Immersive Analytics: Crossing the Gulfs with High-Performance Visualization

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Abstract— Several trends are accelerating the flow from the analysis of data to the production of human knowledge. Powerful hardware and efficient software are producing large amounts of simulation and sensor data products. Analytic and decision-making environments are fusing more and more data sources and types for human sense-making. In this article, we present an approach to scaling High-Performance Visualizations (HPV) for human design, decision-making, and discovery. We consider visual analytics as an optimization problem of information channels between mind and computer, seeking to optimize throughput based on both computational and perceptual/cognitive principles. We reflect on the deployment of HPV display platforms in a university setting and consider the challenges and opportunities for scaling human interaction and perception in immersive analytics.

Index Terms— Scientific Visualization, Visual Analytics, Virtual Environments

Figure 1: Visualization Platforms in the Visionarium: Deep Six with X3D BioVis [1], VisCube with X3D NetVis [2]

1. Introduction

Faced with the stark asymmetry between the volume, variety and velocity of data and the capacity of the human analyst, it is clear that we must use our computing machines to do most of this work for us: transforming, representing, rendering our information into digestible, actionable chunks. This article describes our approach to scaling immersive technologies. At interactive frame-rates, more pixels and more perceptual cues (such as stereo or head tracking) can provide more information to the user through the computer-mediated experience. For example, we can scale the computer-mediated experience by varying the frame-rates, total pixels, and perceptual cues such as stereo and head tracking.

However, we quickly approach the limits of the human sensory system and working memory. In order to use those pixels and cues more efficiently and effectively, we consider the Cognitive Ergonomics approach of Donald Norman [3] and that of Colin Ware and his collaborators on considering perception for design [4]. This research is the genesis for our Information Theoretic approach to visualization and perception in Information-Rich Virtual Environments: to understand the carrying capacity of multiple sensory channels between human and machine, and to understand their attenuation and interactions when optimizing for information throughput.

There is a growing literature on the benefits of Immersion and HCI design approaches to 3D User Interfaces [5]. In this field, ‘Immersion’ is defined as objective technological components that can enable the subjective experience of ‘Presence’, harnessing the power of perceptual cues in the graphical message and the physiological cues in embodied interaction for better *human performance* (user productivity, insight, comfort, satisfaction). The productivity of users with computing tools requires usability; approaches like Usability Engineering [6] provide an effective lens to focus on the challenges of productivity and scale for end-users. Specifically in HPC and HPV systems characterized by **throughput**, we extend the metaphor to the communication between machine and mind and consider the design of interactive visualizations as an optimized transmission problem across multimodal channels (The ‘Gulf of Evaluation’ and the Gulf of Execution’. Our approach to High-Performance Visualization is ‘user-centered’ in that we consider user activities, tasks, their cognitive and perceptual capacities, biases and physiological factors as a primary focus.

In the Virginia Tech Visionarium Lab (vis.arc.vt.edu), we design, develop, and evaluate how different types of information can be transmitted across different displays and input devices. The lab provides a *spectrum of immersion* from mobile devices to game consoles to immersive projection systems (e.g. Figure 1). This enables us to study the task performance effects of various factors of Immersion such as: color gamut and brightness, screen size, screen resolution, stereoscopy, Field of Regard (FOR, screen surround), virtual camera aperture (software Field-Of-View, FOV), and head-tracking. It seems intuitive that these immersive platforms provide more bandwidth for the transmission of information between mind and machine; but how much? We must also consider the human side of the equation when trying to improve throughput within the given display and input channels. In this paper we attempt to frame the problem at the union of two rich research fields: Information Visualization and Virtual Reality.

2. Related Work

In this section, we review the literature on large high-resolution displays and the benefits of immersive technologies. There are fundamental trade-offs and questions that must be addressed in the visual design and delivery of immersive analytic environments. Through International Standards, such as

Extensible 3D (X3D), user interfaces to all the information services of the WWW can now include tracked projection environments, Stereo TVs, game controllers, and touch screens: across the spectrum, they provide varied and unique opportunities for natural and magic interactions across displays big and small [web3d.org]. Yet in order to leverage these additional channels that virtual environments provide for 3D visual analytic workspaces, we must make visualization design decisions that include finding appropriate: representation, lighting, materials, shading, scale, display and input devices, and the metaphors for navigation, selection and manipulation [7].

