Scaptics and Highlight-Planes: Immersive Interaction Techniques for Finding Occluded Features in 3D Scatterplots

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ABSTRACT

Three-dimensional scatterplots suffer from well-known perception and usability problems. In particular, overplotting and occlusion, mainly due to density and noise, prevent users from properly perceiving the data. Thanks to accurate head and hand tracking, immersive Virtual Reality (VR) setups provide new ways to interact and navigate with 3D scatterplots. VR also supports additional sensory modalities such as haptic feedback. Inspired by methods commonly used in Scientific Visualisation to visually explore volumes, we propose two techniques that leverage the immersive aspects of VR: first, a density-based haptic vibration technique (*Scaptics*) which provides feedback through the controller; and second, an adaptation of a cutting plane for 3D scatterplots (*Highlight-Plane*). We evaluated both techniques in a controlled study with two tasks involving density (finding high- and low-density areas). Overall, Scaptics was the most time-efficient and accurate technique, however, in some conditions, it was outperformed by Highlight-Plane.

CCS CONCEPTS

• **Human-centered computing → Virtual reality**; **Interaction design**; **Empirical studies in visualization**;

KEYWORDS

3D Scatterplot, Vibrotactile feedback, Virtual Reality, Haptic

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1 INTRODUCTION

This paper is concerned with techniques for the visualisation of quantitative attributes associated with discrete data points, i.e. *scatterplots*. For data points with two quantitative attributes, scatterplots offer a direct mapping from the attribute to 2D position in a plane orthogonal to the viewer (typically a screen or page). Such axis-aligned spatial position is well accepted as the most effective channel for visual representation of continuous quantities [40]. With the rising popularity of immersive virtual reality (VR) and augmented reality (AR) headsets, it is tempting to exploit three spatial dimensions for representation of data points with three quantitative attributes. The creation of such 3D scatterplots is supported by a number of very widely available tools, both free (e.g. *R*, *PlotLy*, *ggplot*) and commercial (e.g. *Spotfire*, *Mathematica*, *SPSS*, *MatLab*, etc.). These occur widely in data science to visualise quantitative attributes, projections of higher-dimensional space [36], or spatial data [46].

However, position in the depth axis relative to eye position is a much less effective channel for representation of quantitative data attributes and issues like occlusion and perspective distortion have also been shown to limit the effectiveness of 3D scatterplots [47]. Head-tracked navigation and stereopsis may improve things, in particular for sparse data where occlusion can be resolved through small head-movements. Yet, seeing features inside dense 3D point clouds remains a challenge.

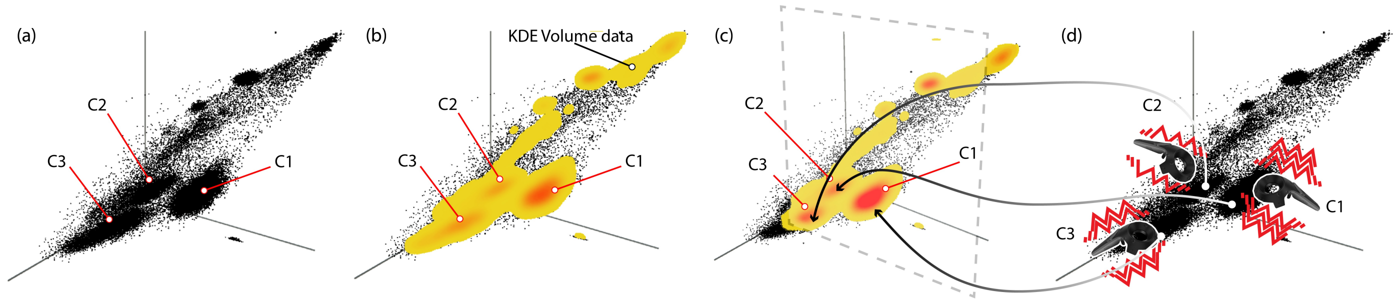


Figure 1: Scaptics pipeline: (a) 3D scatterplot with several dense clusters (C1,C2 and C3 are the largest ones). (b) overlay of the volume data produced by our 3D Kernel Density Estimation technique (KDE volume is not visualised in the actual technique). (c) sliced view of the KDE volume showing that C1 is more dense than C2 and C3. (d) controller vibration (red lines) according to the value of intensity read into the 3D volume (arrows) - i.e. the controller vibrates more intensely in C1.

In 3D volume visualisation (especially in medical imaging) there have been a number of interactive techniques to help viewers uncover occluded features. Loosely, these can be categorised as space-distorting techniques, which transform space to reduce occlusions, or data-removal techniques, which remove part of the data to give a clearer view. A past survey [18] warns against using spatial distortion for scatterplot data, where the close correspondence of spatial position to underlying data attributes is paramount. Our pilot studies indicated that straightforward adoption of a cutting-plane, a commonly used data-removal technique, is inappropriate for scatterplot data. Therefore, our first contribution is a redesigned cutting-plane technique called *Highlight Plane*.

Our second contribution explores supporting user understanding of occluded local scatterplot density using the vibrotactile feedback function now commonly available in VR controllers. Again, we found that past solutions, which employ a simple mapping of density to vibration at each point in the volume, do not adapt well to scatterplot data. Instead, we employ Kernel Density Esimation (KDE) to create an inferred density field that provides information about proximity to discrete points. We call this technique *Scaptics*.

Since this is the first work to employ consumer-level VR controllers for vibrotactile data representation, we also perform a Just-Noticable-Difference (JND) study of users' sensitivity to vibration intensity. The resulting six-level intensity scale, is our third contribution.

We offer these techniques as an exploration of the use of VR affordances to inspect density features in 3D scatterplots, and do not claim either technique to be optimal. Nonetheless, our final and main contribution is an assessment of these preliminary implementations. In comparison to a baseline visualisation, we find that both interactive techniques, Scaptics and Highlight-Plane, improve user performance on most tested tasks. However, Scaptics affords better performance for the assessment of the density of clusters, while Highlight Plane is, in some cases, better for identifying void regions. These encouraging results indicate that both techniques deserve further exploration to improve the use of VR for scatterplot exploration.

2 RELATED WORK

Scatterplots are an efficient way to display a small amount of data. However, display limitations can produce cluttered visualisations [31], leading to well-known perception issues such as occlusion and overplotting. To manage overplotting, Piringer et al. [44] proposed visual cues (e.g. halo, size, color), interactive linked visualisations, and 3D histograms on the 2D faces of a 3D scatterplot. However, the efficiency of such methods is not evaluated. Poco et al. [45] used density information to automatically detect clusters. To bring out interesting patterns, Bachthaler and Weiskopf [8] used density to transform discrete scatterplots into continuous volumes. Yu et al. [58, 59] used density information to improve selection in point-clouds. However, in each of these, the density information itself is not transmitted to the user. In this paper, instead of using this information to achieve a higher-level goal, we make it available for user exploration.

Previous research in 3D dense- and cluttered-graph visualisation has demonstrated the benefits of immersion [1, 53]. Raja et al. showed that immersion improves users' performance in visualisation tasks (finding outliers, determining trends and finding clusters). More recent studies have shown benefits of immersive platforms for navigation [22] and interaction [7] for data analysis. Overall, immersive environments show promise for visualisation of 3D scatterplots, but occlusion and overplotting are still problematic when dealing with large datasets. In this paper, we propose techniques to overcome both problems in VR.

