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An Immersive Approach for Exploring Multiple Coordinated 3D Visualizations in Immersive Virtual Environments

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"If I have seen farther than others,

it is because I stood on the shoulders of giants."

— Sir Isaac Newton

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ABSTRACT

Multiple coordinated views have often been used in visual analytics applications over the years. They are widely and successfully used on 2D displays, but the current multiple 3D visualizations in 2D conventional displays lack usability and do not guarantee the usefulness that the extra dimension would provide. Immersive visualization techniques can potentially fulfill these gaps by improving 3D visualizations with novel 3D interaction techniques. This dissertation presents studies that assess the approach we proposed for interacting with multiple coordinated visualizations in immersive virtual environments. We use a 3D-WIMP-like concept, which are virtual cubes that we call Spaces, for encapsulating views that the user can freely control in the virtual environment. A first user study was conducted to compare our immersive approach to a 3D desktop version for evaluating its performance when dealing with compound tasks. Results have shown that our approach has advantages since it allows a comfortable and precise exploration. Then, with the purpose of improving and expanding the Spaces approach, a second study was conducted to evaluate multiple coordinated 3D visualization techniques. We compared variants of 3D scatterplots like Animation, Overlaid Trails, and Small Multiples to assess the effectiveness of such techniques in immersive environments. Results have shown that Overlaid Trails perform the best time overall, followed by Animation and Small Multiples, while accuracy is task-dependent. We demonstrate in both studies that our approach presents good results in terms of user comfort and immersion and is potentially useful in solving analytical tasks.

Keywords: Multiple Coordinated Views. Immersive Analytics. Virtual Reality. Trends Visualization. 3D Visualizations.

Uma abordagem imersiva para explorar múltiplas visualizações 3D coordenadas em ambientes virtuais imersivos

RESUMO

Nos últimos anos, múltiplas visualizações coordenadas têm sido freqüentemente usadas para fins de análise visual. Elas são amplamente usadas em *displays* 2D, mas múltiplas visualizações 3D em monitores convencionais ainda carecem de usabilidade e não garantem a utilidade que a dimensão extra forneceria. Técnicas de visualização imersiva podem preencher potencialmente essas lacunas através de visualizações 3D associadas a novas interações. Esta dissertação apresenta estudos que avaliam uma abordagem para interagir com múltiplas visualizações coordenadas em ambientes virtuais imersivos. A nova abordagem denominada *Spaces* é baseada num conceito semelhante a 3D-WIMP, ou seja, cubos virtuais que encapsulam visualizações e que o usuário pode controlar livremente no ambiente virtual. Um primeiro estudo de usuário foi conduzido para comparar essa abordagem imersiva com uma versão 3D desktop, avaliando seu desempenho ao lidar com tarefas compostas. Os resultados mostram que a abordagem *Spaces* apresenta vantagens, pois permite uma exploração confortável e precisa. Com o objetivo de aprimorar e expandir a abordagem, foi realizado um segundo estudo para avaliar múltiplas técnicas de visualização diferentes. Foram avaliadas a eficácia e a precisão de três variantes de diagramas de dispersão 3D, *Animation*, *Overlaid Trails* e *Small Multiples*, em ambientes imersivos. Os resultados mostram que *Overlaid Trails* têm o melhor desempenho no geral, seguido por *Animation* e *Small Multiples*, enquanto que a precisão depende da tarefa. Ambos os estudos mostram que a abordagem apresenta bons resultados em termos de conforto e imersão do usuário e é potencialmente útil na realização de tarefas analíticas.

Palavras-chave: Múltiplas Visualizações Coordenadas, Immersive Analytics, Realidade Virtual, Visualizações de tendências, Visualizações 3D.

LIST OF ABBREVIATIONS AND ACRONYMS

WIMP	Windows, Icons, Menus, Pointer
HMD	Head-mounted Display
VR	Virtual Reality
AR	Augmented Reality
VE	Virtual Environment
VA	Visual Analytics
MCV	Multiple Coordinated Views
IA	Immersive Analytics
HCI	Human-Computer Interaction
FOV	Field of View
SUS	System Usability Scale
UMUX	Usability Metric for User Experience
SD	Standard deviation

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1 INTRODUCTION

The increasing power of computers and other devices and the widespread use of sensors result in continuous production and accumulation of data reaching exorbitant figures, which exceeds our ability to analyze them. Visual Analytics (VA) aims at helping to fulfill the need for flexible, precise, and straightforward techniques for such analyses tasks (THOMAS; COOK, 2005). This area is based on information visualization (MUNZNER, 2014), an ever-growing field, where we can find many techniques that range from conventional plots shown in 2D displays to complex visualizations using immersive technology that are less used due to some limitations.

When data is plotted in 2D, the main limitations can be the screen size and the reduced spatial dimension to render the information. Many investigations focus on the study of strategies to render data using different approaches, for example, dimensionality reduction techniques (NONATO; AUPETIT, 2019), color-based encoding (WARE, 2020), and multiple views (BALDONADO; WOODRUFF; KUCHINSKY, 2000). Immersive technologies extend beyond that typical screen (MOH, 2018), allowing the analysts to be immersed in the data. Also, 3D data visualizations can offer several advantages in different contexts, especially when the data analysis requires understanding the three-dimensional geometric structure of objects or scenes (MUNZNER, 2014).

Those immersive technologies, such as virtual and augmented reality (VR/AR), provide a different perspective to *visualize* and *interact* with data. The stereoscopic displays with natural interaction are the reasons why the researchers began to explore data visualizations in immersive environments. The area that comprises both fields is called Immersive Analytics (CHANDLER et al., 2015).

Immersive Analytics (IA) is defined as an interdisciplinary field where any technology that removes barriers between users and their data can be used for building tools to support data exploration, communication, reasoning, and decision making (MARRIOTT et al., 2018). Technologies like Augmented Reality (AR) let users navigate the physical environment to interact with different devices such as multiple displays (RAN et al., 2019). The use of multiple devices helps collaborative tasks involving multiple views (SERENO et al., 2020), while Virtual Reality (VR) techniques allow the user to be completely unaware of the surroundings providing a feeling of reality to the end-user (CHANDLER et al., 2015). Technologies for virtual and augmented reality applications provide the means to visualize complex information in a physical space, supporting complex data analysis scenarios (BILLINGHURST et al., 2018). They help the identification of meaningful patterns and the analysis of multidimensional clusters, trends, and outliers (BUTSCHER et al., 2018). Moreover, the human-computer interaction (HCI) field has contributed with a variety of studies and techniques targeting 3D visualization and interaction within the context of multiple coordinated views (BÜSCHEL et al., 2018). A recent survey on immersive analytics (FONNET; PRIé, 2021) found more than one hundred papers related to VR, and only 15 employing AR technologies from 1991 to 2019, which shows a general preference for VR technology. The authors concluded that the IA community should focus on real-life scenarios that require novel methods for interacting with multiple views.

1.1 Motivation

The complexity and volume of the data to be analyzed in several domains have motivated the use of multiple visualizations (BALDONADO; WOODRUFF; KUCHINSKY, 2000). Multiple Coordinated Views (MCV) are among the most commonly used ways of composing visualization techniques to offer different perspectives of the same or potentially correlated data to facilitate insight into a complex dataset (JAVED; ELMQVIST, 2012a). Such an approach is especially suited for Visual Analytics (VA) applications (THOMAS; COOK, 2005). Depending on the data, using multiple 2D views in conventional 2D displays demands the use of large displays, while for 3D visualizations, such setup may not guarantee a useful tool.

Interaction techniques for 3D visualization exploration have been studied for decades, and the technology to provide better usability than keyboard-and-mouse used to be touching displays (YU et al., 2010; BüSCHEL et al., 2017). Regarding multiple views, earlier studies showed that the interaction with multiple 3D visualizations in 2D displays does not meet usability criteria (SANTOS; GROS, 2002). This lack of usability could be overcome if the exploration happens in immersive environments, where the user has an extra degree of freedom for interacting with 3D visualizations (GREFFARD; PICAROUGNE; KUNTZ, 2014). Additionally, human spatial awareness and organizational capabilities can help the analytical process performed interactively with the visualizations (KNUDSEN; CARPENDALE, 2017). Immersive analytics approaches have taken advantage of these characteristics.

Aiming at improving the interaction with multiple coordinated views in immersive environments, we designed the $Spaces$ approach, which is based on a 3D version of WIMP (windows, icons, menus, pointer) graphical user interfaces for manipulating three-dimensional visualizations. To evaluate our approach, we first designed a similar desktop version to compare with a VR version and decided to focus a first study on the following research question: *Do our Spaces approach improve the manipulation of multiple coordinated 3D views when they are explored in an immersive virtual environment? How does the approach differ from a 3D conventional desktop version?*

Since in the first study we obtained positive results, we improved the interactive features by including near and far interaction and virtual navigation and used them to evaluate three different visualization techniques in a fully immersive environment. This second study compared temporal trends visualizations using three 3D-scatterplot variants following the research question: *Do 3D scatterplot variants as Animation, Small Multiples, and Overlaid Trails lead to the detection of trends when they are explored in an immersive environment? How do they differ?*

Both studies confirmed that the *Spaces* approach presented good results regarding (1) user comfort and interaction over the corresponding desktop version and (2) usefulness for comparative tasks using three-dimensional visualization techniques in a virtual reality environment.

1.2 Objectives and Contributions

The primary goal of this work was to develop and evaluate a helpful approach for interacting with multiple coordinated views that show 3D visualizations in immersive environments. Our technique uses a virtual cube as a 3D-WIMP version – we call it $Space$, inspired by a previous work by Mahmood et al. (2018). Each *Space* encapsulates a view, and allows two modes of interaction: the *macro* mode for interacting with the $Spaces$, and the *micro* mode for interacting with the data displayed in the $Space$. To achieve our primary goal, we designed two user studies that evaluate the following aspects of our approach:

- **Seamless interaction with multiple 3D visualizations in a VR environment.** Immersive technologies demand different possibilities to access the virtual space. The manipulation of objects inside it is essential to obtain multiple perspectives of the data. The interaction techniques developed in this work are simple ways to interact with data.

- **Multiple interaction techniques for coordinating visualizations.** Interaction with multiple coordinated views have been studied over the years. Our approach must be compatible with any interactive techniques which might be needed. Also, multiple views demand composing tasks, and the way to resolve them will depend on the implemented techniques. The coordination between views is a crucial part for getting insights from the views.

- **Multiple different visualization techniques.** The possibility of displaying different visualizations in the views gives opportunities to analyse data and confirm/reject hypotheses. The use of our approach in the two studies involving different datasets and different visualizations indicates its compatibility for exploring several immersive analytics scenarios.

In summary, our main contribution is the $Spaces$ approach for interacting with multiple coordinated views that shows 3D visualizations as a 3D-WIMP-like concept in VR, each Space encapsulating one view. This work was conducted within a research project approved by the research committee of our Institute and is registered at our University under the number 37021.

1.3 Structure of the Dissertation

The remainder of the dissertation is organized as follows. Firstly, related works in the relevant areas for our research are reviewed in Chapter 2. The $Space$ approach is presented in Chapter 3 and its evaluation against a desktop version is presented in the same chapter. Our second study is presented and discussed in Chapter 4. Finally, Chapter 5 summarizes our conclusions and points directions for future works.

2 RELATED WORK

Data visualization in immersive environments involves several aspects. Our work began by surveying relevant topics, starting with immersive analytics (Section 2.1), followed by multiple coordinated views (Section 2.2) and its use in immersive environments (Section 2.3). These works helped us to shape our general goal. Additionally, to evaluate the suitability of our approach to any visualization technique, we decided to explore visualizations for trends analysis because it is relevant in immersive analytics. Then, we surveyed scatterplot variants for trend analyses (Section 2.4), including the ones used in immersive environments (Sections 2.5 and 2.6).

2.1 Immersive Analytics

Immersive Analytics (IA) has gained increasing attention in the data visualization community (MARRIOTT et al., 2018). It refers to the use of immersive technologies for data analysis. Indeed, IA involves several areas such as information visualization, immersive environments, and human-computer interaction (ENS et al., 2021). 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. Previously, immersive visualization research has focused on large displays as CAVEs (CRUZ-NEIRA; SANDIN; DEFANTI, 1993; FEBRETTI et al., 2013). However, with the release of head-mounted displays (HMDs), several works started to show the potential of HMDs for perception and interaction (BACH et al., 2017) and collaboration (CORDEIL et al., 2016) in data analysis tasks.

In a survey of IA, covering papers until 2018, Fonnet and Prié (2021) found that various categories of data types have been explored. These categories were mapped to Ben Shneiderman's taxonomy (SHNEIDERMAN, 1996): Spatial, Temporal, Spatio-Temporal, Multidimensional, and Graphs and Trees. Also, they identified interaction techniques used in the literature and challenges. Recently, Ens et al. (2021) discussed challenges for IA systems to reach full potential regarding situated visualization, interaction, collaborative analyses, and evaluation (Table 2.1). Similarly, Kraus et al. (2021) reflected on when and how immersion may be appropriate for data analysis. They presented four guiding scenarios similar to Ens et al. (2021).

Table 2.1 – Grand Challenges in Immersive Analytics.

