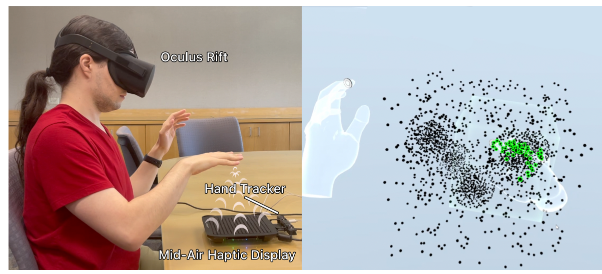


Figure 2: User study setup and a view of the visual scene.

3.2 Hardware Setup

We used the Oculus Rift headset for the VR headset. The headset is connected to the main system (Lenovo Legion 5 with GeForce RTX 2060, Intel i7 1070H, and 16GB RAM) to run the TangibleData application. We also used a mid-air haptics display (Ultraleap STRATOS Explore Development Kit) to provide mid-air haptic sensations on the user's palm and fingers. The mid-air haptic display consists of a 2D array of ultrasound transducers, each of which can produce ultrasound waves at 40 kHz of frequency [10, 47]. These transducers are triggered at slightly different times so that their sound waves coincide at a single focal point. This focal point applies enough pressure to make a small dent in the skin and creates a vibration in mid-air. For hand tracking, we used Ultraleap Stereo IR 170 to track the user's hand movements. The hand tracker has a $170 \times 170^\circ$ field of view using stereo cameras operating at 90 frames per second with an operating wavelength of 850 nm.

3.3 Software Framework

The software framework of TangibleData consists of UI components, data management, and data exploration. We used the Unity3D game engine as our primary software to build the tool. The UI components include hand gestures and a menu system to support the natural manipulation of 3D representations. Data processing converts the dataset into visual and haptic representations.

3.3.1 UI Components. The basic UI components consist of a set of hand gestures and a menu system. We used a leap motion hand tracker to allow the user to perform scaling, rotation, and translation of 3D visualization with the MRTK toolkit (version 2.6). A two-pinch hand gesture was designed to allow users to scale and shrink dataset quickly for scaling. A one-handed pinch gesture is used to translate and rotate objects.

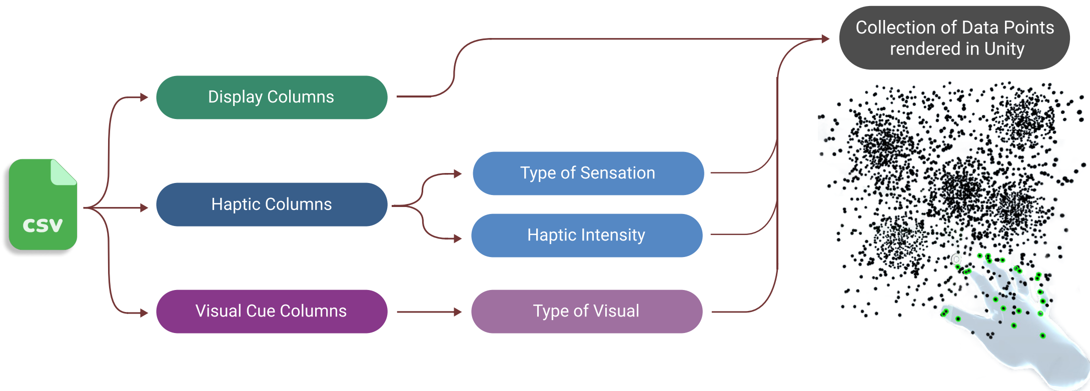


Figure 3: Mapping a 3D dataset with visual and haptic representations. Each data point is mapped to a relevant sensation type.

We designed a menu system that is similar to the TULIP (Three-Up, Labels in Palm) menu [7], which allows users to select the menu items attached to their hand (see Figure 1c). The menu system is activated by flipping their left hand and deactivated by flipping them back, allowing users to access the menu items only if needed and explore the dataset with full hands otherwise. The menu system is also used when switching between different layers in the volume rendering dataset.

3.3.2 Data Mapping for Multisensory Representations. We mapped a 3D dataset with visual and haptic representations (see Figure 3). A CSV file is converted into a 3D scatter plot with visual and haptic cues. Visual and haptic feedback can be applied to a single data point or a group of data points by specifying them in the data columns. For bar charts, haptic feedback can be applied by selecting the data column required to be plotted in the haptics column. For 3D charts, extra columns need to be defined as z-axis columns. We mapped each layer in an interface for better data navigation for the volume-based dataset as they are multilayered datasets. Mapping haptic feedback is described in Section 3.4.

3.3.3 Data Interaction. We designed two data exploration modes: direct touch mode as mentioned in Figure 4(a) and 4(c) and indirect touch mode as mentioned in Figure 4(b) and 4(d). While direct touch mode has the advantage of intuitive and straightforward interaction, indirect touch mode provides a better sense of control for exploring the dataset.

Direct Touch Mode. This mode uses virtual hands to explore the dataset directly. Users can engage with the datasets by using their bare hands to employ mid-air gestures for scaling, rotation, and translation. We keep the same haptic intensity for scaling, no matter whether the user is zooming in or out. However, the contact area for the clusters changes depending on the zoom level, and the user perceive the same intensity of haptic feedback in the contact area. We believe that this is the most natural approach to perceiving haptic feedback. It allows users to feel haptics where they interact with the dataset to improve comprehension and cognition [50].