2.1 Large High-Resolution Displays

More pixels could mean that more information can be portrayed at once, but how perceptually scalable are visualizations on such large, high-resolution displays? Our collaborators at Virginia Tech also carried out a study to find out if some visualization designs can be more perceptually scalable than others on large displays [8]. Three different visualizations were used:

- Two were space-centric designs using embedded visualizations where the multidimensional data is overlaid onto a single large spatial structure, in this case a map of the United States
- One was an attribute-centric design where each attribute of the multidimensional data is on a separate spatial structure.

The independent variables were display size, visualization design, and task. Results showed that the designs used were perceptually scalable – that is, not resulting in an increase in normalized performance time or a significant decrease in accuracy. Accuracy only decreased from 95% to 92%, and a 20x increase in data resulted in only a 3x increase in task completion times.

Using a combination of perceptual abilities and physical navigation people were able to effectively use a 32 Mp display (2x Ware's proposed 16 Mp display). Results also showed that relative comparison between designs with respect to time and accuracy was typically the same regardless of the display size. However, based on user preference and workload, graphical encoding seems to be more important with less data on a small display whereas spatial grouping seems to be more important with more data on a large display. On the large display, both embedded visualization designs were generally significantly faster than small multiples. User preferences also switched on large displays, with most users preferring both of the embedded designs.

Cate et al. [9] conducted a study relevant to user perception in large displays: specifically their effect on ventral system processing. The ventral system of the visual cortex is generally considered the 'What' pathway (in contrast to the dorsal processing stream of "Where"). Users were asked to judge the concavity of shapes on a display with both a large FOV and a smaller FOV. Subjects consistently judged convexity for shapes that appeared large and concavity for smaller appearing shapes.

Studies conducted by Tan et al. [10] describe the importance of considering physical size of the display when designing display systems. The four experiments they conducted show that even with no additional performance aids, physically large-displays resulted in better performances across a wide range of tasks as opposed to smaller displays such as standard desktop monitors. The effects of physically-large displays persisted even when performing complex tasks such as 3D navigation. Their studies reveal that the effects of large displays were independent of other factors that induce immersion or improve performance.

Andrews et al. [11] have discussed in detail the critical issues that designers face for large, high-resolution displays and have also given an overview of the challenges and scope of opportunities for designing visualizations for these displays. They have raised several research questions, specifically, how to use additional screen space effectively, the order of effectiveness of various types of visual encodings, and types of spatial interactions with visualizations on large displays. In particular, they have emphasized the importance of physical navigation in supporting perception and interaction with visualizations on such large displays. They have also provided a set of design guidelines that may aid designers in creating effective information visualization applications for such displays.

In their early paper, Zhang & Norman [12] presented a theoretical framework for distributed representations which was based on the principle that a representational system is a set of both internal and external representations and that they together represent the structure of the task. They also proposed a methodology of representational analysis for the study of distributed cognitive tasks. They analyzed the Tower of Hanoi problem using their methodology. Their study helps in understanding the nature of cognition and in providing design principles for effective representations.

The spatialization of memory has a long tradition from the Greeks' mnemotechnics and this could be useful in the design of workspaces. For example, consider re-finding web pages in the Data Mountain - a 3D document management system proposed by Robertson et al. [13]. In the Data Mountain, the users could informally arrange their space in a personalized manner by placing the documents in arbitrary positions on an inclined plane. This user interface takes advantage of the user's spatial memory (i.e., the ability to remember where they kept an object). They ran a user study comparing Internet Explorer's Favorites mechanism (IE4), to an initial version of the Data Mountain and a revised version that incorporated the design changes proposed by the users of the first version of Data Mountain. In objective metrics such as Reaction Time, Number of incorrect retrievals and Failed Trials, the second version of Data Mountain performed better than IE4 and the first Data Mountain. Although the users of the first Data Mountain preferred Internet Explorer, eight out of twelve users of the second Data Mountain voted for Data Mountain.

Fink et al [14] studied the analytic tasks performed by Cyber Security professionals on large, high resolution displays. Their studies confirmed that large displays were indeed advantageous because of the amount of information that could be displayed. Over 533,000 snort alerts could be legibly displayed without the need of any interactions such as panning, zooming and aggregation. Their study concluded that the large, high resolution displays combined with more flexible and compelling visualization tools would make the core components of a usable workspace for cyber analysts. They also presented a set of design principles for usable workspaces for cyber analysts.