Topics		Challenges
SPATIALLY SITUATED DATA VISUALIZATION	C1	Placing Visualisations Accurately in Space
	C2	Extracting and Representing Semantic Knowledge
	C3	Designing Guidelines for Spatially Situated Visualization
	C4	Understanding Human Senses and Cognition in Situated Contexts
	C5	Applying Spatial Visualization Ethically
INTERACTING WITH IMMERSIVE ANALYTICS SYSTEMS	C6	Exploiting Human Senses for Interactive Immersive Analytics
	C7	Enabling Multi-Sensory Feedback for Immersive Analytics
	C8	Supporting Transitions around Immersive Environments
	C9	Coping with Immersive Analytics Interaction Complexity
COLLABORATIVE ANALYTICS	C10	Supporting Behaviour with Collaborators
	C11	Overcoming Constraints of Reality
	C12	Supporting Cross Platform Collaboration
	C13	Integrating Current Collaboration Practice
	C14	Assessing Collaborative Work
USER SCENARIOS AND EVALUATION	C15	Defining Application Scenarios for Immersive Analytics
	C16	Understanding Users and Contexts for Evaluation of Immersive Analytics
	C17	Establishing an Evaluation Framework for Immersive Analytics

Source: Ens et al. (2021)

Our work is related to the challenge *Supporting Transitions around Immersive Environments* (Table 2.1) because there is a need for interaction methods capable of achieving the functionalities of the predominant WIMP (windows, icons, menus, pointer) approach used for visual analysis tasks (LEE et al., 2012). Additionally, our work addresses the challenge *Coping with Immersive Analytics Interaction Complexity* since our approach supports multiple interaction techniques and different visualization techniques.

2.2 Multiple Coordinated Views

Multiple views provide a solution for displaying different visualizations of complex data to facilitate the analyses of massive amounts of information. They have been used for years (ROBERTS, 2007), but due to the cognitive overload that might be introduced by interacting with multiple views, designers might ask themselves when and to what extent multiple views should be used.

Baldonado, Woodruff and Kuchinsky (2000) proposed some rules to help to decide when multiple views should be used:

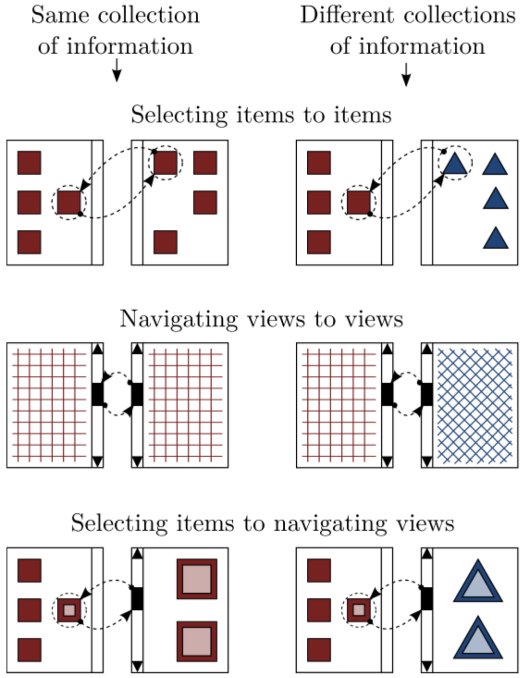
- *Rule of diversity*, when there is a diversity of attributes, models, and/or levels of abstraction,
- *Rule of Decomposition*, when it is necessary to partition complex data,
- *Rule of Complementarity*, when different views bring out correlations or disparities, and
- *Rule of Parsimony*, which states that multiple views should be used minimally.

Each of these rules solves part of the challenges of visual analytics. These authors also identified a list of issues of multiple views systems, where the first four concern to cognitive aspects, and the last three, to system requirements:

- The time and effort required to *learn* the system,
- the *load* on the user's working memory,
- the effort required for *comparison*,
- the effort required for *context switching*,
- the *computational requirements* for rendering the additional display elements,
- the *display space* requirements for the additional views, and
- the *design, implementation, and maintenance* resources required by the system.

Multiple coordinated views (MCV) explore the premise that users understand their data better if they interact with the resented information and view it through different representations (SANDSTROM; HENZE; LEVIT, 2003). They share a relationship that is used for coordinating them. Scherr (2008) analyzed coordination techniques, the most common one being *brushing* where, given a selection of elements in one view, the same or related elements are highlighted in the other linked views. There is also *navigational slaving* that describes the relation between views and data, based on a $2x3$ taxonomy:

Figure 2.1 – 2x3 taxonomy of multiple window coordinations.



Source: Scherr (2008)

selecting items – selecting items, navigating views – navigating views, and selecting items – navigating views. Figure 2.1 shows the $2x3$ taxonomy.

Multiple coordinated views approaches implement the concept of *composite visualization views* (CVVs) (JAVED; ELMQVIST, 2012a). Javed and Elmqvist (2012a) used the concepts of *visual composition*, *visual structure* and *view* based on Card et al.'s pipeline (CARD; MACKINLAY; SHNEIDERMAN, 1999). While *visual composition* is the placement or arrangement of multiple visual objects and *visual structure* corresponds to the graphical result of a visualization technique, *view* is the physical display where a visual structure is rendered. A "composite visualization" is the *visual composition* of two or more *visual structures* in the same *view*. These authors identified different forms of composing visualizations and came up with *CVVs design patterns* as follows (Figure 2.2): *juxtaposition*, that corresponds to placing visualizations side-by-side; *superimposition*, which corresponds to overlaying two visualizations in a single view; *overloading*, which uses the space of one visualization for another; *nesting*, which is having the contents of one visualization inside another visualization, and *integrating*, which places visualizations in the same view with visual links.

Figure 2.2 – Four different visual composition operators (from the left): juxtaposition, superimposition, overloading, and nesting.

Source: Javed and Elmqvist (2012a)

2.3 Multiple Coordinated Views in Immersive Analytics

Several immersive analytics studies have used diverse strategies to provide multiple views (KNUDSEN; CARPENDALE, 2017) regarding different CVVs design patterns, coordination techniques and settings. In this section, we briefly review the studies mostly related to ours, highlighting the limitations and challenges addressed by them.

2.3.1 Multiple Views on Large Displays

Several authors have explored multiple views in wall-sized displays, usually adopting a *juxtaposition* pattern. Febretti et al. (2014) presented OmegaLib, a software framework for supporting the development of immersive applications using Hybrid Reality Environments (HREs), which integrates high-resolution wall-sized displays with immersive technologies. This framework allows the linking of 2D and 3D views, and is designed for a group to discuss the visualizations showed in a wall display, while another group using laptops is in charge of the control management of the multiple views. With OmegaLib, they try to overcome known problems of these alternative approaches: the static spatial allocation of 3D and 2D used in most systems and the lack of unified interaction between the 2D and 3D visualizations.

Similarly, Langner, Kister and Dachselt (2019) presented a study based on an MCV system using interaction on a wall-sized display for analyzing the behavior of multiple users exploring more than 45 coordinated views. Their study implemented a general layout with multiple number and different sizes of views, and users could swap the views' positions (*juxtaposition*). The authors highlight that view management was not the focus of their study. To support interaction from varying positions, they combined direct touch and distant interaction using mobile devices. To interact with views, the users had to select the region's border showing the desired visualization. It is worth noting the importance of interactions for free navigation and the use of the border to change the mode for manipulating the data shown in the view.

A hybrid application developed by Su, Perry and Dasari (2019) allowed the user to visualize 2D and 3D information using a Large High-Resolution Display (LHRD) and VR technology, respectively. The study qualitatively compared 2D/3D coordination data displayed in 2D displays, 2D/3D data without coordination, and 2D/3D coordinated data displayed in the 2D display and in the VR environment. The visualizations used in the study were: a geolocation map, chord and horizon time plots in 2D views, and a 3D scene of a city. The 2D visualization shows the location and link data over time for the highlighted assets and links in the 3D visualization. The location trail is *superimposed* to the 2D and 3D maps, while the chord and time plots show coordinated actions. The results favored the 2D/3D coordinated environment in understanding and interactivity, but 2D/2D was the global favorite due to the facility of staying in one context only. The participants showed signs of discomfort because removing the headset was too disruptive for the data analysis workflow. Nonetheless, the users agreed there are benefits in using hybrid environments.

2.3.2 Multiple Views in AR and VR Environments

An alternative way to avoid the problem of changing the environment is to adopt augmented reality (AR) solutions. Mahmood et al. (2018) proposed a 3D version of a conventional MCV designing a workspace containing multiple coordinated 3D "spaces”. AR techniques were used to integrate a physical environment and to combine 2D views and virtual 3D spaces, such as 2D displays with virtual 3D visualizations. This workspace is built by obtaining positions of 2D surfaces, and then plotting 3D spaces onto these positions (see Figure 2.3). The workspace area is adjusted and subdivided into multiple spaces with similar sizes. The visualization methods used were based on 2D WIMP, displaying 3D parallel coordinates that linked real or virtual views (*overloading*) and topographic maps with *superimposed* scatterplots. Three-dimensional visualizations contained maps and 3D scatterplots included in 3D spaces. The interaction techniques implemented were data/view selection, scaling, and translating (allowing *juxtaposing* views), show/hide visualizations, and creation of history, which saves a configuration of the workspace, all with the help of hand gestures and voice commands provided by the Microsoft HoloLens. This work focused mainly on Coordinated Spaces for supporting immersive analytics in a physical environment and motivated our approach.

Figure 2.3 – Multiple visualizations and interactions from different devices are used in this AR approach. Visualizations can be placed in the Spaces that are built by the positions of the 2D surfaces (left). At the same time, the interactions by the user are obtained by gesture and voice commands provided by the AR device (right).

Source: Adapted from Mahmood et al. (2018)

The number of works using MCVs in VR environments has been increasing over time. ImAxes (CORDEIL et al., 2017) is an interactive tool that allows users to manipulate multiple charts' axes like physical objects in a VR environment to design visualizations. The user can manipulate one axis for observing a 1D histogram. Two or three axes placed perpendicularly create 2D and 3D scatterplots, while parallel coordinates are created distributing the axes in parallel in the VR environment. ImAxes was used by experts for economic analysis in a subsequent study by Batch et al. (2019). Since ImAxes is based on placing axes in the VR environment, users can *juxtapose* them. In addition, the proximity between visualizations can create linked 2D and 3D scatterplots (*integration* pattern).

Another study using the *juxtaposition* pattern is presented by Johnson et al. (2019). In Bento Box, a VR technique is used for exploring multiple 3D visualizations juxtaposed in a grid, like small multiples. Their tool was evaluated within a CAVE, and results showed that the users found it good for data analysis because it facilitates collaborative discussion. More recently, Liu et al. (2020) also used 3D visualizations as small multiples in an immersive environment.

Coordination techniques were studied by Prouzeau et al. (2019b). The authors proposed a design space for routing visual links between multiple 2D views in immersive environments, which we classify as the *integration* pattern. Their real-time algorithm allows them to draw links to connect multiple visualizations considering their coordination and the users' views. These visualizations were evaluated without interactive techniques showing the challenges of strategies for MCVs applied in VR.

Two recent works describe approaches that allow users to interact with multiple views in a way close to ours. Satriadi et al. (2020) describe the exploration of multiple 2D maps in a VR environment. Each map view could be created, scaled, and arranged by the users. Their study focused on the exploration of user-generated patterns with the maps views. Based on a *juxtaposition and overload* patterns, their work shows an interesting way to arrange 2D maps to better understand how users arrange the views. More recently, Lee et al. (2021) developed FIESTA, a system for collaborative data analysis in immersive environments using VR. FIESTA uses static visualizations floating in a virtual room (*juxtaposition*). Its interactions are based on direct contact with user interface elements and distant contact using a laser pointer.

2.4 Evaluation of Scatterplot Variants for Trend Analyses

Typically time-series analysis tasks involve finding trends, correlations, and variations at multiple time scales such as hourly, daily, weekly, and seasonal (MUNZNER, 2014). Formally, trend estimation is a statistical technique to identify trend lines or trend curves (BIANCHI; BOYLE; HOLLINGSWORTH, 1999). The most common (and informal) procedure to recognize a temporal trend in data is to plot variable's values on a line plot or bar chart and look for a general increase or decrease over time, which is perceived as an upward or downward trend. No changes indicate a constant trend. A general increase and decrease that reverses direction denote a reversing trend, while if there are more than a few reversals, it appears to be cyclic or noisy data, and no trend is perceived (ROBERTSON et al., 2008).

There are several tools to visualize trends based on conventional desktop environments. A well-known example is Gapminder Trendalyzer (Gapminder Organization, 2020), which uses an animated bubble chart to show populational statistics, social, economic, and environmental indicators about nations. This 2D scatterplot variant maps attributes to x and y axes, and the size of points (bubbles) (TUFTE, 1983; VIEGAS et al., 2007), and animates changes over time. The bubbles' trail allows perceiving the variation on values through time. Hans Rosling used this popular tool in TED (Technology, Entertainment, Design) presentations (ROSLING, 2006; ROSLING, 2007), where the attendees had to observe the informal trend estimation.