Indirect Touch Mode. This mode allows users to interact with dataset in a distant position using a haptic plane. The haptic plane

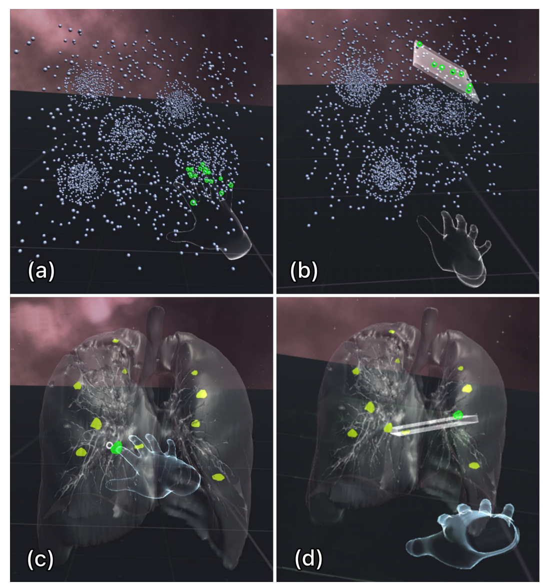


Figure 4: Scatterplots using (a) Direct Touch and (b) Haptic Plane; Human Lungs Volume Dataset using (c) Direct Touch and (d) Haptic Plane.

is a rectangular shape plane aligned with the user's hand on the z-axis and provides haptic feedback based on the intersection of the plane with the dataset. The offset distance between the hand and haptic plane was set to 120 cm, and the size of the plane can be adjusted based on the size of the target visualization and area of interest, yielding more flexibility to explore the dataset. Having an offset distance between the hand and the target provides a better sense of agency, which refers to the feeling of control over actions [2]. Multiple studies showed that modified sensory feedback (visual cues with and without offset) provides a greater sense of agency [2, 33, 48]. This mode can be helpful for certain tasks like searching for a specific target in a large volume rendering dataset.

3.4 Data Encoding with Haptics

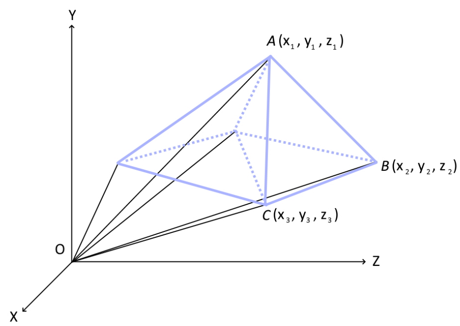


Figure 5: Calculation of 3D Volume.

Data encoding with mid-air haptics is challenging. It requires mapping data points with ultrasound haptic focal points correctly by considering types of dataset and corresponding parameters (e.g., frequency, amplitude, and intensity). Once the point of contact in the user's palm is calculated using a hand tracking device, an ultrasound display is activated to trigger an ultrasound haptic focal point with data encoded according to the corresponding parameters. Here, we describe three data encoding techniques.

Density. In massive clustered datasets, understanding the density of clusters can be challenging, especially when there is a lot of noise near clusters. Due to a lack of depth perception, a lot of manipulation is required to visualize the clusters. The ostensible density of clusters may be misleading due to occlusion. Presenting density data with only visual cues may not be an efficient solution as it will be difficult to provide its amount and spatial information in 3D space. We believe that adding haptic feedback can help give this density information through human tactile channels.

$$KDE(x) = \frac{1}{n * h} \sum_{i=1}^{n} G(\frac{x - x_i}{h}) \tag{1}$$

We created a python script to use this Kernel Density Estimation (KDE) to classify data points into different clusters based on their position (Eq. 1). Then, we converted raw data into normalized 3D coordinate values. These values are then used to identify density by calculating the number of data points on each clustered group. These data points are then mapped as haptic sensation sources with an intensity-dependent on the density calculation. This serves as spatial density information on the user's hand and helps users understand whether a cluster is hollow or dense while exploring the entire volume of the cluster with visual information.

Volume Encoding. In the medical field, many procedures to cure tumors or cancer are dependent on the volume of tissues [8]. Searching and understanding the volume of irregularly shaped tissues through visual inspection in 3D space is not easy. We believe that adding haptics can play a vital role in improving performance.

We referred to the work of Zhang et al. [52] to devise a function to calculate the volume of irregular shapes. We imported the dataset and estimated the volume of the mesh by fitting simple shapes like tetrahedrons (see Figure 5). Then, we add all the values to calculate the entire volume (see Eq. 2 and 3). These volume calculations can then be mapped to different intensity levels of haptic feedback, allowing users to provide a more accurate method of analyzing volumes of multiple irregular shapes in volume rendering datasets.

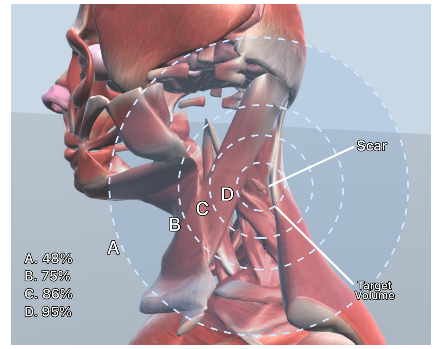


Figure 6: Haptic intensities based on the distance from the scar. Intensity on the scar is 100%.

