Immersive Analytics: A User-Centered Perspective

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ABSTRACT

Researchers have explored using VR and 3D data visualizations for analyzing and presenting data for several decades. Surveys of the literature in the field usually adopt a technical or systemic lens. We propose a survey of the Immersive Analytics literature from the user's perspective that relates the purpose of the visualization to its technical qualities. We present our preliminary review to describe how device technologies, kinds of representation, collaborative features, and research design have been utilized to accomplish the purpose of the visualization. This poster demonstrates our preliminary investigation, inviting feedback from the VRST community. Our hope is the final version of our review will benefit designers, developers, and practitioners who want to implement immersive visualizations from a Human-Centered Design perspective, and help Immersive Analytics researchers get a better understanding of the gaps in current literature.

CCS CONCEPTS

• **Human-centered computing → Visualization**; • **General and reference → Surveys and overviews**.

KEYWORDS

datasets, neural networks, gaze detection, text tagging

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1 INTRODUCTION

Immersive data visualizations are used to help users effectively analyze data in fields like design [3], Human Factors [7, 10], and medicine[9]. A recent survey of the Immersive Analytics (IA) literature [5] describes the technologies that have been used to create such visualization systems. The purpose of our study is to survey the IA literature from the user's perspective rather than a systemic lens, that relates the purpose of the visualization for the user to its technical qualities. We investigate how different technologies, representations, collaborative features, and research designs have been used to accomplish the purpose and benefit users.

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2 METHODS

For this preliminary review we took an unstructured approach to literature discovery. The researchers on the team searched databases in their fields (i.e., design, HCI, medical sciences, and human factors). Most papers we found talked about the visualizations as a tool to be used by researchers or professionals in any domain. These domain-agnostic papers made up 28.6% of our corpus. The next most popular domains were sciences (15.9%), medicine (9.5%), and archaeology (9.5%). The venues with the highest representation are IEEE VR (19.1%), IEEE TVCG (16.2%), IEEE VIS (4.4%) and ACM VRST (4.4%). We expanded our search by reading papers referenced in our initial corpus. Of the 64 papers analyzed, 43 were from 2015 or later, and the earliest paper was from 1993. Our corpus is publicly accessible, along with the metadata including keyword distribution, domain, year of publication, and the venue at https://bit.ly/IAbibliography.

3 PRELIMINARY RESULTS

We explore the relationship between the purpose of the visualization (analysis or presentation) to other factors including its technical implementation (kind of display technology, input devices etc.), type of representation (concrete or abstract), the kind of research design (for empirical studies), and the presence or lack of collaborative features. There are several ways of categorizing the "purpose" of a visualization tool. We have categorized the corpus by whether the main purpose of the system was to *present* a data set to the user or to allow the user to go deep into the data set and *analyze* the visualized data. We did not notice a variation in the purpose of the visualization by the year of publication. Researchers have been exploring visualizations as a means for analysis as well as presentation equally frequently since 1993.

3.1 Technical Implementation

Many technologies have been used over the years for IA. We included papers that explained a system using 3D visualizations. We did not restrict our search by the medium (VR, AR, MR, desktop-based Virtual Environments (VE), Tangible UI (TUI)), display technology (HMD, CAVE, 2D and stereographic screen, and shape display), or input technologies (keyboard and mouse to 6-DOF VR controllers and gestural input). The use of HMD-based display technologies in IA has skyrocketed since 2014, making up 42 of the 64 reviewed papers. Screen- and CAVE-based systems were much more common pre-2010. Some recent papers use novel displays like shape displays and three of the papers allowed the user to use multiple display technologies to access the visualization tool.

3.1.1 Level of interaction. A direct by-product of the technical implementation is the level of interaction that the system affords the user (passive vs. active consumption). Of the 45 papers we have categorized so far, 28 implemented an active interaction system, where the user was supposed to actively engage and manipulate the data representation. On the other hand, the 17 papers that implemented a passive interaction system mainly focused on observing the data rather than to manipulate. Simple interactions like walking around the data or viewing it from different perspectives were categorized as "passive" interactions. We conducted a chi-square test of independence between the level of interaction and the purpose of the visualization (presentation or analysis), and found a significant association between the two in our corpus (χ^2 (1, N = 61) = 16.41, $P < .001$). Visualizations created for analysis were more likely to have active interaction, while those designed to present a system to the user tended to not have much interactivity.