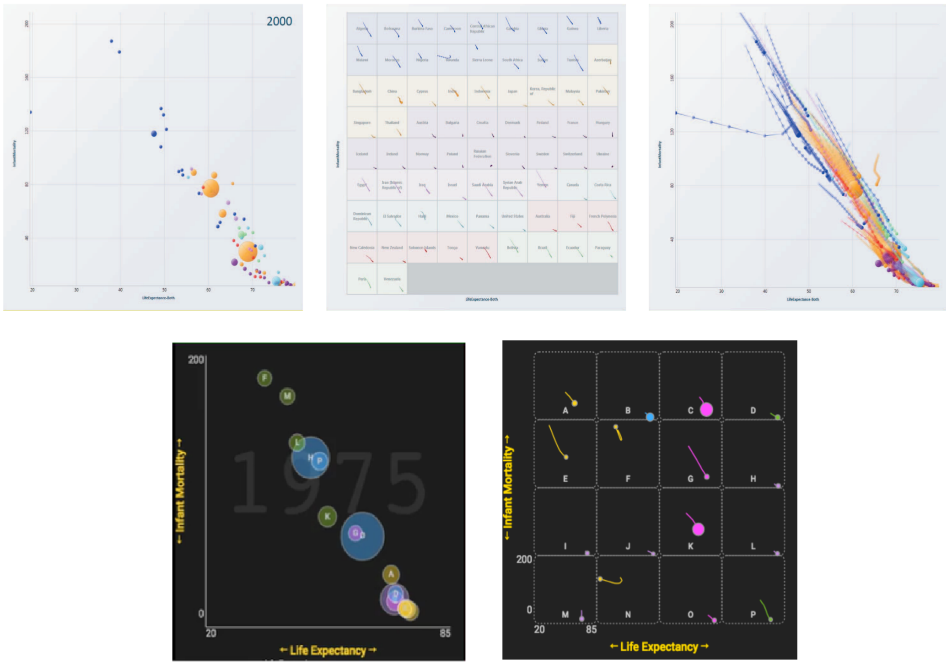
Some studies analyzed tasks requiring trend interpretation using conventional 2D scatterplots. Robertson et al. (2008) evaluated the effectiveness of analyzing trends in multidimensional data. Their study compared the animated bubble chart technique like the one in Gapminder Trendalyzer (Gapminder Organization, 2020) and two other static scatterplot variants: Small Multiples and Overlaid Traces (Figure 2.4-top). A static scatterplot shows all data changes in a single chart, the bubbles corresponding to a single data item connected by a trail as time evolves. In Small Multiples, the trail of each data item is displayed in a single chart, while Overlaid Traces shows all data in a single view simultaneously.

The evaluation described by Robertson et al. (2008) was based on two conditions: the *Analysis* condition, simulating analyst users, where participants discovered trends using visualization and interaction tools on desktop displays, and the *Presentation* condition, simulating a conference talk, where a narration described a relevant trend shown in the chart, and the participant was invited to answer the actual task without guidance. The results showed that participants performed better with the animated bubble charts in the Presentation condition than in the Analysis condition. Animation was more fun but less effective for both conditions, while the static Traces, and Small Multiples were better in the Analysis condition.

Recently, Brehmer et al. (2019) analyzed how effective trend visualizations are on mobile phones, comparing Animation and Small Multiples techniques (Figure 2.4-bottom). They adapted Robertson et al.'s tasks for representing possible trend scenarios with the trajectories of target and distractor items. Figure 2.5 shows the adapted tasks. The user study was performed with a subset of 16 items from the United Nations Common Database (DATABASE, 2019), which was also used by Robertson et al. (2008). Furthermore, the Small Multiples version was slightly modified. In their version, each nation is plotted as a point and its corresponding trail, showing the end year and the changes over time, respectively. Moreover, they do not provide interactive features, i.e., users performed the tasks only observing the two conditions, Small Multiples and Animation. The evaluation focused on analyzing individual tasks' characteristics because Robertson et al. found advantages of Small Multiples over Animation while using large displays. Their results showed that in terms of completion time, the Small Multiples variant was faster than Animation but not necessarily more accurate, unlike Robertson et al.'s study. In our work, we aim to analyze whether those visualization techniques would remain to be a viable design choice for immersive environments.

Other works explored the use of Small Multiples and Animation in different con-

Figure 2.4 – Trend visualization designs using 2D scatterplots variants for desktop and large displays (top) and mobile displays (bottom). The left is a frame of animation from the Gapminder Trendalyzer animation tool, the top-middle and bottom-right are the Small Multiples static variant, while the top-right is the Overlaid Traces.



Source: Adapted from Robertson et al. (2008) and Brehmer et al. (2019)

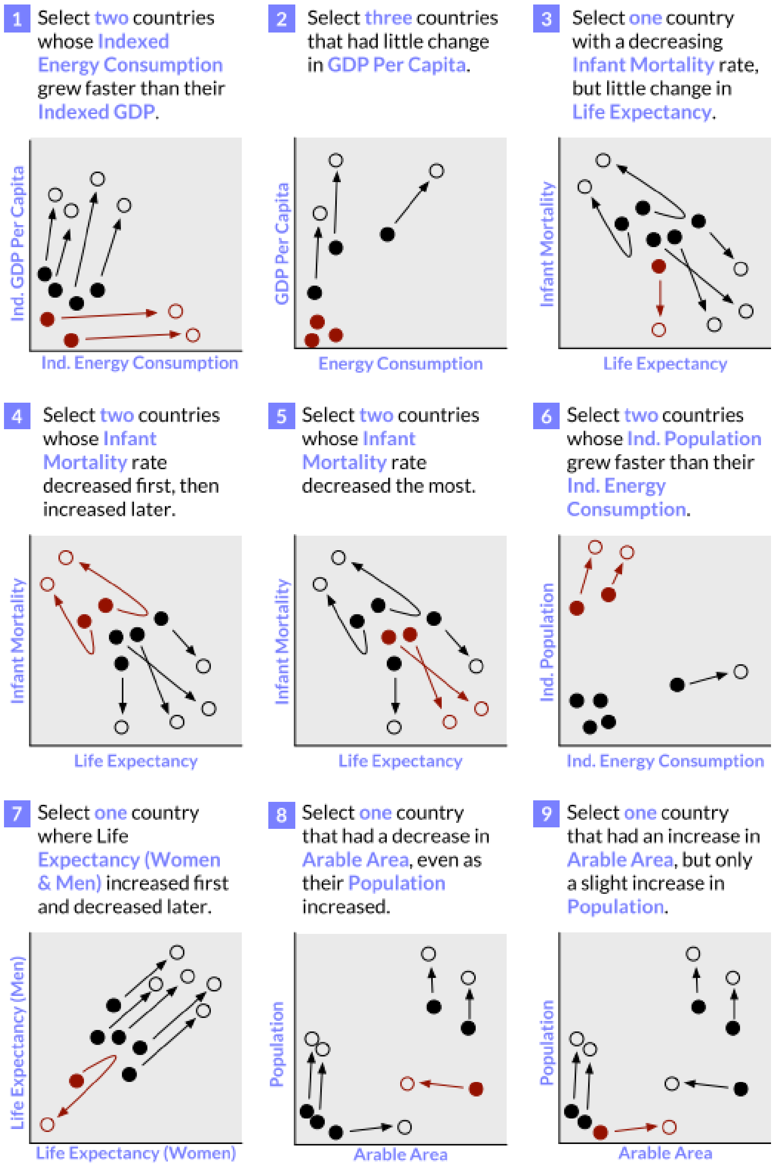
texts, like clusters identification (GRIFFIN et al., 2006), flow maps (BOYANDIN; BERTINI; LALANNE, 2012), multidimensional metamodels (GEBHARDT et al., 2018), geographical propagation phenomena (ARAYA; BEZERIANOS; PIETRIGA, 2020), mental maps (Archambault; Purchase; Pinaud, 2011) and dynamic networks (BACH; PIETRIGA; FEKETE, 2014; LU et al., 2020).

2.5 3D Scatterplot Variants and Immersive Analytics

The latest technologies for VR and AR have contributed to improving the effectiveness of immersive visualization techniques (KRAUS et al., 2019) by providing more comfort and overcoming the limitations of hardware that existed initially (CORDEIL et al., 2016). Immersive Analytics explores complex datasets using new technologies (BACH et al., 2016), enhancing spatial perception and complex scene understanding, and minimizing memory workload (MCINTIRE; LIGGETT, 2014).

Several immersive analytics applications have adopted 3D scatterplots for visualizing multidimensional data (BACH et al., 2017; CORDEIL et al., 2017; FONNET et

Figure 2.5 – Representative diagrams of the tasks performed in mobile phones. The starting and ending positions of target and distractor items are indicated by filled and unfilled circles, respectively.



Source: Brehmer et al. (2019)

al., 2018; WAGNER-FILHO et al., 2018; PROUZEAU et al., 2019a; YANG et al., 2020). However, few works explore scatterplot variants in immersive settings.

Onorati et al. (2018) proposed a 3D bubble chart version to verify user understanding of hierarchical data in virtual reality. A 3D bubble chart is also provided in VRIA (BUTCHER; JOHN; RITSOS, 2019), a framework for VR on the web. This framework provides several visualizations and interactive techniques for developers of any level.

Small Multiples (LIU et al., 2020; JOHNSON et al., 2019) and trails(PROUZEAU et al., 2019b; HURTER et al., 2019) visualizations were also explored in immersive scenarios. Fiberclay by Hurter et al. (2019) used an animated scatterplot variant, where trajectories of data points from large datasets are visualized as animated dots. It also uses Small Multiples to display multiple facets. Unlike VRIA, IATK (CORDEIL et al., 2019) is a desktop framework that enables the design of scatterplot matrices for studying correlations, among other charts.

Simpson et al. (2016) proposed an immersive tool based on multidimensional data to explore climate-economy models by displaying trails in scatterplots. They aim at understanding how immersion improves multi-objective decision-making that is typical of such integrated assessment models. Similar visualization techniques showing trails as a sequence of points are also found in DXR (SICAT et al., 2019) to represent flow lines.

2.6 Trends Visualization in Immersive Environments

We found different applications or tools that we can classify as providing immersive visualizations to distinguish trends over time. An application by the Wall Street Journal (KENNY; BECKER, April, 2015 (accessed November 02, 2020)) lets users virtually walk on a line chart like a staircase to experience the rise and sudden fall of the Nasdaq index during a stock market crash. ImAxes is an interactive tool that allows users to manipulate chart axes like physical objects in a VR environment to design visualizations (CORDEIL et al., 2017). It provides several charts, like histograms, 2D-3D scatterplots, and parallel coordinates. Histograms can be built by manipulating one axis. Two or three axes can be placed perpendicularly to build 2D or 3D scatterplots or parallel to obtain parallel coordinates visualization. ImAxes allows the analysis of trends based on the density of lines or points in some regions of multiple visualizations. In subsequent work, Batch et al. (2019) developed a study including experts, where the ImAxes approach is used for economic analysis.

Butscher et al. (2018) designed ART, a collaborative AR tool for identifying clusters and outliers and analyzing trends in multidimensional data. Data points in multiple 2D scatter plots are linked, creating a 3D parallel coordinates visualization anchored to a touch-sensitive tabletop.

Recently, an interesting VR application uses a 3D representation of multiple time series axes stacked uniformly along the third dimension (KLOIBER et al., 2020). The WaveChart visualization represents the time series of different sensors captured during a single cycle or different cycles captured from one sensor. It is manipulated in VR using a proxy to explore and detect anomalous behaviors in the time series.

2.7 Summary

An increasing number of works report experiments with multiple views and highlight the limitations of the methods provided to control composite visualizations with coordinated interactions using 2D/3D views. For example, the studies surveyed herein commonly used the juxtaposition pattern followed by superimposition, which is typical of geographical maps. The absence of methods and practical guidelines to use composite views in IA induced the development of different strategies, which showed disadvantages, especially in VR environments (GRAČANIN, 2018). Our work presents an approach to allow users to compose visualizations, and moving MCVs for improving the scene layout, facilitating data exploration. Furthermore, studies evaluating the effectiveness of Animation over static alternatives emerged using large and small displays. Herein, we expand previous studies towards the design space for immersive environments using our approach. Evaluating 3D scatterplot variants is a timely research problem since Immersive Analytics keeps evolving as a field and still needs a better understanding of how users analyze data in VR environments.

3 AN IMMERSIVE APPROACH FOR EXPLORING MULTIPLE COORDINATED 3D VIEWS

This chapter presents the *Spaces* approach, which uses a virtual cube called $Space$, inspired by Mahmood et al.'s work (MAHMOOD et al., 2018), for encapsulating each view and provides two modes of interaction with the views: the *macro* mode for interacting with the Spaces, and the *micro* mode for interacting with the data displayed in the *Space*. In addition to standard interaction techniques, the approach also provides “cloning" and “coordinated interactions" features. In this chapter, we also describe the first experiment designed for evaluating the approach by comparing it with a similar desktop version. The *Spaces* approach was published recently (QUIJANO-CHAVEZ; NEDEL; FREITAS, 2021a).

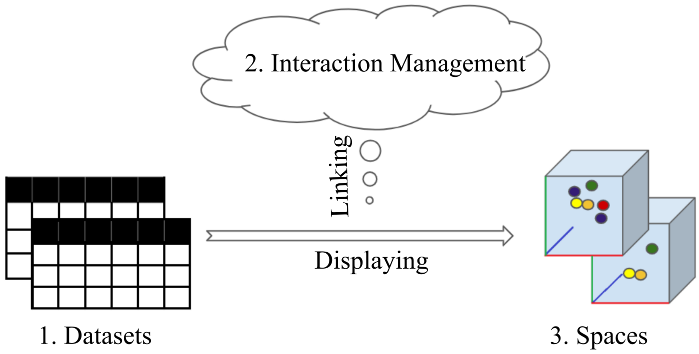
3.1 The $Spaces$ Approach

The change from standard 2D to 3D WIMP induces differences in perception and interactivity (MARRIOTT et al., 2018). Following the design space of composite visualization (JAVED; ELMQVIST, 2012a), where multiple “visual structures" are combined in the same “view", we designed our approach based on similar concepts. The “visual structure" is mapped to a virtual cube where it is rendered. The virtual cube is called $Space$ inspired by Mahmood et al. (MAHMOOD et al., 2018). An overview of the approach is shown in Figure 3.1 and its details are presented below.