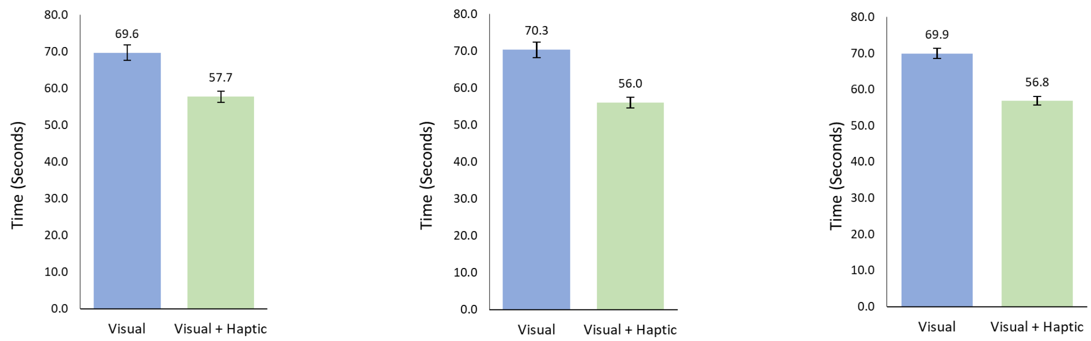
$$\begin{aligned} V_i' = \frac{1}{6}(&-x_{i3}y_{i2}z_{i1} + x_{i2}y_{i3}z_{i1} + x_{i3}y_{i1}z_{i2} \\ &-x_{i1}y_{i3}z_{i2} - x_{i2}y_{i1}z_{i3} + x_{i1}y_{i2}z_{i3}) \end{aligned} \tag{2}$$

$$V_{total}' = \sum_i V_i' \tag{3}$$

Feature Exploration. Many 3D volume rendering datasets consist of multiple layers, and in many cases, it is challenging to provide distinct information regarding those layers. Exploring any hidden elements inside those multiple layers takes considerable time and requires constant shifting between layers. We provided haptic feedback by adapting distance-to-tactile encoding. The distance-to-tactile encoding is a technique that provides distance information through tactile channels and has been widely used for visually impaired people as a guidance cue [45] and as a sensory substitution method [9]. In our approach, the intensity of haptic sensation is mapped to the distance to the target: a stronger haptic sensation implies that the target is closer, and a weaker sensation suggests that the target is farther. This technique can be helpful for a searching task that involves a multi-layered dataset.

4 USER STUDY 1: PERFORMANCE OF MID-AIR HAPTIC FEEDBACK

This user study aims to investigate the effect of mid-air haptic feedback on occlusion problems. Occlusion causes a distorted perception of the depth and density of data points that are clustered together. In many cases, it is challenging to interpret the differences in dense clusters under noisy conditions. Because of the occlusion generated by the noise points, clusters that are not dense can appear dense, depending on the angle from which users observe them. This experiment was designed to validate the effect of mid-air haptic feedback on identifying clusters with the highest density in noisy conditions.



(a) (b) (c)

Figure 7: Completion Time. (a) Low noise conditions, (b) High noise conditions, and (c) Both noise levels.

4.1 Participants

We recruited 16 participants (11 males, 5 females, mean age = 25.06 and SD = 2.4) who had no experience in mid-air haptic displays. None of them reported any known sensory or motor impairment. Participants signed an informed consent form after we explained the goals and procedure of the experiment. Each participant was paid with a $10 gift card after the experiment. All the experiments were approved by the Institutional Review Board (IRB) of the University of Texas at Dallas (IRB-21-194).

4.2 Experimental Design

We used a within-subjects design: two modalities ($MODALITY$) of visual (V) and visual + haptic (VH) × two noise environments $NOISE$ of low and high × eight repetitions, yielding 32 trials per participant. Thus, there would be four conditions: V_{Low} (visual feedback in low noise environment), VH_{Low} (visual and haptic feedback in low noise environment), V_{High} (visual feedback in high noise environment), and VH_{High} (visual and haptic feedback in high noise environment). The order of conditions was randomized, and a Latin square was used to counterbalance the order.

The task was to find a cluster with the highest density among the five clusters as fast and accurately as possible. We created a scatter plot with a size of 26 cm (L) × 26 cm (W) × 26 cm (H). A total of 1,250 noise data points were randomly distributed in high noise conditions, and a total of 625 noise data points were randomly distributed in low noise conditions, respectively. Each noise data point was a sphere with a radius of 0.25 cm. To highlight the cluster region and induce an occlusion effect, a boundary of noise points was drawn around the clusters. To create the boundary of clusters, we used five spherical regions with a diameter of around 7 cm, having 150 to 176 noise spots around the circumference of the spherical region. A 5 cm diameter zone within each spherical region was added with extra points to create the embedded clusters. The density of clusters was controlled by varying the number of points ranged from 162 to 349 data points among five clusters. This distribution was randomized among the target cluster (i.e., highest density cluster) and the other clusters.

Visual feedback was added to the data points to inform the users what was being touched. A green outline was highlighted around the data points when the data was being touched (see Figure 4(a)). These visual cues were consistently provided for all conditions. Haptic feedback was provided in VH_{Low} and VH_{High}. We created a circular-ripple sensation of tactile stimulus with a radius of 0.8 cm with a frequency of 70 Hz for noise data and a circular sensation of tactile stimulus with a radius of 1 cm with a frequency of 60 Hz for cluster data. The haptic feedback was mapped per data point. The density of clusters was mapped with different levels of haptic feedback signal intensity: 100%, 86%, 75%, 60%, and 48%. The levels of intensity among the five clusters were decided based on Rutten et al. [41]. The intensity of haptic signals for noise data was set to 60%. We measured task completion time and task execution error as quantitative performance measures and subjective measures.

4.3 Procedure

Before starting the main experiment, participants completed a demographic questionnaire and a training session. During the training session, participants were asked to perform a given task in each condition. The main experiment started with an experimenter explaining the task to find the cluster with the highest density among the five clusters presented in the 3D space. In each trial, five randomly distributed clusters appeared in the scene in random order. Each cluster was labeled as C1 through C5, and the label only appeared when its cluster was being touched by the user's hand. Participants were allowed to touch any clusters multiple times in each trial. After exploring all the clusters, they were asked to select one of five choices (i.e., C1 to C5) in the menu. Participants were asked to take a break at any time to avoid arm fatigue. After completing all trials, questionnaire sheets were provided to measure the participant's 3D data exploration experience in two areas: *Density* – It helped understand the densities of the clusters; *Occlusion* – It was helpful in overcoming the problem of occlusion. Participants were asked to respond to each question by marking a check on a horizontal line (visual analog scale) with a label on each end: 'Strongly Disagree' and 'Strongly Agree.' The participants were also debriefed regarding their experiences with TangibleData. The study lasted about an hour for each participant.