3.1.2 Data representation. We also found a clear link between the purpose of the visualization tool and the type of representation of the data (concrete vs. abstract). We define a concrete representation as one which uses visual representation that are akin to the physical manifestations of the data being visualized. On the other hand, an abstract representation is an abstraction of the property being visualized. A chi-square test of independence revealed a significant association between the data representation type (concrete and abstract) and the purpose of the visualization (presentation or analysis) within our corpus (χ^2 (1, N = 61) = 16.41, $P < .001$). Since concrete representations are usually authentic representations of the entities, they tend to be used more frequently for presenting a specific insight. On the other hand, visualization systems that were created for users to analyze the data were more likely to have an abstract representation.

3.1.3 Collaborative features. Collaborative environments are becoming more important in IA. Immersive spaces can facilitate connections between members and the environment in different ways (collective, connective, collaborative, or cooperative) [11], which can open the door to discussions on the use of data. A chi-square test shows that the presence of collaborative features is independent of the purpose of the visualization (presentation or analysis) (χ^2(1, N = 61)=0.85, $P = 0.36$). However, collaborative visualization tools implement higher levels of interaction (i.e. active interaction) typically focused on data analysis rather than simple presentation. This is confirmed by a chi-square test of independence between collaborative features and the level of interaction (passive consumption vs. active interaction). We get a significant association (χ^2 (1, N = 61) = 4.43, $P = 0.04$). Of 16 papers that have collaborative features, 13 of them implemented an active interaction.

3.2 User Study Design

We also investigated how the user study design contributes to the development, evaluation, and improvement of IA systems. Out of 35 empirical studies, 12 papers that include the documented procedures and results of the user study were reviewed.

From the reviewed studies, two different types of user study designs were identified: (1) exploratory and informal user studies, and (2) structured user studies with methods and tools to evaluate and improve certain aspects of usability for the developed system. No reviewed paper focused on user study to develop IA system.

Most of the reviewed user studies conducted observations, surveys, and collected informal feedback. While several studies identified evaluation methods and tools, including usability questionnaire [9], Think Aloud [9], task completion (quality and/or quantity) [1, 2, 9], SUS questionnaire [1], exit questionnaire [2], many studies did not document the methods and tools.

The presented results of user studies from the reviewed papers are categorized as follows: task completion time[1, 2], usability and presence[9], the level of precision[2], reduced abstraction[6], key features of interface[6, 8], educational aspect[6], the impact of the system[1], and subjective results[9].

4 DISCUSSION AND FUTURE WORK

The survey results show that the purpose of visualizations is clearly related to the level of interaction implemented in the tool and their kind of representation. Abstract representations lend themselves well to be visually manipulated. A concrete representation, however, is associated with a semantic meaning, which makes it easier to understand for layman users. They are often used for simple data presentations with passive consumption. It might be interesting to explore the use of concrete representations in implementations with active interaction from the user for data analysis (e.g. [4]).

We conducted an unstructured search of the visualization literature in order to build our relatively small corpus. A large part of this was due to the ambiguity in Immersive Analytics' definition, which makes it difficult to develop specific inclusion / exclusion criteria and define keywords. Additionally, much relevant work related to IA is done without dissemination in academic venues, like technical demonstrations on personal blogs, and we would like to include such contributions in future work. We would also like to better define our taxonomies and make sure there are no confounding variables.

We would like to explore how collaborative analysis and interaction with data are implemented in IA at a deeper level, such as investigating the correlation between the collaborative environment and technologies, interaction style, type of the data, and the purpose of the study. Investigating large amounts of data and complex scenarios in a collaborative manner is another growing aspect in the field of IA that would be addressed in future renditions. We would also like to more formally investigate and categorize user study evaluation methods and tools used to identify different types of issues and findings.

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