3.1.1 The $Space$ concept

A $Space$ is a container for one visualization only and can be manipulated similarly to an object but without physics, weight, or texture associated. The objective of a $Space$ is to facilitate the interaction across multiple visualizations. We chose a cuboid shape to represent a $Space$ to have a reference point for the coordinate system, and added a title identifying the dataset being visualized in the $Space$. It can be cloned, and then the title is customized with the version number to distinguish it from the original $Space$ (see Figure 3.2-left). To interact with a $Space$, the interacting agent must be in *macro* mode, while to interact with the data displayed inside a *Space*, it must be in *micro* mode (see

Figure 3.1 – Overview of the *Spaces* approach: reading from the datasets (1); a visualization instance is added to the interaction manager (2) for coordination techniques (Brushing and Navigational Slaving); data is rendered in the virtual environment, in the *Spaces* graphical representation (3).



Source: The author

Subsection 3.1.2).

Figure 3.2 – The proposed macro/micro modes of interaction allow the user to interact with the Spaces and the data. The Spaces can be grabbed and overlaid to facilitate comparison of the data represented inside each one (left). The two virtual hands are independent from each other: the user can grab a Space with one hand and explore its information with the other one (center). Our approach allows the exploration of Multiple Coordinated Spaces (right).

Source: The author

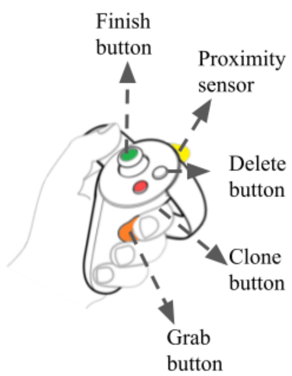
In a VR environment, the interacting agent used is the virtual hand, which is considered the most natural interaction paradigm (BOWMAN et al., 2004) for 3D interaction with near objects. The user can change between macro and micro modes of interaction through the proximity sensor of the index finger. For evaluation purposes, we developed a similar 3D desktop version. In that version, the mouse cursor is the interacting agent, and the mode change is based on events. We present the distribution of the events for both the VR and desktop versions in Figure 3.3.

3.1.2 Interaction Techniques

The standard WIMP functions are moving, close, and minimizing or maximizing. We developed similar functions for both the VR and desktop versions of our approach for manipulating the $Spaces$, except for minimizing and maximizing. These functions are presented in Figure 3.3.

As mentioned before, the interaction techniques are divided into $macro$ and $micro$ modes.

Figure 3.3 – Distribution of actions for each interactive command used in the Virtual Reality and Desktop versions. We propose two easily interchangeable modes of interaction, the *micro* mode to manipulate data displayed in the $Space$, and the *macro* mode to interact with the $Spaces$. A **controller module** manages how the user interacts with the $Spaces$ and data, while an **interaction module** connects data to $Spaces$. All features needed for coordinating interactions are provided by this module.



Target	Action	Virtual Reality	Desktop
Container (macro)	Select	Hand collision	Pointer collision
	Grab/Translate/Rotate	Select + Grab button	Select + Right click
	Clone	Select + Clone button	Select + Space bar
	Scale	Grab container with both controllers	Select + Mouse wheel
	Delete	Select + Delete button	Select + Delete button
Data (micro)	View detail	Index finger collision	Cursor pointer
	Highlight	View detail + Grab button	View detail + left click
Navigation	Virtual movement	Head movement	FPS control (A/W/S/D buttons)
System	Finish task	Finish button	Enter button

Source: The author

3.1.2.1 Macro mode interaction.

For ***selecting*** a $Space$, the *virtual hand* must be inside it. The $Space$ chosen will slightly change color, avoiding perception changes in the visualization technique. In order to ***grab*** a $Space$, the user must keep the Grab button pressed, allowing to grab one Space per hand. We selected the Grab button because it resembles the behavior of holding an object. Once grabbed, the user can ***move*** and ***rotate*** the $Space$ freely according to their movement. To ***scale*** a $Space$, the user must grab it with both hands, and by separating or joining them, the scale will increase or decrease the size of the $Space$, accordingly. To ***clone*** a $Space$, it is necessary to select it and press the Clone button: a copy of the $Space$ will be created, including the same visual features. To ***remove*** a $Space$, one must select the $Space$ and then press the Delete button: a confirmation window will open on the user's hand to verify whether or not the $Space$ should be deleted.

3.1.2.2 Micro mode interaction.

Two commands are available in the $micro$ mode. The ***view*** interaction is based on touching a data item with the virtual hand: it shows details about the data on the $Space$ at hand. The second command is ***highlight***, which allows changing the color of a data item for contrasting with others. The way to highlight or remove the highlight is to point at the data item and press the Grab button.

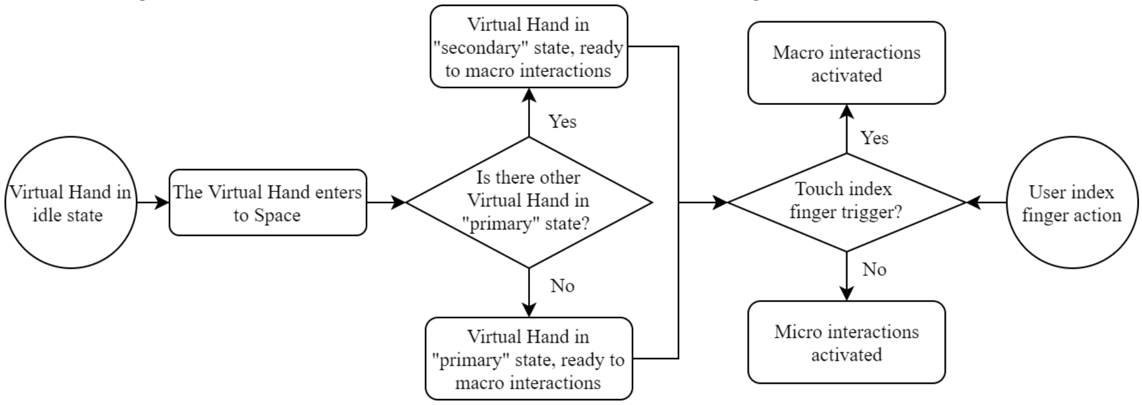
3.1.2.3 Coordinated interactions

Multiple coordinated $Spaces$ are based on **coordinate interactions**. Each time a $Space$ is rotated, the linked spaces will rotate too (***navigation slaving***). When the data is highlighted or not, the linked data will undergo the same change, thus providing the ***linking-and-brushing*** functionality.

3.1.3 Implementation Details

We developed our proof-of-concept prototype using the Unity game engine, C#, and the SteamVR plug-in to build a tool compatible with the HTC Vive and Oculus Rift head-mounted displays. As we can see in Figure 3.1, datasets are read, and the visualizations are created in $Spaces$. A reference to the dataset and $Space$ is instantiated in the **interaction module**, which is responsible for the interaction management thus linking both data and $Space$ to support coordination. Also, each $Space$ can be linked to other $Spaces$ for *navigational slaving* and *brushing-and-linking* interactions. Each $Space$ keeps track of the virtual hands that are inside it managed by the **controller module**, allowing the communication between them for *scaling* interaction. Axes of the coordinate system of each $Space$ are drawn, which is useful when the user superimposes $Spaces$ for comparison purposes, for instance.

Figure 3.4 – Overview of the interaction flow and change of interaction modes.



Source: The author

The **controller module** manages the *macro/micro* modes of interaction (Figure 3.4). We use three states for managing the modes. The *idle* state is the default state, which indicates that the virtual hands are not inside any $Space$. The **primary use** state indicates that a virtual hand is ready to interact or is interacting with a $Space$, and the **secondary use** state is used for controlling interactions that need two virtual hands. Also, to differentiate the *macro/micro* modes for the virtual hands, the controller device is shown in the VR environment every time the *macro* mode is active. The method chosen for the mode change is the index finger's proximity sensor.

3.2 Evaluation

The evaluation of our approach of multiple coordinated 3D views in VR using the $Spaces$ approach was performed through an experiment with users. We implemented a VR-based and a similar 3D desktop version with the same interactions to standardize the experiment variables. The *First Person* navigation technique was implemented for the desktop because it is more immersive than a third-person point of view (POV) (DENISOVA; CAIRNS, 2015) approach. Our user study compares the users' behavior while handling 3D visualizations in the desktop and virtual reality settings.

3.2.1 Hypotheses

To evaluate if our approach improves the MCV issues (mentioned in Section 2.2) (BALDONADO; WOODRUFF; KUCHINSKY, 2000), we focused on the comparative performance between the desktop (3D) and the virtual reality (VR) versions. We excluded the learning issue because it is challenging to have non-expert users available. Furthermore, issues related to infrastructure and implementation capacity were also not addressed because we assume that new technologies such as HMDs give support for those. The hypotheses that guided our first experiment are:

- **H1:** It will be faster to complete tasks using multiple coordinated views in VR than in 3D. Although there are several interaction techniques mapped to the desktop version, which can lead to interaction difficulties, the familiarity with mouse + keyboard can overcome those and allow a fair comparison.

- **H2:** The user will keep more information in VR than in 3D. We aim to analyze the first impression of the environment's data. The VR environment can be more fun for the user, and they would pay less attention to the data than in the desktop with physical space limitation. However, proprioception can help users in the VR version.

- **H3:** It will be easier to compare views in VR than in 3D. We aim to analyze the use of multiple visualizations, including cloning them.

- **H4:** The context switching will be hardest in VR than in 3D. The composed tasks let the user change visualization with different data interpretation. We displayed bar chart filters in one scene and increased the scatterplot chart filters in another.

- **H5:** Interacting with multiple coordinate views will be more comfortable in VR than in 3D.

- **H6:** Interacting with multiple coordinated views using the Spaces approach will be more efficient in VR than in 3D.

- **H7:** Multiple coordinated views using the Spaces approach will be easier to use in VR than in 3D.

3.2.2 Use Case

The use case we designed for testing our hypotheses is the exploration of a music dataset because music is a well-known topic that does not demand introduction effort.

The dataset used is the same previously used by Liang et al. (LIANG; GU; O'CONNOR, 2011), and it contains the following data for each music album: year, artist, genre, and also feature data from sound signals. For the experiment, the dataset was processed to avoid missing data. Finally, a total of 338 tracks were chosen.

The visualizations implemented are 3D scatterplots of music tracks, artists, and genres, obtained from a multidimensional projection technique, and bar charts showing the number of tracks per year, artist, and genre. The primary view is a scatterplot showing music tracks, and the other visualizations operate as music filters by brushing. Each visualization result is displayed in a $Space$.

The coordination between $Spaces$ allows obtaining data corresponding to the intersection of filters applied to different visualizations and data corresponding to the union when more than one filter is applied to a single visualization. The $Spaces$ of the genre and artist scatterplots are linked to the $Space$ of the music scatterplot letting the *navigational slaving* interaction.

The 3D scatterplots are the result of the dimensionality reduction technique t-SNE (MAATEN; HINTON, 2008) configured as follows: 100,000 iterations and perplexity equal to 40. We selected these parameters because they provided the best possible clusterization of genres. Then, to obtain the artist and genre scatterplots, we calculate the centroid using an average of their tracks' positions. Additionally, the centroids were multiplied by a weight (20) because more than one centroid was overlapping.

The implemented *brushing* interaction is based on highlighting data. Initially, the data is displayed with a shade that is sufficient for viewing details about the data item. A limitation of our brushing technique is that the information on the number of tracks is not refreshed (nor the height of the bar plots). The year, genre, and artist visualizations filter directly to the music scatterplot. Additionally, the user can clone any visualization for saving filtered data.

3.2.3 Tasks

For our user study, we designed composed tasks involving the manipulation of multiple views. The contexts used are artist, genre, and music tracks. Our test tries to emulate real system solutions. To finish each task, the user had to state the answer. A confirmation dialog similar to deleting cloned $Spaces$ was used to confirm the end of each task.

- **T1. Select the artist with more music tracks of genre Punk between 2005 and 2010.** A comparison of dense selected data from different filters is required. Cloning and comparing $Spaces$ is the expected goal. Given multiple comparisons, this task exclusively tests H3 and helps to measure time for H1.

- **T2. Select the closest artist to the music most different from the majority of genre Folk between 2005 and 2010.** This task aims at two objectives, the selection of the most atypical filtered data and the selection of the nearest data to a different context. We look for the overlapping $Spaces$ – this task measures time to evaluate H1 and the accuracy to evaluate H4.

- **T3. Given to the user 2 min of free exploration, answer ten questions** about genres, years, and artists with more and fewer music tracks (we asked 6 medium level questions), the more similar artists (2 difficult level questions) and music genres from the year 1991 and 1995 (2 very difficult level questions). With this task, we want to measure the memorization rate related to H2.

The hypotheses H5, H7 are evaluated through questionnaires, while H6 is assessed through the correct responses in tasks T1 and T2.

3.2.4 Training and Pilot Test

After signing the Term of Consent, the participants received a brief description of the environment (VR and desktop), data, and visualizations. The instructions of use for each environment were also explained at this time. The first training took approximately 15 minutes (10 min to VR and 5 min to 3D Desktop) and included *macro* and *micro* interactions.

In a pilot test, we noted that the users could not perform the tasks taking advantage of the functionalities of cloning, overlaying, and walking navigation, and consequently, the tasks would demand too much time. In order to reduce the testing time, we extended the training, inviting them to walk over the virtual area to improve confidence. Also, short recommendations were given to deal with tasks that involved overlapping and cloning.