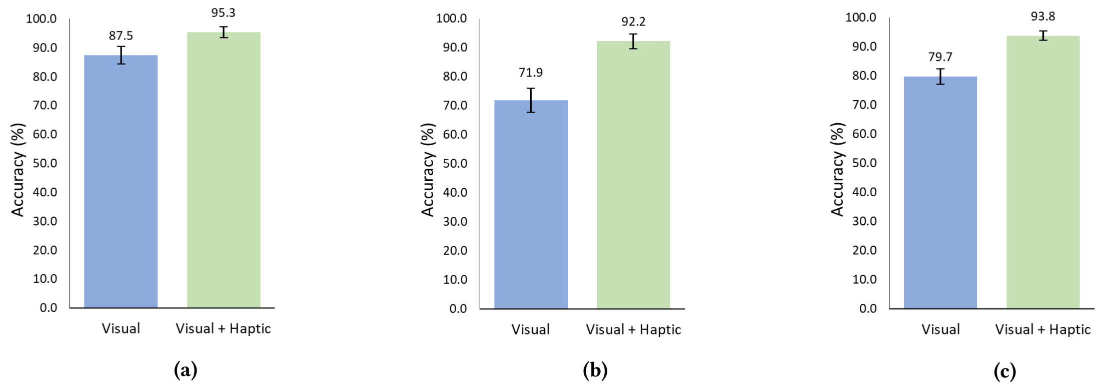


Figure 8: Accuracy. (a) Low noise conditions, (b) High noise conditions, and (c) Both noise levels.

4.4 Results and Discussion

A two-way ANOVA with repeated measures was conducted for analyzing quantitative measures. The mean task completion time T is shown in Figure 7. On average, VH was 13.1 seconds faster than V. $MODALITY$ had a statistically significant effect on T ($p < 0.001$), but $NOISE$ did not ($p = 0.792$). The interaction between $MODALITY$ and $NOISE$ was also not significant ($p = 0.507$). It clearly shows that VH significantly outperformed regardless of noise levels.

Figure 8 shows the mean task accuracy A in the experiment. Overall, VH shows higher accuracy over V by 14.1%. We found that both $MODALITY$ ($p < 0.001$) and $NOISE$ ($p < 0.01$) were statistically significant on A. The interaction between $MODALITY$ and $NOISE$ was significant ($p < 0.05$). A post hoc Tukey test revealed that there was a significant difference between V_{High} and VH_{High} ($p < 0.001$), but no significant difference between V_{Low} and VH_{Low} ($p = 0.228$). This suggests that mid-air haptic feedback can play a vital role in high noise conditions. We also noticed that there was no significant difference between VH_{Low} and VH_{High}, suggesting that haptic feedback is beneficial regardless of noise conditions.

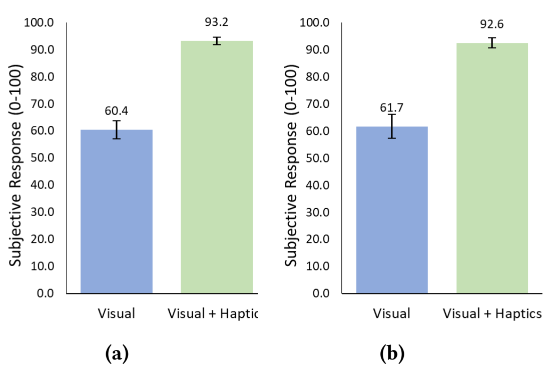


Figure 9: The VAS ratings. (a) Density and (b) Occlusion.

Figure 9 shows the mean scores of *Density* and *Occlusion*. A one-way ANOVA revealed that $MODALITY$ had a significant effect on both *Density* (p<0.001) and *Occlusion* (p<0.001). We confirmed that combining visual feedback with mid-air haptic cues helps understand the density of clusters and overcome occlusion. The results clearly show that combining visual feedback with mid-air haptic cues outperforms visual-only conditions, and the benefits are more evident for accuracy measures.

During the experiment, we asked participants about their strategies for completing the experiment. In V condition, they used combinations for rotation and zooming for different perspectives to narrow down their search. However, in VH condition, they primarily focused on the two clusters that appeared the densest and then used the haptic feedback to select the correct one. Almost all participants used this strategy for their search, showing the clear benefit of using haptics.

5 USER STUDY 2: EFFECT OF SPATIAL POSITION OFFSET

This second user study aims to identify the strengths and weaknesses of direct and indirect touch modes by comparing one mode to another. The indirect touch mode provides haptic interaction with spatial position offset by allowing users to interact with visualization in a distant position using a haptic plane.

5.1 Participants

We recruited another 16 participants (12 males, 4 females, mean age = 26.0 and SD = 2.39) who did not participate in the first experiment. None of them reported any known sensory or motor impairment. Each participant was paid with a $10 gift card after the experiment.