Endert et al.[15] analyzed the sensemaking task performed on a large, high resolution display using a system called LightSPIRE that provides basic text analysis functionalities such as searching, highlighting a text, annotating and document positioning. They analyzed the final layouts created by the users as well as the interactions they performed. They found that specific interactions can indicate important and distinguishing structures in the dataset. For example, they discovered that term co-occurrence metrics proved less useful since the clusters formed by the users were more focused on process-level concepts rather than keywords. Most of the clusters were formed based on transitive relationships between the documents of a cluster. When the user performed a search, important documents were returned as results more frequently than the non-important documents. The phrases that users highlighted within a document were sometimes important to the cluster definition. Thus the paper suggests that models can learn such higher-level concepts by taking cues from user interactions.

2.2 Why Immersion?

While Presence is possible to achieve with top-down methods (such as meditating, reading a book), Immersion focuses on bottom-up processing and therefore on using technology to create rich, believable sensory stimuli. Thus, immersive platforms provide additional sensory cues (information) for users beyond the graphics themselves: stereoscopy and head -tracking are two examples where the display modality provides more perceptual cues (visual, vestibular / somatic veridicality) to aid user comprehension.

Network Data

Immersive environments can improve performance for tasks involving 3D; we ran a study to examine the role of display fidelity (i.e., the realism provided by the display output) affects task performance for a variety of 3D spatial understanding tasks [16]. We hypothesized that higher display fidelity (specifically, increased FOR and the addition of stereo and head tracking) would lead to improved performance on 3D spatial inspections. We also expected an interaction effect between display fidelity and the level of visual complexity, where the higher display fidelity would yield greater advantages for visualizations with greater visual complexity. Similarly, we expected to see greater benefits of the enhanced spatial cues of higher display fidelity for more advanced task scope.

Using the Visionarium VisCube to display an abstract environment with a 3D undirected graph, we ran a 2x3x2x4x2 mixed experimental design for display fidelity (high and low), visual complexity (low, medium, and high), participant spatial ability (low and high), task type (intersection search, path following, connection identification, and length comparison), and task scope (simple and advanced), respectively. Participants in the high-fidelity condition used all four screens, view the imagery in stereo, and had head- tracking enabled. Participants in the low-fidelity condition did not have stereo or head tracking enabled, and only had one screen (the front) available to complete the tasks.

Display fidelity and spatial ability were studied between subjects, while visual complexity, task type, and task scope were varied within subjects. Our results show a strong positive effect of the level of display fidelity on speed for performing tasks, as well as a clear effect of visual complexity and task scope with higher levels of either type of complexity leading to slower performance. Since we use a generic 3D graph and tasks, our results can be extended for a variety of applications.

Volume Isosurfaces

A similar study was carried out in the VisCube with isosurface visualization, to investigate the effect of different levels of VR system fidelity (field of regard (FOR), stereoscopy (ST), and head tracking) on task performance with volume datasets [17]. The researchers chose to have two levels each: FOR (90º _and 270º), ST (on and off), and HT (on and off). The task categories include the following:

1. Search—searching for a feature in the dataset or counting the number of a particular type of feature
2. Pattern recognition—recognizing repeated characteristics or a trend through the dataset
3. Spatial judgment—judging the position and/or the orientation of a feature in a 3D spatial context, on an absolute or relative basis.
4. Quantitative estimation—estimating the numeric value of some property (e.g., density, size) of the dataset, a region, or a feature
5. Shape description—describing qualitatively the shape of either the whole or some part of the dataset

The study found that higher levels of fidelity resulted in improved task performance. In particular, stereo had the strongest effects on task performance (among FOR, ST and HT), with significantly better performance on several search and spatial judgment tasks. FOR improved performance in two spatial judgment tasks, and HT improved confidence in one search task.

Visual Scanning

Last year, a study was published on how immersive VR systems can provide more effective training [18]. The researchers investigated the effects of the realism, or fidelity, of the system, in particular they studied the effects of the training system's field of view (FOV) and visual complexity (the amount of detail, clutter, and objects in a scene) for visual scanning tasks. Their design follows the assumption that the purpose of the training is to prepare for a real-world scenario that would have high visual complexity and unrestricted FOV. To this end, participants trained in a VR system with a given combination of the FOV and complexity levels. Then, for a controlled comparison, they performed the task in a high-fidelity VR scenario with high visual complexity and high FOV.

