This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2019.2929033, IEEE Transactions on Visualization and Computer Graphics

Survey of Immersive Analytics

Adrien Fonnet and Yannick Prié

Abstract—Immersive analytics (IA) is a new term referring to the use of immersive technologies for data analysis. Yet such applications are not new, and numerous contributions have been made in the last three decades. However, no survey reviewing all these contributions is available. Here we propose a survey of IA from the early nineties until the present day, describing how rendering technologies, data, sensory mapping, and interaction means have been used to build IA systems, as well as how these systems have been evaluated. The conclusions that emerge from our analysis are that: multi-sensory aspects of IA are under-exploited, the 3DUI and VR community knowledge regarding immersive interaction is not sufficiently utilised, the IA community should focus on converging towards best practices, as well as aim for real life IA systems.

Index Terms—Immersive analytics, survey, virtual environments, immersive environments, data visualization, information visualization, scientific visualization, visual data mining.

1 Introduction

Immersive analytics (IA) was defined in 2015 as ”the applicability and development of emerging user-interface technologies for creating more engaging and immersive experiences and seamless workflows for data analysis applications” [1], and more recently as ”the use of engaging, embodied analysis tools to support data understanding and decision making” [2].

The idea to use immersive technologies to carry out visual data analysis tasks is not new [3] and many proposals have been made since the early nineties. Indeed, the interest of researchers in the use of immersive technologies has been driven by the ability to represent 3D data in 3D, as well as the possibility to better exploit human perception capabilities, and to make use of embodied perception and interaction. The contemporary development and structuring of the field (attested by scholar meetings [4], [5] and conference workshops [6], [7], [8], [9] in the last years) is mainly related to recent technological breakthroughs providing affordable and high-quality immersive hardware and software.

This availability of supporting technology led to a rising number of system proposals and scientific contributions. However, no survey article has been published that would help newcomers embrace the variety of three decades of developments in IA. The most notable surveys in the field focus on specific scientific domains, and do not cover IA as a whole. For instance, Bryson et al. [10], Simpson et al. [11] and Van Dam et al. [12] focus on scientific visualization through the use of Virtual Reality (VR) technology, and Ben Said et al. [13] focus on visual data mining exclusively. Therefore, our aim is to provide readers with an exhaustive survey of IA works from 1991 [14] up to the present day. In particular we want to provide a quick access to all the technologies, sensory mappings[1], and interaction techniques that have been implemented in IA systems, as well as propose directions worth investigating.

• *A. Fonnet and Y. Prié are from LS2N UMR6004 CNRS Univ. of Nantes. E-mail: {adrien.fonnet,yannick.prie}@univ-nantes.fr*

Manuscript received December 20, 2017; revised February XX, 2018.

1. We use the term *sensory mapping* over *visual mapping* since IA systems are meant to use all senses.

1.1 Method: corpus building and analysis

Since no clear IA domain had been established before 2015, no particular venues or keywords specifically gather contributions together. We therefore conducted a systematic but open investigation with the main scientific search engines (IEEE Xplore, ACM Digital Library, Science Direct, Springer Link, or Google Scholar), using search terms that cover both data analyze processes (e.g. visual data mining or data visualization) and immersive technologies (e.g. immersive environment or virtual reality). Specific journals, conferences, and workshops were also covered, such as TVCG, IEEE Vis, or IEEE VR, as well as the full bibliography of key scientists. The search stopped when papers' references were not bringing any new articles to the survey's collection.

The initial criterion for a paper to be included in our corpus was that it must contain a thorough description of an Immersive Analytics system. First, we favored the definition of [1] over that of [2] since it provides clearer limits, and therefore is better suited for a survey paper. Second, as the visual channel is the most commonly used to provide immersion, we considered that the ”emerging user-interface technologies” of [1] must at least have 3D graphics, stereo, and head tracking (see Section 2). Third, the systems had to be interactive (i.e. at least with navigation and selection) for users to perform data analysis (i.e. explore data representations and gather insights). However, our criteria excluded many papers that we deemed important, especially after so many years without a survey covering the domain, such as evaluation papers focusing on the effect of rendering technology, or position papers discussing the future of IA. That is why we also included papers without full IA system descriptions, but that clearly stated in their introduction that their goal was to contribute to the design of interactive immersive systems supporting data analysis

The search, completed by the end of year 2018, constituted our corpus (n=177). The analysis of the publication dates (Fig. 1) shows a steady increase, with a slight peak in the late nineties and a recent burst.

Initially, the corpus revealed the domination of two main types of papers, those describing an *IA system* and those

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2019.2929033, IEEE Transactions on Visualization and Computer Graphics

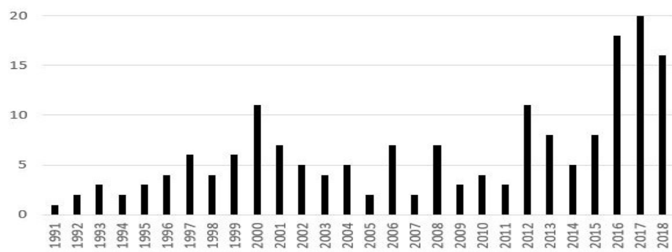

Fig. 1: Literature corpus over the years

related to *evaluation* linked to IA research (papers could be both). For each type of paper, we further extracted relevant information in a systematic way.

For the *system* papers (n=127)[2], we extracted the system name, target users, application domain, and the purpose of the application. We categorized systems by immersion category, leading to one hundred and four papers concerned with virtual reality (VR), fifteen papers with augmented reality (AR), and six with wall displays. Two papers [15], [16] used an atypical solution, that is why their category remained blank. We also described the rendering technology used to display the visualization. Then, we focused on the data, gathering the description of the dataset used by the application and its main category. Dataset categorization was inspired by Shneiderman's taxonomy [17] and resulted in the following distribution: spatial (36 papers), temporal (7), spatio-temporal (43), multi-dimensional (24), and graphs & trees (17). We also described sensory mappings, i.e. how the dataset attributes were represented in the visualizations. Moreover, we systematically analyzed each system according to the low-level interaction tasks it allowed. These tasks, based on the taxonomy of Brehmer and Munzner [18], are the following: navigate, select, details on demand, arrange, change, filter, aggregate, annotate, import, derive, and record. If a task was available, we completed its description with the input device(s), the action to be performed, and the output. Last, we checked if the system featured collaboration. There were fifteen papers that adhered to this criterion, and we completed their description by capturing aspects of the collaboration such as synchronous/asynchronous, same/different physical place, same/different visualization, and modes of communication.

For the *evaluation* papers (n=68), we split the category between IA system evaluations (28), evaluations comparing IA with non-IA systems (26), and evaluations assessing which technologies, representations, or interactions were better within the same IA system (14). We extracted data types and representations, dependent and independent variables, tasks, quantitative, and qualitative results.

The remaining papers (n=21) were categorized based on their type, i.e. survey paper, position paper, or framework, and the main idea they conveyed was described.

1.2 Structure of the survey

The main objective of this survey is to provide a quick access to all the technologies, sensory mapping, and techniques that have been implemented in IA systems over the last three decades. Based on the quantity of papers describing IA systems and the quantity of information to convey, we decided to focus our survey on these papers, that is why the first four sections are dedicated to the description of IA systems. To ease the reader's understanding, we start in section 2 by presenting the various immersive technologies used, so as to provide a description of the physical systems. Then, we focus on data representation and analysis goals in section 3 (summarized in table 1), and on interactions means in section 4 (summarized in table 2). Section 5 is dedicated to the study of the specific aspects of collaborative IA systems. Section 6 then covers evaluation papers. Our second objective is to determine the main challenges of IA and directions worth investigating in the near future. Each section ends in a discussion, while Section 7 gathers our findings and builds upon them to outline some orientations for IA.

2 Technologies

Various technologies have been used in IA systems. Our choice to determine if a technology is immersive is to focus on its fidelity aspect, instead of considering a presence feeling, as stated by Slater [19]. Therefore, our criteria in this paper are that those systems must offer 3D graphics, stereo vision, and head tracking. In each subsection we focus on one immersive rendering technology, and on the main associated input devices, following a chronological order (see Fig. 2 for an overview timeline).

2.1 BOOM: Binocular Omni Orientation Monitor

The Binocular Omni Orientation Monitor (BOOM) is a counterbalanced CRT-based stereoscopic display implemented in 1990 [20]. It is composed of a robotic arm fixed on the ground with each joint angle managed by microprocessors and motors to ensure moving the structure requires low energy from the user. A stereoscopic display is located at the end of the arm where the user places his head to enter the immersive environment. Position and orientation are computed owing to sensors located at each joint.

This system was used by Bryson et al. to implement scientific visualization applications such as the virtual wind-tunnel [14]. The goal of the system was to effectively visualise 3-dimensional unsteady flow patterns to understand them despite their complexity. It allowed the user to inject particles and observe their trajectories within a pre-computed unsteady flow (3D vector field) while the simulation was running. Distributed computing was employed to ensure interactivity and attain the minimum frame rate (8 fps) required to guarantee immersive illusion [21]. One cluster of computers was dedicated to compute the result of the simulation and a second to compute the visualization's rendering, both communicating through a network.

All BOOM IA systems used two input devices: a classical keyboard and a data glove. The ease of entering and leaving the immersive environment made it easy to use a keyboard to change visualization parameters, although it broke immersion. Data glove interaction in immersion used electromagnetic field tracking, which required the control of

2. Those systems are described in more details on the companion website at http://www.immersiveanalyticssurvey.org.

Fig. 2: Timeline of the rendering technologies used to implement immersive analytics system

the workspace environment not to disturb the measure, as well as a calibration phase prior to each use.

2.2 Surround-Screen Display

The first surround-screen display technology, called Cave Automatic Virtual Environment (CAVE), was implemented by Cruz-Neira et al. in 1993 [22]. This initial implementation consisted of four walls (right, front, left, and floor) each one associated to a 120Hz projector. Head-Tracking was managed via electromagnetic sensors allowing the capture of the position of the stereoscopic glasses. The CAVE was used for scientific visualization, e.g. simulation about the formation of the universe, 3D reconstruction of MRI data, or climate data visualization [23]. Multiple concessions had to be made to reach the required frame-rate (10 fps), e.g. limiting the size of the dataset, simplifying algorithmic calculation with approximation, and decreasing the quality details of the rendered scene [24]. Multiple declinations of the CAVE were implemented during the first decade of the twenty-first century, with different numbers of walls (from 2 to 6) of varying sizes, and hardware improvements (cluster of computers, projectors, tracking technology).

The next decade led to more radical changes. Allosphere is a 10-meter spherical-shaped CAVE built in 2007 [25]. The associated Allobrain project led to the implementation of an IA application for immersive navigation of brain data extracted from functional Magnetic Resonance Imaging (fMRI) [26]. The CAVE2 [27] and the Reality Deck [28] are CAVE-like systems that were built respectively in 2013 and 2015 from the ground up for IA, focusing on the collaborative aspects of data analysis. These systems used tiled-display instead of projectors, greatly improving the resolution over classical CAVE. Floor projection was also discarded to ease the occupation of the central space by a full team, hence cutting on the immersion to provide more physical collaborative space.

The main source of input for CAVE were 3D mice tracked over 6 degrees of freedom, with multiple buttons and a joystick, called a wand. They combined the advantages of introducing the position of the user's hand to the virtual world with a simple controller input. A few works also explored the use of data gloves in CAVE [29], [30].

2.3 FishTank VR

The FishTank VR concept was introduced by Ware et al. in 1993 [31]. It consisted of a monitor screen combined with stereoscopic glasses and an external head-tracker, providing all the required components for an immersive experience at an affordable cost. The field of view was limited, but resolution and brightness were superior to projections-based systems. Another characteristic of FishTank VR was the use of a keyboard as the main source of input, since the overall setup is close to a 2D desktop. Ware et al. used this technology to visualize object-oriented software with a network representation. They confirmed their initial hypothesis that adding an immersive component to a system, i.e. stereo and head-tracking, increased both the perceived and understood information for graph analysis [32].

2.4 Responsive Workbench

The responsive workbench appeared in 1995 [33]. It used stereoscopic glasses and external head-tracking with a projection based horizontal screen. This choice was made to target specific workers for whom the workbench metaphor, i.e. working over a table, was deemed useful such as doctors (medical training), automotive engineers (windtunnel), and architects (architectural design) [33]. Input devices were diverse: data glove [34], wand [35], or tracked stylus [36].

Like the CAVE and the FishTankVR, such systems only provided one user with the correct perspective, which led to issues in collaborative settings, e.g. finger pointing to show a point of interest did not work. A two users' solution for the responsive workbench was developed in 1997: both users had head-tracking while the screen displayed 4 images per frame (2 users $\times$ 2 images for the stereo) [37].

2.5 HMD: Head Mounted Display

Head Mounted Display (HMD) has been used to render immersive environments since Ivan Sutherland's first prototype [38]. However, the small resolution of the system was judged unfit for data analysis until the late nineties. Indeed, the oldest IA references in our corpus that use HMD were published in 1997 with the Virtual Data Visualizer for VR molecular data simulation analysis [39], and the Studierstube, for augmented reality (AR) dynamical system analysis using the Virtual IO i-glasses [40]. Use of HMD remained sparse in the context of IA after year 2000, with only a few attempts, e.g. [41], [42], but the arrival of the Oculus Rift DK1 in 2012 brought about a renewed interest. This first version was still limited due to the lack of positional head-tracking and researchers had to overcome this first hurdle with external tracking systems to generate proper immersive environments [43]. The last generation of HMD —such as Oculus Rift [44], HTC Vive [45], Meta 1 [46], or Microsoft HoloLens [47]— provided high resolution, stereoscopic rendering, and head-tracking, while remaining affordable, putting them in a perfect position to become privileged IA hardware for the years to come [48].

HMD systems have been associated with various input means for IA. Data gloves were used in the late nineties

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2019.2929033, IEEE Transactions on Visualization and Computer Graphics

e.g. in [41]. The use of bare hand(s) movement was later explored to interact with the virtual or the augmented world, with Oculus Rift HMD and LeapMotion [49] trackers [50], or HoloLens [51]. IA researchers also rapidly adopted controllers as soon as they were shipped with VR HMDs (e.g. HTC Wand and Oculus Touch) [52]. IA HMD-based systems have mostly been designed for standing users.

HMDs have also been used for IA in conjunction with high resolution displays. For instance, Nagao et al. [53] used the Meta 1 with a 8K screen, allowing the preview and tuning of parameters of a visualization in the HMD, before computing the entire scene for the screen, thus saving a lot of computation power and ensuring adequate frame rate while managing complex visualizations and datasets. Another approach was to provide dedicated information in the HMD while the main screen or table was used for shared information in collaborative settings [54], [55].

2.6 Discussion

The rendering technologies used in IA are constantly changing. The BOOM was used in the nineties but there is no mention of it in our corpus after 1994. The CAVE had to evolve to remain relevant, switching from projectors to tiled-display. FishTank and workbench systems have been widely used, but not so much in the past few years, maybe because of the current focus on HMDs pushed by the gaming industry. In addition, a variety of new input devices have regularly been proposed that open the design space of interaction possibilities for IA, such as data gloves or trackers which allow the tracking of all 6 degrees of freedom of any object they are attached to. It must also be underlined that in the past 6 years the most used immersive technologies (HMDs) have not been built with IA as their main target, and researchers using them had to compose within their limitations. As a conclusion, the lasting IA dependency on the relatively volatile available technology may have induced volatility in the field, which is still struggling to develop its core concepts and techniques.

3 Data and Sensory Mapping

Various categories of data have been used for immersive analytics. We considered the five categories defined in Ben Shneiderman's taxonomy [17]: *Spatial*, *Temporal*, *Spatio-Temporal*, *Multi-Dimensional*, and *Graphs and Trees*, and we focused on data representations and sensory mapping. We use the term *sensory mapping* to describe the projection of data attributes onto sensory channels, as a generalization of *visual mapping* that is more appropriate for IA.

Table 1 provides an overview of the papers presented in this section. The column category is based on Nesbitt's four main modalities to encode data [56]: spatial, visual, sound, and haptics. The spatial category has been renamed as "position" to avoid confusion with the spatial data type.

3.1 Spatial Data

Being spatial in nature, immersive environments are a natural choice for presenting spatial data.

Position is the main channel used to encode spatial data information, with two main approaches: data elements can be placed on top of a map, or relative to a 3D model. For geo-localized data, the battlefield decision-making Dragon system [35] displayed units over a 3D representation of a map, at the location of latest report. A similar application was recently proposed to help fight against maritime smugglers and coordinate action between agencies [55]: entities such as boats and drones, were displayed on top of a tangible map of the maritime shore using AR. Archaeological systems also used such mapping by placing each found item at its position of extraction over a representation of the excavation site. The ARCHAVE system opted for a flat dark gray texture to represent the excavation site [66], [67] while VITA (Visual Interaction Tool for Archeology) [42] and ArtifactVis2 [68] implemented photogrammetry. The ENDURANCE project [57] proposed a reconstruction of Lake Boney in the Antarctic on top of which measurements (bathymetry scanning and water chemistry profiling) were positioned. Lechner et al. system [127] allowed visualization of water chemistry measurements made in the mid-Atlantic states of the USA. VRGE [59] displayed a 3D representation of earth mineral resources showing various layers and measurement uncertainties. Mahmood et al. system [58] supported bio-diversity analysis by displaying animal species' locations over multiple 2D maps occupying the 3D volume.