5.2 Experimental Design

In this experiment, we designed two tasks: $TaskLungs$ and $TaskScar$. $TaskLungs$ was a task to search for the biggest cancer tissue in the human lungs dataset. There were 11 cancer tissues in the task, with volumes ranging from 156.8 to 433.9 cubic units. The dataset is a 3D model of a CT scan of the lungs, and the distribution of tissue volumes was randomized between the target (highest volume) and the other tissues. $TaskScar$ was designed to search for a scar in a human head dataset consisting of three layers (skin, skeleton, and muscle). In each trial, only one layer was presented. The dataset was 46 cm × 72 cm × 51 cm in size, and the scar had a radius of 3 cm. In both tasks, participants were asked to explore the volume dataset freely.

The same within-subjects design for *TaskLungs* and *TaskScar* was used, which consisted of two touch modes (*MODE*): Direct Touch (*DT*) and Haptic Plane (*HP*). With eight repetitions, each participant performed 16 trials for each task. The order of trials was randomized, and a Latin Square was used to balance the order. All participants performed the *TaskLungs* first, followed by the *TaskScar*. For a fair comparison between the two modes, a dataset of the same size was used, and no rotation, translation, and scaling of the dataset was allowed.

In *TaskLungs*, we added a green outline to highlight the tissues whenever the user's hands collided with the tissues. These visual cues were consistent for both modes (see Figure 4(b) and Figure 4(c)). We used a circular sensation with a radius of 5 cm with a frequency of 60 Hz for haptic feedback. The levels of intensity among the 11 tissues were decided based on Rutten et al. [41]. All these values of draw frequency, direction, and radius for the sensations were selected from our pilot study results. Haptics was kept consistent for both modes.

In *TaskScar*, different areas in hand were highlighted with green color to provide visual cues of contacted area (see Figure 4(d)). The distance-to-tactile encoding method was used to provide haptic feedback. This method changes the haptic feedback intensity based on the distance to the target (i.e., scar). We used a ray cast from the center of the interaction point to the center of the scar. This distance was used to create different haptic areas ranging in intensity from 48% to 100% as shown in Figure 6 to provide feedback that varies based on the distance from the scar. Haptic feedback was provided whenever there was contact with the volume dataset (a circular sensation with a radius of 3 cm with a frequency of 60 Hz).

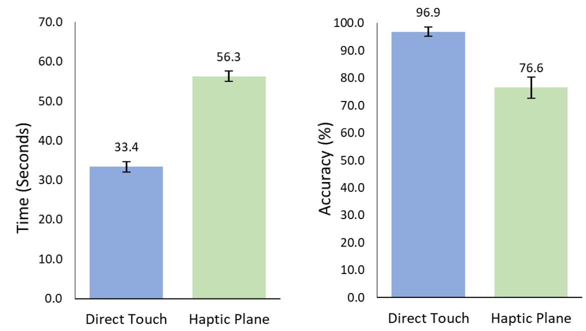
5.3 Procedure

Similar to the first experiment, participants had a training session to learn how to access the menu and perform two tasks (*TaskLungs* and *TaskScar*) using two modes: *DT* and *HP*.

TaskLungs. For each trial in this task, 11 randomly distributed tissues appeared in a human lungs dataset. Each tissue was labeled as T1 through T11, and a label appeared when the tissue was touched, indicating the most recently touched tissue. In each trial, participants were allowed to touch any tissue multiple times. When the label indicated the name of the tissue they want to select, they were instructed to press the exit button, and the name on the label was used to determine the task's correctness.

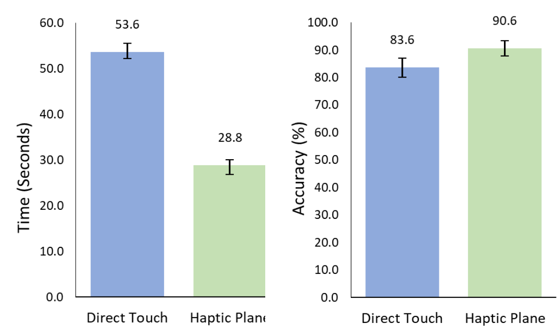
TaskScar. In each trial, a human head dataset with a random layer (skin, muscle, bone) appeared in the scene with a scar at a random position on the surface of the layer. Participants searched the dataset for the location that provided the highest intensity haptic feedback. As the volume of the scar compared to the dataset was only .06%, which was very small and pinpointing such a small volume is difficult, so we defined a target volume that equals 5% of the dataset volume as shown in the Figure 6, which was used to determine the correctness of the task. When participants found the scar, they held the exploration *TOOL* in place while flipping their other hand, creating its clone fixed in that position. The original hand was then used to exit the task, and the clone's position was recorded for result analysis.

For each trial, the answer and duration were recorded for data analysis. After completing all trials, questionnaire sheets were provided to measure the participant's responses to their 3D data exploration experience in the two modes. Participants were encouraged to take breaks at any time to reduce arm fatigue. The study lasted about an hour for each participant.



(a) (b)

Figure 10: Results for the Lung Task. (a) Time taken to identify the largest tissue and (b) Accuracy in correctly identifying the largest tissue.



(a) (b)

Figure 11: Results for the Scar Task. (a) Time taken to identify the scar location and (b) Accuracy in correctly identifying the scar location.

5.4 Results and Discussion

All statistical analyses reported below were done using one-way ANOVA with repeated measures.

TaskLungs. The mean task completion time T and accuracy A are shown in Figure 10. On average, *DT* was 22.9 seconds faster than *HP* ($p < .001$). *DT* also showed higher accuracy than *HP* by 20.3% ($p < .001$). The results clearly showed that *DT* was faster and more accurate than *HP*.

TaskScar. Figure 11 shows the mean task completion time T and accuracy A. We found that HP was faster than DT by 24.7 seconds. We found that $MODE$ was statistically significant on T ($p < .001$). We also found that HP was more accurate than DT by 7% on average, but the result was not significant ($p = 0.939$). To summarize, HP was faster than DT in identifying the location of interest, but both modes performed similarly in obtaining an accurate location.