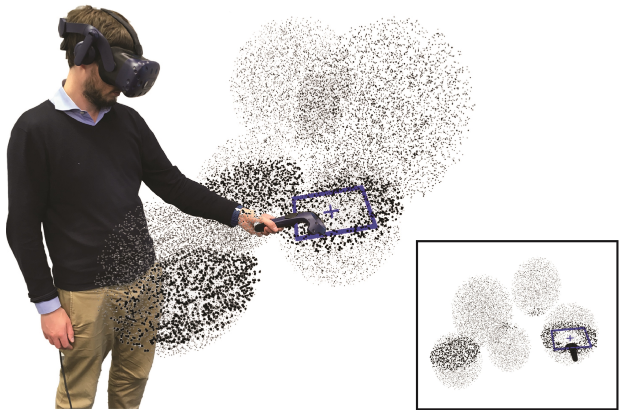


Figure 2: The Highlight Plane technique preserves the overall visualisation by increasing the size of data points that intersect the plane attached to the controller (blue). The user has found a void in the 3D point cloud at the center of the cutting plane. Inset shows a first person view.

Interactions to overcome occlusion and overplotting

Elmqvist [18] identifies *target invariance criteria*, properties of visualisations which occlusion management techniques should avoid perturbing. Key among these for scatterplots is the location of points. Occlusion management techniques which do not disrupt the location of points are *space preserving*, as opposed to *space distorting*.

Space-distorting techniques. To overcome occlusion, Cowperthwaite et al. proposed the use of a repulsive lens [17]. Hurter et al. [27] proposed a similar but attribute-driven lens. However, such techniques are not recommended for visualisation of quantitative data attributes, as they alter the location of data points and impair understanding [18].

Space-preserving techniques. One space-preserving approach for encoding density is the use of visual cues, however these have been identified as inefficient [44]. Another approach is the use of a *cutting plane* [25], which avoids occlusion by extracting a 2D cross-section of the data. This cross-section can be either visualized in a separate view [13, 16, 32]—which can lead to divided attention between the different displays—or directly within the 3D visualisation [28, 30, 37]. Such a technique has previously been applied in AR, to compare the suitability of different platforms [6, 7].

A new opportunity for datavis: haptic feedback

Another direction which has been explored for conveying density information in volume visualisation—but not discrete scatterplots—is the use of haptic feedback. Haptics [9, 11, 50] include both tactile and kinesthetic displays. Tactile displays employ the *cutaneous* sense that allows users to understand properties of a physical item via skin contact. Kinesthetic displays employ the *proprioceptive* sense, through which users perceive their own body position and movement. Vibrotactile displays employ vibrational feedback to induce tactile sensations [15], e.g. to fingers [49], hands [57], or arms [52].

Pfeiffer and Stuerzlinger [43] showed that vibrotactile feedback was as efficient as visual feedback for mid-air target acquisition in a 3D stereoscopic environment. A similar study in a VR environment showed that bimodal feedback (e.g. visual + vibrotactile) leads to fewer errors. Vibrotactile feedback in VR has also been shown to allow exploration of basic volumes [33] to increase awareness, and to provide users with the ability to feel forces and textures [3, 10].

The use of haptic feedback has been studied in scientific visualisation as a way to broaden the information bandwidth between users and system (see [39] for a review). More specifically, Iwata and Noma described *Volume Haptization* [29], a set of methods to map force to volume data. They found that force-haptic feedback with a pantograph device was better than visual only. Similar results have been found with a phantom arm [5, 20]. Few studies focused on vibrotactile feedback. Menelas et al. found that vibrotactile feedback, when coupled with visualisation, was preferred by users and allowed them to quickly identify an area of interest [38]. On a similar task, Ammi and Katz [2] showed that such feedback, coupled with audio, was more efficient than vibrotactile feedback alone.

The use of haptics for quantitative data exploration has mostly been studied for 2D visualisation (see [41] for a review). Vibrotactile feedback has been mainly used to communicate high-level information (e.g. vibrotactile icons or *tactons*) and not as a channel to encode data values. A few examples that do encode values with vibrotactile feedback include barcharts [51] and 2D scatterplots [23]. Most evaluations did not focus on performance but showed that such feedback was usable. A rare example of haptic feedback for 3D abstract visualisation demonstrates a simple force-based haptic model in a 3D scatterplot that conveys an overview of the density. As this model was not evaluated, this paper—to the best of our knowledge—is the first to evaluate haptic feedback for 3D scatterplot exploration.

Summary and Definitions. In Table 1 we classify techniques by data type, sensory channel and spatial interaction.

Data types. Following Munzner [40] we make a distinction between *field* and *discrete* data. *Field* data has values at all points of a given space. Typically, scientific and medical data, e.g. 3D MRI/CT scans, photogrametry or fluid simulations are continuous field data. *Discrete* data corresponds to values in multidimensional tables.

		Data Type	
		Field	**Discrete** (scatterplots)
Channels	Visual	volume	points/glyphs
	Vibrotactile	density $\rightarrow$ intensity [2, 38]	inferred intensity, ***Scaptics*** [Sec. 3]
	Force-feedback	inferred vector [5, 20, 29, 39]	inferred vector [42]
Spatial interaction	Space-preserving	cutting plane [13, 16, 25, 28, 30, 32, 37]	cutting plane[6, 7], ***Highlight-Plane*** [Sec. 3]
	Space-distorting	fisheye[17], ColorTunneling[26]	MoleView [27] ***not recommended*** [18]

Table 1: high-level framework for 3D data representation using haptic and visual channels, by data type.

Sensory Channels. In this paper we consider two *sensory channels* for conveying density information: *visual* and *haptic*, with the latter further divided into *vibrotactile* and *force-feedback*. The visualisation of 3D field data usually involves rendering a grid of voxels. A transfer function maps density at each grid cell to colour. Transparency can be controlled to isolate density layers (e.g. filtering skin density to show organs in an MRI scan). In the case of 3D scatterplots of discrete data, coloured glyphs (dots or spheres) are mapped to discrete positions in space. A perception of density emerges from the separation between glyphs and can be controlled by adjusting transparency, size and style of the glyphs. In the case of haptic feedback, density can be mapped to vibrotactile or force feedback, using for instance a Phantom Arm or Pantograph device. For field data, where a density value is present in the data at every point in space, the mapping from density to vibrotactile intensity is direct and trivial. Mapping density fields or discrete points to force feedback requires inference of a direction of force, which has been examined in a number of papers, as listed in Table 1. The table reveals the first gap in this framework in the application of vibrotactile feedback to discrete scatterplot data. We require a function to map the proximity of points relative to controller position to vibration intensity. This gives rise to our design of the *Scaptics* technique, described in Section 3.

Spatial Interaction. The use of *space-distorting* techniques with discrete data is not recommended [18]. Of the *Space-preserving* techniques, cutting planes are most widely used for volume visualisation but we know of only one effort to use cutting plane interaction with discrete scatterplots [7], and this did not evaluate the cutting plane against other interaction techniques. Therefore, the second technique developed in this study is an adaptation of cutting planes for scatterplots: *Highlight-Plane*, see Section 3.

Summary. To sum-up, our framework showed that the use of vibrotactile and force feedback have not been extensively studied for abstract visualisation, but it showed promising result with field data (i.e. scientific visualisation). Force feedback cannot be provided by classic VR equipment we want to use. We, thus, focus on the use of vibortactile feedback with our technique *Scaptics.* Regarding the spatial interaction techniques, again, both space preserving and distorting techniques have been extensively studied for field data, but their use for abstract data is limited, and not evaluated. Because literature does not recommend the use of space-distorting techniques with abstract data [18], we choose to focus on the study of space-preserving techniques with our *Highlight-Plane*.

3 INTERACTION TECHNIQUES

In this section we give the design rationale for our *Scaptics* and *Highlight-Plane* techniques, which aims to support users' perception of obscured density features in a 3D scatterplot and support inspection of very dense clusters.