Other proposals used virtual or real 3D models as their base for spatial data placement, mostly in the medical imaging context. Some systems proposed 3D model of brains reconstructed from CT (computerized tomography), MRI (Magnetic Resonance Imaging) and fMRI (functional MRI) data [60], [62], [64], [128]. This type of 3D body model representation could also be complemented with 2D slices for doctors to import their previous scans inside the immersive visualization [63], [69]. Instead of using a classical network approach with force placement algorithm, Keiriz et al. [65] took advantage of the spatial structure of the brain to place connectome data in their NeuroCave system: each node was located at its true position in the brain. Gillet et al. [61] placed electrostatic field representations using AR around a tangible model of a macro-molecule.

The AR ARSAM tool for industrial factory layout planning allowed users to modify layouts in-situ and then visualize the production line [51].

Visual. The main strategy for representing geo-localized data elements is to use 3D glyphs. Several archaeological systems described findings by associating shapes to findings' types and colors to cultural origins or materials [42], [66]. The Dragon System [35] represented troop squads with boxes and more prominent units (tanks, ships, and planes) with 3D models. Color, opacity and 3D icons were used to depict allegiance: allied units were represented with a semi-transparent blue texture with an American flag located next to them, while enemy troops appeared with darker red skull flag. Color was also used in medical imaging to encode transfer function [64], or degree of anisotropy [128].

Sound was used by two systems in our corpus. Frölich et al. [70] proposed a system to analyze well log data where one numerical attribute was encoded using a Geiger counter metaphor, the velocity of the ticks indicating the value of the attribute. Lombardo et al. [71] proposed a visualization of macro-molecules using solvent extruded surfaces for ligand-receptor interaction study. The selected ligand emitted a 3D

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2019.2929033, IEEE Transactions on Visualization and Computer Graphics

TABLE 1: Overview of the sensory mappings proposed in the IA literature

Data Type	Category	Sensory Mapping	References
Spatial	Position	Geo-localized data on top of a map representation	[35], [55], [57], [58], [59]
		Localization over a 3D model	[60], [61], [62], [63], [64], [65]
	Visual	3D model	[35], [51], [55], [61], [64]
		3D Glyph - Shape, Color, Opacity	[42], [58], [59], [65], [66], [67], [68]
		Texture - 2D slice in medical imaging	[63], [64], [69]
	Sound	Geiger counter metaphor	[70]
		Simple tone to indicate structure presence	[71]
	Haptics	Surface force feedback	[72], [73]
Temporal	Position	3D Scatterplot	[74], [75], [76], [77]
	Visual	Dots	[74], [78]
		Basic shape with color	[75], [76], [77]
	Sound	-	-
	Haptics	-	-
Spatio-temporal	Position	Particle/molecule position in simulation volume	[14], [39], [79], [80], [81], [82], [83], [84], [85]
		Geo-localized data on top of a map representation	[37], [50], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98]
		Axes to represent non spatial attributes	[39], [90], [91], [99], [100]
	Visual	Size of 3D object	[95], [101]
		Arrows for vector field	[82], [88], [89], [101]
		Isosurface	[82], [88], [89], [101]
		Heatmap	[94]
		Colors	[37], [39], [79], [84], [90], [91], [92], [94], [97], [101]
		Lines to represent trajectories	[37], [93], [94], [97], [98], [99]
	Sound	Midi notes to represent an averaged value	[80]
		Air-rushing metaphor	[81]
	Haptics	-	-
Multi-dimensionnal	Position	3D scatterplot	[41], [102], [103], [104], [105], [106], [107], [108], [109]
		Parallel Coordinates	[52], [110]
		Based on clusterization algorithm	[111], [112]
		Based on query result	[113]
	Visual	Colors	[41], [102], [103], [104], [105], [106], [108], [109], [113]
		Size	[41], [102], [103], [104], [105], [106], [108], [109]
		Shape	[102], [103], [104], [105], [106], [108], [109], [113]
		Texture	[106], [109]
		DOP (Dynamic Object Properties)	[104], [108]
		Line	[52], [110], [113]
	Sound	Spoken number for categorical attribute	[108]
		Pitch interpolation for numerical attribute	[108]
	Haptics	-	-
Graphs and trees	Position	Node/edge diagram	[32], [114], [115], [116], [117]
		Encapsulation of element	[118], [119], [120], [121], [122], [123], [124], [125], [126]
	Visual	City metaphor	[118], [121], [124], [125], [126]
		Other metaphor (World, Solar system)	[119], [120], [121], [122], [123]
		Node/edge properties	[115]
	Sound	-	-
	Haptics	-	-

sound to indicate its localization, so that its position was always available to the user even when occluded.

Haptics was only used by two systems, both dedicated to macro-molecules visualization, the user being able to feel the outside surface of spheres [72], [73] or the inside of curved tubes [73] with a haptic pen device.

3.2 Temporal Data

Temporal data seems to be under-represented in our corpus, we hypothesize that this is due to its non-spatial nature and its arguably less complex nature compared with multi-dimensional or graphs and trees data, making it less attractive for immersive environments.

Position. Moere et al. [78] proposed a system to investigate the financial data of their university in a CAVE, considering budgets, departments, and number of students over time. They introduced the concept of infoticles where each datapoint was represented by a particle generated by a circular seed point that represented a specific table of the dataset. Each particle had a limited timespan based on the actual timespan of the entity in the university, and was affected by attractive forces generated from filters (see section 4.6 for more details). Nesbitt et al. [74] implemented an IA system to support traders in their stock market data analysis. Time was represented with an axis, and the time window ranged from a single day to several months. Stock prices, volumes, and moving average prices over a period were encoded using the two remaining axis. HeloVis [77] was a radar signal IA tool that allowed signal intelligence operators to determine the source of each signal. Datapoints were placed on a helical scale representing time. The IDEA system [75] presented users activity logs as a 3D cylindrical scatterplot: each axis encoded one of the main attributes (date/time, users, and event types), and was represented by an arrow with ticks and labels. DebugAR [76] presented distributed system logs to programmers for debugging purposes. Each event was represented by a sphere in augmented reality on top of a tablet placed horizontally on a desk. The height encoded time, the current analyzed time step being placed at the desk level. The messages exchanged between systems were encoded by a line.

Visual. Color is largely used to provide additional information about temporal data elements. HeloVis [77] used color to encode frequency, level, or width of the pulse, IDEA [75] to encode event types. In DebugAR [76], datapoints and lines colors respectively encoded the system emitting the logs, and the types of messages.

Sound and Haptics were not exploited for temporal data

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2019.2929033, IEEE Transactions on Visualization and Computer Graphics

in the papers of our corpus.

3.3 Spatio-Temporal Data

Spatio-temporal data have been used in IA systems since the virtual windtunnel [14] (see section 2.1). Displaying results of 3D simulations with both complex and inherently 3D data was indeed one of the driving forces that pushed the development of IA systems.

Position is logically used to display spatial positions of simulation data. Molecular simulations have been visualized in immersive environments to provide insights to chemists and doctors, e.g. deep understanding of drug compound interactions [39], [79], [80] or blood damage analysis [85], showing particles at their computed location for each time step. CFD simulation used 3D flow fields [14], [81], [82], [84]. Moreover, as it was the case for purely spatial data, temporal geo-localized data have also been largely used in IA systems. One important domain is atmospheric and oceanographic data analysis to support climatologists, objects of interest being placed on top of map representations [50], [86], [87], [88], [89], [90], [91], [92], [95], [101]. Trajectory data are also geo-localized data but are represented by lines that cover the full duration of the trajectory instead of discreet elements [37], [93], [94], [97], [98]. Cunningham et al. allowed users to explore law enforcement's texts logs [96]. They represented each text entry with a graph of its named entities, figured as icons, and relations, the icons being linked to a 2D map if they referred to a location. Interestingly, a few works used one spatial dimension of the environment to represent non-spatial information. The Virtual space time allowed physicists to observe the complex geometry of curved space time by displaying geodesics [99] with one dimension encoding the time; the virtual data visualizer [39] could encode molecule velocities on one spatial dimension, similarly to [90], [91] which displayed the power of earthquake on the height axis. The tangible Braille plot [100] was a supportive system to analyze movements of entities, e.g. people or vehicles, around a location of interest (LOI). It used a cylindrical coordinates system where radius and angle encoded the distance and orientation from the LOI, and height the time.

Visual. Flow field for CFD simulation have been represented with arrows providing direct perception of the direction and orientation of the flow [14], [82]. Similar representations have been used for atmospheric simulation and analysis to represent water and wind flows [86], [87], [101]. Isosurfaces could represent environmental variables, e.g. temperature, water density, or pressure [86], [87], [88], [89], [101]. Color has been used for all types of spatio-temporal data: the virtual data visualizer [39] used it to encode molecule velocity, [84] for air pressure, [90], [91] for the magnitude of the earthquake, [92] for the disease's category of a new reported case, and I-flight [94] for the bees' roles or behaviors when analyzing bees' trajectories. Color gradient was used in [97] to display the orientation of plane trajectories, line width encoding traffic. Last, [95] represented weather precipitation values as measured by sensors directly with the heights of a 3D bars.

Sound has been used in two papers: Wesche et al. [81] used sonification to display the flow field magnitude of a CFD simulation with an air-rushing sound metaphor; [80] used it to display the overall energy of the molecular system in the current simulation step by playing a specific pitch.

Haptics has not been used in any paper of our corpus to encode attributes of spatio-temporal data .

3.4 Multi-Dimensional Data

Systems in this section have all been designed for visual data mining, where users try to obtain insights from correlations, clusters, or outliers. The datasets vary a lot, from classical machine learning iris or wine databases [106], [112], to car [107], [129], demographic [41], [52], [102], genomics [111], [130], or forest databases [104], [105], [108].

Position is most commonly used to encode one attribute per dimension of the 3D environment, effectively creating 3D scatterplots. Indeed, 11 papers out of 17 use such representation [41], [102], [103], [104], [105], [106], [107], [108], [109], [129], [131]. Other possibilities have been explored, such as 3D parallel plane coordinates [52], [110], projected 2D scatterplots corresponding to the physical position of the user within the virtual environment [130], algorithmic positioning with SOM (Self Organizing Map) [112] or BLAST [111], user query based so that relevant datapoints move close to the user [113], or even self-created by the user with ImAxes [129].

Visual. Additional attributes of 3D scatterplots datapoints have been encoded using various visual channels: color [103], [104], [105], [106], [108], [109], [131], shape [105], [106], [108], [109], size [103], [105], [106], [108], [109], [131], or texture [106], [109]. The 3DVDM (3D Visual Data Mining) approach added dynamic object properties, proposing to use vibration, rotation, or blinking of 3D glyphs to encode additional attributes [104], [105]. For parallel plane coordinates, the lines' colors were used to encode more information and de-clutter the visualization [52], [110], [129].

The **Sound** channel has only been used once in our corpus to encode numerical and categorical attributes in a second version of 3DVDM [108]: the numerical attributes were represented with pitch interpolation and categorical attributes with spoken numbers. Only the datapoints in a sphere centered on the analyst were emitting sound, the analyst controlling its diameter.

The **Haptics** channel was not used by the papers in our corpus to encode additional attributes.

3.5 Graphs and Trees

Position. Software visualization has been one of the driving domains for tree data use in IA, with the objective to make it easier and faster for code maintainers to familiarize with source code, and detect important and interesting areas in it. Most systems used a city metaphor to represent source code [118], [119], [120], [122], [123], [124], [125], [126], position being used to organize elements based on their proximity in the tree. For graph data, node placement has generally been determined by force generation algorithms to limit the occlusion of the node-link visualization [32], [114], [116], [117].

Visual. FileVis (1998) [118] represented each file with a pedestal with an icon depicting its type (sphere for definition, or cylinder for declaration). Color similarity

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2019.2929033, IEEE Transactions on Visualization and Computer Graphics

indicated two pedestals had the same file names. Small blocks representing functions were placed on pedestals, the blocks heights encoding the number of lines, and the colors reflecting the complexity, from low (deep blue) to high (bright red). SofwareWorld (1999) [119], [120] represented the whole software as a world, a package being a country, a file a city, a class a district, and a method a building. The size of a building represented the numbers of lines of the method, the number of doors the number of parameters, and the number of windows the number of declared variables. The color of a building indicated whether the method was private or public. Imsovision (IMmersive SOftware VISualizatiON, 2001) [122], [123] represented a class with a platform, whose size encoded the total number of methods and attributes. Attributes were represented as red spheres near the platform, their size encoding their type. Members functions were represented by columns placed on the platforms, with colors encoding their type, i.e. constructor, accessor, and modifier, and height the number of lines of code. SkyscrapAR [124] considered software evolution: the user could look at the evolution of the city by moving between multiple versions of the software. This allowed representation of attributes such as code churns (number of modified, added, and deleted lines over the life of a file), and biggest lines of code (highest number of line for a file based on all its versions). These were represented within the building metaphor with building height linked to code churn, the base area encoding the current lines of code, while a green square at the bottom represented the surface occupied by the building in its biggest state using a garden metaphor. Such representation quickly allowed maintainers to see which part of the code had gone through many changes (skyscrapers), or to find deprecated functions (large gardens with tiny buildings). ExplorViz proposed a novel attribute representation by showing communications between packages as orange lines, whose widths encoded call frequencies [125], [126].

A few systems used visual mapping to provides additional information about graph data attributes. Genome3DExplorer [115] allowed the exploration of the Yeast gene block duplication (chromosome database): nodes were represented as spheres, their values being encoded by size, shape, transparency and color, the values of edges were encoded by length, shape, transparency, and color. Russo Dos Santos et al. [121] also proposed a metaphor of a solar system to represent network services data.

Sound and Haptics were not exploited for graphs and trees data representation in the papers of our corpus. A unique paper falls outside Nesbitt's taxonomy by exploring the use of smell for crypto-currency market analysis [132]: the average transaction rating of an entity was converted into a nominal attribute with six distinct values, and displayed through six different smells, such as citrus or floral.

3.6 Discussion

IA systems cover a wide spectrum of datasets and analysis objectives, from scientific visualization of CFD simulation or brain data to software visualization. This huge variety of works leads to additional complexity when it comes to federating a community and building best practices, though a few attempts in that direction have been made for multi-dimensional data representation [104], [133]. Some trends can also be noted in specific domains: software visualization often used a city metaphor, multi-dimensional datasets have mainly been visualized with 3D scatterplots, and oceanography and climatology solutions always used isosurfaces and vector fields. Last, despite the multi-sensory aspect of IA, the focus of research is heavily biased toward visual representation. Only two papers in our corpus made use of the haptic channel to encode information, and sound has been scarcely used.

4 INTERACTIONS

This section is dedicated to presenting the interaction modalities for the IA systems in our corpus, organized by data analysis tasks. The tasks are taken from the taxonomy of Brehmer and Munzner [18]. We chose it over the taxonomy of Laha et al. [153], whose goal oriented-approach did not fit our focus on interaction, and that of Keefe and Isenberg [154], which is more interaction-oriented but lacks critical low-level tasks, such as annotate or record. Table 2 gives an overview of the tasks and main interaction modalities. Tasks have been sub-specified into categories to further structure the sub-sections.

4.1 Navigate

The navigate task covers interactions that alter the viewpoint of the user. Most immersive technologies include head tracking, allowing their users to navigate virtual worlds with physical movements. Additional navigation modalities must, however, be implemented when the total volume of the visualization becomes bigger than the available physical space. Only BOOM solutions (where movement range is determined by the robotic arm) altered the 1 to 1 movement law between the user head and the camera displacement by having a faster virtual movement outside of the data volume [14]. All other solutions have used additional control that we categorized as follows: walking/flying, scaled world grab, world-in-miniature, and zooming.

Walking (gliding) is a classical movement modality for applications based on first person view such as video games, it is therefore popular for IA systems. For example, GeoVisor allowed movement over a giant 2D map [52] using the input from a VR controller's joystick. **Flying** is a 3D movement that requires an additional direction, in general, the orientation of the wand or VR controller serves this purpose [39], [75], [95].