Results clearly demonstrate that in tasks based on exploration of a single significant characteristic, HP has an advantage over DT but when analyzing numerous small areas, DT is more accurate and efficient compared to HP

During the experiment, participants were asked which touch mode they preferred and whether they felt a difference in haptic sensation between the two touch modes. All participants indicated that in *TaskLungs* they preferred the direct touch mode, with some of them citing that it was more precise. For *TaskScar*, a majority of participants indicated that they preferred the haptic plane as it was able to scan a larger area in less time. Around half of the participants felt a difference in haptic sensation between the two touch modes. They mentioned that direct touch provided them with a stronger tactile sensation than they received from the haptic plane. This is an interesting finding as the intensity of haptics was consistent across two modes.

6 GENERAL DISCUSSION

We presented TangibleData that allows haptic interaction with 3D data visualization. We showed that utilizing mid-air haptic feedback can help increase the efficiency of data exploration and provide additional information through tactile channels. We introduced how we encoded density information into clusters and provided it through tactile channels as an efficient solution for delivering spatial information. We also applied the distance-to-tactile encoding technique to 3D data visualization for an efficient searching task in a multi-layered dataset. We finally explored the effect of spatial position offset in indirect touch mode by comparing it with direct touch mode.

After examining participants' comments on TangibleData, we discovered room for integrating more gestures to control the data visualization interface. We believe that improving hand gestures and interaction techniques can improve the efficiency of data visualization. While participants enjoyed TangibleData with mid-air haptic feedback, some suggested several interaction techniques. P2 recommended a pointing interaction technique that would allow users to see additional information on target data points. P7 suggested a selection technique that enables users to select a section of data points to highlight or apply filters on. We are interested in improving TangibleData by designing and implementing more gestures and interaction techniques. We will consider various user assessments to provide multimodal feedback for more natural and intuitive interaction with 3D visualization.

In this study, we have implemented three types of haptic encoding: Density Encoding, Volume Encoding, and Feature Exploration. Density Encoding is able to approximate destiny at any given location by identifying the amount of nearby data points. This worked for our implementation, but it is missing some features such as supporting weighted values and factoring in the distance of the points from the location density is calculated for. Volume Encoding is able to efficiently determine the volume of 3D meshes for haptic and visual feedback, but it ignores other potential features of interest for irregular shapes such as surface area. Feature exploration allows for tactile navigation through its distance-to-tactile encoding, but it is currently limited to using absolute distance, which may not be as helpful in guiding users around empty spaces within objects. Our implementations of haptic encoding could be improved by allowing for a greater amount of customization as each implementation is currently limited to performing a single type of computation. In its current state, however, we believe that our haptic encoding can aid in the visualizations of datasets beyond those used in our experiments. Haptics can be employed in 3D bar charts to show the highs and lows of the graph by using varied haptic intensity, as well as on the peaks of 3D contour graphs to better understand the surface.

Our findings are promising for further research into interactive ways of exploring 3D datasets. In the future, a haptic mapping workflow for volume rendering datasets would be a significant step forward in the field of scientific visualization. By producing texture-based haptic sensations, mid-air haptics can be used to offer information about the surface of distinct layers in medical datasets. We hope to include multiple ultrasound haptic displays to provide a larger interaction zone for mid-air haptics interaction with data visualization. This will also aid in boosting the overall intensity of mid-air haptics, resulting in a more immersive experience. An enhanced hardware setup that can adjust the orientation of the haptic display based on hand orientation could be created to ensure a consistent haptic experience without worrying about the orientation of their hands. Other important functions like selecting scatter plots and slicing for volume are also planned in our future work. Finally, we plan to study how haptics can play a role in improving perception using real-time data.

7 CONCLUSION

In this paper, we presented TangibleData, an interactive, tangible 3D data visualization system for VR. The system enabled users to have touchable interaction through hand gestures with mid-air haptics. We demonstrated the system using two user studies: the performance of mid-air haptic feedback and the effect of spatial position offset. The results of the first user study showed that combining visual with haptic feedback outperformed visual feedback alone while examining clusters of data points in a 3D scatter plot. The results demonstrated that visual feedback with a mid-air haptic improved the user's performance by mitigating the occlusion issue. We also compared direct and indirect touch modes to identify their strengths and weaknesses. Our results showed that the direct touch mode is better in comparing multiple small features. In contrast, the indirect mode performed better in identifying a single feature in a large volume dataset.

ACKNOWLEDGMENTS

We would like to thank Nicolas Chevrie and Henry Kim for their efforts in creating VR scenes.

REFERENCES

[1] Mehdi Ammi and Brian FG Katz. 2014. Intermodal audio-haptic metaphor: improvement of target search in abstract environments. *International journal of*