Scaptics: Scatterplot Haptics

Rationale. Haptic devices such as the Phantom Arm have been used to explore 3D data (Section 2), but these devices have distinct disadvantages for data visualisation: first, they can operate in only a limited volume of space (tens of centimetres per side); second, they are extremely expensive (tens of thousands of USD). By contrast, the current generation of commercial VR controllers come equipped with programmable vibrating motors that can provide adjustable vibrotactile feedback over a large interaction volume and their cost is in the hundreds of dollars. Thus, for the foreseeable future immersive data visualisation is accessible to a much greater audience using the latter setup. But the use of vibrotactile feedback for 3D scatterplots is not explored. A first option consists of triggering the vibration of the VR controller when it collides with a 3D data point. With such a design, getting a sense of the local density requires the user to browse in space to collide with each datapoint.

A more promising alternative is to derive volume information from the 3D scatterplot in order to create a field of density information and map the intensity of the field to the intensity of vibration of the controller. In the following, we detail how we create such a volume and how we carefully mapped resulting spatial density to the vibrating motors of a VR controller.

Design and implementation. We created a 3D Kernel Density Estimation (KDE) map of the data to create volume density information from a 3D scatterplot. KDE techniques [35] find spatial density of a data distribution and provide an overview of the density by displaying isocontours or surfaces around the dense areas of a visualisation. Technically, KDE maps are produced by applying a *Kernel* function to all data points that produce surface and volume information.

Our approach consists of using a solid Gaussian sphere as a kernel, centred on each point of the 3D scatterplot. A Gaussian function G is used to define the intensity of each voxel of the sphere kernel, according to their distance to the centre (i.e. a given point of the 3D scatterplot).

The KDE function is defined as follows: for a point $x \in \mathbb{R}^3$, the density estimation is given by the sum of the Gaussian sphere kernels:

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

Technically, we initialised a 3D grid with white transparent voxels. Then the kernel spheres were drawn in "additive mode", i.e. the colour intensity of each grid cell is a multiple of the number of spheres that cover it. The sum of the Gaussian kernels G yield high intensity volume information in the dense areas of the scatterplot (Figure 1 (b,c)).

For illustration purposes, Figure 1 (b,c) shows a volume rendering of the density KDE overlaid on a 3D scatterplot. The resulting colour of the voxels is a gradient of the density information (yellow for low density to red for high density). The thumbnail (c) is a slice of this volume that shows the intensity difference inside the three clusters and C1 is the the most red indicating that it is the densest region.

The aim of the *Scaptics* technique is to transform the color of the voxels into a vibrotactile feedback. As the 3D KDE technique provides a grid of voxels that encode continuous volume density information of the 3D scatterplot, the last step to create the *Scaptics* technique consists of mapping the density at a given point to a vibration strength.

To realise the Scaptics technique, we employ the HTC Vive Pro VR system and SDK[1]. It provides the location of a tracked controller in 3D space and a **TriggerHaptics(int strength)** function that triggers a vibration in the controller. Hence, by continuously reading the position of the controller in the grid of voxels, vibrations are triggered indicating the level of density. This *scaptics* interaction makes it possible to reach directly into the 3D scatterplot and by using continuous movements, to inspect volumes and surfaces. The perceived vibrations provide high-level information of the features (e.g. voids and density) that may not be visible directly in the scatterplot. Figure 1 (d) illustrates the interaction. The red lines on the HTC Vive controller indicate the intensity of the vibration on the controller. The controller at C1 vibrates more intensely than at C2 and C3, and the controller at C3 vibrates more intensely than at C2. In order to find a proper scale mapping of perceived vibrations and make sure one can discriminate different levels of vibration intensity, we performed a Just Noticeable Difference (JND) study (see Section 4). The JND study provided the smallest difference necessary to differentiate two vibrations. This difference follows Weber's Law [21] by increasing with intensity of the vibration. We selected 6 levels of vibration (strength values to the TriggerHaptics function), with a difference between them more than 2 times JND: 0, 200, 400, 700, 1100, 1600.

Highlight-Plane

Rationale. Our framework showed another opportunity for the design of a cutting plane to explore density in a 3D scatterplot, plotted directly from discrete data. The challenge was to design a cutting plane that shows 2D slices of data points to enable a user to see inside the 3D scatterplot to assess density and spatial arrangements. Our first approach was to generate a cutting plane from the orientation and position of the VR controller. We tried two typical cutting plane designs:

Design 1: display only the data points within a small distance of the cutting plane surface and completely remove the rest. This was the technique demonstrated by [7].

Design 2: remove the data points that are between the viewer and the cutting plane.

In piloting the tasks for our studies both designs proved problematic for discrete scatterplot data. Design 1 works for volume visualisation because the cutting plane cross section presents a complete 2D image. However, for discrete scatterplot data our pilot participants found this technique difficult to use, as the context of the remaining points was lost. They struggled to navigate and complete the tasks.

Thus, we modified the technique to Design 2, which is again common in volume visualisation applications, where it has the advantage that much more of the surrounding model remains visible. It works well in this case because the cutting plane cross-section is an opaque surface. There is no visual interference from voxels behind the cutting plane. For discrete point data in scatterplots, however, the points behind the cutting plane are visible through the gaps between the points intersecting the cutting plane surface and they make it very difficult to tell precisely which points are actually on the cutting plane. Thus, again, our pilot participants struggled to complete the tasks with this technique.

We therefore adopted an approach of highlighting points near the cutting plane, while reducing the visual saliency of the remaining points in order to achieve a pre-attentive *pop-out* (or Gestalt Grouping) effect [24] without harming the overall 3D abstract visualisation. A first approach was to use two colours to discriminate the data points selected on the cutting planes. This approach did not prove to be very efficient. Similarly, adjusting transparency did not achieve a strong pop-out effect. Our **final design** involved increasing the size of the data points intersected by the plane. Further

[1]www.vive.com/us/product/vive-pro/ (Accessed on the 01/10/2019)

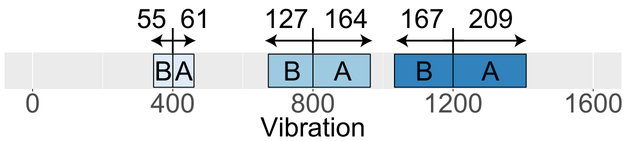


Figure 3: The 6 different JND (top of the figure) found for the 3 different vibrations (200, 800, 1200) and the two approaches (A: Above and B: Below).

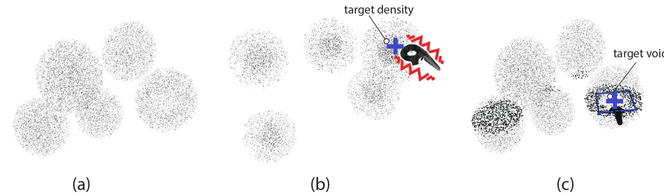


Figure 4: Example stimuli used to test Scaptics and Highlight Plane: (a) background noise; (b) *TaskClusters* task with *Scaptics*; (c) *TaskVoid* task with the *Highlight-Plane*.

piloting indicated a stronger pop-out effect than the use of colour. We name this final design: *Highlight-Plane*.

Design and implementation. The size of the dots in the Highlight-Plane is multiplied by a scale factor of 3 (Figure 2). We implemented the Highlight-Plane by calculating at each frame the distance of each scatterplot point to the plane defined by the orientation of the VR controller. The interaction results in a continuous highlighting effect that enhances the perception of the spatial arrangement and the density of data points inside dense regions of the plot.

4 VIBRATION JND

Before assesing the effects of vibrotactile feedback for visualisation, it is necessary to understand people's ability to discriminate between different levels of vibration from the HTC Vive handheld controller. To accomplish this, we conducted a *Just Noticeable Difference* (JND) study, a widely-accepted measure of such discriminatory abilities. JND is defined as minimum perceivable property difference between two stimuli [21]. JND studies have been applied to different types of perceptual stimuli such as color and sound. While previous work has focused on vibration perception, it has not yet been applied, to our knowledge, to vibrotactile stimulus from handheld controllers such as the HTC Vive controllers.