3.2.5 Experiment

The experiment was carried out in a 4 x 4 meters room; the users were aware of the space where they could walk. A similar virtual room was set up to improve immersion. Additionally, an existing TV in the room was also modeled in the VR environment for displaying the tasks (see Figure 3.5).

Figure 3.5 – The virtual room had a TV that showed the tasks. The participants started the exploration in the middle of the room, and the visualizations were displayed around them. Users interacted with the visualizations using keyboard + mouse (left), while in the VR environment they used controllers as virtual hands (right).

Source: The author

The user study followed a within-subjects design, combining VR and 3D desktop environments, 6/4 $Spaces$, where genre and artist scatterplots were added in the second case, and three tasks (independent variables). A Latin-square design counterbalanced the order of the environments and the number of $Spaces$. Each participant performed four sessions, where they started using 4 and 6 $Spaces$ (or vice-versa) in the VR environment and later continued in a similar order on the desktop version (or vice-versa). Each of these scenarios started with a short training (learned from pre-testing) followed by the experimental session. We collected the time to complete each trial and correct answers as dependent variables.

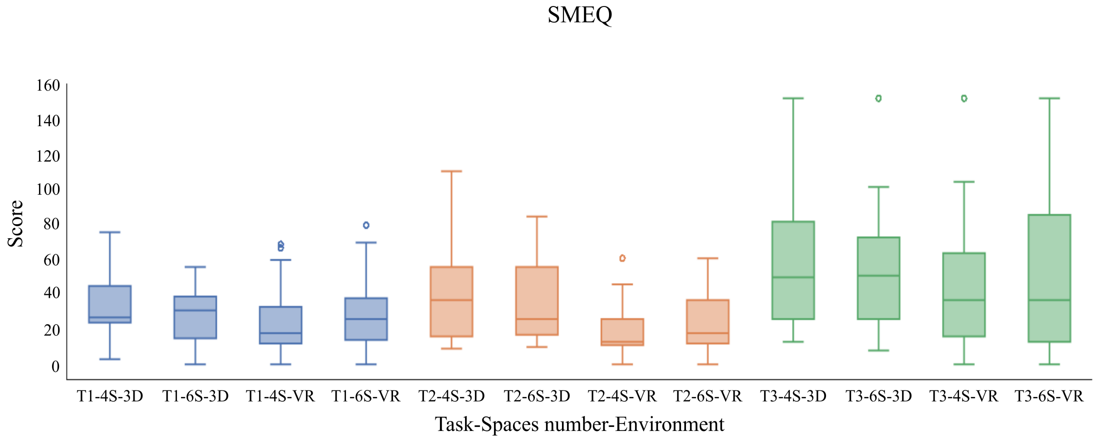
The average training time was 30 minutes (20 min for VR and 10 min for 3D Desktop). After completing a task, the users were consulted through a Web version of the Subjective Mental Effort Questionnaire (SMEQ) (SAURO; DUMAS, 2009), and one-select Emocards (DESMET; OVERBEEKE; TAX, 2001) used to validate H7 and H5, respectively. Finally, completing the number of $Spaces$ series (6 or 4), a UMUX-lite form was asked to analyze H7.

The target population consisted of 19 participants (16 males and 3 females), where

18 were computer science students and 1 was a student on ecology. Their average age was 23 years. The majority of the participants had none or minimal experience with VR headsets; only three reported high experience.

3.3 Results

Figure 3.6 – Box-and-whiskers plot of SMEQ scores for each trial. For T1, the VR version with 4-Spaces was the easiest (Mean = 26.57, SD = 21.16), the 3D Desktop version with 4-Spaces was the most difficult (Mean = 34.21, SD = 20.24). Also, T2 in the VR version with 4S was the less difficult (Mean = 18.26, SD = 16.40) and the 3D Desktop version with 4-Spaces, the most difficult (Mean = 39.94, SD = 29.89). T3 had similar result, the VR version was hardly less difficult (Mean = 47.50, SD = 41.24) than 3D Desktop (Mean = 55.28, SD = 36.55).



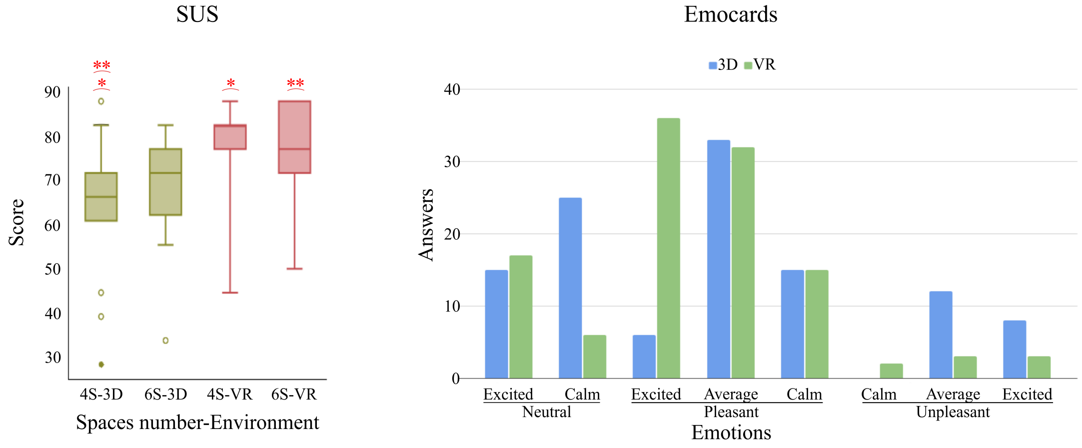
Source: The author

To validate the usability of the environments, we compared the perceived difficulty of the tasks T1 and T2 with the SMEQ “How difficult or easy was to conclude the Task overall?”. Results (Figure 3.6) showed a normal distribution by Shapiro-Wilk, and the statistical analysis by ANOVA indicates that VR was easier than 3D Desktop (p = .0163).

Additionally, the System Usability Score (SUS) was calculated based on the UMUX-lite (LEWIS; UTESCH; MAHER, 2013) questionnaire. ANOVA analysis was used for finding the effects of the number of $Spaces$ using the SUS score (normal distribution validated by Shapiro-Wilk), resulting in significant differences. Post-hoc analysis by Tukey’s HSD suggests that using 4 Spaces in VR is significantly more usable than in a 3D Desktop with 4 Spaces (p = .0121) and 6 Spaces in VR shows a higher usability score than in 3D Desktop with 4 Spaces (p = .0184). H7 is validated in both analyzes (results can be visualized in Figure 3.7-left).

Analyzing the duration of tasks for validating H1, the time showed a normal dis-

Figure 3.7 – Box-and-whiskers plot (left) of SUS score for each condition. * and ** indicate significant differences. Histogram of emocards (right) selected by users per environment (VR and 3D).



Source: The author

tribution validated by Shapiro-Wilk. We found through ANOVA that there was no significant difference for T1 (p = .7380) and T2 (p = .2830) in the duration of tasks.

We selected the correct answers to calculate the efficiency for validating H3, H4 and verify H6. From 152 answers, we obtained only 8 wrong answers in T1, and 17 errors in T2. The time of correct answers did not show significant differences for T1 (p = .9170) and T2 (p = .9070). The efficiency distribution can be observed in Figure 3.8.

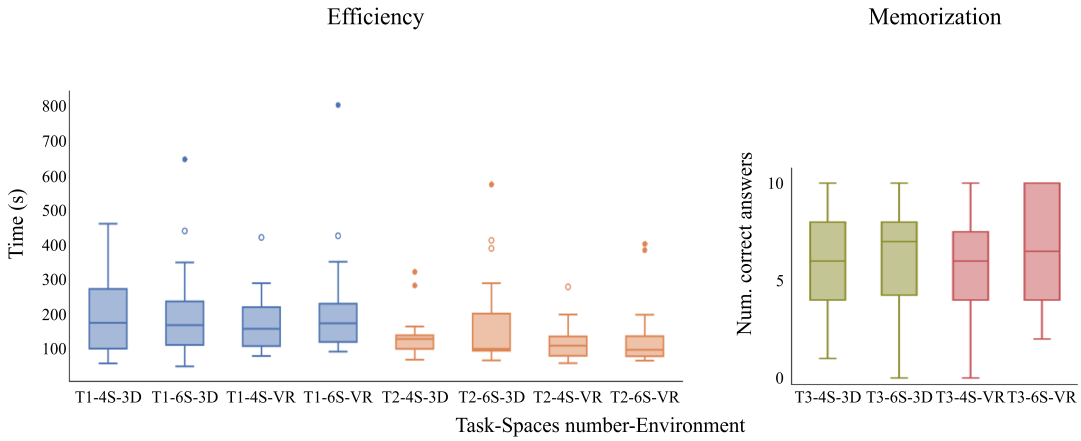
Friedman test was performed to compare the number of correct answers for T3 (Shapiro-Wilk showed no normal distribution). Results demonstrate that there are no significant differences (p = .7960), not validating H2 (see Figure 3.8-right).

The comfortability of each environment was evaluated based on emotional categories using emocards (Figure 3.7-right). We calculated Cohen's kappa of 114 responses (6 answers by user), evaluating the two environments per categorical answers ("pleasant", "unpleasant" and "neutral"). The results are summarized in Table 3.1. Cohen's kappa was 0.26 and conducted a reliability "fair" (LANDIS; KOCH, 1977). We concluded that the VR version was "average pleasant" (Mdn = 3) over the "calm pleasant" for 3D Desktop (Mdn = 4) with fair reliability validating H5.

The SUS ranged from 28.32 to 87.90 for 3D Desktop (M = 66.80, SD = 13.07) and from 44.57 to 87.90 for the VR version (Mean = 77.64, SD = 10.44). According to surveys that compare SUS scores for different systems, our VR version is ranked as "Good" (BANGOR; KORTUM; MILLER, 2009).

In summary, only H5 had significant differences and was validated, showing that

Figure 3.8 – Box-and-whiskers plot of time (seconds) for correct answers for T1 and T2 (left). Similar distributions were obtained for T1 in the 3D Desktop version (Mean = 187.54, SD = 104.33) and VR (Mean = 202.68, SD = 136.39), and T2 in the 3D Desktop version (Mean = 135.57, SD = 74.58) and VR (Mean = 123.44, SD = 86.31). Box-and-whiskers plot of trials per number of correct answers (right). No significant differences were found.



Source: The author

Table 3.1 – Results of 114 emotional answers per environment.

		3D Desktop			
		Pleasant	Neutral	Unpleasant	Total
VR	Pleasant	46	24	13	83
	Neutral	6	15	2	23
	Unpleasant	2	1	5	8
	Total	54	40	20	114

Source: The author

our approach is more comfortable than the 3D version. The other hypotheses could not be proved nor rejected due to lack of statistical significance.

3.4 Discussion

While visual analytics systems often use multiple coordinated views to explore and analyze complex datasets in 2D desktop environments, literature shows that fully-immersive analytics applications lack well-established techniques to use similar approaches.

We analyzed the difficulties of multiple coordinated views and proposed and evaluated an approach to provide multiple three-dimensional views in immersive Virtual Reality. Our method allows the user to use virtual hands to grab the visualizations displayed in three-dimensional versions of WIMPs (the $Spaces$) for free interaction in *macro* mode and interacting with the data items in *micro* mode. This way, the approach divides the interaction between *Spaces* and data, respectively. Moreover, the use of two modes for each *virtual hand* increases the number of grouped interactions that can be implemented (*macro, micro, macro - macro, micro - micro, macro - micro*). Another significant aspect is that our approach does not depend on the user's dominant hand.

3.4.1 Findings

The evaluation of our approach was based on comparing it with a 3D desktop version for testing 7 hypotheses. We designed and conducted an experiment where 19 subjects explored a music dataset, employing 4 and 6 coordinated views in both environments.

Before the actual experiment, a pilot test with five users made us recognize that although the case study was easy, the manipulation of multiple views required users with experience in data exploration. Interactions, as navigation and visualization grabbing, cloning, and overlaying, were not known, so they did not learn the most optimal manner to perform the tasks, and the tests demanded excessive time. The training was then improved, reducing the experiment time and the difficulties of the tasks.

However, the pilot test also showed that the usability of grabbing and manipulating visualizations had good results in comfort, in favor of our VR version. The three-dimensional visualization could be placed in different locations for better exploration. In addition, the training in physical walking for navigation caused the users to trust our system. This is reflected in the comfort results and comments. Furthermore, the navigation for the 3D desktop version was intuitive because most users knew the FPS format, but the translation and rotation interactions were hated due to the depth.

Concerning the hypotheses, although the quantitative results indicated no significant differences between the VR and 3D desktop, some interesting findings came from the questionnaires.

As for hypothesis **H1**, "It will be faster to complete tasks using multiple coordinated views in VR than in 3D." (tasks T1 and T2), one might assume that the familiarity with mouse + keyboard could lead the desktop version to be faster than VR but that was not confirmed. This might suggest that our approach did not introduce difficulties even for users with no experience in VR, presenting competitive execution times.

Regarding hypothesis **H2**, "The user will keep more information in VR than in 3D", it was evaluated based on the correct answers for task T3. Results were also non-significant, most likely due to a learning effect. We noticed that the participants acquired memorization strategies after completing task T3 and applied them to the other tasks. The shuffled questions ordering did not avoid the learning effect as we assumed it would.