human-computer interaction 30, 11 (2014), 921–933.
[2] Kei Aoyagi, Wen Wen, Qi An, Shunsuke Hamasaki, Hiroshi Yamakawa, Yusuke Tamura, Atsushi Yamashita, and Hajime Asama. 2021. Modified sensory feedback enhances the sense of agency during continuous body movements in virtual reality. *Scientific reports* 11, 1 (2021), 1–10.
[3] Ricardo S Avila and Lisa M Sobierajski. 1996. A haptic interaction method for volume visualization. In *Proceedings of Seventh Annual IEEE Visualization'96*. IEEE, 197–204.
[4] Benjamin Bach, Ronell Sicat, Johanna Beyer, Maxime Cordeil, and Hanspeter Pfister. 2017. 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 (2017), 457–467.
[5] Lonni Besançon, Paul Issartel, Mehdi Ammi, and Tobias Isenberg. 2016. Hybrid tactile/tangible interaction for 3D data exploration. *IEEE transactions on visualization and computer graphics* 23, 1 (2016), 881–890.
[6] Alberto Betella, Enrique Martínez Bueno, Wipawee Kongsantad, Riccardo Zucca, Xerxes D Arsiwalla, Pedro Omedas, and Paul FMJ Verschure. 2014. Understanding large network datasets through embodied interaction in virtual reality. In *Proceedings of the 2014 Virtual Reality International Conference*. 1–7.
[7] Doug A Bowman and Chadwick A Wingrave. 2001. Design and evaluation of menu systems for immersive virtual environments. In *Proceedings IEEE Virtual Reality 2001*. IEEE, 149–156.
[8] David J Brenner. 1993. Dose, volume, and tumor-control predictions in radiotherapy. *International Journal of Radiation Oncology* Biology* Physics* 26, 1 (1993), 171–179.
[9] Leandro Cancar, Alex Díaz, Antonio Barrientos, David Travieso, and David M Jacobs. 2013. Tactile-sight: A sensory substitution device based on distance-related vibrotactile flow. *International Journal of Advanced Robotic Systems* 10, 6 (2013), 272.
[10] Tom Carter, Sue Ann Seah, Benjamin Long, Bruce Drinkwater, and Sriram Subramanian. 2013. UltraHaptics: multi-point mid-air haptic feedback for touch surfaces. In *Proceedings of the 26th annual ACM symposium on User interface software and technology*. 505–514.
[11] David J Cowperthwaite, M Sheelagh T Carpendale, and F David Fracchia. 1996. Visual access for 3D data. In *Conference Companion on Human Factors in Computing Systems*. 175–176.
[12] Sanmathi Dangeti, Yingjie Victor Chen, and Chunhui Zheng. 2016. Comparing bare-hand-in-air Gesture and Object-in-hand Tangible User Interaction for Navigation of 3D Objects in Modeling. In *Proceedings of the TEI'16: Tenth International Conference on Tangible, Embedded, and Embodied Interaction*. 417–421.
[13] Niklas Elmqvist and Philippas Tsigas. 2008. A taxonomy of 3d occlusion management for visualization. *IEEE transactions on visualization and computer graphics* 14, 5 (2008), 1095–1109.
[14] Rickard Englund, Karljohan Lundin Palmerius, Ingrid Hotz, and Anders Ynnerman. 2018. Touching data: Enhancing visual exploration of flow data with haptics. *Computing in Science & Engineering* 20, 3 (2018), 89–100.
[15] Barrett Ens, Benjamin Bach, Maxime Cordeil, Ulrich Engelke, Marcos Serrano, Wesley Willett, Arnaud Prouzeau, Christoph Anthes, Wolfgang Büschel, Cody Dunne, et al. 2021. Grand challenges in immersive analytics. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–17.
[16] Adrien Fonnet and Yannick Prie. 2019. Survey of immersive analytics. *IEEE transactions on visualization and computer graphics* (2019).
[17] LR Gavrilov and EM Tsirulnikov. 2012. Focused ultrasound as a tool to input sensory information to humans. *Acoustical Physics* 58, 1 (2012), 1–21.
[18] Hyunjae Gil, Hyungki Son, Jin Ryong Kim, and Ian Oakley. 2018. Whiskers: Exploring the use of ultrasonic haptic cues on the face. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–13.
[19] Keisuke Hasegawa and Hiroyuki Shinoda. 2013. A method for distribution control of aerial ultrasound radiation pressure for remote vibrotactile display. In *The SICE Annual Conference 2013*. IEEE, 223–228.
[20] Ken Hinckley, Randy Pausch, John C Goble, and Neal F Kassell. 1994. Passive real-world interface props for neurosurgical visualization. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 452–458.
[21] Christophe Hurter, Alexandru Telea, and Ozan Ersoy. 2011. Moleview: An attribute and structure-based semantic lens for large element-based plots. *IEEE Transactions on Visualization and Computer Graphics* 17, 12 (2011), 2600–2609.
[22] Inwook Hwang, Hyungki Son, and Jin Ryong Kim. 2017. AirPiano: Enhancing music playing experience in virtual reality with mid-air haptic feedback. In *2017 IEEE World Haptics Conference (WHC)*. IEEE, 213–218.
[23] Paul Issartel, Florimond Guéniat, and Mehdi Ammi. 2014. Slicing techniques for handheld augmented reality. In *2014 IEEE symposium on 3D user interfaces (3DUI)*. IEEE, 39–42.
[24] Hiroo Iwata and Haruo Noma. 1993. Volume haptization. In *Proceedings of 1993 IEEE Research Properties in Virtual Reality Symposium*. IEEE, 16–23.
[25] Bret Jackson, Tung Yuen Lau, David Schroeder, Kimani C Toussaint, and Daniel F Keefe. 2013. A lightweight tangible 3D interface for interactive visualization of thin fiber structures. *IEEE transactions on visualization and computer graphics* 19, 12 (2013), 2802–2809.
[26] Yvonne Jansen, Pierre Dragicevic, and Jean-Daniel Fekete. 2013. Evaluating the efficiency of physical visualizations. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 2593–2602.
[27] Yvonne Jansen, Pierre Dragicevic, Petra Isenberg, Jason Alexander, Abhijit Karnik, Johan Kildal, Sriram Subramanian, and Kasper Hornbæk. 2015. Opportunities and challenges for data physicalization. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. 3227–3236.
[28] Frederic Kaplan. 2009. Are gesture-based interfaces the future of human computer interaction?. In *Proceedings of the 2009 international conference on Multimodal interfaces*. 239–240.
[29] Chaowanan Khundam. 2015. First person movement control with palm normal and hand gesture interaction in virtual reality. In *2015 12th International Joint Conference on Computer Science and Software Engineering (JCSSE)*. IEEE, 325–330.
[30] Jin Ryong Kim, Stephanie Chan, Xiangchao Huang, Kenneth Ng, Limin Paul Fu, and Chen Zhao. 2019. Demonstration of refinity: an interactive holographic signage for new retail shopping experience. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–4.
[31] Tijmen Klein, Florimond Guéniat, Luc Pastur, Frédéric Vernier, and Tobias Isenberg. 2012. A design study of direct-touch interaction for exploratory 3D scientific visualization. In *Computer Graphics Forum*, Vol. 31. Wiley Online Library, 1225–1234.
[32] Benjamin Long, Sue Ann Seah, Tom Carter, and Sriram Subramanian. 2014. Rendering volumetric haptic shapes in mid-air using ultrasound. *ACM Transactions on Graphics (TOG)* 33, 6 (2014), 1–10.
[33] Christos Lougiakis, Akrivi Katifori, Maria Roussou, and Ioannis-Panagiotis Ioannidis. 2020. Effects of virtual hand representation on interaction and embodiment in HMD-based virtual environments using controllers. In *2020 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*. IEEE, 510–518.
[34] Michael J McGuffin, Liviu Tancau, and Ravin Balakrishnan. 2003. Using deformations for browsing volumetric data. In *IEEE Visualization, 2003. VIS 2003.* IEEE, 401–408.
[35] Bob Menelas, Mehdi Ammi, Luc Pastur, and Patrick Bourdot. 2009. Haptical exploration of an unsteady flow. In *World Haptics 2009-Third Joint EuroHaptics conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems*. IEEE, 232–237.
[36] Bob-Antoine J Menelas. 2014. Virtual Reality Technologies (Visual, Haptics, and Audio) in Large Datasets Analysis. In *Innovative Approaches of Data Visualization and Visual Analytics*. IGI Global, 111–132.
[37] Harald Piringer, Robert Kosara, and Helwig Hauser. 2004. Interactive focus+context visualization with linked 2d/3d scatterplots. In *Proceedings. Second International Conference on Coordinated and Multiple Views in Exploratory Visualization, 2004.* IEEE, 49–60.
[38] 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*. 1–12.
[39] Stefan Reifinger, Florian Laquai, and Gerhard Rigoll. 2008. Translation and rotation of virtual objects in Augmented Reality: A comparison of interaction devices. In *2008 IEEE International Conference on Systems, Man and Cybernetics*. IEEE, 2448–2453.
[40] Ted Romanus, Sam Frish, Mykola Maksymenko, William Frier, Loïc Corenthy, and Orestis Georgiou. 2019. Mid-air haptic bio-holograms in mixed reality. In *2019 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct)*. IEEE, 348–352.
[41] Isa Rutten, William Frier, and David Geerts. 2020. Discriminating Between Intensities and Velocities of Mid-Air Haptic Patterns. In *International Conference on Human Haptic Sensing and Touch Enabled Computer Applications*. Springer, 78–86.
[42] Kittasil Silanon and Nikom Suvonvorn. 2011. Real time hand tracking as a user input device. In *Knowledge, information, and creativity support systems*. Springer, 178–189.
[43] Jaemin Soh, Yeongjae Choi, Youngmin Park, and Hyun S Yang. 2013. User-friendly 3D object manipulation gesture using Kinect. In *Proceedings of the 12th ACM SIGGRAPH International Conference on Virtual-Reality Continuum and Its Applications in Industry*. 231–234.
[44] Peng Song, Wooi Boon Goh, William Hutama, Chi-Wing Fu, and Xiaopei Liu. 2012. A handle bar metaphor for virtual object manipulation with mid-air interaction. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 1297–1306.
[45] Markus Straub, Andreas Riener, and Alois Ferscha. 2009. Distance encoding in vibro-tactile guidance cues. In *2009 6th Annual International Mobile and Ubiquitous Systems: Networking & Services, MobiQuitous*. IEEE, 1–2.
[46] Tomomi Takashina, Mitsuru Ito, and Yuji Kokumai. 2019. Midair Haptic Representation for Internal Structure in Volumetric Data Visualization. In *SIGGRAPH Asia 2019 Posters*. 1–2.
[47] UltraLeap. [n.d.]. *How does Ultrahaptics technology work.* https://developer.ultrahaptics.com/knowledgebase/haptics-overview/