Method. We applied a *staircase procedure* [54], which consists of a series of comparisons between varying pairs of stimulus levels, one *base level* and one higher or lower level[2].

Our implementation uses the HTC Vive SDK function "TriggerHapticPulse", which controls the level of vibration with values ranging from 0 (for no vibration) to 4000 (for the highest level of vibration). However, pilots showed that it was almost impossible to discriminate vibration over 1600. We chose 3 *base values* evenly distributed in the remaining usable range : 400, 800, and 1200. Each *base value* was then compared with both higher (*Above* approach) and lower (*Below* approach) values. In total, each participant did the staircase procedure 6 times (3 *base values* $\times$ 2 *approaches*).

Participants and Procedure. We recruited 9 participants (1 female) for this JND study. Participants held the controller in their dominant hand. To begin each trial, participants were required to place their thumb on the pad of the controller. Then they were presented with two levels of vibration (the base value and the comparative value) in a random order. These were presented consecutively, without a pause between them. Participants were asked to indicate which vibration was the strongest by pressing the left or right button of the controller's pad.

Once all data were collected, we calculated the average JND across all participants for each of the 6 procedure variants showed in Figure 3.

5 CONTROLLED USER STUDY

Our study focuses on the use of Scaptics **(S)** and Highlight-Plane **(H)** to reveal obscured features in a 3D scatterplot in VR. At a high level, we investigated questions relative to data density such as:

–It seems that there is a hole there, or that the density is low inside that volume. Is there really a hole?

–I can see that those two clusters seem very dense from the outside, but which one is the most dense?

We designed two tasks that simulate these two questions and allow us to control such issues. We compare the performance of our two new techniques against a *visualisation only* **(V)** baseline condition. In this condition participants only relied on the depth cues provided by the immersive VR environment (i.e. parallax motion and stereoscopic vision).

Tasks and stimuli. We designed two tasks that required participants to search for low and high densities in a 3D scatterplot. The low density task (*TaskVoid*) can be seen as a *void* finding task, e.g. find zones of the 3D scatterplot that contain no or very few data points. The high density task (*TaskClusters*) can be seen as a *densest cluster* finding task, e.g. given several dense zones, find the densest one. Both patterns used in the tasks (clusters and voids) have been identified as typical scatter patterns which can be found in real-world dataset in 2D [55] and 3D [58].

Stimuli used in tasks followed the same basic pattern. Initially, five ovoid regions (balls) roughly 25cm in diameter were filled with 1,000 randomly distributed points (noise), see Fig. 4(c). These balls were placed and oriented randomly

[2] See [48] and [14] for a detailed description and example of the procedure.

		Density			
		Low		High	
		TV	TC	TV	TC
Density Difference Diff. Den.	Low	T: 0% D: ≈50%	T: 400% D: ≈300%	T: 20% D: ≈50%	T: 800% D: ≈600%
	High	T: 0% D: ≈100%	T: 400% D: ≈200%	T: 20% D: ≈100%	T: 800% D: ≈400%

Table 2: Summary of the density of the *target*(T) and *distractors*(D) for each condition (Density and Diff. Den.) for the *TaskVoid* (TV) and *TaskClusters* (TC). Each density is expressed in percentage of the noise density of the surrounding ball.

within a cube, one meter to a side. This basic pattern was adjusted differently in each task.

For *TaskClusters*, a 15cm diameter region within each ball was augmented with additional points to make embedded clusters, see Figure 4(b). Again the number of points added varied to control for cluster Density, relative to the density of noise in the surrounding ball, from 200% to 800%. The task was to find the densest cluster (*target*) against the *distractors*. In real-world dataset, such as an HSV-space distribution of pixels from an image, clusters represent the main coloured features.

For *TaskVoid*, a hole (void) of 15cm diameter was created within each ball by removing a random number of points, the number chosen to control for Density, such that the void regions had density of points varying between completely empty (0% Density) and the same density as the surrounding ball of noise (100% Density), see Fig. 4 (c). The task was to find the least dense void (*target*) against the *distractors*. In real-world dataset, voids can be indicative of missing data.

We controlled the difficulty of both tasks by varying the Density levels of the *target* and the difference of density (Diff. Den.) between the *target* and the *distractors* (see Table 2 for details). The results of the JND study were used to ensure a noticeable vibration difference between similar density levels, especially between the *target*'s Density and the *distractors*. Overall, each generated dataset contains between 10k and 20k points (in function of the conditions). It is representative of datasets commonly used in visual analytics.

Apparatus and participants. We used a virtual-reality desktop (GeForce GTX1080, intel i7, 32GB of RAM) with an HTC Vive-pro headset to ensure a high-frame rate for a comfortable VR experience. The visualisation was developed using Unity[3]. We recruited 15 participants (12 males, 3 females, mean age= 28.8 and SD=5) using word of mouth and direct communication. Participants were postgraduate students and faculty. 12 participants reported being familiar with data visualisation (2 experts) and 9 were familiar with VR and 12 with gaming.

Design. We used a within-subjects design which consisted of: 2 Tasks (*TaskClusters* and *TaskVoid*) × 3 Techniques (*Visual Only*, *Scaptics* and *Highlight-Plane*) × 2 Density (Low and High) × 2 Diff. Den. (*Low* and *High*). We did 3 repetitions which yielded 72 trials per participant. We collected a total of 72 x 15 participants = 1080 trials. A Latin Square was used to counterbalance the order of techniques. The order of trials for each Technique and each tasks have been randomised, but fixed between Techniques and participants. Since the aim of this study was not to compare task performance, the tasks were not counter balanced, and all participants started with the *TaskVoid*, and then did the *TaskClusters*. As this is an exploratory study, we don't have strong hypotheses regarding performance of each technique. Our goal is to observe the nuances of each techniques and how they compare to each other. However, the metric and the analysis methods were determined before the study.

Procedure. The session started with a short training session on the 3 Techniques for all participants. Then participants performed all trials of *TaskVoid* and followed by *TaskClusters*. Participants were asked to start each trial from a precise position indicated on the ground by a blue arrow in the virtual environment. Participants answered each task by placing a blue 3D virtual cross in the chosen sphere (Figure 4 (b,c)) by pressing the controller trigger. For each Techniques, participants started with 4 training trials of increasing difficulty, which they had to redo until they found the correct answer.

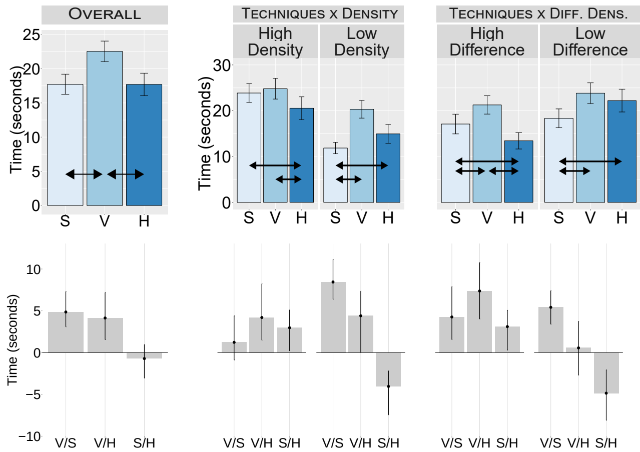
Participants completed a demographic questionnaire before the study and a post study questionnaire after. The study was approximately 1 hour, and participants were able to take a break at any time if they felt uncomfortable.