World grab proposes a different way to navigate through an immersive environment by moving the position of the visualization instead of that of the user. Swipe gestures have been used to pan the visualization in 2D, either by tracking a data glove over a workbench display [34] or by detecting classical swipe gestures on a touch table associated to an AR display [64], [110]. ExplorViz used a metaphor of "grab & drag" [125], [126]: a fist gesture (captured by a Kinect V2) followed by a drag movement with the right hand translating the visualization. For 2D rotation, Shen et al. [62] used a joystick input from the wand in a CAVE, while La Viola Jr et al. [34] proposed a two-finger pivot gesture with

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2019.2929033, IEEE Transactions on Visualization and Computer Graphics

TABLE 2: Overview of interaction tasks in IA literature

Task	Category	Interaction	References
Navigate	walking (gliding) /flying	direct controller input	[39], [52], [75], [95]
	world grab	direct controller input	[62], [70], [134]
		markers displacement	[107], [124]
		hand gesture	[34], [87], [125], [126]
	world-in-miniature	grab-move-release	[41], [66], [67], [135]
		swipe gesture	[64]
	zooming	direct controller input	[124], [136]
		virtual menu	[35]
		magnifying glass metaphor	[39], [39], [81], [81]
		hand gesture	[34], [125], [126]
Select	single-object	raycasting	[35], [55], [75], [79], [95], [106], [112], [122], [123], [137]
		swipe gesture	[138]
	multi-object	brushing	[98], [127], [136]
		box selection	[36], [39], [139], [140], [141]
Details on Demand	reactive	pop-up window	[35], [55], [75], [95], [112], [137], [138]
		360 photo	[137]
		interactive lens	[142]
	predictive	gaze	[143]
		proximity	[78]
	2D screen	text information	[122], [123], [144]
		multimedia information	[106]
Arrange	datapoint	grab-move-release	[145]
		heat model	[30]
		attraction model	[78]
	view components	grab-move-release	[14], [21], [34], [70], [146]
		touch press	[110]
	views	grab-move-release	[69], [95], [129], [138], [147]
Change	highlight	opacity	[50], [81]
		glow	[122], [123]
		3D glyph	[29], [102]
	mapping	data position (axes)	[41], [110]
		data visual	[39], [94]
	representation	-	[52], [107], [129], [148]
Filter	direct selection	box selection	[36], [39], [139], [140]
		voice command	[34]
		slice selection	[128]
	abstract layer	visual menu	[65], [75], [82], [94]
		voice command	[115]
		embodied control	[64], [134], [148]
Aggregate	edge-bundling	-	[148]
Annotate	free annotation	-	[149]
	predefined annotation	-	[150]
Import	load new dataset	-	[65]
	load new data element	-	[42]
Derive	-	-	-
Record	undo selection	-	[39]
	record visualization state	-	[29], [34], [151], [152]
	record video	-	[34]

a data glove over a workbench. Multiple solutions have been implemented for 3D rotation: grabbing edges of the visualization box with a data glove [87], performing a fist and drag gesture [125], [126], physically rotating a fiducial marker [107], [124], or rotating a specific controller, based on the shape of the visualization, its orientation being directly connected to the visualization orientation [70], [134].

World-in-miniature allows navigation while keeping the context in mind by providing a scaled down version of the visualization for the user to choose where he will be teleported. ARCHAVE [66], [67], Wizard [41], Interactive Slice WIM [64], and BEMA [135] systems used it; they all had data volume representations big enough for users to easily lose the context of their position.

Zooming. Multiple input types have been used for zooming: keyboard [124], controller buttons [136], 3D menu selection [35], or hand gestures [34], [125], [126]. As an example, for the latter, ExplorViz used a pushing and pulling box metaphor: zoom occurs when both closed hands approach the torso of the user, while opening both hands and pushing them away from the torso triggers unzoom. Other systems feature virtual tools such as magnifying glass grabbed with data a glove [39], [81], or a stylus [36], [140], the movement of the input device changing the visualization scale.

4.2 Select

The select task covers datapoint(s) selection. In general this is to activate details on demand (see 4.3), highlight (see 4.5) or filtering (see 4.6).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2019.2929033, IEEE Transactions on Visualization and Computer Graphics

Single-object selection. IA systems in our corpus all relied on raycasting, with differences in raycast source and orientation. ExplorViz [122], [123], Dragon [35], CAVE-SOM [112] and Disz et al. system [79] all used a wand. The origin was the position of the wand, and the ray direction was mapped on its orientation. Obelisk-xR [137], IDEA [75] and the river disaster management system of Ready et al. [95] applied the same principle replacing the wand by a VR controller. VRMiner [106] detected a pointing gesture of the data glove to activate the raycast, using index orientation as direction. The maritime smuggler detection system of Franz et al. [55] used the head-tracking of the Microsoft Hololens to produce the raycast: the head position defined the origin and the user gaze provided the direction. Keefe et al. [138] went a bit further: the raycast was first used to select a general zone of the visualization, then a swipe gesture on an Ipod touch allowed to move the selection in the direction of the swipe, for higher precision. The use of one finger or two fingers for the swipe determined the distance of the jump to the next object.

Multi-object selection. Two approaches have been explored for multi-selection. The first technique, *brushing*, has been implemented in Lechner et al. [127] and Brunhart et al. [136] systems with a similar principle: users grabbed a virtual tool, represented by a lamp, that projected a cone with a limited height. Any datapoint entering in contact with the cone was selected. FiberClay [98], a system to analyze planes' trajectories, used a simple raycast for brushing: any trajectory that came into contact with the raycast —activated by pressing the trigger of a VR controller— was added to the selection. Performing the same action with the second controller removed trajectories from the selection. The second technique relied on *box selection*. In the Cosmic explorer [139] for visualization of galaxy formation simulation, the user could select a slice of the visualization volume through a series of hand gestures tracked by a data glove. Slice selection was possible for all three main coordinates resulting in the equivalent of a box selection. In the Virtual data visualizer, users grabbed a box virtual tool with a wand, that activated the zone selection mode [39]. A diagonal of the cube was defined by pressing a button twice, each press defining a point of the diagonal at the position of the wand. The cube was oriented parallel to the world coordinates axes. Hentschel et al. system [141] used the same method. DeHaan et al. proposed the plexipad [36], [140] to offer free orientation of the selection box. Plexipad was a square of plexiglass with a 6-degree of freedom tracker. The first face of the box was defined by the face of the plexipad while the last point needed to define the full geometry was positioned with the help of a tracked stylus.

4.3 Details on Demand

This task covers interactions aimed at displaying detailed information about the data. Some approaches take place inside the virtual environment, others make use of an external 2D screen.

Reactive approaches. The most common way to get details on demand is a simple single-object selection, followed by the appearance of a pop-up window filled with text information. For instance, the Dragon system [35] displayed all the details of a selected army unit, a similar approach being used for boat or drone entities in the maritime smugglers detection system [55], neuron information in the CAVE-SOM [112], demographic data in Keefe et al. system [138], and logs in IDEA [75]. The river disaster system of Ready et al. [95] displayed a 2D curve of the weather sensor value over time. The Obelisk-xR [137] also used a pop-up window to present detailed information about the selected stone, one characteristic being that it could then transport the user into a 360° photo of the location where the stone was extracted, upon selection of the location value in the pop-up window. Last, Mota et al. [142] proposed a spherical virtual lens to enrich the representation of the delimited zone, for multi-geometry 3D visualization. The lens position was directly controlled by the movement of a VR controller.

Predictive approaches. Another way to get supplementary information related to objects is to try and automatically determine the interest of the user. For instance, infoticles displayed the labels of the particles close to the user [78]. In [143] multiple 2D maps of oil spill simulation were visualized through a Microsoft HoloLens. They were positioned on top of each other, the one looked at by the user being scaled up while the others moved aside.

Additional 2D screen. The use of a second screen has been explored in IA systems. Imovision displayed the C++ source code of the selected class or method directly on a 2D screen next to the CAVE [122], [123]. Azzag et al. [106] used a second screen located next to their main 3D screen to display multimedia data, e.g. images and videos. Baumgartner et al. [144] allowed users to grab, with a data glove, a datapoint representing a document from their 3D screen, and move it on top of a tablet resulting in the full document text appearing on the tablet.

4.4 Arrange

The Arrange task refers to interactions that spatially organize visualization elements. The following describes proposals to organize datapoints, view components, and multi-views.

Arranging datapoints in IA systems is rare, due to the fact that their positions are used to encode information. Infoticles [78] used an indirect solution to manipulate datapoints' particles: the user could create an attractor object which was associated with a particular value for an attribute. Any data sharing the same value as the attractor for this attribute was then attracted by it. Osawa et al. [30] proposed a node/edge 3D representation of network data. Nodes were initially placed with a force-directed placement algorithm, but they could be "heated" to change their positions. Each node, indeed, possessed a virtual temperature. The higher its temperature, the more the other nodes would be repelled from it. Edges could also transport temperature, so nodes linked to a heated node became heated, which made the network of the selected node more apparent. Users could adjust a node temperature with a data glove, by touching it with their fingers, opening their thumbs, and doing a rotation of their wrists. They could also create a heat cone to affect multiple nodes at the same time, by pointing the index finger without touching a node, the opening of the thumb defining the cone angle. Nodes could also be locked in place, by pinching them with the index finger and thumb and then doing a wrist rotation, mimicking a key into keyhole movement. Last, Yi-Jheng et al. [145] allowed users to arrange nodes and edges through direct hand gestures, making a fist to grab the object, then moving the hand before opening the fist to lock it in a new position.

Arranging view components can be found in CFD. Data gloves-equipped users could move particle injectors to new positions, either through pinch gestures followed by a movement [14], [21] or by using voice commands to grab the element closest to the hand, followed by a movement and then a "drop" voice command [34]. RSVP system [146] and the seismic cube visualization [70] showed three 2D slices perpendicular to each main axis. RSVP proposed a slider control over a 2D UI while Fröhlich's system used a specific controller called the cubic mouse, which allowed lateral positioning of those slices with sliding rods which went through the whole controller. Each rod was on a different face of the cube to make the relation to its associated slice intuitive. In their parallel coordinate system for presenting 2D scatterplots on top of a touch table, Butscher et al. [110] provided the possibility to invert the axis of one representation with a touch press on a menu button.

Arranging views. Most of the systems in our corpus use the same paradigm, namely grab-move-release. Each proposal uses a specific input to link the movements of the controller to the movements of the view until another input discards the link. Saalfeld et al. [69] added virtual windows around their multiple views, taking inspiration from computer windows. Grab was done by a button press when a raycast projected by a stylus was in contact with the title of the window, release was done by the same button press. Ready et al. [95] river disaster management system allowed to arrange pop-up windows by grabbing them with a trigger input while in contact with the window, while release was done via the same trigger. Keefe et al. [138] demographic analysis tool allowed the user to arrange details-on-demand windows by selecting them then moving them around through swipe gestures on an Ipod touch. ImAxes [129] let users build their own visualization by grabbing and arranging axes (see 4.5), thus creating multiple views. A view could be grabbed by pressing a trigger on the VR controller while in contact with the view volume, and release was done by pressing the trigger again. A similar solution was used to arrange views for DICE model visualization [147].

4.5 Change

The Change task refers to interactions that alter visual encoding. This includes highlight of specific datapoints, changes in attribute mapping for one representation, and changes of representations.

Highlighting. One way to highlight datapoints is to control their opacity. Wesche et al. [81] implemented in the CFD system the possibility to change the opacity of a particle injector, which in turn changed the opacity of all its outgoing particles. To do so, the user grabbed a virtual tool and placed it in contact with the particle injector, followed by a wrist rotation to determine the resulting opacity. Moran et al. [50] allowed a user of their tweet analysis system to change the opacity of the buildings with a virtual menu activated by a LeapMotion hand-gesture. The 3D scatterplot proposed by Symanzik et al. [102] featured a pre-set of 3D shapes that could be grabbed with a pinch-gesture of the data glove, and put in contact with datapoints to change their appearance. Arms et al. [29] used a virtual brush tool metaphor: the user could create a virtual brush with specific color, size, and shape selected from a raycasting pointing gesture of the data glove, and then touch datapoints of the 3D scatterplot to change their color, size, and shape accordingly. The software visualization system ExplorViz [122], [123] allowed users to quickly display relationships between entities: overloaded methods were highlighted with a glow effect when the user selected a method by placing the wand on top of it.

Changing attribute mapping for one representation is done by using menus in all the systems in our corpus. I-flight [94] used a 3D menu with raycasting selection to switch between two color mappings related to bees' roles or behaviors, or change the environmental variable isosurface representation. Butscher et al. [110] system allowed changes to the dimensions displayed on the 2D scatterplot axes of their 3D parallel coordinate representation via a touch table menu. The selected 2D scatterplot appeared on the table and the user could touch an axis to display a list of the dataset attributes, then select one. The Wizard system [41] used one-handed interaction to select the variables displayed on each axis of a 3D scatterplot. A menu was displayed on top of the user hand, each phalanx had a "button" on top of it, and the thumb was used to press on the selected buttons. The user first selected the axis, then the attribute to map to it. The virtual data visualizer [39] could group data into classes that the user could map to a specific 3D glyph using a workbench metaphor: class selection was done via a 3D menu with raycasting selection from the Wand, shape selection by grabbing a 3D model from a drawer, color by pointing on a color map on top of the workbench, and size with a slider on top of the workbench.

Changing representations. GeoVisor [52] used VR controller button press to switch through available representations such as 3D scatterplot, 3D parallel coordinates, or node-link diagrams. Hurter et al. [148] represented a 3D cubic volume of plane trajectories in AR with Hololens. If the user physically stepped inside the volume, the representation changed into 2D projections on each face of the 3D volume. As seen earlier, ImAxes [129] allowed users to build their own multi-dimensional data representation. Grabbing, moving and releasing the relative positions of axes with a VR controller changed the representation, for instance, from 2D scatterplot to parallel axes. Meiguins et al. [107] allowed the users of their mobile AR system for multi-dimensional data analysis to generate histograms or pie charts to be displayed in conjunction with a 3D scatterplot. To do so, the user could interact with a virtual menu by occluding buttons with his hand, selecting the type of the additional graph, as well as the attribute to be visualized.

4.6 Filter

Filters determine exclusion or inclusion criteria for visualization elements. Filtering interactions can be done directly on the visualization, or by manipulating an abstract layer.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2019.2929033, IEEE Transactions on Visualization and Computer Graphics

Direct selection. Filtering elements can be the direct result of a selection action. The virtual data visualizer [39], the cosmic explorer [139], as well as the system of De Haan et al. [36], [140] triggered a filtering action upon box selection completion, hiding any datapoint outside of the box. Slicing of the 3D model is often allowed in medical imaging. In Zhang et al.'s system [128] the slice position was determined by the displacement of the wand while pressing a button, resulting in hiding the 3D model parts outside of the slice. Laviola Jr et al. CFD's system [34] allowed the removal of any particle injector, hence the related datapoints, by placing the data glove near it and using the voice command "remove".

Abstract layer. Menus can be used to filter objects without prior selection. VFIVE [82] and I-flight [94] both used a 3D raycasting menu selection to toggle the display of trajectories based on categorical attributes. NeuroCave [65] offered a similar functionality with a classical 2D WIMP interface on the supportive 2D display. Genome3DExplorer [115] offered to filter visual elements such as nodes, edges, or labels through voice commands ("hide nodes" or "show labels"). IDEA [75] displayed a menu on top of a physical tablet attached to a roller chair, bringing haptic feedback to menu selection. The query was then materialized by a "selection cube" that could be activated or deactivated at will to filter data. Jackson et al. [134] proposed a tangible controller for their visualization of thin fiber structures, with the form of a long thin cylinder made from rolled paper. The 3D orientation of the cylinder allowed the filtering out of any fiber not sharing the same orientation based on a user-defined angle threshold. The Interactive Slice WIM [64] allowed the definition of a complex hull on a 2D slice with a multi-touch screen and any streamline going through it was made apparent. Last, Hurter et al. [148] proposed to link the filter threshold for a numerical attribute directly to the user body position in a room. Therefore, they used one dimension of the room as a slider and its position was determined by the user's physical position.

4.7 Aggregate, Annotate, Import, Derive and Record

All remaining low-level interaction tasks are regrouped here, since they are far less common in IA literature.

The **Aggregate** task covers interactions that change the granularity of visualization elements. Hurter et al. [148] employed an edge bundling technique for their 2D graph visualization using the Microsoft HoloLens. The users could change the force coefficient of the edge bundling algorithm from weak to strong by moving their bodies in the room over a virtual line.

The **Annotate** task covers interactions allowing users to add graphical or textual annotations to the visualization. The network visualization system BuesnoSDIAS [149] proposed to associate text notes to selected elements, nodes or edges, by integrating a physical keyboard into the virtual world. TaggerVR [150] allowed users to select slices of one of the views, and associate some predefined tags to it through hand gestures captured via LeapMotion.

The **Import** task covers the addition or the replacement of data elements from new data sources. The archaeological VITA system [42] allowed users to import 3D models of a discovered artifact by grabbing them out of a 2D screen, directly putting data gloves in contact with the 2D screen and performing a closing fist motion. NeuroCave [65] let the user switch datasets from within the HMD, but no further details were given.

The **Derive** task covers the computation of new data elements from already available data. No paper in our corpus referred to such interactions.

The **Record** task covers interactions designed to capture visualization elements, or interaction logs. Undo actions were available in the virtual data vizualizer [39] through 3D menu raycasting selection. VR-Gobi [29] used an equivalent menu to save the visualization state, color, shape, and size of each glyph in a text file. Drouhard et al.'s system [151], [152] allowed users to save their current positions and orientations in the virtual world, also in a text file. However, no detail was provided on how the IA system state could be loaded from such files. Last, Laviola Jr et al. [34] proposed to record a snapshot and a video of the visualization with voice commands, respectively using "remember this view" and "recording". The saved view could then be accessed through the voice command "show me the saved view" and the video with the voice command "playback". One limitation was that only the last recording could be accessed.