The time spent and correct answers for tasks T1 and T2 allowed us to evaluate hypothesis **H3**, “It will be easier to compare views in VR than in 3D" and **H6**, “Interacting with multiple coordinated views using the *Spaces* approach will be more efficient in VR than in 3D". Both hypotheses were not statistically confirmed. However, participants commented that they had better confidence using the VR version, probably by novel technology. Also, most of them liked being able to organize the visualizations in the 3D virtual environment.

Regarding **H4**, “The context switching will be hardest in VR than in 3D", was also assessed by task T2, which was far more complex than the others. Since there were no significant differences in time or number of correct answers between the VR and 3D versions, this hypothesis was also not confirmed. Such a result might suggest that our approach did not increase the cognitive effort demanded to complete the task compared to a well-known setting such as the desktop.

Finally, the hypotheses **H5**, “Interacting with multiple coordinate views will be more comfortable in VR than in 3D", and **H7**, “Multiple coordinated views using the *Spaces* approach will be easier to use in VR than in 3D", were evaluated through questionnaires. The results showed that the comfort of handling multiple *Spaces* is higher in our fully-immersive environment than in the 3D desktop version, which probably might have influenced the same good result regarding usability.

3.4.2 Limitations

When designing our approach regarding the composite visualization patterns, we chose to support the juxtaposition and superimposition patterns. However, our application's architecture separates interaction with the *Spaces* (macro mode) from interaction with the data (micro mode), allowing a *Space* to be used with any data visualization. Therefore, overloading (by proximity) and integration (showing linking) are feasible patterns to evaluate in future works.

Another limitations are related to our experimental application. Multiple views are used to solve complex tasks, which is not feasible with non-expert participants. Having only non-expert users as subjects may be the most probable cause of not finding significant differences.

The brushing technique also introduced a limitation because the information on the number of music tracks is never updated. If we had that feature, we could have proposed other comparison tasks. Finally, the interaction techniques are based on direct contact between the users' hands and the virtual cube representing the $Spaces$. So, far interaction strategies using ray casting were missing.

3.5 Summary

Motivated by the challenges related to multiple views (BALDONADO; WOODRUFF; KUCHINSKY, 2000; JAVED; ELMQVIST, 2012b; KNUDSEN; CARPENDALE, 2017) and the increasing use of immersive analytics applications (MARRIOTT et al., 2018), in this first study we proposed an approach that allows composite visualization patterns in VR and comfortable and easy ways of interacting with multiple 3D visualizations in such environments. Our results show that the Desktop version is not significantly better than the VR version in terms of time and accuracy despite using the standard FPS approach with keyboard and mouse. Multiple 3D views are not typically used in desktop versions, and this could be the reason for the non-significant results. Subjective results show that our VR approach is significantly better than the Desktop version. We infer that the participants are not able to explore multiple 3D visualizations with common desktop interaction devices.

4 COMPARING SCATTERPLOT VARIANTS FOR TEMPORAL TRENDS VISUALIZATION IN IMMERSIVE VIRTUAL ENVIRONMENTS

In this chapter we present the second experiment, where we evaluated the effectiveness of 3D scatterplot variants for trends comparison tasks using the *Spaces* approach. The techniques are three-dimensional Small Multiples and Overlaid Trails (static versions), and Animation. In this study, we focus on informal ways of finding trends, i.e., those that allow perceiving trends without statistical estimation, based on visualizations only. This study has already been submitted for publication (QUIJANO-CHAVEZ; NEDEL; FREITAS, submitted).

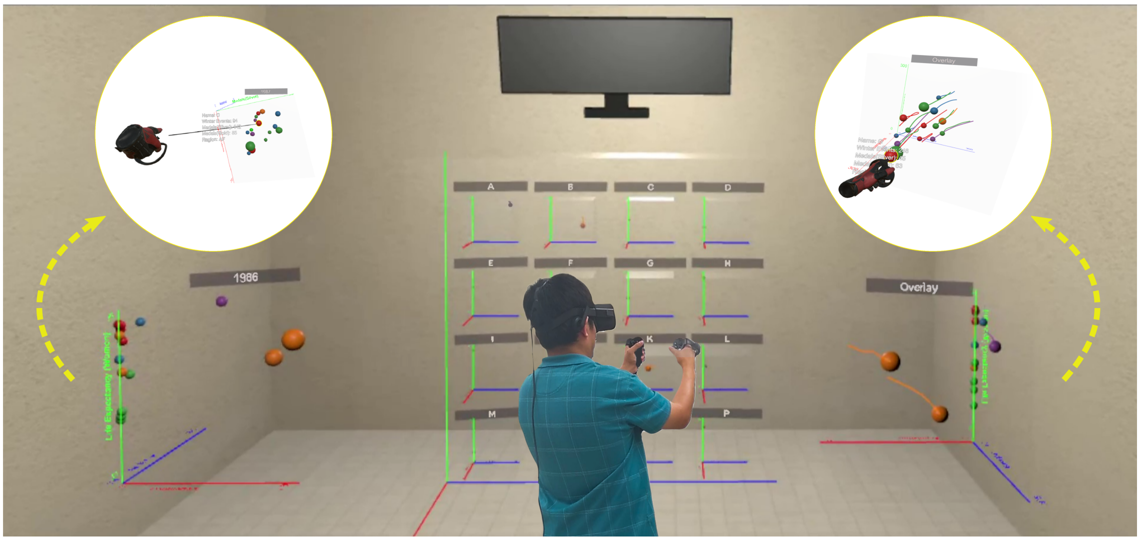
4.1 Introduction

Our second experiment was inspired by the previous studies presented by Robertson et al. (2008), and Brehmer et al. (2019). In Section 2.4, these two previous works were briefly described. Robertson et al. (2008) assessed two static bubble chart techniques (Small Multiples and Overlaid Traces) in trend analysis tasks, contrasting with the conventional Animation technique. The Overlaid Traces technique follows the principle of superposition (GLEICHER et al., 2011) showing the bubbles' trajectories overlaid simultaneously in one chart, while Small Multiples follows the principle of juxtaposition (GLEICHER et al., 2011) by displaying separate, side-by-side line plots for each item. Brehmer et al. (2019) studied the efficacy of two conditions on mobile phones (Animation and Small Multiples variants of scatterplots) for comparing trends in multivariate datasets. They designed possible trend scenarios, illustrating trajectories of target and distractor items (Figure 2.5). These studies were based on displaying two or three dimensions simultaneously on 2D displays. The time was one of them plotted as the position on the x-axis or the trail from the starting to the ending value of the period.

Regardless of the diversity of contexts in which animation, overlaid traces, and small multiples have been compared in 2D, we did not find studies in the literature about the effectiveness of such techniques in immersive environments. Inspired by the fact that Immersive Analytics keeps evolving as a field and we need a better understanding of how users analyse data in such environments, we decided to focus our study on the following question: *Do 3D scatterplot variants as Animation, Small Multiples, and Overlaid Trails* *lead to the detection of trends when they are explored in an immersive environment? How do they differ?*

Our second experiment was a user study comparing each visualization technique (Animation, Small Multiples, and Overlaid Trails) regarding completion time, accuracy, and subjective preferences using our *Spaces* approach. Also, we included a scene with all three techniques as the last phase of the experiment (Figure 4.1) for analyzing user's choices and preferences. To further interpret our results, we characterized each trend comparison task and offered reflection about future studies.

Figure 4.1 – Trends analysis tasks using the *Spaces* approach with three interactive 3D scatterplot variants. Ray casting and virtual hand are used as far and near interaction modes, respectively (details in the circles at both sides of the figure). Information on a data point is shown when the user reaches the corresponding marker in any mode.



Source: The author

4.2 Study Design

The change from standard 2D to 3D context induces many differences, primarily regarding perception and interactivity. (MARRIOTT et al., 2018).Since we adopted the tasks defined by Brehmer et al., we followed the same analyses' methodology to allow a fair comparison.

In this section, we describe all aspects of the second user study, which allowed us to evaluate the *Spaces* approach with different visualization in a temporal data analysis scenario.

4.2.1 Datasets

Since we followed a within-subjects approach differently from Brehmer et al.'s between-subjects experiment, we used two datasets to prevent learning effects.

We adopted the mobile dataset employed by Brehmer et al., obtained from the United Nations Common Database (DATABASE, 2019). Therefore, we had economic and public health indicators for 16 nations from 26 years (1975 to 2000). Since we wanted to use a second dataset with behavior similar to the mobile dataset regarding trends, we analyzed the dimensions involved in each task for the mobile dataset. Then, we manually generated the data, but the dimensions' names were set to a different theme, sports (LIN et al., 2020). Both datasets are included in a public repository (QUIJANO-CHAVEZ; NEDEL; FREITAS, 2021b).

4.2.2 Visualization Techniques

In all three visualization techniques (Animated, Small Multiples, and Overlaid Trails) (Figure 4.1), we used spheres as points to represent nations, totalizing 16 spheres by visualization. Then, we map quantitative dimensions (indicators) to the three axes and the nation's population to the size of the points. It is important to mention that we have carefully chosen the third axis to avoid overlaying points that could make the tasks difficult or impossible to perform. Each *Space* contains a scatterplot variant with axes distinguished by blue, red, and green colors. Appropriate labels for the minimum and maximum values are shown for each axis. The data points are color-coded depending on the nation's region. Each region color is selected using Color-Brewer (BREWER; UNIVERSITY, 2013), based on "Quality scheme color" because it is suited to representing nominal or categorical data (the region in our case). Since labeling each point would cause occlusion (YU et al., 2020), we show the data associated with each point during the interaction technique only (see details in Figure 4.1). The data includes each nation's name anonymously renamed with one letter (A–P) and additional information like the x, y, and z values, region, and year. We also provided intuitive interaction (CORDEIL et al., 2017) both with the *Space* that can be grabbed, moved, rotated and scaled, and within each visualization technique.

Animation. This technique is based on a single scatterplot, where the changes of attribute values over time are presented as successive frames, with the values being interpolated to create a smooth transition between each time step. We mapped the entire 26-years timeline to a 12-second animation, resulting in ≈0.462s interval between consecutive years. The scatterplot is located in a single *space* with a 1-meter side. For providing equivalent levels of interactivity across techniques, our implementation was inspired by the non-interactive Brehmer et al.'s condition, so the users are not allowed to reach any year-step. The animation plays in a continuous loop, and the current year is shown on the chart title. The user can only grab the *space* and scale it.

Small Multiples. Small multiples follow the juxtaposition arrangement approach (GLEICHER et al., 2011) to allow visual comparisons through a tiled display of charts or models using the same axes and measure system.In our experiment, we used Small multiples to represent each nation in a 3D cell of a 4x4 grid since it is suited for displaying small multiples in immersive spaces, and this was the size used by Brehmer et al. (LIU et al., 2020). Each cell is a *space* with a side of 0.4m, as well as the entire grid, that is arranged as a curved surface, so the cells are facing the user. All cells have identical dimensions and respond coordinately to scale and rotate interactions, similar to a previous design study (LIU et al., 2020). Grabbing cells allows for rotation, while the grid container translates the entire matrix. In each chart, the nation is plotted as a point at the location corresponding to the country attributes' values in the initial year. The changes over time are represented as a trail (interpolation is used for smoothing it) through the positions corresponding to each year. The nations are ordered alphabetically in the grid, and each nation's name is shown in its chart title.

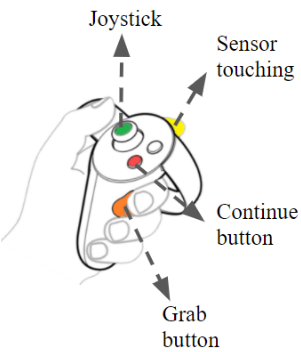
Overlaid Trails. This technique uses the principle of superposition (GLEICHER et al., 2011), where charts are overlaid one over another. Similar to Robertson et al.'s study (ROBERTSON et al., 2008), in our implementation of Overlaid Trails, the visual representation of nations and their timelines are identical to the Small Multiples technique, except that all nations are displayed in a single chart in a *space* with a side of 1m. The nation's point is located at the initial year, while the end of the trail represents the last year. Grab and scale interactions are the same as in Animation.

4.2.3 Interaction and Navigation Techniques

Visual data exploration requires interaction over three categories: data, view, and process to allow efficient analysis (HEER; SHNEIDERMAN, 2012). We provide several interactive techniques (Figure 4.2) to be used with each visualization in data analysis tasks. They are available in the two interaction modes we implemented: virtual hand (BOWMAN et al., 2004) and ray casting, which allow near and far interaction, respectively. The 3D *Space* manipulation using ray casting is similar to a previous study (GRANDI; DEBARBA; MACIEL, 2019). In our virtual implementation, we show the controllers because of the button hints needed throughout the experiment. Furthermore, both interaction modes can be alternated quickly by the user: while the index finger is closed, the ray is enabled; when the index finger is open, the virtual hand is enabled and ray casting disabled.

Interaction with Data. The users interact with data points to obtain details about each entity by pointing to the corresponding sphere either with the index finger in virtual hand mode or using ray casting (see Figure 4.1). So, brushing is not a need for task progress. The neighbors' within a range of 0.05 units from a sphere pointed by the user are displayed with an opacity of 30% to facilitate perception. Furthermore, a data point can be highlighted when the participant presses the *select* button: the sphere is shown with intense green to stand out from others. At the same time, in visualizations with trails, it is displayed with the same visual effects. Lastly, the data points have a binary state (*selected/unselected*), and the user can swap between both conditions as many times as required.

Figure 4.2 – Distribution of buttons for interaction and navigation techniques in our virtual environment.