Measures. We recorded completion time (i.e. time to pull the controller trigger and hence place the cross). Correctness was based on whether the cross was placed within the *target*. At the end of the experiment, confidence, physical and cognitive demand were measured using Likert scales and preference using a ranking. Finally, participant's reported their strategies in solving the task.

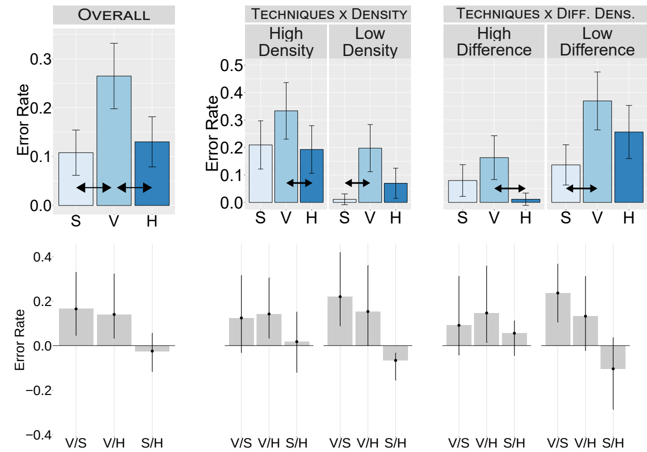
6 RESULTS

Statistical Method. Following APA recommendations [4], we report our analysis using estimation techniques with effect sizes and confidence intervals (i.e., not using p-values) following recent precedents in HCI [12, 56]. Our confidence intervals were computed using BCa bootstrapping, and the term effect size here refers to the measured difference of means. Error bars in our images reporting means are computed using all data for a given condition. When comparing means, we average the data by participants/groups and compare the three conditions globally by computing the CI of

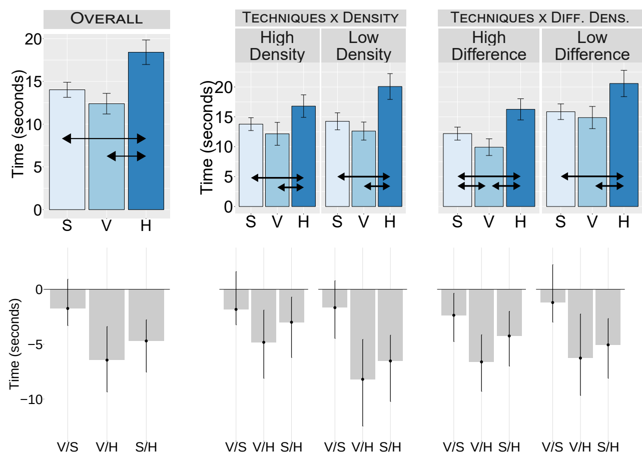
[3]https://unity3d.com/ (Accessed on the 01/10/2019)



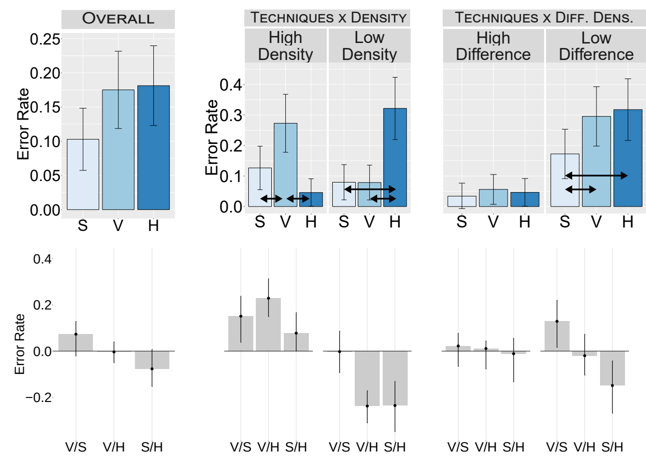
(a) ***TaskVoid*: Time**



(b) ***TaskVoid*: Error rate**



(c) ***TaskClusters*: Time**



(d) ***TaskClusters*: Error rate**

Figure 5: In each figure, the top charts show Means and CIs for all measures for TECHNIQUES (*Highlight-Plane* (H), *Scaptics* (S) and *Visual Only* (V)) across conditions. The bottom charts show Corresponding 95% CIs for the mean difference between TECHNIQUES. Arrows indicate significant difference between two conditions.

the set of differences. A difference is considered as significant when the CI of the difference do not cross 0. In our images we display the computed CI of the differences. While we make use of estimation techniques, a p-value-approach reading of our results can be done by comparing our CIs spacing with common p-value spacing as shown by Krzywinski and Altman [34]. All the results reported in the analysis are significant, unless explicitly stated otherwise.

TaskVoid Results

Time. Overall, participants took more time to finish the task in the *Visual Only* condition (Figure 5a-left – 5 seconds slower). When we look separately at each DENSITY (Figure 5a-center), we can see that *Scaptics* is fastest (10 seconds faster than *Visual Only*, 5 faster than *Highlight-Plane*) for *Low* density. For *High* density, *Highlight-Plane* is fastest (by around 5 seconds). Looking at DIFF. DEN. (Fig. 5a-right), both *Scaptics* and *Highlight-Plane* are faster than *Visual Only* with high density difference (between 5 and 10 seconds faster). When DENSITY decreases, performance decreases for *Highlight-Plane* and *Visual Only*, but not for *Scaptics*, which is faster than the two others (around 5 seconds faster).

Error. Most above results are reflected in the error rate (Fig. 5b). Participants made around 20% more errors in the *Visual Only* condition (Figure 5b - left). They made fewer errors in the *Low* DENSITY condition (Figure 5b-center) with *Scaptics* than with *Visual Only* (20% fewer). In the *High* DENSITY condition,

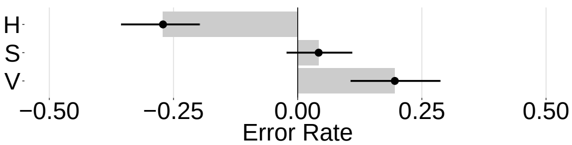


Figure 6: 95% CIs for the mean difference between the error rate in *TaskClusters* for each Techniques between the *Low* and the *High* Density.

the only difference is between the *Highlight-Plane* and the *Visual Only* (around 15% fewer with the *Highlight-Plane*). When we look at each Diff. Den. (Figure 5b-right), we can see that there are no any differences between the three conditions, participants did not make many errors, however, their performance decreases with decreasing Diff. Den., however, it is again almost stable for *Scaptics*, with which participants did 20% fewer errors than with *Visual Only*.

TaskClusters Results

Time. Overall, participants took more time to finish the task in the *Highlight-Plane* condition (Figure 5c-left – 5 seconds slower). We found the same result in all the conditions (Figure 5c-center and right).

Error. Overall, there is no effect on the error rate (Figure 5d-left). If we look at each Density, analysis showed that participants made more error in *High* density in the *Visual Only* condition (20-25% more errors), while they made more errors with the *Highlight-Plane* in the *Low* condition (>20% more errors). It is interesting to note that when looking at the difference of error rate between the *Low* and the *High* density (Fig. 6), participants made fewer errors in *High* density with the *Highlight-Plane* than in the *Low* (>25% more), but it is the opposite with in the *Visual Only* condition (>20% more errors in the *High* density). However, with *Scaptics*, accuracy across both Density is stable and high. Regarding the Diff. Den. (Figure 5d-right), there is no effect for *High* Diff. Den. and for *Low* Diff. Den. *Scaptics* is >15% more accurate than either *Highlight-Plane* or *Visual Only*.