4.8 Discussion

Two interaction modalities dominate: raycast selection with a controller and virtual tool metaphor. raycast selection is an attempt to convert the classical mouse pointing of 2D interfaces to a 3D world and provides the advantage of not limiting the distance at which the user interacts, even though the farther the object is, the harder it is to point at it. The virtual tool metaphor aims to emulate the "natural" interactions of humans in daily life, by using tools to perform specific actions. Though IA is defined as a multi-modal experience by Chandler et al. [1], other interaction modalities are under-represented, for instance, only a few systems make use of speech. Also, there is a lack of guidelines and best practices for interaction in IA. However, this may be changing, as illustrated by two recent works: Badam et al. [155] proposed an affordance table of interaction modalities for low-level tasks, and there is a whole chapter dedicated to interaction [156] in the IA Book published in 2018 [157], where the interested reader may find valuable resources for IA system design. This leads us to an important conclusion for IA research: so far only basic interactions have been used in IA systems, while VR, AR and 3DUI community literature is full of innovative means to perform 3D interactions, together with best practices. Such knowledge would most likely benefit IA systems design.

A few remarks can be added. First, navigation design needs to consider cyber-sickness [149]. IA systems are meant to be used for extended periods of time, and user comfort is very important [158]. However, such comfort is often overlooked in papers, even when smooth locomotion is used. Second, IA allows large scale data worlds to be explored but context aware navigation techniques such as WIM are not exploited enough even though they are critical for the user [41]. And last, IA systems tend to overlook supportive

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2019.2929033, IEEE Transactions on Visualization and Computer Graphics

low-level tasks, i.e. aggregate, annotate, import, derive, and record, which nevertheless continue to be needed if fully-fledged data analysis systems are to be built.

5 Collaboration in Immersive Analytics

Collaborative Immersive Analytics (CIA) is defined as "the shared use of immersive interaction and display technologies by more than one person for supporting collaborative analytical reasoning and decision making" in the CIA section of [159]. This section discusses the collaboration-related features of the 15 CIA systems in our corpus, it can serve as an IA system-oriented prologue to [159]. We describe how users interact with each other, focusing first on systems that allow physical interaction, and then on those that use virtual representations of users. We chose this presentation over the usual same vs. different place categorization because IA systems bring additional complexity: users can be in the same physical space, but have different virtual representations, or on the contrary be in different physical spaces but within the same virtual environment.

5.1 Physical Collaboration

Physical collaboration in IA started by placing multiple users in the same room using the same virtual reality technology, e.g. multiple users in front of a Fishtank [71], a workbench [33], [81], or inside a CAVE [128]. This has the advantage of letting users interact naturally, but presents the major drawback of providing a correct representation of the virtual world only for the head-tracked user. Gestural communication is also impacted since finger pointing to show a point of interest cannot work in this context. One solution proposed by [128] is to use a controller to project a raycast for finger pointing. Another solution is to head track multiple users as seen earlier for Agrawala et al. [37] workbench. The new generation of CAVE was designed from the beginning for CIA [27]. For instance, CAVE2 was built to allow any collaborator to share flawlessly individually owned data with the group by displaying it either through classical 2D representations or via the immersive environment. CAVE2 offers the possibility to visualize mixed views, where a part of the screen is dedicated to immersive representations and the other to 2D ones. Such choice to decrease immersion was made to improve collaboration because, according to the authors, it is "at best extremely difficult to integrate multiple useful representations into the same virtual world" and "multiple representations can often be better than a single shared representation" [160].

Augmented reality technology has also been used to provide physical collaborative IA. In 2004, VITA [42] allowed multiple archaeologists to enter the same virtual representation of an excavation site in AR. Users reported enjoying the interaction with their colleagues in a direct manner, but stated that the AR glasses were hiding the collaborator's eyes causing a discomfort in the interaction. In their system to prevent maritime smuggling, Franz et al. [55] used the Microsoft HoloLens combined with a tangible map of the shore. This representation allowed all the users to share the same position of entities, allowing quick finger pointing gestures to share objects or potential movement strategies, while allowing each user the freedom to have individual additional information displayed on the headsets. Butscher et al. [110] proposed a similar solution, using a touch table as the central point of representation, and a headset for each user: the same virtual world was shared among all users and all interactions were done using the multi-touch table.

Last, the principle of "datatar" has been presented by Chen et al. [16] as a combination of the words "data" and "avatar". Each user/datatar embodied one tuple of a multi-dimensional dataset and had to collaborate with other datatars to solve dimension reduction problems.

5.2 Virtual Collaboration

Virtual collaboration gathers users from different physical places who are connected to the same IA session through various hardware. The earliest work was the distributed virtual windtunnel in 1992 [21]. Two users could connect to the same representation of CFD simulation, each using a BOOM. The system allowed users to leave or join the session at any time. Conflicts were solved on a first come first serve basis, preventing, for example, users moving the same particle injector at the same time. The CAVE6D [88], [89] and the TIDE [131] systems allowed connection between CAVE and workbench users. Both proposals focused on interdisciplinary analysis of oceanographic and climate data. Users communicated directly via a voice chat and with gestures. Each user was represented by a simple avatar composed of a head and a hand, both following the tracked user's movements. A raycast was attached to the user's hand to facilitate pinpointing locations. A characteristic of the CAVE6D was the ability to let each user filter parameters either locally, affecting only his visualization, or globally, affecting everyone's visualization. This led to positive feedback from users, since they were able to investigate the data without disturbing their collaborators before sharing it with them. Cordeil et al. [93] used HMDs in their plane trajectory analysis system to connect users to the same virtual world. Leap Motion was used to provide virtual avatars with complete hands, letting users compose with a broader freedom for non-verbal communication.

Last, MICA (Meta-Institute for Computational Astrophysics) experimented with the Second Life social virtual world as a way to connect people for data analysis [15], e.g. the analysis of the output of a dynamical simulation of a star cluster. The main goal was to see the impact of "virtual environment as an educational and outreach platform", and the platform could be used without any requirement other than a Second Life account. Feedback from users was highly positive but it was not enough to ensure their return on a regular basis.

5.3 Discussion

We have two main conclusions. First, only fifteen papers out of the one hundred and twenty-seven system papers in our corpus have focus on collaboration, which represents less than 12% though collaboration is defined as a critical component for the success of IA [161], [162]. Second, no asynchronous collaborative system is mentioned, leaving a whole area unexplored. This point may be explained by a lack of attention to low-level interaction tasks required for asynchronous collaboration, such as annotate and record.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2019.2929033, IEEE Transactions on Visualization and Computer Graphics

6 IMMERSIVE ANALYTICS USER STUDIES

The second main category of papers in our corpus is related to evaluation. Twenty-eight papers focus on IA systems evaluation, twenty-six compare IA and non-IA solutions, and fourteen compare technologies (5), interactions solutions (7), or representations (2) within the same IA system. This section is organized along this subdivision.

6.1 Evaluating IA systems

The most common way to evaluate an IA system in our corpus is by gathering feedback from users while or after they have used the system. In general, domain expert users participated in the studies when available.

Twelve papers used an **informal evaluation approach** where final users were invited to use the system. In some cases they had participated in the design process. Krüger et al. [33] asked doctors, engineers and architects to validate their initial concept of the responsive workbench, obtaining suggestions for improvements, such as adding haptic feedback for the medical application, or increasing resolution for the industrial one. The virtual data virtualizer was used by computational physicists and the VR depiction was considered more “real and immediate” than a workstation display [39]. Ai et al. [80] received positive feedback for their molecule analysis system, which was deemed to be close to using real plastic models. Zhang et al. [128] had positive comments from doctors and senior medical students about the ease of use of their system. Hentschel et al. system [85] collected user feedback to define the type of visualization needed for blood damage analysis. The Bema system [135] was used by an ancient Greek rhetoric and oratory scholar to obtain insights into political assemblies at the Pnyx. This specialist stated that his experience had given him “a lot of confidence in what this [showed]” compared to using his imagination, or pictures. VR Miner [106] was used by biostatisticians and dermatologists who appreciated its features for detecting correlations between skin photographs and other data dimensions, checking the quality of discovered clusters, and presenting the data to a panel of experts. Using the CAVE2, experts expressed that it allowed them to get “more done in 2 days than in 6 months of email, Skype, and Google Hangout” [160]. GBR Tour [54] received feedback about the lack of resolution of their system and the need to improve navigation. Ferey et al. [115] genomic database IA system was used by biologists but they give no precision on the gathered feedback. Cunningham et al. [96] invited three experts to use their visualization of law enforcement narratives. The think aloud feedback they collected showed, for instance, that “the visualization was not as crowded in VR...and much more understandable” than usual tools. An informal evaluation approach with non-domain expert users was also used, e.g. [34] gathered feedback from “a number of people” who said that voice command was great but gets annoying when commands are not recognized, especially in a noisy environment. Ready et al. [95] enrolled people from their laboratory that had never seen their system before, the feedback was that it was not intuitive initially, but became great to use after some training and explanation.

Twelve papers used a **formal evaluation approach**, with dedicated sessions, seven of them with domain expert users. Sessions all had the same structure: system introduction, training on the main features of the system, a set of tasks to be performed, and questionnaire and/or interview. However, the evaluation objectives differed between studies, leading to different tasks. When expert users were available, the objective was to determine the usefulness of the system for data analysis, so experts had the freedom to explore interaction and analyze data as they saw fit. For instance, ARCHAVE was evaluated by two groups of archaeologists, the first one willing to analyze the lamp finds in the Petra temple, while the second wanted to explore the relation between the temple and the neighboring ancient sites [66], [67]. For the formal evaluation of the VITA system, archaeologists were asked what they intended to investigate prior to the evaluation session, and the tasks were designed accordingly [42]. Helbig et al. [101], Cantu et al. [77], Butscher et al. [110] and Hurter et al. [98] also let users freely use their IA system. When evaluation was conducted with non-expert users, the goal was to evaluate the usability of the interactions. In this case the choice was made to guide users who had no experience in the dataset by precisely defining the tasks to perform, such as in the Wizard [41], Interactive Slice WIM [64], ExplorViz [125], IDEA [75], and Saalfeld et al.'s [69] systems' evaluations.

Three systems succeeded in reaching the milestone of being used in real work environments. The Dragon system was used during two training military operations: “the Hunter Warrior advanced warfighting experiment in March 1997 and the Joint Counter Mine advanced concept tactical demonstration in August and September 1997” [35]. The ArtifactVis2 was extensively used to analyze an Iron Age site in Southern Jordan during the entire duration of the excavation project [68]. Jackson et al. system [134] was “used [...] in their lab” by the two biophotonic experts that collaborated in its development.

Our last system evaluation paper is more difficult to categorise. Fuhrmann et al. [40] make strong claims about their AR system, such as enhanced interaction capabilities or reduced abstraction, but provide no details of their evaluation or how such conclusions have been reached.

6.2 Questioning the benefits of immersion

The potential benefits of IA over non-immersive solutions appear to be dependent of data types. We will successively focus on graph, multi-dimensional, and spatial data. Let us state that there was no evaluation paper in our corpus directly comparing immersive and non-immersive solutions for temporal, spatio-temporal, or tree data. A summary of the findings can be found in table 3.

Graphs. 3D representations have long been disregarded in the graph community, as it was considered they had significant problems mainly due to perceptive and navigational conflicts when exploring 3D worlds using 2D interfaces and screens [163]. Immersive environments were also disregarded for the same reason. It can, however, be argued that IE provide very different experiences by offering their users “true” 3D together with embodied interaction, and that it is, therefore, not possible to apply previous conclusions to IE systems [158].

Ware et al. [32], [164], [165] consistently proved the benefits of IA systems for network visualization. They performed multiple user studies comparing 2D with 3D stereo, simple head-tracking, or both combined (FishTank) visualizations. For instance, users were asked to determine if a path of length 2 was connecting two highlighted nodes, for varying graph sizes (24 to 132 nodes). The results showed that the error rates were proportional to the number of nodes. The FishTank could display three times the number of nodes of the 2D solution before reaching the same error rate, while head tracking alone brought this number down to 2.2 and stereo alone to 1.6. In 2008, a new study used the same principles [166]: the resolution of the screen was brought up to 9.2 million pixels per eye to display image "at the limit of the resolution of the human eye". Four graph-size conditions were considered: 33, 100, 333 and 1000 nodes. The results showed that non-experienced users were able to achieve a 92% accuracy using IA with the 333 nodes condition, while experts achieved 90% accuracy for 1000 nodes. Similar accuracy was only reached by non-experts in 2D with 33 nodes. Belcher et al. [114] used the same protocol as the early Ware's studies, i.e. same tasks and 21 to 75 nodes. The main difference in their study was that they compared 2D, 3D and AR solutions (the graph was displayed on top of a disk with a fiducial marker). AR and 3D solutions proved significantly more accurate, but this result must be mitigated since the 2D solution was a projection of the 3D solution with no possibility to rotate the graph, while it was possible in the two other conditions. Greffard et al. [167] compared 2D with 3D stereo, with no head tracking, for node/link representation, resulting in the 2D solution being better for simple graph but 3D stereo being better for complex graph. Samavati et al. [168] compared a wall (no stereo, no head-tracking) to a CAVE-4 wall for multiple tasks such as intersection search, path following, connection identification, and length comparison. The results showed significantly greater accuracy for intersection search and connection identification for the IA solution, but no difference for length comparison tasks.

Multi-dimensional data. 3D representations have been explored very early, but most researchers have long disregarded the use of 3D, considering that 2D conventional techniques were sufficient for typical tasks related to pattern, trend, or outlier discovery [169]. Immersive technologies, however, bring in a new type of 3D together with embodied interactions which is worth exploring.

Wickens et al. [170] compared 2D and 3D scatterplotting in 1994, using a 3D stereo screen, resulting in better accuracy and completion times for 3D scatterplots for complex questions such as "which datapoints have the highest value on all 3 variables?". However, it is important to note that the dataset only consisted of 8 points. X-gobi, a desktop system, and VR-Gobi, a CAVE system, aimed at analyzing multi-dimensional data with 2D or 3D scatterplots and grand tour technique (permanent revolution of the representation around a vertical axis [171]) have been compared in [29], [172]. VR-Gobi showed significantly better accuracy for cluster identification tasks on datasets ranging from 74 to 500 tuples. Raja et al. [173] compared multiple systems for 3D scatterplot representation using FOR (Field of Regard) and HT (Head-Tracking) as independent variables. Tasks covered search, cluster, outlier, and trend detection. The combination of higher FOR and HT significantly diminished completion times. Another study focused on the impact of FOR: Yost et al. [133] compared a 2Mp with a 32Mp screen for search and trend determination tasks using a multi-view representation. Each view kept the same scale in both conditions, therefore the 32Mp condition displayed an enhanced number of views. Increasing the dataset size by a factor of 20, both in dimensions and tuples, for the higher FOR condition, i.e. 32Mp screen, resulted only in a three times increase in completion time with no significant effect on accuracy. Filho et al. [174] compared two dimensionally-reduced data scatterplot representations (2D on a screen, 3D in a VR HMD) for the analysis of the original dataset with search and outlier discovery tasks. Result showed that IA was both the most accurate and the most engaging, while desktop remained the fastest and the most intuitive. These results show that IA may be beneficial even for abstract visualization. Last, Bach et al. [175] compared Microsoft Hololens AR, tablet AR, and desktop for the analysis of dense 3D scatterplots. The tablet was the worst performing solution for all tasks, and participants agreed. For distance evaluation tasks, desktop was faster than HoloLens with no impact on accuracy. For cluster identification and selection tasks, desktop was the fastest but HoloLens was the most accurate. For plane cutting tasks, HoloLens was the fastest and hinted on a better accuracy than desktop. Participants preferred desktop for manipulation and the HoloLens for perception.

Spatial data naturally benefits from 3D representations as it is inherently 3D. Therefore, the main question is to explore what benefits immersive 3D can bring over 3D displayed on 2D screens.

The earliest user study on spatial data in our corpus was from Gruchalla et al. in 2004 [176]. The study compared users trying to position an oil well over an oil field using either a 2D desktop or a CAVE. CAVE proved to be significantly faster and more accurate. Similar results were found in the inspection of underground caves: Schuchardt et al. [177] found that for detailed search tasks (identify cave connection), or relative measurement tasks (compare the sizes of caves), CAVE performed significantly faster and more accurately than 2D. Focusing on the same type of data, Ragan et al. [178] went a step further, considering field of regard (FOR, total area available to the user to see the representation), stereo (ST), and head tracking (HT) as independent variables. FOR was controlled by using 1 or 4 CAVE walls, while ST and HT were turned on and off. FOR and HT combined improved accuracy, while the combination of HT and ST improved completion time. Van Schooten et al [179] used stereo and motion as independent variables for a study on maze structure data representation. Participants had to follow one particular path through the maze. Motion was simply the ability to control the panning and rotation of the representation, it proved to significantly increase the completion speed. Interestingly stereo provided benefits over non-stereo only when associated to motion. Ragan et al. [180] also used an underground cave system for their study, with multiple attributes being displayed throughout the cave (e.g. ground density with 3D bar charts). They compared a high-fidelity (CAVE 4-wall with ST and HT) setup with a low fidelity (CAVE 1-wall, no ST, no HT) one. The task was to find the highest value of a component inside

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2019.2929033, IEEE Transactions on Visualization and Computer Graphics

the cave, the high fidelity condition was the fastest and the most accurate. For medical imaging, Laha et al. [181], [182] showed that FOR and HT improved accuracy but did not find significant effects for completion time. In addition, Prabhat et al. [183] obtained better accuracy for CAVE over 2D-desktop for confocal microscopy data analysis. One study did not demonstrate the benefit of immersive solution for spatial data [184]. However, only two sizes of screens and ST were investigated, and HT was not available despite its critical importance for IA.