Target	Action	Virtual hand (Index finger opened)	Ray casting (Index finger closed)
Container	Select	Hand collision	Pointer collision
	Grab/Translate/Rotate	Select + Grab button	
	Scale	Grab container with both controllers	
Data	View detail	Index finger collision	Pointer collision
	Highlight	View detail + Grab button	
Navigation	Virtual movement	Joystick	
System	Next step	Continue button	

Source: The author

Interaction with the View. As mentioned before, the visualizations are displayed within a *space* represented by a box container. The user can grab, scale, rotate, and translate any box container. This set of actions is activated when the user pointer (virtual hand or ray) is in the *space* but not pointing to any sphere, and the *grab* button is pressed.

Each interaction in the space affects the visualization. For Animation and Overlaid Trails techniques, their *space* can be rotated and translated while grabbed, this way being widely used (FONNET; PRIé, 2021). On the other hand, since Small Multiples is in a single grid container and divided into cells, only rotation and scale are enabled over cell spaces, and they affect all cells' spaces coordinately. For the whole grid space, we do not allow rotation to avoid overload. Each of these interactions can be performed with any hand except for scale. To scale, we need both hands to calculate the distance for resizing.

Navigation. Recent studies recommend different navigation techniques to operate in distinct room-sizes (YANG et al., 2020), mainly to simulate walking in VR applications (LEE; KIM; KIM, 2017; LANGBEHN; LUBOS; STEINICKE, 2018; Brument et al., 2019; DROGEMULLER et al., 2020). We implemented joystick-based navigation to be used in addition to physical exploration, mainly when the user is in boundary positions on the real room. In our joystick-based navigation scheme, the participant can move forward by pressing "forward" on the joystick. Users could explore the scene using any method (physical or virtual). Furthermore, the joystick function does not interrupt other interactions, and the user is free to use it at any time.

Table 4.1 – The tasks are characterized by the trajectories of target and distractor items over time (*characteristic*), number of indicators (*axes queried*), and distribution of items (Figure 4.6). Description refers to the United Nations Common Database dataset. Our study evaluated Small Multiples (S), Overlaid Trails (O), and Animation (A) regarding Completion time, Correct and Partial responses using Confidence Intervals (CIs). We map the significant results of each task to soft colors to represent the 95% CIs and intense colors the 99% CIs. The higher results are marked with a *.

			Completion time			Correct responses			Partial responses		
Characteristic	**Task**	**Description**	**S**	**O**	**A**	**S**	**O**	**A**	**S**	**O**	**A**
Finding similar trends	10	Select 1 country that had similar change in Life Expectancy, Infant Mortality and Arable Area.									
Finding a specific trend in two dimensions	3	Select 1 country with a decreasing Infant Mortality rate, but small change in Life Expectancy.	*				*				
					*		*				
	8	Select 1 country that had a decrease in Arable Area, even as their Population increased.	*								
			*								
	9	Select 1 country that had an increase in Arable Area, but only a slight increase in Population.	*								
Finding reversals	7	Select 1 country where Life Expectancy (Women & Men) increased first and decreased later.				*					
						*					
	4	Select 2 countries whose Infant Mortality rate decreased first, then increased later.	*				*			*	
					*		*			*	
Comparing two dimensions	6	Select 2 countries whose Ind. Population grew faster than their Indexed Energy Consumption.	*						*		
			*								
	1	Select 2 countries whose Indexed Energy Consumption grew faster than their Indexed GDP.	*								
			*								
Finding long trails	5	Select 2 countries whose Infant Mortality rate decreased the most.				*			*		
	11	Select 3 countries whose Life Expectancy (Men & Women) and Infant Mortality rate changed the most.									
Finding small changes on overlaid points	2	Select 3 countries that had small change in GDP Per Capita.	*			*			*		
								*			*

Source: The author

4.2.4 Tasks

Since the study carries an associated complexity from the necessary immersive 3D interaction, we defined 9 tasks replicating the trend behaviors from previous works to compare results. We defined two additional tasks to assess the third dimension, resulting in 11 formal tasks for trend analysis. They are listed in Table 4.1 and illustrated in the first column of Figure 4.6.

Different aspects could affect the user performance when using each visualization to complete the 11 formal tasks. These aspects are the distribution of items, trajectories of target and distractor items over time, and task complexity based on the number of indicators involved in the task. We propose to examine the performance across tasks by *axes queried* and *characteristic*. The *axes queried* pattern is related to the number of indicators (variation in axes) analyzed by the user to perform the task. We called 1D, 2D, and 3D tasks to distinguish if the task involves one, two, or three indicators, respectively. This allows assessing abstract tasks that are represented in the first column of the Figure 4.6. The *characteristic* pattern involves the remaining two aspects. We categorized the tasks as:

Finding similar trends. Given three dimensions, we wanted to know how difficult it is to find trends using three axes, asking the variation across dimensions (Task 10). The distractors' trails were not similar between dimensions. Since the beginning, we knew this is the most demanding task.

Finding a specific trend in two dimensions. The tasks asked to find the trail with a specific condition in two dimensions (Tasks 3, 8, and 9). The distractors show similar conditions, but the target items have a slight movement difference.

Finding reversal trails. When a point shows a reversal in its direction in any dimension, we identify it as a reversal (Tasks 4 and 7). The distractors here start the trail in the same direction as target items.

Comparing two dimensions. The participant has to identify the trail(s), where one dimension decreases or increases more than another dimension (Tasks 1 and 6). Some distractors share similar length and direction trails.

Finding long trails. The participant has to observe the length of trails to respond. We take as the length the point's path over time, including reversal trajectories. Long trails are asked in Tasks 5 and 11. Distractors also have long trails but not subjectively similar.

Finding small change on overlaid points. When minor changes occur in the data, a short trail is plotted. This task looks to find constant values. This task (Task 2) aims to evaluate the effectiveness of exploration in an overlaying points context (distractors), where the change of trends is not perceived easily using one view. We expect that Small Multiples would be advantageous because of the multiple coordinated view approach (BALDONADO; WOODRUFF; KUCHINSKY, 2000; SCHERR, 2008).

The 11 tasks are grouped by their characteristic in Table 4.1. Also, the tasks are illustrated in Figure 4.6, where the first column shows the representative task and abstract instruction. Moreover, Tasks 1, 2, 4, 5, 6, and 11 admit multiple responses. When using the Animation technique, the response can be chosen after the first loop ends only.

4.3 Experiment

Since the study involves VR hardware, we wanted the physical environment and devices identical to all participants. Moreover, we knew that we would have a limited number of participants. Then, the experiment was designed as a within-subjects study with the Visualization technique (Animation, Small Multiples, and Overlaid Trails) as the sole independent variable of the study. We evaluated the effectiveness of the visualization techniques for the 11 tasks, each one in a virtual scene. In addition, similar to previous studies (Brehmer et al., 2019; BREHMER et al., 2019) we inserted a *quality control task* between two of the formal tasks in the shuffled task ordering to test the participants' attention and essentially their ability to interpret a scatterplot. Specifically, this quality control task asked participants to *Select the two nations having the largest Population in the year 1975.* The nation's populations were redundantly encoded to both the x-position and the size of their corresponding points. Furthermore, this task did not require any judgment of change over time, as the two nations corresponding to the correct responses had the largest population no matter the year. Additionally, one *mixed scene* with the three visualizations (placed aleatory in each trial) was included at the end for exploring decision patterns (ROBERTS et al., 2021) and gathering subjective measures.

Before the actual experiment, we performed a pilot study with two volunteers. Results allowed us to improve some instructions.

4.3.1 Participants and Safety Measures

We recruited 19 participants (not including those in the pilot study), but 18 completed the experiment (14 males and 4 females). Age ranged from 21 to 29 (M = 26.44, SD = 2.28). Seventeen were graduate students in Computer Science and only one in Veterinary. Two reported no previous experience with VR devices, 9 low, 4 medium, while only 3 were high experienced. All had normal or corrected-to-normal vision. They were all volunteers and did not receive any compensation.

Due to the COVID-19 pandemic, we took safety measures for the experiment (STEED et al., 2020) and planned the study to be performed either in person or remotely. Also, since the use of non-uniform apparatus is a potential threat to validity in remote VR studies, to avoid it in the participants' recruitment, we specified the target hardware. Only two users accepted our online invitation, but one of them had to retreat due to hardware failures. A problem in the controller did not allow the use of the joystick appropriately, and the user was invited to leave. The one we could perform remotely was managed via Google Hangout. We verified that the remote participants' performance supported the findings in a pre-analysis. Consequently, we included them in the overall analysis. For the other subjects, we provided two physical environments with hardware setup and sanitary measures. Each environment could be used only once a day. The devices were sanitized before and after use. Some participants that live together were allowed to participate on the same day. We respected the distance and used face shields during all the experiment duration. The guidance was verbal without any physical contact. These conditions allowed the participants to feel safe to accept and complete the experiment.

4.3.2 Apparatus and Implementation

We used the Oculus Rift (1080×1200 pixels per eye, 90Hz refresh rate, $\approx 100^\circ$ field of view) with Touch Controllers and the Unity3D game engine (version 2018.3.10f1) to implement the application. We also used SteamVR version 1.3.10 to implement interactive and compatibility functionalities. The source code is available under the MIT open source license on GitHub (QUIJANO-CHAVEZ; NEDEL; FREITAS, 2021b).

4.3.3 Measures

We defined the following primary measures that apply to all eleven tasks: (1) **Completion Time**: measured from the moment the participant starts reading the task statement until they answer; (2) **Accuracy**: measured at two levels of granularity, the **Proportion of Correct Responses**, computed as binomial proportions per task (number of correct answers per task over the total number of repetitions), and the **Partial Correctness**, computed as the number of correct answers for the tasks requiring multiple responses; (3) Self-reported **confidence** on the responses; (4) the **perceived visualization's ease of use** to perform the tasks; and (5) **visualizations used** in the *mixed scene*.

As secondary measures, we collected interaction techniques used (and their duration) per task, and responses from the cybersickness (SSQ (Bimberg; Weissker; Kulik, 2020)) and usability questionnaires (Umux-lite (LEWIS; UTESCH; MAHER, 2013)) and the overall ranking of the three techniques at the end of the experiment.

4.3.4 Procedure

At first, we sent an e-mail message containing a link to a Google Form and a *counterbalance code number* to distribute the participant according to the within-subjects design. The form began with a consent term, user profile, and pre-cybersickness questionnaires. Then, the form instructed a step-by-step setup of the application. The VR session started just after it. The *counterbalance code number* was required before putting the headset on. In the VR session, each participant had to follow instructions shown on the TV (see Figure 4.1) to perform the tutorial about the visualization and interaction techniques followed by the experimental session. A *finalization code* was provided so the user could continue with the post-experiment questionnaires (cybersickness, usability) and the overall ranking question). We counterbalanced the visualization technique and datasets order using a Latin square model.

The experimental session started with 3 training tasks for each visualization. The *mixed scene* was not included because it is the last scenario, and the participant would already know each technique. We used the first dataset for the tutorial and training. These instructions were replicated from the previous study (BREHMER et al., 2019) where the instructions requested different behaviors from the formal tasks. Then, the experiment proceeded with the 11 formal tasks.

The participants were placed in the center of a virtual room (height = 3m, width = 4m, depth = 4m). For each task, a single visualization is presented to the user in the virtual environment, which also contains a TV that shows instructions. For the last task, a *mixed scene* including all three visualizations is presented, and the users can freely choose which ones they prefer to perform the task. In this case, the Animation technique is shown on the left side, Small Multiples at the front, and Overlaid Trails on the right side.

Each visualization technique was adjusted dynamically to the participant height. The 11 tasks and a quality-control task were shuffled, and we randomized the assignment of nations to letters A through P and the assignment of colors to regions. This procedure was replicated from Brehmer et al.'s work and modified for our variants.

After completing the tasks in each scene, the participant had to answer two subjective questions (self-reported confidence and the perceived visualization's ease of use) and was invited to rest if wanted.

We logged the sessions, device setups, headset tracking, interaction techniques used and duration, users' answers for each task, and responses to the questionnaires.

4.4 Results

The experiment took from a minimum of 61 minutes to at most 188 minutes (M = 119), including questionnaires, rest time, and the VR session composed by tutorial + each scene: 3 training tasks (*mixed scene* with no training), and 12 measured tasks (including one quality control task). In total, the experiment gathered data from 18 participants $\times$ (9 training tasks + 4 scenes $\times$ 12 tasks) = 1026 trials.

We analyzed, reported, and interpreted our inferential statistics using interval estimation instead of p-values (CUMMING, 2014; DRAGICEVIC, 2016). The Confidence Intervals (CIs) are calculated using bootstrap (BESANÇON; DRAGICEVIC, 2017). The collected data and analysis scripts, and the dataset that we generated are provided alongside the application source code in our Github repository (QUIJANO-CHAVEZ; NEDEL; FREITAS, 2021b). All participants performed the quality control task right. We excluded training and quality control tasks from our analyses and verified that counterbalancing technique and task order did not have a consistent effect on performance by comparing the Confidence Intervals (CIs) of each (condition + ordering) group for each task and response metric. We analyzed the effectiveness of the visualization techniques and their manipulation using interaction techniques. The *mixed scene* was used to obtain subjective and interaction data. We report 95% and 99% CIs similar to Brehmer et al.'s study (BREHMER et al., 2019) indicating the range of plausible values for the mean completion time, the proportion of correct responses, and correctness.

4.4.1 Overall Results across Tasks

We analyzed measures for all tasks grouped by the visualization technique and the number of axes queried.