[48] Paul Winkler, Philipp Stiens, Nadine Rauh, Thomas Franke, and Josef Krems. 2020. How latency, action modality and display modality influence the sense of agency: a virtual reality study. *Virtual Reality* 24, 3 (2020), 411–422.
[49] Tae-Heon Yang, Jin Ryong Kim, Hanbit Jin, Hyunjae Gil, Jeong-Hoi Koo, and Hye Jin Kim. 2021. Recent Advances and Opportunities of Active Materials for Haptic Technologies in Virtual and Augmented Reality. *Advanced Functional Materials* (2021), 2008831.
[50] Nesra Yannier, Ali Israr, Jill Fain Lehman, and Roberta L Klatzky. 2015. FeelSleeve: Haptic feedback to enhance early reading. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. 1015–1024.
[51] Kazuma Yoshino and Hiroyuki Shinoda. 2014. Contactless touch interface supporting blind touch interaction by aerial tactile stimulation. In *2014 IEEE Haptics Symposium (HAPTICS)*. IEEE, 347–350.
[52] Cha Zhang and Tsuhan Chen. 2001. Efficient feature extraction for 2D/3D objects in mesh representation. In *Proceedings 2001 International Conference on Image Processing (Cat. No. 01CH37205)*, Vol. 3. IEEE, 935–938.