User Feedback

Questionnaire responses are summarised in Figure 7. More than 50% of the participants rated their confidence at 4 or 5 with *Highlight-Plane* and *Scaptics* (>75% with *Highlight-Plane*). On the other hand, 50% rated it at 1 or 2, and <25% rated it at 4 or 5 with *Visual Only*. Physical and mental demand results are similar, <25% rated a high demand (4 or 5) with *Highlight-Plane* and *Scaptics*, while >50% reported high-demand with *Visual Only*. No participant rated their mental demand higher than 3 with *Scaptics*. Finally, >50% of participants ranked *Highlight-Plane* first, *Scaptics* second and *Visual Only* third.

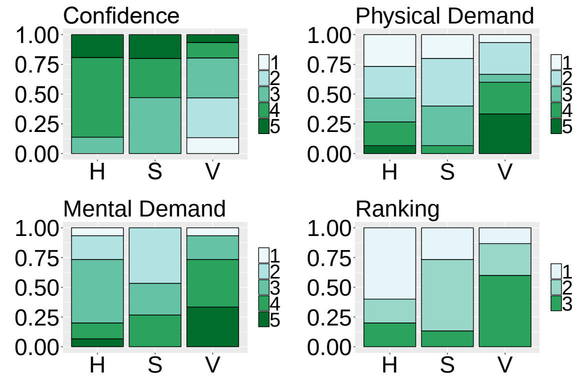


Figure 7: Summary of participants' answer to the post-study questionnaire about the three Techniques.

	LD	HD	LDD	HDD
VT - Time	S	H	S	H
VT - Accuracy	S>V	H>V	S>V	H>V
CT - Time	S,V	S,V	S,V	S
CT - Accuracy	S,V	S,H	S	-

Table 3: Summary of the result for the *TaskVoid* (VT) and *TaskClusters* (CT), for the different condition: *Low* and *High* Density (LD and HD), and *Low* and *High* Diff. Den. (LDD and HDD). Cells contain either the best Techniques(s) or, if no best, the significant difference.

Strategies. With the *Visual Only*, participants mostly reported putting directly their head inside the cluster (7/15), especially for the *TaskVoid*. For the *Scaptics*, most users reported trying to identify first the best candidates visually and then compare them using the controller (7/15), others reported trying directly all the candidates (5/15). Interestingly, one participant actually reported using the sound of the vibration instead of the tactile feeling. Finally, with the *Highlight-Plane*, participants reported also trying to identify candidates visually and then comparing using the plane (3/15). However, others used the plane with different angle to optimise the number of clusters intersected, to optimise the comparison (6/15).

Participants' Subjective Comments. When asked to explain their ranking, participants explained that *Highlight-Plane* allowed side-by-side comparison (5/15) and in 2D (2/15), which were condidered as easier. Some complained about the fact that *Scaptics* required more movement (3/15), and wondered if the resolution was high enough for low difference of density (4/15). Finally, *Visual Only* was considered as efficient only in obvious case (4/15).

Discussion

Our observations combined with participants' feedback in the questionnaire show that they took advantage of VR to solve the tasks (e.g. some participants put their head in the spheres, walked around and moved their head to use parallax motion to solve the task). In the following we discuss the results for each task, summarised by Table 3.

TaskVoid. The purpose of this task was to see if the techniques support participants in finding and comparing void-like (non-existent or low density) features in a scatterplot. Overall, we can see that both interaction techniques improved participants' performance compared to the baseline. If we look at different conditions we can see that both techniques are actually complementary, especially in conditions that were considered as more difficult: *High* DENSITY (When the density of the *target* is not equal to 0) and *Low* DIFF. DEN. (when the difference between the *target* and the *distractors* is low). In the first one, the difficulty was due to a lower difference of density between the noise and the target. The *Highlight-Plane*, by increasing the size of the points, actually increases this difference and makes the task easier. A challenge with the *Highlight-Plane* technique occurs when trying to compare more than three features that do not lie on a plane, i.e. when it is not possible to intersect the plane with all features at once. By contrast, the *Scaptics* technique allows only one feature to be inspected at a time.

TaskClusters. The purpose of this task was to see how the techniques help participants in finding and comparing dense clusters in a scatterplot. The only general result for this task is that the *Highlight-Plane* is slower than *Scaptics* and Visual only. If we look at accuracy, we can see that the performance of *Scaptics* is consistently good across conditions (except for the *High* DIFF. DEN. where accuracy was high for all techniques). A possible explanation is that this task was easier visually. As reported, participants used the visual density in the easy cases (which is faster) and used *Scaptics* when it was not enough (like in the *Low* DIFF. DEN. condition). As *Scaptics* is designed to differentiate close densities, it led to high accuracy. This strategy was less popular with the *Highlight-Plane*, maybe because participants preferred using directly 2D visual comparison. This led to a better accuracy than Visual only for very dense clusters. This could be due to the fact that contrary to the previous task, the *Highlight-Plane*, by highlighting only a subset of points of the cluster, reduces the visual density which facilitates comparison in accordance with Weber's law [21]). On the contrary, with low density clusters, a condition which was considered as easy with the Visual only, the performance of the *Highlight-Plane* worsens significantly. Such effects should be studied in the future.

To conclude, for finding and comparing void-like spatial features, the use of interaction techniques is beneficial, and *Scaptics* and *Highlight-Plane* each have their own benefits, which could be complementary. Regarding clusters, *Scaptics* is in general faster and more accurate than *Highlight-Plane*. This confirms previous work about vibro-tactile feedback from studies with similar setup but different tasks like exploring basic volumes [33] or identify areas of interest [38]. It is worth saying that the good performance of *Scaptics* is partially due to the stepped vibration-density mapping which ensured that the difference in vibration intensity between target and distractors was always noticable. However, participants reported that their confidence was negatively affected when they visually perceived different densities in nearby regions, but could not feel the difference if the density mapping fell within the same vibration intensity band. The design and use of such mappings should be investigated.

7 CONCLUSION AND FUTURE WORK

In this paper we contributed two novel techniques to explore obscured features in 3D scatterplots in VR: *Scaptics*, that uses vibrotactile feedback on a tracked controller; and *Highlight-Plane*, a redesign of cutting planes for 3D scatterplots. Our study assessed the performance of each technique against a non interactive baseline. We find that both interactive techniques, Scaptics and Highlight-Plane, improve user performance for identifying void regions. Scaptics afforded better performance for the identification of clusters.

The designs of our techniques would need to be refined, but we believe that this first study showed the promising potential in the use of VR controllers and additional sensory channel for the exploration of 3D abstract information. Furthermore, while further study is required, our results potentially have application in other immersive environments, for example in mixed reality—to support situated analytics scenarios [19]—or touch screens with vibrotactile feedback.

Our designs and preliminary results are encouraging for further investigation of interactive techniques and techniques that employ additional sensory channels to support exploration of 3D scatterplots in immersive VR environments. In future work, we want to further explore interactions based on vibrotactile feedback on controllers (e.g. explore particular vibrating patterns to encode spatial information). Moreover, we plan to explore other 3D volume generation techniques that can be employed to find more relevant spatial features in 3D scatterplots (e.g. convolutions on the KDE volume to encode cluster edges). Cutting planes for 3D scatterplots also need more attention as they can be a great means to explore dense 3D scatterplots. In particular we hope to explore the combination of *Scaptics* and the *Highlight-Plane* to take benefits of both. Finally, other sensory channels could be investigated, such as sonification [2].