The experiment followed a 3x3 between-participants design with FOV (high, medium, and low) and visual complexity (high, medium, and low) as the independent variables. Participants had to search virtual city streets to find between 12 and 18 targets in each trial. The study concluded that designers of VR training systems should use a high level of visual realism for tasks that involve visual scanning or visual search in visually complex environments. Also, the authors provided evidence that the direct measurement of learning is a better measure of training effectiveness than raw task performance.

The empirical value of large, high-resolution displays and immersive technologies for a diverse set of data types and task types leads us next to consider the union of these research areas.

Figure 2: Oculus DK2 with LeapMotion navigation in an X3D/X3DOM document analysis application (via WebVR)

3. Immersive Analytics

Immersive technology seeks to achieve a transparent cognitive experience and enable Insight through interactive, computational support. For example, more embodied cues for parallax (head tracking), or binocular disparity (stereopsis) or screen surround for natural management of focus and periphery can render more information to the human user. Meanwhile, the trends of hardware technology are bringing such virtual environment technology to users in the home and workplace. We consider two main approaches to using such immersive technologies:

1. to increase the bandwidth of the sensory modalities (display and input) or

2. increase the throughput of the existing channels (display and input). In the first case, we look at increasing the portrayal resources and the input channels of the system; in the second case, we seek to optimize the use of those resources (usability, efficiency).

3.1 Visual Display Bandwidth

We conducted an initial analysis of visual display bandwidth by looking at several measures attempting to quantify the amount of information that can be portrayed:

- The number of *v*isible pixels
- The number of *visible* pixels in the workspace (resolution x * y)
- The visual angle of visible workspace (vFOV * hFOV) in degrees

  The number of *available* pixels in the workspace (resolution x * y)
- The visual angle in degrees of available workspace (hFOR * vFOR)

In this analysis, we assume the refresh rate and the rendering frame rate are equal are equal across displays.

- The two LCD screen desktop workstation was measured as a 32.5 vertical FOV and a 96 horizontal FOV viewed at a distance of 60 cm. The screen pixel count was 3942000.
- We measured an HD TV with a vFOV of 87 and an hFOV of 154 at a distance of 100 cm.
- DeepSix tiled LCD display at 5750×2400 resolution; vFOV of 67.4, hFOV of 93.6 viewed at approximately 90cm; pixel count 13824000 (Figure 1, top)
- Oculus Rift (DK2) 960x1080 resolution was considered 100 degree FOV squared (Figure 2)
- The VisCube is our immersive CAVE-style system with three walls and floor, using Infitech passive stereo where 1920x1920 pixels are projected per 3.2 meter back-projected wall (top down for the floor). In March 2016 we are upgrading the projection system to 2560x2560 pixels active stereo per wall, this is the *HyperCube system*. The stereo glasses limit the vFOV to 102.6 and the hFOV to 116.8; the screens are typically viewed at an average distance of 1.6 m. (Figure 1, bottom)

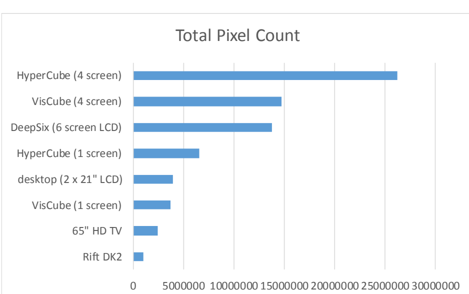

Figure 3: Total Pixel count of displays tested

We collected the best measures of vertical and horizontal Field of View for each platform and then multiplied them for a visual angle basis: total square FOV of the visible workspace (Figure). Pixels / degree is a measure of how densely information can be distributed in the workspace. Up to the limits of the human visual system, we expect some increase in (legible) information. Here we divide the total pixels by total FOV.

The Field Of Regard (FOR) is a measure of visual angle describing where graphic imagery of the virtual environment are potentially visible. This measure is used to describe virtual reality displays with screen surround such as the VisCube/HyperCube, or Head-Mounted Displays such as the Oculus Rift. In this case we can consider these displays as a separate class, which are qualitatively different than desktops or DeepSix: the increased available workspace in the periphery can provide an external, persistent Working Memory store above and beyond the active visible workspace.