To conclude, there seems to be concurring evidence that IA provides benefits over non-IA for the analysis of graph and spatial data when the complexity of the scene exceeds the limits of 2D displays. Results for multi-dimensional data are more mitigated depending on the tasks.

6.3 Assessing technologies, interaction or visualization techniques

Technology. The availability of numerous immersive technologies has led researchers to try and determine which were better suited for IA, especially when some of them, like the CAVE, are a lot more expensive than others. Demilrap et al. [185] compared a FishTank with a CAVE for visual search tasks in a stream tube representation of the human brain. FishTank was significantly faster and more accurate and users reported their preference for its increased brightness and resolution. However, the full model was always visible on the screen in the two conditions so as to lower the impact of the limited FOR of FishTank due to its small screen. Qi et al. [73] compared a FishTank with an HMD for an overview visual search task in volumetric data. FishTank was also found to be significantly faster and more accurate. However, users were placed inside the volume to be investigated when using HMD, while in Fishtank they had an overview, all tasks being related to the investigation of the full volume. Laha et al. [186] compared a HMD with a CAVE to determine if both led to the same results for volume data analysis, hence allowing previous conclusions drawn with CAVE to be applied to HMD. The absence of significant differences is a step towards the validation of this hypothesis. Cordeil et al. [187] compared the benefit of their CAVE2 solution with a VR HMD for collaborative analysis of graph data to see if the added cost of the CAVE2 was justified. The tasks were simple, such as finding the shortest path between two nodes, or counting the number of nodes. Both conditions led to similar accuracy and completion times. Last, Merino et al. [188] compared a city metaphor for software visualization that could be experienced in a VR HMD or with a 3D printed representation. Finding the outliers proved to be faster with the printed representation, but the immersive environment was significantly better for recollection of the insights.

Interaction. Studies in comparing navigation techniques for IA systems have also been conducted. Henry et al. [116] compared egocentric (flying metaphor, see 4.1) and allocentric (rotating the visualization) navigations techniques for a node/link representation displayed in a CAVE, with no conclusive result. Simpson et al. [189] conducted a similar experiment in an HMD for the analysis of 3D scatterplots, comparing egocentric (walking physically around the visualization) to allocentric (rotating the visualization) navigation for a 3D scatterplot. No significant differences were found in either, as success was mostly driven by user preferences, even though users with low spatial abilities performed better in the walking condition. Another study from Buschel et al. [190] compared egocentric and allocentric navigations by either moving physically around an augmented reality representation on a tablet or by moving it by touching the tablet. No conclusive result could be found from quantitative data but participants preferred the egocentric solution. The egocentric vs allocentric navigation comparison from Coffey et al. [64] had a small difference: egocentric navigation could be user controlled or automatically animated with no user control. The controlled navigation was the most accurate while the animated one was the fastest. Zielasko et al. [117] compared five types of navigations while using an HMD in a seated position at a desk: gamepad, shake your head (SYH), leaning, walking in place (WIP) and pedal. Walking metaphor, i.e. SYH and WIP, were significantly slower than the others. Drogemuller et al. [191] compared four different navigation techniques for graph analysis using a VR HMD while standing up: teleportation, one handed flying, two-handed flying and world-in-miniature (WIM). Two-handed flying was the fastest and most preferred solution for tasks purely based on navigation, but WIM was the most efficient solution for tasks that required an overview of the scene, as it helped users keep the context in sight.

One paper [145] studied the impact of two different input modalities for the Arrange low-level task in a node/link representation on a stereo screen: participants could move nodes and edges with gesture-based interaction or classical 3D mouse. Quantitative results showed no impact on accuracy but for the most complex graph the gesture condition was significantly faster. Qualitative results indicated a significant preference for gesture-based interaction.

Visualization. Two papers focused in 2018 on comparing visualization techniques within IA systems. Fonnet et al. [192] compared three representations of a cartesian coordinate system for 3D scatterplots: 2D grid, 3D grid, and a metaphoric representation of an apartment hall. Participants had to find the coordinate values of highlighted points. No significant result was found for accuracy, but some users changed their behavior in the hall: they began to use their arms to measure distances. Yang et al. [97] compared various representations of trajectories over a 2D map: 2D straight lines, 2D curved lines and 3D curved lines. The task was to define which trajectory was the longest for selected trajectories. 3D curved lines ended up being the most accurate solution, 2D straight lines being the fastest.

6.4 Discussion

First, IA system evaluation is not systematic in our corpus: only 22% of the papers describing a system also describe its evaluation. Also, higher system fidelity, i.e. higher FOR, using ST, or HT, seems to bring benefits with regard to accuracy for complex tasks, especially for graph and spatial data, cf. table 3. For completion times, however, results are more uncertain. System fidelity studies are also lacking when it comes to other data types such as temporal, spatio-temporal, or tree data. In addition, we only found a recent

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2019.2929033, IEEE Transactions on Visualization and Computer Graphics

Data Type	Measure	Better than non-immersive	Worse than non-immersive
Spatial	acc	[176] : big FOR+ST+HT [177] : big FOR+ST+HT (detailed feature search & relative measurement) [183] : big FOR+ST+HT [184] : big FOR [181] : big FOR [182] : big FOR [178] : big FOR, HT	
	time	[176] : big FOR+ST+HT [177] : big FOR+ST+HT (detailed feature search & relative measurement) [178] : ST+HT [179] : ST	[184] : big FOR, ST
Temporal	acc		
	time		
Spatio-Temporal	acc		
	time		
Multi-Dimensional	acc	[29] : big FOR+ST+HT (clustering & radial sparness) [172] : big FOR+ST+HT (clustering & radial sparness) [174] : ST+HT [170] : ST (if question involve 3 or more attributes)	[175] : ST
	time	[133] : big FOR	[174] : ST+HT [175] : ST+HT, ST
Graph	acc	[32] : ST [164] : ST+HT, HT, ST [165] : ST+HT [114] : ST+HT, ST [166] : ST [168] : big FOR+ST+HT [167] : ST (for large graphs)	[167] : ST (for small graphs)
	time	[168] : big For+ST+HT	[114] : ST+HT [167] : ST
Tree	acc		
	time		

TABLE 3: Recapitulative table of the benefits of immersive solutions compared to non-immersive ones. Significant results are organized by data types and quantitative measures: accuracy (acc) and completion time (time). FOR: Field of Regard, ST: stereoscopy, HT: head tracking.

study comparing different visual mappings [97], a fact that may explain the apparent lack of best practices for data representation in IE. Also, user studies on interaction modalities have been limited to navigation tasks, with the only exception being [145]. This may appear too limited as, if real immersive data analysis systems are to be built, user studies need to cover most of the low-level tasks we reviewed in Section 4. An explanation for this limitation may be that the topic is already covered in general VR papers; however, we could argue that the specific tasks related to data analysis require specific ways of interacting.

7 Historical summary and Challenges

We conclude this survey with an historical summary of the development of IA from its beginning in 1991 until today, and a presentation of three main challenges. They complete the discussions we have provided in each section.

7.1 Historical Summary

Immersive Analytics began in the research teams that were building immersive technologies: Bryson's team for the BOOM, Cruz Neira's for the CAVE, Ware's for the FishTank VR, and Kruger's for the responsive workbench. During the late nineties, they were joined by other researchers when immersive technology started to be adopted by other laboratories. However, its huge costs drove the use of data that was directly related to the funding sources, leading mostly to scientific visualization systems, e.g. CFD, chemistry, and climatology. At the beginning of the century, technology remained heavily biased towards the CAVE, but application domains became more diverse, with software visualization, archeology, visual data mining, or brain analysis. "Canonical visualizations" began to emerge in a few domains, such as city metaphors for software visualization, the use of 3D vector fields with isosurfaces for climatology, particle injectors into a 3D vector fields for CFD, or 3D scatterplots for visual data mining. The next decade saw new generations of technologies: second generation of CAVE more focused on collaboration than immersion (CAVE2 and the Reality deck); cheap VR HMD associated to easy ways to develop content (Unity3D) that allowed many labs to join the IA movement; and a new generation of HMD AR devices renewing the interest for AR IA after only a few attempts [40], [42], [107], [124]. This wide variety of both fast-evolving technologies and application domains may explain the small number of IA software framework proposals[3], since these would have been useful only to a small amount of people and very quickly become obsolete.

Control input devices did not greatly evolve, six degrees of freedom controllers remain as the universal solution, even

3. For computational fluid dynamics, [193] proposed a framework offering streamline or isosurface representations that allowed any interaction hardware to be added, Vista FlowLib [83] focused on high performance rendering and parallel computing. The GEOMI framework [194] was dedicated to network data analysis, it provided numerous representations, and a high-level plug-in for immersive interaction. More recently, [162] proposed a general architecture for a number of distributed users to analyze data in a collaborative way.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2019.2929033, IEEE Transactions on Visualization and Computer Graphics

if their shapes have varied a great deal between wands, stylus, VR gamepads, or tracked gloves. This has led to two main ways of interacting with IA systems, either raycast menu selection, or virtual tools metaphor where objects may be grabbed with controllers. However, only a few low-level interaction tasks have been targeted, and a lot are still missing, such as import, derive, annotate, record, and aggregate. It should also be noted that collaboration has always been considered important since the beginning of IA research, the first IA collaborative system appearing in 1992. However, as seen earlier, a striking fact is that only synchronous collaboration has been considered so far.

Despite these three decades of research, IA has long lacked unity as a research area. As shown by the evaluation papers in our corpus, researchers have mainly focused on justifying the value of their systems with respect to non-immersive ones (from Ware in 1993 [32] to the present day [174]), rather than evaluating as a community what the best representations or interaction techniques could be. The first definition of IA was proposed in 2015 [1], as a tentative to provide a unifying label around the use of "emerging user-interface technologies for creating more engaging and immersive experiences". Three years later, the second definition [2] focused on "the use of engaging, embodied analysis tools to support data understanding and decision making", shifting the core of IA from technology to embodied analysis.

7.2 Challenges

In this survey, we focused on immersive technology, with an embodied stance related to our head-tracking condition. We identified three main challenges for IA to develop as a unified research area.

Foster multi-sensory and embodied interactive IA. Immersive environments provide the unique benefit of having fully immersed users, and the full potential of IA may not have been discovered yet. This calls both for new representations that engage all the senses of the users, and new interaction paradigms that exploit full body immersion to its full extent. First, most data representations focus on the visual channel, with a lack of proposals making use of sound and/or haptics. Also, many of the 3D data representations proposals are extensions of 2D ones. All those representations have proved useful but are likely not to be the only possibilities in IE. Second, IA researchers may not have experimented sufficiently with interaction: most interactions focus on six DoF controllers that are either used for raycast selection over virtual menu, or to grab virtual tools. There is, however, no reason to limit to these types of interactions or controllers. As an example, single-object selection may not only rely on simple raycast, and may benefit from the rich literature from VR and gaming community [195], [196]. As a matter of fact, taking into account 3DUI and VR findings [197] seems mandatory to fully integrate the embodied interaction paradigm to the IA field. An interesting example is ImAxes [129], which allows users to create new representations by simply empowering them with the control of axis arrangement.

Converge towards best practices. Work on IA began three decades ago, but the unifying term "Immersive Analytics" was only proposed three years ago. Access to immersive technology has long been limited to a few teams, as well as exchanges between a small number of experts of different types of systems, resulting in a lack of acknowledged best practices. To reach such goal it seems to us that work must be largely shared, and by this we mean sharing the actual users' experiences. Indeed, research usually mainly focuses on sharing knowledge through words and images but this may be insufficient for IA [198]. As for any immersive system, IA systems must be experienced for peers to be able to understand their full extent, which calls for open sourcing IA systems (as did ImAxes [199]) or toolkits (such as the recent DXR [200] and IATK [201]), or at least sharing 3D videos of experiences. Another point is that only fourteen papers in our corpus focused on assessing best solutions for IA (section 6.3), and comparing rendering technologies or navigation techniques have been the only two focus points for over 20 years. Data representation as a whole, as well as low-level interaction tasks (with the exception of navigation) were not investigated in any of the evaluation papers in our corpus until 2017. This means that a large part of the IA's area is yet to be explored and defined, and that an alternative route to reach maturity is to systematically aim at evaluating and assessing the validity of IA systems components for representation, interaction, etc.

Aim at real life IA systems. Data analysis having become a major industry concern, combined with the fact that VR/AR technologies are entering the corporate world, might lead to a new interest in enterprise IA systems[4]. Therefore, it seems important for IA researchers to focus on real life scenarios for systems they build. This means, as we have already seen, that these must integrate the full package of low-level interaction tasks defined by [18]. Inspiration can come from other fields, such as the use of annotation in immersive environments for 3D CAD models, leading to the possibility of asynchronous collaboration [203], [204]. Additional considerations for the design of IA systems are also required, related to their integration in the workplace and in the workflows of data analysts. This calls for research on user comfort and session durations, interoperability of 2D and immersive applications, transitions between corporate and immersive worlds, etc. Such conclusions are in line with those proposed by Wernert et al. [205] for the "immersive visualization community". This also calls for interdisciplinary work between IA, design, workplace and cognitive ergonomics, CSCW, sociology of organization, etc. [206] as well as partnership with industry [207].

8 Conclusion

We presented a survey of Immersive Analytics, as it emerges from the study of an extensive corpus covering three decades. We described one hundred and twenty seven IA systems focusing on their technologies, usages, sensory mappings, low-level interactions tasks, and collaborative capacities. A companion website is available where each system is systematically described and illustrated. The second part of the paper was dedicated to evaluation in Immersive Analytics, as well as a discussion of the main challenges.

4. Well-funded start-ups have begun to appear [202]

ACKNOWLEDGMENTS

This work is part of the IDEA project (Immersive Data Exploration and Analysis) funded by the *Pays de la Loire* French region through the West Creative Industries program.

REFERENCES

[1] T. Chandler, M. Cordeil, T. Czauderna, T. Dwyer, J. Glowacki, C. Goncu, M. Klapperstueck, K. Klein, K. Marriott, F. Schreiber, and E. Wilson, "Immersive Analytics," in *Proc. Big Data Visual Analytics*. Hobart, TAS, Australia: IEEE, sep 2015, pp. 1–8.

[2] T. Dwyer, K. Marriott, T. Isenberg, K. Klein, N. Riche, and F. Schreiber, "Immersive Analytics: An Introduction," in *Immersive Analytics*. Springer, 2018, pp. 12–34.

[3] M. A. Fisherkeller, J. H. Friedman, and J. W. Tukey, "PRIM-9: An interactive multidimensional data display and analysis system," in *A.E.C. Scientific Computer Information Exchange Meeting*, 1974.

[4] T. Dwyer, N. H. Riche, K. Klein, W. Stuerzlinger, B. Thomas, and T. Dwyer, "Dagstulh Seminar 16231 on Immersive Analytics," Schloss Dagstuhl, Dagstulh, Report 6, 2016.

[5] K. Marriott, T. Itoh, F. Schreiber, and U. Wössner, "Shonan Meeting No.074 on Immersive Analytics," NII Shonan, Tokyo, Report 2016-2, 2016.

[6] G. de Haan, B. Hentschel, D. F. Keefe, and O. Kreylos, "Immersive Visualization Revisited: Challenges and Opportunities," in *Workshop at IEEE VR*, California, US, 2012.

[7] B. Bach, S. Carpendale, C. Collins, R. Dachselt, T. Dwyer, and L. Bongshin, Eds., *Immersive Analytics: Exploring Future Interaction and Visualization Technologies for Data Analytics*, Niagara Falls, Canada, 2016.

[8] B. Bach, M. Cordeil, T. Dwyer, B. Lee, B. Saket, A. Endert, C. Collins, and S. Carpendale, Eds., *Immersive Analytics: Exploring Future Visualization and Interaction Technologies for Data Analytics*, Phoenix, USA, oct 2017.

[9] J. Chen, G. E. Marai, K. Marriott, F. Schreiber, and B. H. Thomas, Eds., *Immersive Analytics (IA)*, Greenville, SC, USA, 2016.

[10] S. Bryson, "Virtual reality in scientific visualization," *Communications of the ACM*, vol. 39, no. 5, pp. 62–71, may 1996.