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REFERENCES

[1] B. Alper, T. Hollerer, J. Kuchera-Morin, and A. Forbes. 2011. Stereoscopic Highlighting: 2D Graph Visualization on Stereo Displays. *IEEE Transactions on Visualization and Computer Graphics* 17, 12 (Dec 2011), 2325–2333. DOI: http://dx.doi.org/10.1109/TVCG.2011.234

[2] 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. DOI: http://dx.doi.org/10.1080/10447318.2014.941277

[3] O. Ariza, P. Lubos, F. Steinicke, and G. Bruder. 2015. Ring-shaped Haptic Device with Vibrotactile Feedback Patterns to Support Natural Spatial Interaction. In *Proceedings of the 25th International Conference on Artificial Reality and Telexistence and 20th Eurographics Symposium on Virtual Environments (ICAT - EGVE '15)*. Eurographics Association, Aire-la-Ville, Switzerland, Switzerland, 175–181. DOI: http://dx.doi.org/10.2312/egve.20151326

[4] American Psychological Association. 2009. *Publication Manual of the American Psychological Association*. American Psychological Association (APA).

[5] Ricardo S. Avila and Lisa M. Sobierajski. 1996. A Haptic Interaction Method for Volume Visualization. In *Proceedings of the 7th Conference on Visualization '96 (VIS '96)*. IEEE Computer Society Press, Los Alamitos, CA, USA, 197–204. DOI: http://dx.doi.org/10.1109/VISUAL.1996.568108

[6] B. Bach, P. Dragicevic, D. Archambault, C. Hurter, and S. Carpendale. 2014. A Review of Temporal Data Visualizations Based on Space-Time Cube Operations. In *EuroVis - STARs*, R. Borgo, R. Maciejewski, and I. Viola (Eds.). The Eurographics Association. DOI: http://dx.doi.org/10.2312/eurovisstar.20141171

[7] B. Bach, R. Sicat, J. Beyer, M. Cordeil, and H. 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. DOI: http://dx.doi.org/10.1109/TVCG.2017.2745941

[8] Sven Bachthaler and Daniel Weiskopf. 2008. Continuous scatterplots. *IEEE transactions on visualization and computer graphics* 14, 6 (2008), 1428–1435. DOI: http://dx.doi.org/10.1109/TVCG.2008.119

[9] Mohamed Benali-Khoudja, Moustapha Hafez, Jean-Marc Alexandre, and Abderrahmane Kheddar. 2004. Tactile interfaces: a state-of-the-art survey. In *Int. Symposium on Robotics*, Vol. 31. 23–26.

[10] Hrvoje Benko, Christian Holz, Mike Sinclair, and Eyal Ofek. 2016. Normaltouch and texturetouch: High-fidelity 3d haptic shape rendering on handheld virtual reality controllers. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology*. ACM, 717–728. DOI: http://dx.doi.org/10.1145/2984511.2984526

[11] Carlos Bermejo and Pan Hui. 2017. A survey on haptic technologies for mobile augmented reality. (2017).

[12] Lonni Besançon, Mehdi Ammi, and Tobias Isenberg. 2017. Pressure-Based Gain Factor Control for Mobile 3D Interaction Using Locally-Coupled Devices. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. ACM, New York, NY, USA, 1831–1842. DOI: http://dx.doi.org/10.1145/3025453.3025890

[13] Lonni Besancon, Paul Issartel, Mehdi Ammi, and Tobias Isenberg. 2017. Hybrid Tactile/Tangible Interaction for 3D Data Exploration. *IEEE Transactions on Visualization and Computer Graphics* 23, 1 (Jan. 2017), 881–890. DOI: http://dx.doi.org/10.1109/TVCG.2016.2599217

[14] Tanja Blascheck, Lonni Besançon, Anastasia Bezerianos, Bongshin Lee, and Petra Isenberg. 2019. Glanceable Visualization: Studies of Data Comparison Performance on Smartwatches. *IEEE Transactions on Visualization and Computer Graphics* 25, 1 (Jan. 2019). DOI: http://dx.doi.org/10.1109/TVCG.2018.2865142

[15] S. Choi and K. J. Kuchenbecker. 2013. Vibrotactile Display: Perception, Technology, and Applications. *Proc. IEEE* 101, 9 (Sept 2013), 2093–2104. DOI: http://dx.doi.org/10.1109/JPROC.2012.2221071

[16] D. Coffey, N. Malbraaten, T. B. Le, I. Borazjani, F. Sotiropoulos, A. G. Erdman, and D. F. Keefe. 2012. Interactive Slice WIM: Navigating and Interrogating Volume Data Sets Using a Multisurface, Multitouch VR Interface. *IEEE Transactions on Visualization and Computer Graphics* 18, 10 (Oct 2012), 1614–1626. DOI: http://dx.doi.org/10.1109/TVCG.2011.283

[17] 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 (CHI '96)*. ACM, New York, NY, USA, 175–176. DOI: http://dx.doi.org/10.1145/257089.257242

[18] N. Elmqvist and P. Tsigas. 2008. A Taxonomy of 3D Occlusion Management for Visualization. *IEEE Transactions on Visualization and Computer Graphics* 14, 5 (Sept 2008), 1095–1109. DOI: http://dx.doi.org/10.1109/TVCG.2008.59

[19] N. ElSayed, B. Thomas, K. Marriott, J. Piantadosi, and R. Smith. 2015. Situated Analytics. In *2015 Big Data Visual Analytics (BDVA)*. 1–8. DOI: http://dx.doi.org/10.1109/BDVA.2015.7314302

[20] 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. DOI: http://dx.doi.org/10.1109/MCSE.2018.03221931

[21] Gustav Fechner. 1966. *Elements of psychophysics. Vol. I.* New York.

[22] J. A. Wagner Filho, M. F. Rey, C. M. Freitas, and L. Nedel. 2018. Immersive Visualization of Abstract Information: An Evaluation on Dimensionally-Reduced Data Scatterplots. In *2018 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, Vol. 00. 483–490. DOI: http://dx.doi.org/10.1109/VR.2018.8447558

[23] S. J. Haase and K. A. Kaczmarek. 2005. Electrotactile perception of scatterplots on the fingertips and abdomen. *Medical and Biological Engineering and Computing* 43, 2 (01 Apr 2005), 283–289. DOI: http://dx.doi.org/10.1007/BF02345967

[24] Christopher G Healey. Retrieved on 2018-09-15. Perception in visualization. (Retrieved on 2018-09-15). https://www.csc2.ncsu.edu/faculty/healey/PP/

[25] 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 (CHI '94)*. ACM, New York, NY, USA, 452–458. DOI: http://dx.doi.org/10.1145/191666.191821

[26] C. Hurter, R. Taylor, S. Carpendale, and A. Telea. 2014. Color Tunneling: Interactive Exploration and Selection in Volumetric Datasets. In *2014 IEEE Pacific Visualization Symposium*. 225–232. DOI: http://dx.doi.org/10.1109/PacificVis.2014.61

[27] C. Hurter, A. Telea, and O. Ersoy. 2011. MoleView: An Attribute and Structure-Based Semantic Lens for Large Element-Based Plots. *IEEE Transactions on Visualization and Computer Graphics* 17, 12 (Dec 2011), 2600–2609. DOI: http://dx.doi.org/10.1109/TVCG.2011.223

[28] P. Issartel, F. Guéniat, and M. Ammi. 2014. Slicing techniques for handheld augmented reality. In *2014 IEEE Symposium on 3D User Interfaces (3DUI)*. 39–42. DOI: http://dx.doi.org/10.1109/3DUI.2014.6798839

[29] H. Iwata and H. Noma. 1993. Volume haptization. In *Proceedings of 1993 IEEE Research Properties in Virtual Reality Symposium*. 16–23. DOI: http://dx.doi.org/10.1109/VRAIS.1993.378268

[30] B. Jackson, T. Y. Lau, D. Schroeder, K. C. Toussaint, and D. F. Keefe. 2013. A Lightweight Tangible 3D Interface for Interactive Visualization of Thin Fiber Structures. *IEEE Transactions on Visualization and Computer Graphics* 19, 12 (Dec 2013), 2802–2809. DOI: http://dx.doi.org/10.1109/TVCG.2013.121