These profiles are interesting, but is there a way to compare the potential immersive bandwidth of the Rift to the HyperCube? For these systems with extra available workspace outside the FOV (e.g. both capable of stereo and head tracking), we considered a ratio of the FOV to the FOR as the fraction of the workspace visible at a given time:

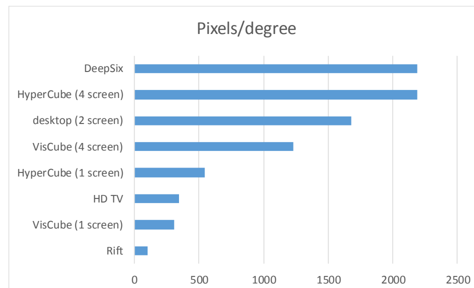

Figure 4: Pixels per Degree

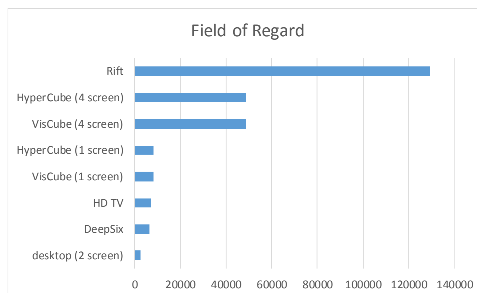

Figure 5: Field of Regard (FOR)

	FOV/FOR
Oculus Rift DK2	0.07716
VisCube/ HyperCube (4 screen)	0.246578

When considering the display systems' total visual bandwidth, for argument's sake, let's assume that all available workspace (FOR) is equal and the window of attention can carry the number of pixels per degree in the FOV. Then:

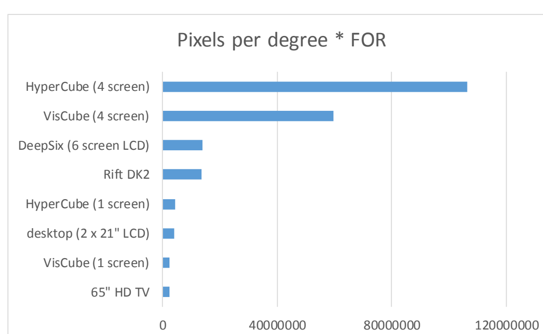

Figure 6: Metric for Total Display Bandwidth

3.2 Throughput

Rendering Big Data

Crucial to achieve the goal of throughput is to keep rendering framerates in the interactive regime. This becomes increasingly difficult with large, complex models. We ran a scaling study on a real dataset which consisted of viscosity, stress, temperature, velocity and vorticity information that illustrates the geophysical evolution of the planet Venus. The dataset consists of 100 time-steps and the visualization included the streamline, slice and glyph filters in ParaView. The mesh was 3,449,952 points and 3,145,728 hexahedral cells. The structured data comes from 96 processors and each processor has 100 files corresponding to each time-step for a total of 9600 files. The cumulative size of the files was observed to be 28GB. The results are shown in Figure 7.

This exercise was repeated for an unstructured mesh generated with 2,067,633 points and 12,790,098 tetrahedral cells with 18 time-steps. The unstructured data exists as a single XDMF file of size 11 GB and this includes the data corresponding to all 18 time-steps (Figure 8). This mesh was generated using Constructive Solid Geometry (CSG) and data in the form of random noise was added to the mesh in the form of a time-series. Structured grids can more easily benefit from spatial domain decomposition for efficient parallelization across multiple processors, but load balancing for unstructured datasets or datasets with no regular memory access patternsis still an open research area.

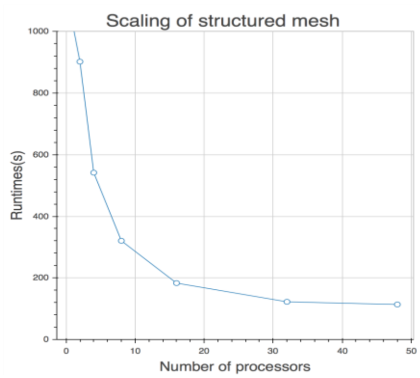

Figure 7: Parallel rendering of a structured mesh

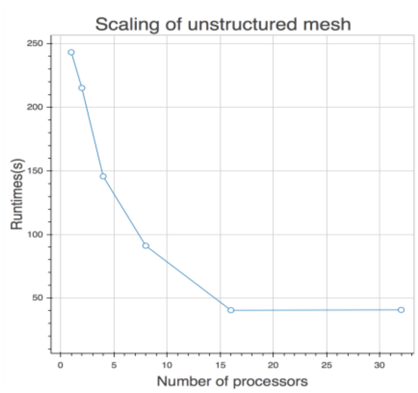

Figure 8: Parallel rendering of an unstructured mesh

Information-Rich Virtual Environments

Since Bowman et al [5] outlined a research agenda for Information-Rich Virtual Environments (IRVEs), a number of studies have shown how performance can be improved with in-scene labeling techniques and navigation types [19] and large displays [20]. We ran a series of studies examining the relative strength of perceptual cues in Information-Rich Virtual Environments (IRVEs) [21]. In these studies, users are required to search and compare information in the environment based on perceptual or abstract criteria.