[11] R. M. Simpson, J. J. LaViola, D. H. Laidlaw, A. S. Forsberg, and A. van Dam, "Immersive VR for scientific visualization: a progress report," *IEEE Computer Graphics and Applications*, vol. 20, no. 6, pp. 26–52, 2000.

[12] A. van Dam, D. H. Laidlaw, and R. M. Simpson, "Experiments in Immersive Virtual Reality for Scientific Visualization," *Computers & Graphics*, vol. 26, no. 4, pp. 535–555, aug 2002.

[13] Z. Ben Saïd, F. Guillet, P. Richard, J. Blanchard, and F. Picarougne, "An Overview of Interaction Techniques and 3D Representations for Data Mining," *Applications of Virtual Reality*, vol. Intech, 2012.

[14] S. Bryson and C. Levit, "The virtual windtunnel-an environment for the exploration of three-dimensional unsteady flows," in *Proceeding Visualization '91*, 1991, pp. 17–24.

[15] S. G. Djorgovski, P. Hut, R. Knop, G. Longo, S. McMillan, E. Vesperini, C. Donalek, M. Graham, A. Mahabal, F. Sauer, C. White, and C. Lopes, "The MICA Experiment: Astrophysics in Virtual Worlds," *Proc. of the SLACTIONS 2012 International Research Conference on Virtual Worlds*, pp. 49–58, jan 2013.

[16] X. Chen, J. Z. Self, L. House, and C. North, "Be the data: A new approach for lmmersive analytics," in *Workshop on Immersive Analytics*, Greenville, SC, mar 2016, pp. 32–37.

[17] B. Shneiderman, "The eyes have it: a task by data type taxonomy for information visualizations," in *Proceedings 1996 IEEE Symposium on Visual Languages*, 1996, pp. 336–343.

[18] M. Brehmer and T. Munzner, "A Multi-Level Typology of Abstract Visualization Tasks," *IEEE Transactions on Visualization and Computer Graphics*, vol. 19, no. 12, pp. 2376–2385, dec 2013.

[19] M. Slater, "A note on presence terminology," *Presence Connect*, vol. 3, 2003.

[20] I. E. McDowall, M. T. Bolas, S. D. Pieper, S. S. Fisher, and J. Humphries, "Implementation and integration of a counterbalanced CRT-based stereoscopic display for interactive viewpoint control in virtual-environment applications," in *Proc. SPIE 1256, Stereoscopic Displays and Applications*, Santa Clara, CA, sep 1990.

[21] S. Bryson and M. Gerald-Yamasaki, "The distributed virtual windtunnel," in *Proceedings of the 1992 ACM/IEEE conference on Supercomputing*, 1992, pp. 275–284.

[22] C. Cruz-Neira, D. J. Sandin, and T. A. DeFanti, "Surround-screen projection-based virtual reality: The Design and Implementation of the CAVE," in *SIGGRAPH*, Anaheim, CA, 1993, pp. 135–142.

[23] C. Cruz-Neira, J. Leigh, M. Papka, C. Barnes, S. M. Cohen, S. Das, R. Engelmann, R. Hudson, T. Roy, L. Siegel, C. Vasilakis, T. A. DeFanti, and D. J. Sandin, "Scientists in wonderland: A report on visualization applications in the CAVE virtual reality environment," in *Proc. IEEE Research Properties in Virtual Reality Symposium*, 1993, pp. 59–66.

[24] T. M. Roy, C. Cruz-Neira, and T. A. DeFanti, "Cosmic Worm in the CAVE: Steering a High-Performance Computing Application from a Virtual Environment," *Presence: Teleoperators and Virtual Environments*, vol. 4, no. 2, pp. 121–129, jan 1995.

[25] T. Höllerer, J. Kuchera-Morin, and X. Amatriain, "The allosphere: a large-scale immersive surround-view instrument," in *Proc. workshop on Emerging displays technologies images and beyond: the future of displays and interacton*, San Diego, CA, 2007, pp. 1–7.

[26] J. Thompson, J. Kuchera-Morin, M. Novak, D. Overholt, L. Putnam, G. Wakefield, and W. Smith, "The Allobrain: An interactive, stereographic, 3D audio, immersive virtual world," *Int Journal of Human-Computer Studies*, vol. 67, no. 11, pp. 934–946, nov 2009.

[27] A. Febretti, A. Nishimoto, T. Thigpen, J. Talandis, L. Long, J. D. Pirtle, T. Peterka, A. Verlo, M. Brown, D. Plepys, D. Sandin, L. Renambot, A. Johnson, and J. Leigh, "CAVE2: a hybrid reality environment for immersive simulation and information analysis," in *The Enginering Reality of Virtual Reality*, vol. 8649, Burlingame, California, US, 2013.

[28] C. Papadopoulos, K. Petkov, A. E. Kaufman, and K. Mueller, "The Reality Deck–an Immersive Gigapixel Display," *IEEE Computer Graphics and Applications*, vol. 35, no. 1, pp. 33–45, jan 2015.

[29] L. Arms, D. Cook, and C. Cruz-Neira, "The benefits of statistical visualization in an immersive environment," in *Proceedings IEEE Virtual Reality*. IEEE Comput. Soc, 1999, pp. 88–95.

[30] N. Osawa, K. Asai, and Y. Y. Sugimoto, "Immersive graph navigation using direct manipulation and gestures," in *Proceedings of the ACM symposium on Virtual reality software and technology - VRST '00*. Seoul, Korea: ACM Press, 2000, pp. 147–152.

[31] C. Ware, K. Arthur, and K. S. Booth, "Fish tank virtual reality," in *Proc. SIGCHI conference on Human factors in computing systems*, Amsterdam, The Netherlands, 1993, pp. 37–42.

[32] C. Ware, D. Hui, and G. Franck, "Visualizing object oriented software in three dimensions," in *Proc. Conference of the Centre for Advanced Studies on Collaborative research: software engineering - Volume 1*, Toronto, Ontario, Canada, 1993, pp. 612–620.

[33] W. Kruger, C.-A. Bohn, B. Frohlich, H. Schuth, W. Strauss, and G. Wesche, "The Responsive Workbench: a virtual work environment," *Computer*, vol. 28, no. 7, pp. 42–48, jul 1995.

[34] J. J. Laviola Jr, "MSVT: A Virtual Reality-Based Multimodal Scientific Visualization Tool," in *third IASTED international conference on computer graphics and imaging*, 2000, pp. 1–7.

[35] J. Durbin, J. E. S. II, J. Colbert, J. Crowe, R. King, T. King, C. Scannell, Z. Wartell, and T. Welsh, "Battlefield Visualization on the Responsive Workbench," in *Proc. Conference on Visualization*. North Carolina, USA: ACM Press, 1998, pp. 463–466.

[36] G. de Haan, M. Koutek, and F. H. Post, "Towards intuitive exploration tools for data visualization in VR," in *Proceedings of the ACM symposium on Virtual reality software and technology - VRST '02*. Hong Kong, China: ACM Press, 2002, p. 105.

[37] M. Agrawala, A. C. Beers, I. McDowall, B. Fröhlich, M. Bolas, and P. Hanrahan, "The two-user Responsive Workbench," in *Proc. 24th annual conference on Computer graphics and interactive techniques - SIGGRAPH '97*, Los Angeles, CA, 1997, pp. 327–332.

[38] I. E. Sutherland, "A head-mounted three dimensional display," in *AFIPS '68 (Fall, part I)*, San Francisco, CA, 1968, pp. 757–764.

[39] R. van Teylingen, W. Ribarsky, and C. van der Mast, "Virtual Data Visualizer," *IEEE Transactions on Visualization and Computer Graphics*, vol. 3, no. 1, pp. 65–74, 1997.

[40] A. Fuhrmann, H. Löffelmann, and D. Schmalstieg, "Collaborative augmented reality: exploring dynamical systems," in *Proc. 8th conference on Visualization*, Phoenix, AZ, 1997, pp. 459–462.

[41] A. Datey, "Experiments in the Use of Immersion for Information Visualization," PhD Dissertation, Virginia Tech, 2002.

[42] H. Benko, E. W. Ishak, and S. Feiner, "Collaborative Mixed Reality Visualization of an Archaeological Excavation," in *3rd Int Symposium on Mixed and Augmented Reality*, 2004, pp. 132–140.

[43] S. Marks, J. E. Estevez, and A. M. Connor, "Towards the Holodeck: Fully Immersive Virtual Reality Visualisation of Sci-

entific and Engineering Data," in *Proc 29th Int Conf on Image and Vision Computing New Zealand*, Hamilton, NZ, 2014, pp. 42–47.

[44] "Oculurs Rift," https://www.oculus.com/rift/, accessed: 2018-07-20.

[45] "HTC Vive," https://www.vive.com/, accessed: 2018-07-20.

[46] "Meta," http://www.metavision.com/, accessed: 2018-07-20.

[47] "Hololens," https://www.microsoft.com/en-us/hololens, accessed: 2018-07-20.

[48] A. Lu, J. Huang, S. Zhang, C. Wang, and W. Wang, "Towards mobile immersive analysis: A study of applications," in *Workshop on Immersive Analytics*, Greenville, SC, mar 2016, pp. 25–30.

[49] "Leap Motion," https://www.leapmotion.com/, accessed: 2018-07-20.

[50] A. Moran, V. Gadepally, M. Hubbell, and J. Kepner, "Improving Big Data visual analytics with interactive virtual reality," in *High Performance Extreme Computing Conference*, sep 2015, pp. 1–6.

[51] D. Herr, J. Reinhardt, R. Krüger, G. Reina, and T. Ertl, "Immersive Visual Analytics for Modular Factory Layout Planning," in *Immersive Analytics Workshop*, Phoenix, USA, 2017, pp. 1–5.

[52] T. V. Billow and J. A. Cottam, "Exploring the Use of Heuristics for Evaluation of an Immersive Analytic System," in *Immersive Analytics Workshop*, Phoenix, USA, 2017, pp. 1–5.

[53] K. Nagao, Y. Ye, C. Wang, I. Fujishiro, and K.-L. Ma, "Enabling interactive scientific data visualization and analysis with see-through hmds and a large tiled display," in *Workshop on Immersive Analytics*, Greenville, SC, mar 2016, pp. 1–6.

[54] H. T. Nim, M. Wang, Y. Zhu, B. Sommer, F. Schreiber, S. E. Boyd, and S. J. Wang, "Communicating the Effect of Human Behaviour on the Great Barrier Reef via Mixed Reality Visualisation," in *Big Data Visual Analytics BDVA*, nov 2016, pp. 1–6.

[55] J. Franz, J. Malloch, D. Reilly, and L. Nedel, "More Than Blips on the Radar : Exploring Immersive Visualization for Maritime Decision Making," in *Immersive Analytics Workshop*, Phoenix, USA, oct 2017, pp. 1–4.

[56] K. V. Nesbitt, "A classification of multi-sensory metaphors for understanding abstract data in a virtual environment," in *Proc. International Conference on Information Visualization*, London, UK, 2000, pp. 493–498.

[57] K. Reda, A. Febretti, A. Knoll, J. Aurisano, J. Leigh, A. Johnson, M. E. Papka, and M. Hereld, "Visualizing Large, Heterogeneous Data in Hybrid-Reality Environments," *IEEE Computer Graphics and Applications*, vol. 33, no. 4, pp. 38–48, jul 2013.

[58] T. Mahmood, E. Butler, N. Davis, J. Huang, and A. Lu, "Building Multiple Coordinated Spaces for Effective Immersive Analytics through Distributed Cognition," in *4th Int Symp on Big Data Visual and Immersive Analytics*, Konstanz, Germany, 2018, pp. 119–129.

[59] D. A. B. Hyde and T. R. Hall, "VRGE : An Immersive Visualization Application for the Geosciences," in *IEEE SciVis 2018 - Short paper session*, no. October, Berlin, Germany, 2018, pp. 1–5.

[60] J. Kniss, J. P. Schulze, U. Wössner, P. Winkler, U. Lang, and C. Hansen, "Medical applications of multi-field volume rendering and VR techniques," in *Proc 6th Eurographics - IEEE TCVG Conf on Visualization*, Konstanz, Germany, 2004, pp. 249–254.

[61] A. Gillet, M. Sanner, D. Stoffler, and A. Olson, "Tangible Interfaces for Structural Molecular Biology," *Structure*, vol. 13, no. 3, pp. 483–491, mar 2005.

[62] R. Shen, P. Boulanger, and M. Noga, "MedVis: A Real-Time Immersive Visualization Environment for the Exploration of Medical Volumetric Data," in *5th Int Conference on BioMedical Visualization*, London, UK, jul 2008, pp. 63–68.

[63] B. Chen, J. Moreland, and J. Zhang, "Human Brain Functional MRI and DTI Visualization With Virtual Reality," *Quantitative Imaging in Medicine and Surgery*, vol. 1, no. 1, pp. 11–16, jan 2011.

[64] D. Coffey, N. Malbraaten, T. B. Le, I. Borazjani, F. Sotiropoulos, A. G. Erdman, and D. F. Keefe, "Interactive Slice WIM: Navigating and Interrogating Volume Data Sets Using a Multisurface, Multitouch VR Interface," *IEEE Transactions on Visualization and Computer Graphics*, vol. 18, no. 10, pp. 1614–1626, oct 2012.

[65] J. J. G. Keiriz, O. Ajilore, A. D. Leow, and A. G. Forbes, "Immersive Analytics for Clinical Neuroscience," in *Immersive Analytics workshop*, Phoenix, USA, 2017, pp. 1–5.

[66] D. Acevedo, E. Vote, D. H. Laidlaw, and M. S. Joukowsky, "Archaeological Data Visualization in VR: Analysis of Lamp Finds at the Great Temple of Petra, a Case Study," in *Proc conference on Visualization*, San Diego, California, 2001, pp. 493–496.

[67] E. Vote, D. A. Feliz, D. H. Laidlaw, and M. S. Joukowsky, "Discovering Petra: archaeological analysis in VR," *IEEE Computer Graphics and Applications*, vol. 22, no. 5, pp. 38–50, sep 2002.

[68] N. G. Smith, K. Knabb, C. DeFanti, P. Weber, J. Schulze, A. Prudhomme, F. Kuester, T. E. Levy, and T. A. DeFanti, "ArtifactVis2: Managing real-time archaeological data in immersive 3D environments," in *Digital Heritage*, Marseille, oct 2013, pp. 363–370.

[69] P. Saalfeld, J. Patzschke, and B. Preim, "An Immersive System for Exploring and Measuring Medical Image Data," in *Mensch und Computer-Tagungsband*, Regensburd, DE, Sept 2017, pp. 73–82.

[70] B. Fröhlich, S. Barrass, B. Zehner, J. Plate, and M. Göbel, "Exploring geo-scientific data in virtual environments," in *Proc Conference on Visualization*, San Francisco, CA, 1999, pp. 169–173.

[71] J.-C. Lombardo, "A Virtual Reality Environment for Macromolecules Exploration," *Virtual Reality and Prototyping*, p. 3, 1999.

[72] M. Guthold, M. Falvo, W. Matthews, S. Paulson, S. Washburn, D. Erie, R. Superfine, F. Brooks, and R. Taylor, *IEEE/ASME Transactions on Mechatronics*, vol. 5, no. 2, pp. 189–198, jun 2000.

[73] W. Qi, R. M. Taylor, C. G. Healey, and J.-B. Martens, "A comparison of immersive HMD, fish tank VR and fish tank with haptics displays for volume visualization," in *Proc 3rd Symp on Applied perception in graphics and visualization*, Boston, 2006, pp. 51–58.

[74] K. Nesbitt, "Interacting with Stock Market Data in a Virtual Environment," in *Proc Joint Eurographics IEEE TCVG Symposium on Visualization*, Ascona, Switzerland, 2001, pp. 273–282.

[75] A. Fonnet, F. Melki, Y. Prié, F. Picarougne, and G. Cliquet, "Immersive Data Exploration and Analysis," in *Student Interaction Design Research conference*, Helsinki, Finland, may 2018, pp. 1–8.

[76] P. Reipschläger, B. K. Ozkan, A. S. Mathur, S. Gumhold, R. Majumdar, and R. Dachselt, "DebugAR: Mixed Dimensional Displays for Immersive Debugging of Distributed Systems," in *Extended Abstracts CHI 2018*, Montreal QC, Canada, 2018, pp. 1–6.

[77] A. Cantu, T. Duval, O. Grisvard, and G. Coppin, "HeloVis: a Helical Visualization for SIGINT Analysis," in *IEEE PacificVis 2018*, Kobe, Japan, 2018, pp. 1–6.

[78] A. Moere, "Infoticles: information modeling in immersive environments," in *Proceedings Sixth International Conference on Information Visualisation*, London, UK, 2002, pp. 457–461.

[79] T. Disz, M. Papka, R. Stevens, M. Pellegrino, and V. Taylor, "Virtual Reality Visualization of Parallel Molecular Dynamics Simulation," in *Int Conference for High Performance Computing, Networking, Storage and Analysis*, San Diego, CA, 1995, pp. 1–5.

[80] Z. Ai and T. Frohlich, "Molecular Dynamics Simulation in Virtual Environments," *Computer Graphics Forum*, vol. 17, no. 3, pp. 267–273, aug 1998.