[31] Daniel A. Keim. 2000. Designing Pixel-Oriented Visualization Techniques: Theory and Applications. *IEEE Transactions on Visualization and Computer Graphics* 6, 1 (Jan. 2000), 59–78. DOI: http://dx.doi.org/10.1109/2945.841121

[32] Tijmen Klein, Florimond Guéniat, Luc R. Pastur, Frédéric Vernier, and Tobias Isenberg. 2012. A Design Study of Direct-Touch Interaction for Exploratory 3D Scientific Visualization. *Computer Graphics Forum* 31, 3 (2012), 1225–1234. DOI: http://dx.doi.org/10.1111/j.1467-8659.2012.03115.x

[33] Julian Kreimeier and Timo Götzelmann. 2018. FeelVR: Haptic Exploration of Virtual Objects. In *Proceedings of the 11th Pervasive Technologies Related to Assistive Environments Conference*. ACM, 122–125. DOI: http://dx.doi.org/10.1145/3197768.3201526

[34] Martin Krzywinski and Naomi Altman. 2013. Points of significance: error bars. *Nature Methods* 10, 10 (Sept 2013), 921–922. DOI: http://dx.doi.org/10.1038/nmeth.2659

[35] O. Daae Lampe and H. Hauser. 2011. Interactive visualization of streaming data with Kernel Density Estimation. In *2011 IEEE Pacific Visualization Symposium*. 171–178. DOI: http://dx.doi.org/10.1109/PACIFICVIS.2011.5742387

[36] Laurens van der Maaten and Geoffrey Hinton. 2008. Visualizing data using t-SNE. *Journal of machine learning research* 9, Nov (2008), 2579–2605.

[37] M. J. McGuffin, L. Tancau, and R. Balakrishnan. 2003. Using deformations for browsing volumetric data. In *IEEE Visualization, 2003. VIS 2003.* 401–408. DOI: http://dx.doi.org/10.1109/VISUAL.2003.1250400

[38] B. Menelas, M. Ammi, L. Pastur, and P. 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*. 232–237. DOI: http://dx.doi.org/10.1109/WHC.2009.4810833

[39] 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*, Mao Lin Huang and Weidong Huang (Eds.). IGI Global, Hershey, Pennsylvania, Chapter 6, 111–132. DOI: http://dx.doi.org/10.4018/978-1-4666-4309-3.ch006

[40] Tamara Munzner. 2014. *Visualization Analysis and Design.* CRC Press. DOI: http://dx.doi.org/https://doi.org/10.1201/b17511

[41] S. Paneels and J. C. Roberts. 2010. Review of Designs for Haptic Data Visualization. *IEEE Transactions on Haptics* 3, 2 (April 2010), 119–137. DOI: http://dx.doi.org/10.1109/TOH.2009.44

[42] Sabrina A. Panëels, Panagiotis D. Ritsos, Peter J. Rodgers, and Jonathan C. Roberts. 2013. Prototyping 3D haptic data visualizations. *Computers & Graphics* 37, 3 (2013), 179–192. DOI: http://dx.doi.org/10.1016/j.cag.2013.01.009

[43] M. Pfeiffer and W. Stuerzlinger. 2015. 3D virtual hand pointing with EMS and vibration feedback. In *2015 IEEE Symposium on 3D User Interfaces (3DUI)*. 117–120. DOI: http://dx.doi.org/10.1109/3DUI.2015.7131735

[44] H. Piringer, R. Kosara, and H. 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.* 49–60. DOI: http://dx.doi.org/10.1109/CMV.2004.1319526

[45] J. Poco, R. Etemadpour, F. V. Paulovich, T. V. Long, P. Rosenthal, M. C. F. Oliveira, L. Linsen, and R. Minghim. 2011. A Framework for Exploring Multidimensional Data with 3D Projections. (2011), 1111–1120. DOI: http://dx.doi.org/10.1111/j.1467-8659.2011.01960.x

[46] Fabio Remondino. 2003. From point cloud to surface: the modeling and visualization problem. *International Archives of photogrammetry, Remote Sensing and spatial information sciences* 34 (2003).

[47] M. Sedlmair, T. Munzner, and M. Tory. 2013. Empirical Guidance on Scatterplot and Dimension Reduction Technique Choices. *IEEE Transactions on Visualization and Computer Graphics* 19, 12 (Dec 2013), 2634–2643. DOI: http://dx.doi.org/10.1109/TVCG.2013.153

[48] Utkarsh Soni, Yafeng Lu, Brett Hansen, Helen C. Purchase, Stephen Kobourov, and Ross Maciejewski. 2018. The Perception of Graph Properties in Graph Layouts. *Computer Graphics Forum* (2018). DOI: http://dx.doi.org/10.1111/cgf.13410

[49] Yuta Takeuchi, Sho Kamuro, Kouta Minamizawa, and Susumu Tachi. 2012. Haptic Duplicator. In *Proceedings of the 2012 Virtual Reality International Conference (VRIC '12)*. ACM, New York, NY, USA, Article 30, 2 pages. DOI: http://dx.doi.org/10.1145/2331714.2331749

[50] A. Talvas, M. Marchal, and A. Lécuyer. 2014. A Survey on Bimanual Haptic Interaction. *IEEE Transactions on Haptics* 7, 3 (July 2014), 285–300. DOI: http://dx.doi.org/10.1109/TOH.2014.2314456

[51] Steven Wall and Stephen Brewster. 2006. Feeling What You Hear: Tactile Feedback for Navigation of Audio Graphs. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '06)*. ACM, New York, NY, USA, 1123–1132. DOI: http://dx.doi.org/10.1145/1124772.1124941

[52] D. Wang, C. Peng, N. Afzal, W. Li, D. Wu, and Y. Zhang. 2018. Localization Performance of Multiple Vibrotactile Cues on Both Arms. *IEEE Transactions on Haptics* 11, 1 (Jan 2018), 97–106. DOI: http://dx.doi.org/10.1109/TOH.2017.2742507

[53] Colin Ware and Peter Mitchell. 2005. Reevaluating Stereo and Motion Cues for Visualizing Graphs in Three Dimensions. In *Proceedings of the 2Nd Symposium on Applied Perception in Graphics and Visualization (APGV '05)*. ACM, New York, NY, USA, 51–58. DOI: http://dx.doi.org/10.1145/1080402.1080411

[54] G. B. Wetherill and H. Levitt. 1965. Sequential Estimation of Points on a Psychometric Function. *Brit. J. Math. Statist. Psych.* 18, 1 (1965), 1–10. DOI: http://dx.doi.org/10.1111/j.2044-8317.1965.tb00689.x

[55] Leland Wilkinson. 2006. *The grammar of graphics.* Springer Science & Business Media.

[56] Wesley Willett, Bernhard Jenny, Tobias Isenberg, and Pierre Dragicevic. 2015. Lightweight Relief Shearing for Enhanced Terrain Perception on Interactive Maps. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*. ACM, New York, NY, USA, 3563–3572. DOI: http://dx.doi.org/10.1145/2702123.2702172

[57] G. Yang, D. Ryu, and S. Kang. 2009. Vibrotactile display for hand-held input device providing spatial and directional information. In *World Haptics 2009 - Third Joint EuroHaptics conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems*. 79–84. DOI: http://dx.doi.org/10.1109/WHC.2009.4810831

[58] 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 (Dec. 2012), 2245–2254. DOI: http://dx.doi.org/10.1109/TVCG.2012.217

[59] L. Yu, K. Efstathiou, P. Isenberg, and T. 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. DOI: http://dx.doi.org/10.1109/TVCG.2015.2467202