We tested several parts of this design space for such 'information-rich' fundamental tradeoff of Association and Occlusion between spatial objects and their labels (annotations). In general, we see that reducing occlusion is positive for Search task time and subjective ratings, but can negatively impact Comparison performance (accuracy, time, navigation distance, and difficulty). Looking across the studies, we also observe that users value Depth and Association cues differently depending on the size of the display. Many of these factors are related: we have also observed an interaction between display size, information layout and software Field-Of-View where high FOV supports Search tasks and low FOW supports comparison tasks [22].

4. Research Agenda

The goal of analytics for the human is first sense-making and then decision-making. Analytics can be characterized by the challenge of fusing heterogeneous data types and sources in a usable and statistically-sound way. In Visual Analytics, we seek to efficiently deliver machine learning tools and visualization interfaces that scale to the strengths and weaknesses of human perception and interaction. In Immersive Analytics, we further that goal by providing a rich multi-modal experience and workspace for insight. There is great potential for using immersive technology to improve the bandwidth and throughput of HCI systems, and a deliberate research agenda is needed.

1.1.1.1 4.1 Displays

Our analysis of displays shows one way we might measure the bandwidth of immersive displays. While perhaps incomplete and controversial, the numbers do suggest some further hypotheses and research. For example, if we enforce the legibility criteria on the pixels/degree, how much information can each of these displays show? Can one read 10 or 40 pages of text from one viewpoint? How valuable is stereopsis for different tasks?

The development of hardware and optics of displays is still an open challenge. Tiled LCD platforms like DeepSix can provide a high contrast range and pixel density, however they can be limited in terms of surround and stereo; for example, the majority of high resolution display environments are flat. Using multi-angled panels in stereo mode presents challenges, such as described in installations like the CAVE2. We also believe that sonification and audio displays will be increasingly used to represent values and context in immersive analytic applications.

The display size is one of many factors effecting a user's perception. It is essential that researchers understand the low-level processes that drive 'chunking' and Working Memory. Many assumptions are built in at a pre-attentive, perceptual level. These may interact or re-inforce the known cognitive biases in humans. There are clear biases in human reasoning including confirmation bias, fundamental attribution error, blind-spot bias, anchoring bias, projection bias and representativeness bias [23] Interactive, decision-making tools can help mitigate and alleviate common mistakes due to these biases i.e. [24]. More studies must be done to understand the effects and mitigations enabled by different displays.

4.2 IRVEs

In immersive environments, we have great flexibility to design our workspaces. The spatial organization of workspaces is still largely unexplored. Prior research has shown how the depth and association cues can impact fundamental tasks like search and comparison; there is also strong evidence that the organization or objects in the world (spatial structure) can aid recall and re-finding. Thus, analytic workspaces and visualization layouts are ripe for investigation- as prior work has shown, the spatial organization of the workspace can drastically improve the usability and the productivity of an analytic interface.

In the case of IRVE layouts, we inventoried perceptual cues from psychology and a descriptive model was proposed. The series of experiments first showed how we can interpret the perceptual cues in a visual association as bits of information and how the receiver (human system) may weigh that information given the task and the other cues available. Rich areas for future exploration are to understand these thresholds of pre-attentive cues and the attenuations of perceptual processing of multivariate and multidimensional data.

4.3 3DUIs

Designers and developers for desktop Information-Rich Virtual Environments face additional challenges of efficient input throughput in mapping 2D render projections and image plane techniques into 6 Degree Of Freedom (DOF) transformations such as for the camera and pointing devices [25]. While adding Degrees-Of-Freedom (DOFs) to an input device does increase the bandwidth of the device, these need to be matched to the task and the human operator [5]. 3D User Interface techniques such as distal pointing, SQUAD [26] can improve user performance (throughput) within a given display and bandwidth. With such research, the metaphors and methods of Immersive Analytics will continue to grow and improve.

5. Acknowledgments

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