[81] G. Wesche, "Three-dimensional visualization of fluid dynamics on the Responsive Workbench," *Future Generation Computer Systems*, vol. 15, no. 4, pp. 469–475, jul 1999.

[82] A. Kageyama, Y. Tamura, and T. Sato, "Visualization of Vector Field by Virtual Reality," *Progress of Theoretical Physics Supplement*, vol. 138, pp. 665–673, apr 2000.

[83] M. Schirski, A. Gerndt, T. van Reimersdahl, T. Kuhlen, P. Adomeit, O. Lang, S. Pischinger, and C. Bischof, "ViSTA FlowLib - A Framework for Interactive Visualization and Exploration of Unsteady Flows in Virtual Environments," in *Workshop on Virtual environments*, Zurich, Switzerland, 2003, pp. 77–85.

[84] J. Sobel, A. Forsberg, D. Laidlaw, R. Zeleznik, D. Keefe, I. Pivkin, G. Karniadakis, P. Richardson, and S. Swartz, "Particle flurries: synoptic 3d pulsatile flow visualization," *IEEE Computer Graphics and Applications*, vol. 24, no. 2, pp. 76–85, mar 2004.

[85] B. Hentschel, I. Tedjo, M. Probst, M. Wolter, M. Behr, C. Bischof, and T. Kuhlen, "Interactive Blood Damage Analysis for Ventricular Assist Devices," *IEEE Transactions on Visualization and Computer Graphics*, vol. 14, no. 6, pp. 1515–1522, nov 2008.

[86] W. L. Hibbard, J. Anderson, I. Foster, B. E. Paul, R. Jacob, C. Schafer, and M. K. Tyree, "Exploring Coupled Atmosphere-Ocean Models Using Vis5D," *The International Journal of Supercomputer Applications and High Performance Computing*, vol. 10, no. 2-3, pp. 211–222, jun 1996.

[87] V. Jaswal, "CAVEvis: distributed real-time visualization of time-varying scalar and vector fields using the CAVE virtual reality theater," in *Proc 8th conference on Visualization*, 1997, pp. 301–308.

[88] G. H. Wheless, C. M. Lascara, J. Leigh, A. Kapoor, A. E. Johnson, and T. A. Defanti, "CAVE6D: A Tool for Collaborative Immersive Visualization of Environmental Data," in *IEEE Visualization*, Research Triangle Pk, North Carolina, USA, 1998, pp. 1–4.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2019.2929033, IEEE Transactions on Visualization and Computer Graphics

[89] K. S. Park, A. Kapoor, and J. Leigh, “Lessons learned from employing multiple perspectives in a collaborative virtual environment for visualizing scientific data,” in *Proc Conf on Collaborative virtual environments*, San Francisco, USA, 2000, pp. 73–82.

[90] T. Ogi, Y. Tateyama, and S. Sato, “Visual Data Mining in Immersive Virtual Environment Based on 4K Stereo Images,” in *Int conf on Virtual and Mixed Reality*, Berlin, 2009, pp. 472–481.

[91] S. Sato, Y. Tateyama, and T. Ogi, “Super High Definition Three-Dimensional Display Environment Applied to Visual Data Mining,” in *13th Int Conference on Network-Based Information Systems*, sep 2010, pp. 414–419.

[92] A. Kjellin, L. W. Pettersson, S. Seipel, and M. Lind, “Different Levels of 3D: An Evaluation of Visualized Discrete Spatiotemporal Data in Space-Time Cubes,” *Information Visualization*, vol. 9, no. 2, pp. 152–164, jan 2010.

[93] M. Cordeil, T. Dwyer, and C. Hurter, “Immersive solutions for future Air Traffic Control and Management,” in *Proc ACM Companion on Interactive Surfaces and Spaces*, Niagara Falls, Ontario, Canada, 2016, pp. 25–31.

[94] H. Nguyen, F. Wang, R. Williams, U. Engelke, A. Kruger, and P. De Souza, “Immersive Visual Analysis of Insect Flight Behaviour,” in *Immersive Analytics workshop*, Phoenix, USA, 2017, pp. 1–5.

[95] M. Ready, T. Dwyer, and J. H. Haga, “Immersive Visualisation of Big Data for River Disaster Management,” in *Immersive Analytics workshop*, Phoenix, USA, 2017, pp. 1–4.

[96] A. Cunningham, J. Walsh, and B. H. Thomas, “Immersive Visualisation of Geo-Temporal Narratives in Law Enforcement,” in *4th International Symposium on Big Data Visual and Immersive Analytics*, Konstanz, Germany, 2018, pp. 31–38.

[97] Y. Yang, T. Dwyer, B. Jenny, K. Marriott, M. Cordeil, and H. Chen, “Origin-Destination Flow Maps in Immersive Environments,” *IEEE Transactions on Visualization and Computer Graphics*, 2018.

[98] C. Hurter, N. H. Riche, S. M. Drucker, M. Cordeil, R. Alligier, and R. Vuillemot, “FiberClay: Sculpting Three Dimensional Trajectories to Reveal Structural Insights,” *IEEE Transactions on Visualization and Computer Graphics*, 2018.

[99] S. Bryson, “Virtual spacetime: an environment for the visualization of curved spacetimes via geodesic flows,” in *Proceedings of the 3rd conference on Visualization ’92*, 1992, pp. 291–298.

[100] J. A. Walsh, A. Cunningham, R. Smith, and B. H. Thomas, “Tangible Braille Plot : Tangibly Exploring Geo-Temporal Data in Virtual Reality,” in *4th International Symposium on Big Data Visual and Immersive Analytics*, Konstanz, Germany, 2018, pp. 167–172.

[101] C. Helbig, H.-S. Bauer, K. Rink, V. Wulfmeyer, M. Frank, and O. Kolditz, “Concept and workflow for 3D visualization of atmospheric data in a virtual reality environment for analytical approaches,” *Environmental Earth Sciences*, vol. 72, no. 10, pp. 3767–3780, nov 2014.

[102] J. Symanzik, D. Cook, B. D. Kohlmeyer, and C. Cruz-Neira, “Dynamic Statistical Graphics in the CAVE Virtual Reality Environment,” in *Proc. Dynamic Statistical Graphics Workshop*, vol. 29, 1996, pp. 41–47.

[103] A. Ammoura, O. R. Zaíane, and Y. Ji, “Immersed Visual Data Mining: Walking the Walk,” *BNCOD*, vol. 18, pp. 202–218, 2001.

[104] H. R. Nagel, E. Granum, and P. Musaeus, “Methods for Visual Mining of Data in Virtual Reality,” *Proceedings of the International Workshop on Visual Data Mining*, pp. 13–27, 2001.

[105] H. R. Nagel, M. Vittrup, E. Granum, and S. Bovbjerg, “Exploring Non-Linear Data Relationships in VR using the 3D visual data mining system,” in *3rd Int Workshop on Visual Data Mining*, Melbourne, FL, US, 2003, pp. 133–150.

[106] H. Azzag, F. Picarougne, C. Guinot, and G. Venturini, “VRMiner: a tool for multimedia database mining with virtual reality,” *Processing and Managing Complex Data for Decision Support*, pp. 318–339, 2006.

[107] B. S. Meiguins, R. M. C. do Carmo, L. Almeida, A. S. Gonçalves, S. C. V. Pinheiro, M. de Brito Garcia, and P. I. A. Godinho, “Multidimensional information visualization using augmented reality,” in *Proc int Conference on Virtual reality continuum and its applications*, Hong Kong, China, 2006, pp. 391–394.

[108] H. R. Nagel, E. Granum, S. Bovbjerg, and M. Vittrup, “Immersive Visual Data Mining: The 3DVDM Approach,” in *Visual Data Mining*, Berlin, Heidelberg, 2008, pp. 281–311.

[109] C. Donalek, S. G. Djorgovski, A. Cioc, A. Wang, J. Zhang, E. Lawler, S. Yeh, A. Mahabal, M. Graham, A. Drake, S. Davidoff, J. S. Norris, and G. Longo, “Immersive and collaborative data visualization using virtual reality platforms,” in *Proc Big Data*, Washington, DC, USA, oct 2014, pp. 609–614.

[110] S. Butscher, S. Hubenschmid, J. Müller, J. Fuchs, and H. Reiterer, “Clusters, Trends, and Outliers: How Immersive Technologies Can Facilitate the Collaborative Analysis of Multidimensional Data,” in *Extended Abstracts CHI ’18*, Montreal QC, Canada, 2018.

[111] I. Rojdestenski, D. Modjeska, F. Pettersson, M. Rojdestvenskaia, and P. Gustafsson, “SequenceWorld: a genetics database in virtual reality,” in *Proc Information Visualization*, London, UK, 2000, pp. 513–517.

[112] D. Wijayasekara, O. Linda, and M. Manic, “CAVE-SOM: Immersive visual data mining using 3D Self-Organizing Maps,” in *The 2011 International Joint Conference on Neural Networks*, San Jose, CA, USA, jul 2011, pp. 2471–2478.

[113] K. Einsfeld, S. Agne, M. Deller, A. Ebert, B. Klein, and C. Reuschling, “Dynamic Visualization and Navigation of Semantic Virtual Environments,” in *Proc Information Visualisation*, London, UK, 2006, pp. 569–574.

[114] D. Belcher, M. Billinghurst, S. Hayes, and R. Stiles, “Using augmented reality for visualizing complex graphs in three dimensions,” in *Proc 2nd IEEE and ACM Int Symposium on Mixed and Augmented Reality*, Tokyo, Japan, 2003, pp. 84–93.

[115] N. Férey, P. E. Gros, J. Hérisson, and R. Gherbi, “Visual data mining of genomic databases by immersive graph-based exploration,” in *GRAPHITE ’05*, Dunedin, NZ, 2005, pp. 143–146.

[116] J. A. Henry and N. F. Polys, “The effects of immersion and navigation on the acquisition of spatial knowledge of abstract data networks,” *Procedia Computer Science*, vol. 1, no. 1, pp. 1737–1746, may 2010.

[117] D. Zielasko, S. Horn, S. Freitag, B. Weyers, and T. W. Kuhlen, “Evaluation of hands-free HMD-based navigation techniques for immersive data analysis,” in *Proc Virtual Reality*, Greenville, SC, mar 2016, pp. 317–318.

[118] P. Young and M. Munro, “Visualising software in virtual reality,” in *Proc 6th Int Workshop on Program Comprehension. IWPC’98*, Ischia, Italy, 1998, pp. 19–26.

[119] C. Knight and M. Munro, “Comprehension with[in] virtual environment visualisations,” in *Proc 7th Unt Workshop on Program Comprehension*, Pittsburgh, PA, USA, 1999, pp. 4–11.

[120] ——, “Virtual but visible software,” in *Proc Int Conference on Information Visualization*, London, UK, 2000, pp. 198–205.

[121] C. Russo Dos Santos, P. Gros, P. Abel, D. Loisel, N. Trichaud, and J. Paris, “Mapping information onto 3D virtual worlds,” in *Proc Conf on Information Visualization*, London, UK, 2000, pp. 379–386.

[122] J. I. Maletic, J. Leigh, A. Marcus, and G. Dunlap, “Visualizing object-oriented software in virtual reality,” in *Proc 9th International Workshop on Program Comprehension*, 2001, pp. 26–35.

[123] J. I. Maletic, J. Leigh, and A. Marcus, “Visualizing Software in an Immersive Virtual Reality Environment,” in *Proceedings of ICSE*, Toronto, Canada, 2001, pp. 12–17.

[124] R. Souza, B. Silva, T. Mendes, and M. Mendonça, “SkyscrapAR: An Augmented Reality Visualization for Software Evolution,” in *Proc. of 2nd Brazilian Workshop on Software Visualization*, Natal, Brasil, 2012, pp. 1–8.

[125] F. Fittkau, A. Krause, and W. Hasselbring, “Exploring software cities in virtual reality,” in *3rd Working Conference on Software Visualization*, Bremen, Germany, sep 2015, pp. 130–134.

[126] ——, “Software landscape and application visualization for system comprehension with ExplorViz,” *Information and Software Technology*, vol. 87, pp. 259–277, jul 2016.

[127] U. Lechner, L. Nelson, D. Cook, S. Pierson, and J. Symanzik, “Using Dynamic Statistical Graphics in a Highly Immersive Virtual Reality Environment to Understand Multivariate (Spatial) Data,” *Bulletin of the International Statistical Institute, 51st Session Istanbul 1997*, vol. 2, pp. 31–34, 1997.

[128] S. Zhang, C. Demiralp, D. Keefe, M. DaSilva, D. Laidlaw, B. Greenberg, P. Basser, C. Pierpaoli, E. Chiocca, and T. Deisboeck, “An immersive virtual environment for DT-MRI volume visualization applications: a case study,” in *Proc Visualization*, San Diego, CA, USA, 2001, pp. 437–441.

[129] M. Cordeil, A. Cunningham, T. Dwyer, B. H. Thomas, and K. Marriott, “ImAxes: Immersive Axes as Embodied Affordances for Interactive Multivariate Data Visualisation,” in *Proc UIST*, Québec, QC, Canada, 2017, pp. 71–83.

[130] R. J. Garcia-Hernandez, C. Anthes, M. Wiedemann, and D. Kranzlmuller, “Perspectives for using virtual reality to extend visual

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2019.2929033, IEEE Transactions on Visualization and Computer Graphics

data mining in information visualization," in *2016 IEEE Aerospace Conference*, Big Sky, MT, USA, mar 2016, pp. 1–11.

[131] N. Sawant, C. Scharver, J. Leigh, A. Johnson, G. Reinhart, E. Creel, S. Batchu, S. Bailey, and R. Grossman, "The Tele-Immersive Data Explorer: A Distributed Architecture for Collaborative Interactive Visualization of Large Data Sets," in *4th International Immersive Projection Technology Workshop*, Iowa, USA, 2000, pp. 1–16.

[132] B. Patnaik, A. Batch, and N. Elmqvist, "Information Olfactation: Harnessing Scent to Convey Data," *IEEE Transactions on Visualization and Computer Graphics*, 2018.

[133] B. Yost and C. North, "The Perceptual Scalability of Visualization," *IEEE Transactions on Visualization and Computer Graphics*, vol. 12, no. 5, pp. 837–844, sep 2006.

[134] B. Jackson, Tung Yuen Lau, D. Schroeder, K. C. Toussaint, and D. F. Keefe, "A Lightweight Tangible 3D Interface for Interactive Visualization of Thin Fiber Structures," *IEEE Transactions on Visualizations and Computer Graphics*, vol. 19, no. 12, pp. 2802–2809, dec 2013.

[135] K. Kim, B. Jackson, I. Karamouzas, M. Adeagbo, S. J. Guy, R. Graff, and D. F. Keefe, "Bema: A multimodal interface for expert experiential analysis of political assemblies at the Pnyx in ancient Greece," in *2015 IEEE Symposium on 3D User Interfaces (3DUI)*. Arles, France: IEEE, mar 2015, pp. 19–26.

[136] N. Brunhart-Lupo, B. W. Bush, K. Gruchalla, and S. Smith, "Simulation exploration through immersive parallel planes," in *Workshop Immersive Analytics*, Greenville, SC, mar 2016, pp. 19–24.

[137] A. Masrur, J. Zhao, J. O. Wallgrün, P. Lafemina, and A. Klippel, "Immersive Applications for Informal and Interactive Learning for Earth Sciences," in *Immersive Analytics workshop*, Phoenix, USA, 2017, pp. 1–5.

[138] D. F. Keefe, A. Gupta, D. Feldman, J. V. Carlis, S. Krehbiel Keefe, and T. J. Griffin, "Scaling up multi-touch selection and querying: Interfaces and applications for combining mobile multi-touch input with large-scale visualization displays," *International Journal of Human-Computer Studies*, vol. 70, no. 10, pp. 703–713, oct 2012.

[139] D. Song and M. L. Norman, "Cosmic Explorer: A virtual reality environment for exploring cosmic data," in *Proc Research Properties in Virtual Reality Symposium*, 1993, pp. 75–79.

[140] M. Koutek, "Scientific visualization in virtual reality: Interaction techniques and application development," PhD Dissertation, Delft University of Technology, 2003.

[141] B. Hentschel, M. Wolter, and T. Kuhlen, "Virtual Reality-Based Multi-View Visualization of Time-Dependent Simulation Data," in *2009 IEEE VR Conference*, LA, USA, mar 2009, pp. 253–254.

[142] R. C. R. Mota and J. D. Silva, "3De Interactive Lenses for Visualization in Virtual Environments," in *IEEE SciVis 2018 - Short paper session*, no. October, Berlin, Germany, 2018, pp. 1–5.

[143] E. Mahfoud and A. Lu, "Gaze-directed Immersive Visualization of Scientific Ensembles," in *Proc ACM Companion on Interactive Surfaces and Spaces*, 2016, pp. 77–82.

[144] S. Baumgärtner, A. Ebert, M. Deller, and S. Agne, "2D meets 3D: a human-centered interface for visual data exploration," in *Extended Abstracts CHI*, San Jose, CA, USA, 2007, pp. 2273–2278.

[145] H. Yi-Jheng, T. Fujiwara, L. Yun-Xuan, L. Wen-Chieh, and M. Kwan-Liu, "A gesture system for graph visualization in virtual reality environments," in *Proc PacificVis*, Seoul, South Korea, apr 2017, pp. 41–45.

[146] V. Gertman, P. Olsoy, N. Glenn, and A. Joshi, "RSVP: Remote Sensing Visualization Platform for Data Fusion," in *Workshop Immersive Visualization Revisited Challenges and Opportunities at IEEE VR 2012*, Costa Mesa, California, US, 2012, pp. 1–5.

[147] M. Simpson, J. O. Wallgrün, A. Klippel, L. Yang, G. Garner, K. Keller, D. Oprean, and S. Bansal, "Immersive Analytics for Multi-objective Dynamic Integrated Climate-Economy (DICE) Models," in *Proc ACM Companion on Interactive Surfaces and Spaces*, Niagara Falls, Ontario, Canada, 2016, pp. 99–105.

[148] C. Hurter, N. H. Riche, M. Pahud, E. Ofek, S. Drucker, B. Lee, D. Brown, and C. Wong, "Into the mixed reality data sphere : mapping user's movements to data exploration tools," in *Immersive Analytics workshop*, Phoenix, USA, 2017, pp. 1–4.

[149] D. Zielasko, M. Bellgardt, A. Meißner, M. Haghgoo, B. Hentschel, B. Weyers, and T. W. Kuhlen, "buenoSDIAs : Supporting Desktop Immersive Analytics While Actively Preventing Cybersickness," in *mmersive Analytics Workshop*, Phoenix, USA, 2017, pp. 1–4.

[150] P. Morse, A. Reading, C. Lueg, and S. Kenderdine, "TaggerVR: Interactive Data Analytics for Geoscience - A Novel Interface for Interactive Visual Analytics of Large Geoscientific Datasets in Cloud Repositories," in *Proc Big Data Visual Analytics*, Hobart, TAS, Australia, sep 2015, pp. 1–2.

[151] M. Drouhard, C. A. Steed, S. Hahn, T. Proffen, J. Daniel, and M. Matheson, "Immersive visualization for materials science data analysis using the Oculus Rift," in *Big Data*, Santa Clara, CA, USA, oct 2015, pp. 2453–2461.

[152] C. A. Steed, J. Daniel, M. Drouhard, S. Hahn, and T. Proffen, "Immersive visual analytics for transformative neutron scattering science," in *Workshop on Immersive Analytics*, Greenville, SC, mar 2016, pp. 38–43.

[153] B. Laha, D. A. Bowman, D. H. Laidlaw, and J. J. Socha, "A classification of user tasks in visual analysis of volume data," in *IEEE Scientific Visualization Conference (SciVis)*. Chicago, IL, USA: IEEE, oct 2015, pp. 1–8.

[154] D. F. Keefe and T. Isenberg, "Reimagining the Scientific Visualization Interaction Paradigm," *Computer*, vol. 46, no. 5, pp. 51–57, may 2013.

[155] S. K. Badam, A. Srinivasan, N. Elmqvist, and J. Stasko, "Affordances of Input Modalities for Visual Data Exploration in Immersive Environments," in *Immersive Analytics Workshop*, Phoenix, USA, 2017, pp. 1–5.

[156] W. Büschel, J. Chen, R. Dachselt, S. Drucker, T. Dwyer, T. Görg, T. Isenberg, A. Kerren, C. North, and W. Stuerzlinger, "Interaction for Immersive Analytics," in *Immersive Analytics*, 2018, pp. 95–138.

[157] K. Marriott, F. Schreiber, T. Dwyer, K. Klein, N. H. Riche, T. Itoh, W. Stuerzlinger, and B. H. Thomas, Eds., *Immersive Analytics*, ser. Lecture Notes in Computer Science. Springer, 2018, vol. 11190.

[158] G. Cliquet, M. Perreira, F. Picarougne, Y. Prié, and T. Vigier, "Towards HMD-based Immersive Analytics," in *Immersive Analytics Workshop*, Phoenix, USA, 2017, pp. 1–5.

[159] M. Billinghurst, M. Cordeil, A. Bezerianos, and T. Margolis, "Collaborative Immersive Analytics," in *Immersive Analytics*, 2018, pp. 221–257.

[160] G. E. Marai, A. G. Forbes, and A. Johnson, "Interdisciplinary immersive analytics at the electronic visualization laboratory: Lessons learned and upcoming challenges," in *Workshop on Immersive Analytics*, Greenville, SC, USA, mar 2016, pp. 54–59.

[161] S. Bonada, R. Veras, and C. Collins, "Personalized Views for Immersive Analytics," in *ACM Companion on Interactive Surfaces and Spaces*, Niagara Falls, Ontario, Canada, 2016, pp. 83–89.

[162] H. Nguyen, P. Marendy, and U. Engelke, "Collaborative Framework Design for Immersive Analytics," in *Big Data Visual Analytics*, Sydney, NSW, Australia, nov 2016, pp. 1–8.

[163] I. Herman, G. Melancon, and M. Marshall, "Graph visualization and navigation in information visualization: A survey," *IEEE Transactions and Visualizations for Computer Graphics*, vol. 6, no. 1, pp. 24–43, 2000.

[164] C. Ware and G. Franck, "Viewing a graph in a virtual reality display is three times as good as a 2D diagram," in *Proc Symposium on Visual Languages*, St. Louis, MO, USA, 1994, pp. 182–183.

[165] ——, "Evaluating stereo and motion cues for visualizing information nets in three dimensions," *ACM Transactions on Graphics*, vol. 15, no. 2, pp. 121–140, apr 1996.

[166] C. Ware and P. Mitchell, "Visualizing graphs in three dimensions," *ACM Transactions on Applied Perception*, vol. 5, no. 1, pp. 1–15, jan 2008.

[167] N. Greffard, F. Picarougne, and P. Kuntz, "Visual Community Detection: An Evaluation of 2D, 3D Perspective and 3D Stereoscopic Displays," in *International Symposium on Graph Drawing*, Eindhoven, The Netherlands, 2011, pp. 215–225.

[168] F. Samavati, K. Hawkey, S. Scerbo, N. F. Polys, M. Setareh, and B. D. Jones, "The effects of display fidelity, visual complexity, and task scope on spatial understanding of 3D graphs," in *Proc Graphics Interface*, Regina, Sascatchewan, Canada, 2013, pp. 25–32.

[169] B. Shneiderman, "Why not make interfaces better than 3D reality?" *IEEE Computer Graphics and Applications*, vol. 23, no. 6, pp. 12–15, nov 2003.

[170] C. D. Wickens, D. H. Merwin, and E. L. Lin, "Implications of Graphics Enhancements for the Visualization of Scientific Data: Dimensional Integrality, Stereopsis, Motion, and Mesh," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 36, no. 1, pp. 44–61, mar 1994.

[171] D. Asimov, "The Grand Tour: A Tool for Viewing Multidimensional Data," *SIAM Journal on Scientific and Statistical Computing*, vol. 6, no. 1, pp. 128–143, jan 1985.

[172] L. Nelson, D. Cook, and C. Cruz-Neira, "Xgobi vs the c2: Results of an experiment comparing data visualization in a 3-d immersive virtual reality environment with a 2-d workstation display," *Computational Statistics*, vol. 1, pp. 39–52, 1999.

[173] D. Raja, D. A. Bowman, J. Lucas, and C. North, "Exploring the Benefits of Immersion in Abstract Information Visualization," *Proc 8th Immersive Projection Technology Workshop*, pp. 61–69, 2004.

[174] J. A. W. Filho, M. F. Rey, C. M. Freitas, and L. Nedel, "Immersive Analytics of Dimensionally-Reduced Data Scatterplots," in *Immersive Analytics Workshop*, Phoenix, USA, 2017, pp. 1–5.

[175] B. Bach, R. Sicat, J. Beyer, M. Cordeil, and H. Pfister, "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*, vol. 24, no. 1, pp. 457–467, jan 2018.

[176] K. Gruchalla, "Immersive well-path editing: investigating the added value of immersion," in *IEEE Virtual Reality*, Chicago, IL, USA, 2004, pp. 157–164.

[177] P. Schuchardt and D. A. Bowman, "The benefits of immersion for spatial understanding of complex underground cave systems," in *Proc ACM symposium on Virtual reality software and technology*, Newport Beach, California, 2007, pp. 121–124.

[178] E. D. Ragan, R. Kopper, P. Schuchardt, and D. A. Bowman, "Studying the Effects of Stereo, Head Tracking, and Field of Regard on a Small-Scale Spatial Judgment Task," *IEEE Trans. on Visualization & Computer Graphics*, vol. 19, no. 5, pp. 886–896, 2013.

[179] B. W. van Schooten, E. M. A. G. van Dijk, E. Zudilova-Seinstra, A. Suinesiaputra, and J. H. C. Reiber, "The effect of stereoscopy and motion cues on 3D interpretation task performance," in *Int Conf on Advanced Visual Interfaces*, Roma, Italy, 2010, pp. 167–170.

[180] E. D. Ragan, A. Wood, R. P. Mcmahan, and D. A. Bowman, "Trade-Offs Related to Travel Techniques and Level of Display Fidelity in Virtual Data-Analysis Environments," in *Joint Virtual Reality Conference of ICAT-EGVE*, Madrid, Spain, 2012, pp. 1–4.

[181] B. Laha, K. Sensharma, J. D. Schiffbauer, and D. A. Bowman, "Effects of Immersion on Visual Analysis of Volume Data," *IEEE Transactions on Visualization and Computer Graphics*, vol. 18, no. 4, pp. 597–606, apr 2012.

[182] B. Laha, D. A. Bowman, and J. J. Socha, "Effects of VR System Fidelity on Analyzing Isosurface Visualization of Volume Datasets," *IEEE Transactions on Visualization and Computer Graphics*, vol. 20, no. 4, pp. 513–522, apr 2014.

[183] Prabhat, A. Forsberg, M. Katzourin, K. Wharton, and M. Slater, "A Comparative Study of Desktop, Fishtank, and Cave Systems for the Exploration of Volume Rendered Confocal Data Sets," *IEEE Transactions on Visualization and Computer Graphics*, vol. 14, no. 3, pp. 551–563, may 2008.

[184] J. Chen, H. Cai, A. P. Auchus, and D. H. Laidlaw, "Effects of Stereo and Screen Size on the Legibility of Three-Dimensional Streamtube Visualization," *IEEE Transactions on Visualization and Computer Graphics*, vol. 18, no. 12, pp. 2130–2139, dec 2012.

[185] C. Demiralp, C. Jackson, D. Karelitz, S. Zhang, and D. Laidlaw, "CAVE and fishtank virtual-reality displays: a qualitative and quantitative comparison," *IEEE Transactions on Visualization and Computer Graphics*, vol. 12, no. 3, pp. 323 – 330, 2006.

[186] B. Laha, D. A. Bowman, and J. D. Schiffbauer, "Validation of the MR Simulation Approach for Evaluating the Effects of Immersion on Visual Analysis of Volume Data," *IEEE Trans on Visualization and Computer Graphics*, vol. 19, no. 4, pp. 529–538, apr 2013.

[187] M. Cordeil, T. Dwyer, K. Klein, B. Laha, K. Marriott, and B. H. Thomas, "Immersive Collaborative Analysis of Network Connectivity: CAVE-style or Head-Mounted Display?" *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 1, pp. 441–450, jan 2017.

[188] L. Merino, J. Fuchs, M. Blumenschein, C. Anslow, M. Ghafari, O. Nierstrasz, M. Behrisch, and D. A. Keim, "On the Impact of the Medium in the Effectiveness of 3D Software Visualizations," in *VISSOFT*, Shanghai, China, sep 2017, pp. 11–21.

[189] M. Simpson, J. Zhao, and A. Klippel, "Take a Walk: Evaluating Movement Types for Data Visualization in Immersive VR," in *Immersive Analytics workshop*, Phoenix, USA, 2017, pp. 1–5.

[190] W. Büschel, P. Reipschläger, R. Langner, and R. Dachselt, "Investigating the Use of Spatial Interaction for 3D Data Visualization on Mobile Devices," in *Proc Interactive Surfaces and Spaces*. Brighton, United Kingdom: ACM Press, 2017, pp. 62–71.

[191] A. Drogemuller, A. Cunningham, J. Walsh, M. Cordeil, W. Ross, and B. H. Thomas, "Evaluating Navigation Techniques for 3D Graph Visualizations in Virtual Reality," in *4th International Symposium on Big Data Visual and Immersive Analytics*, Konstanz, Germany, 2018, pp. 50–59.

[192] A. Fonnet, T. Vigier, G. Cliquet, F. Picarougne, and Y. Prié, "Axes and Coordinate Systems Representations for Immersive Analytics of Multi-Dimensional Data," in *4th International Symposium on Big Data Visual and Immersive Analytics*, Konstanz, Germany, 2018, pp. 91–100.

[193] S. Bryson, S. Johan, and L. Schlecht, "An extensible interactive visualization framework for the virtual windtunnel," in *Proc International Symposium on Virtual Reality*, Albuquerque, NM, USA, 1997, pp. 106–113.

[194] A. Ahmed, T. Dwyer, M. Forster, X. Fu, J. Ho, S.-H. Hong, D. Koschützki, C. Murray, N. S. Nikolov, R. Taib, A. Tarassov, and K. Xu, "GEOMI: GEOmetry for Maximum Insight," in *Graph Drawing*, Limerick, Ireland, 2006, pp. 468–479.

[195] R. Grasset, A. Mulloni, M. Billinghurst, and D. Schmalstieg, "Navigation Techniques in Augmented and Mixed Reality: Crossing the Virtuality Continuum," in *Handbook of Augmented Reality*. Springer New York, 2011, ch. 20, pp. 379–407.

[196] F. Argelaguet and C. Andujar, "A survey of 3D object selection techniques for virtual environments," *Computers & Graphics*, vol. 37, no. 3, pp. 121–136, may 2013.

[197] J. J. LaViola, E. Kruijff, R. P. McMahan, D. A. Bowman, and I. Poupyrev, *3D User Interfaces: Theory and Practice*. Redwood City, CA, USA: Addison Wesley, 2017.

[198] R. Sadana, V. Setlur, and J. Stasko, "Redefining a Contribution for Immersive Visualization Research," in *Proc ACM Companion on Interactive Surfaces and Spaces*, Niagara Falls, Ontario, Canada, 2016, pp. 41–45.

[199] "ImAxes," http://github.com/MaximeCordeil/ImAxes, accessed: 2018-07-20.

[200] R. Sicat, J. Li, J. Y. Choi, M. Cordeil, W. K. Jeong, B. Bach, and H. Pfister, "DXR: A Toolkit for Building Immersive Data Visualizations," *IEEE Trans. on Visualization and Computer Graphics*, 2018.

[201] "IATK: Immersive analytics toolkit," https://github.com/MaximeCordeil/IATK, accessed: 2018-12-17.

[202] "Virtualitics," http://www.virtualitics.com/, accessed: 2018-07-20.

[203] A. Irlitti, S. Von Itzstein, L. Alem, and B. Thomas, "Tangible interaction techniques to support asynchronous collaboration," in *Int Symposium on Mixed and Augmented Reality (ISMAR)*, Adelaide, SA, Australia, oct 2013, pp. 1–6.

[204] A. Nassani, H. Bai, G. Lee, and M. Billinghurst, "Tag it!: AR annotation using wearable sensors," in *SIGGRAPH ASIA 2015 Mobile Graphics and Interactive Applications on - SA '15*. Kobe, Japan: ACM Press, 2015, pp. 1–4.

[205] E. A. Wernert, W. R. Sherman, P. O'leary, and E. Whiting, "A Common Path Forward for the Immersive Visualization Community," in *Workshop Immersive Visualization Revisited Challenges and Opportunities at IEEE VR 2012*, Costa Mesa, California, US, 2012, pp. 1–8.

[206] D. Keefe, D. Acevedo, J. Miles, F. Drury, S. Swartz, and D. Laidlaw, "Scientific Sketching for Collaborative VR Visualization Design," *IEEE Transactions on Visualization and Computer Graphics*, vol. 14, no. 4, pp. 835–847, jul 2008.

[207] R. Hackathorn and T. Margolis, "Immersive analytics: Building virtual data worlds for collaborative decision support," in *Workshop on Immersive Analytics*, Greenville, SC, mar 2016, pp. 44–47.

Adrien Fonnet is a PhD student investigating immersive analytics at Nantes University, France. He holds an Engineering Degree of digital mock-up and virtual reality. He became interested in data analysis during his two years as a Master Data expert in an international agribusiness group and consolidated his skills in virtual and augmented reality technology by working for a year as a research engineer for the Computer Graphics Center in Guimaraes, Portugal.

Yannick Prié holds an Engineering Degree in Computer Science, a Master's degree in Artificial intelligence and Cognitive science, and a PhD in Computer Science. He is currently a Professor of Computer Science at Nantes University. His research interests include Human-Computer Interaction, Information Visualization, and User experience, with a focus on interdisciplinary approaches for the study of human-machine coupling and co-development.