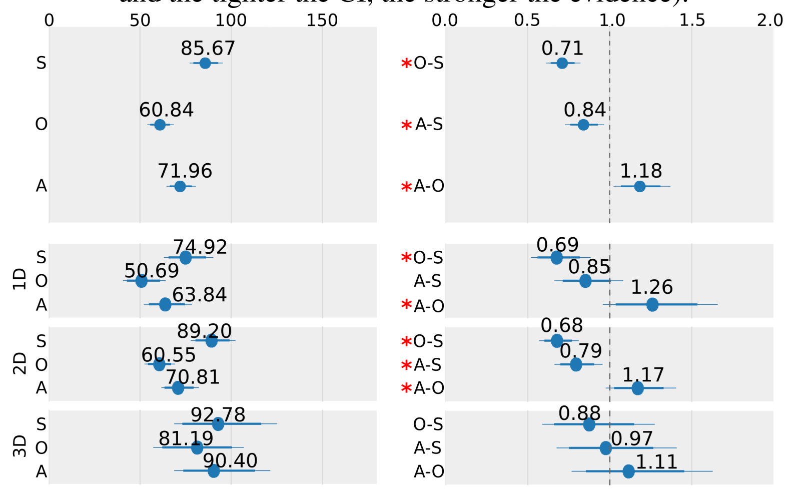
4.4.1.1 Completion Time

We log-transform participants' completion times to correct for positive skewness and present anti-logged geometric mean completion times (DRAGICEVIC, 2016; SAURO; LEWIS, 2010). For comparing whole completion times, we compute differences in log-transformed values and present these differences as anti-logged ratios between geometric means (BESANÇON; DRAGICEVIC, 2017).

Most participants took more than one minute to complete each task. Figure 4.3-top shows completion time for all tasks grouped by visualization technique. Mean times are shorter for Overlaid Trails (60.84s), followed by Animation (71.96s) and Small Multiples (85.67s). The observed differences (Figure 4.3-top) are strong evidence that Overlaid Trails is faster by 0.71 on average than Small Multiples and by 1.18 on average than Animation. There is also strong evidence that Animation is faster than Small Multiples by 0.84.

Figure 4.3-bottom shows completion time for all tasks grouped by the number of axes queried and visualization technique. The CIs show that mean times for 3D tasks are shorter than those for 2D and 1D tasks, with Overlaid Trails and Animation conditions having the most considerable differences: 30.50s and 26.56s on average, respectively for 1D tasks, and 20.64s and 19.59s, for 2D tasks. Additionally, the CIs size represents a large variability of observations resulting in no evidence across their conditions (CUMMING, 2014). In conclusion, we do not have sufficient evidence to suggest differences in completion times over 3D tasks. For 1D-2D tasks, differences showed strong evidence that Overlaid Trails is faster. There is also evidence that Animation is faster than Small Multiples in 2D tasks by 0.79.

Figure 4.3 – Mean Completion Time in seconds and pairwise comparisons for each visualization (top), and grouped by the number of axes queried (bottom) for all tasks. S = Small Multiples, O = Overlaid Trails and A = Animation. Evidence of differences are marked with *. Thick error bars represent 95% CIs, while thin error bars are conservative 99% (the further away from 1.0 ratio and the tighter the CI, the stronger the evidence).



Source: The author

4.4.1.2 Proportion of Correct Responses

Concerning the proportion of participants who responded to the tasks correctly, without considering partial correctness, we computed binomial proportions similarly to Brehmer et al.'s study (BREHMER et al., 2019). For comparing differences, when the CI overlaps 0%, this means insufficient evidence of a difference in accuracy.

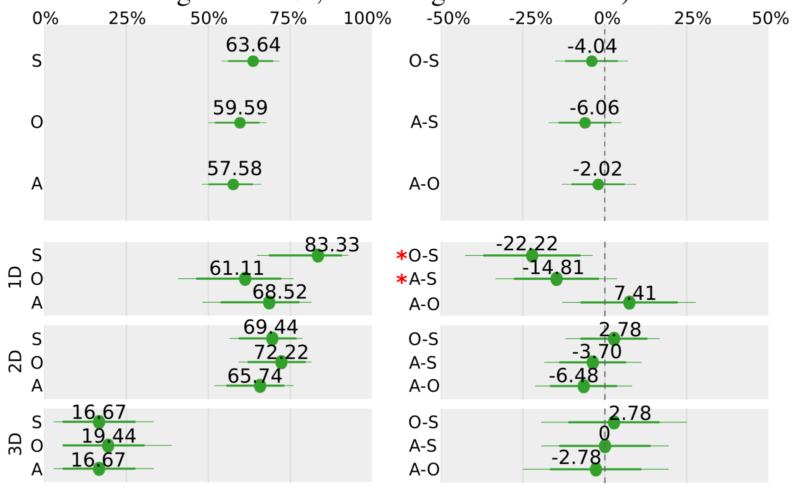
As can be observed in Figure 4.4-top, at least 50% of the participants responded to the tasks successfully. Proportions are smaller for Animation (57.58%), followed by Overlaid Trails (59.59%) and Small Multiples (63.64%). There is no evidence that the proportion of participants that responded correctly are different across techniques.

On the other hand, Figure 4.4-bottom shows that the participants had a lot of difficulties to successfully complete the 3D tasks, the proportion is less than 25%. For 1D tasks, differences show strong evidence that participants completed more successfully the responses using Small Multiples than Overlaid Trails by 22.22%. Also, there is evidence that Small Multiples is 14.81% more accurate than Animation. There is no evidence of differences in 2D-3D tasks (Figure 4.4-bottom).

4.4.1.3 Partial Correctness

We report means and CIs of partial correct answers for tasks requiring multiple responses (Tasks 1, 2, 4, 5, 6 and 11). As in the previous analysis, differences are interpreted

Figure 4.4 – Proportion of correct responses and pairwise comparisons for each visualization (top), and grouped by the number of axes queried (bottom) for all tasks. S = Small Multiples, O = Overlaid Trails and A = Animation. Evidence of differences are marked with *. Thick error bars represent 95% CIs, while thin error bars are conservative 99% (the further away from 0 and the tighter the CI, the stronger the evidence).



Source: The author

when the CI overlaps 0%.

Figure 4.5-top shows that mean correctness is shorter for Overlaid Trails (76.39%), followed by Animation (80.71%) and Small Multiples (85.34%). There is strong evidence that Small Multiples is more accurate than Overlaid Trails by 24.07% (Figure 4.5-top). Also, Animation is more accurate than Overlaid by 15.74%.

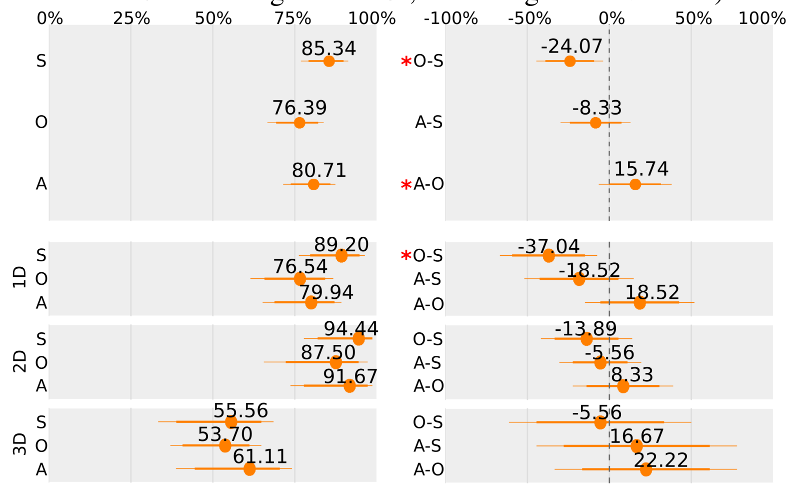
Figure 4.5-bottom presents partial correctness with the differences grouped by number of axes queried and visualization technique, showing that 3D tasks are less accurate than 1D and 2D tasks. Pairwise comparisons show evidence that Small Multiples is more accurate than Overlaid by 37.04% in 1D tasks (Figure 4.5-bottom).

4.4.2 Results per Tasks

We also report results on completion time and correct responses for each task. While Figure 4.6 shows such results for all tasks, Figure 4.7 presents the partial correctness of tasks with multiple responses. We interpret our results based on the tasks' characterization presented in Section 4.2.4, using both Figures. 4.6 and 4.7. Additionally, we summarize the significant results in Table 4.1.

Comparing two dimensions (Tasks 1 and 6). There is strong evidence that Small Multiples is slower by 0.72 on average than Overlaid Trails and by 0.62 than Animation in Task 1, and by 0.53 than Overlaid Trails and by 0.57 than Animation in Task 6 (Fig-

Figure 4.5 – Mean partial correctness and pairwise comparisons for each visualization (top), and grouped by the number of axes queried (bottom) for multiple responses tasks. S = Small Multiples, O = Overlaid Trails and A = Animation. Evidence of differences are marked with *. Thick error bars represent 95% CIs, while thin error bars are conservative 99% (the further away from 0 and the tighter the CI, the stronger the evidence).



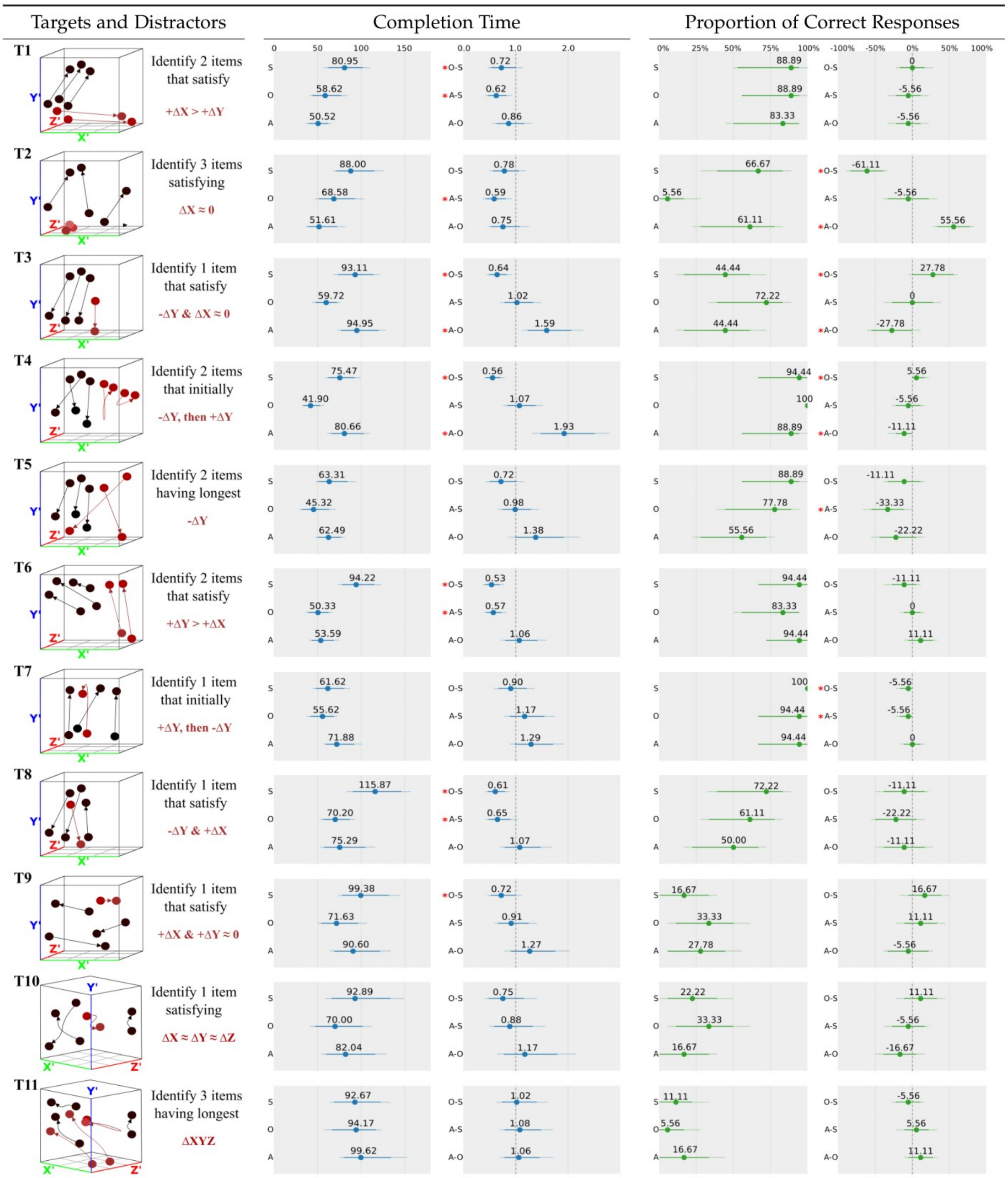
Source: The author

ure 4.6). Also, Animation is the fastest in Task 1 (50.52s), while Overlaid Trails is fastest in Task 6 (50.33s). The proportions of correct responses (Figure 4.6) and partial correctness (Figure 4.7) in Task 1 show an evident ceiling effect. For Task 6, proportions suggest that Overlaid Trails is more error-prone than Animation and Small Multiples (both by 11.11%) without evidence, opposite to correctness where Small Multiples is more accurate than Overlaid by 27.78%.

Finding a specific trend in two dimensions (Tasks 3, 8, and 9). There is strong evidence that Small Multiples is slower than Overlaid by 0.64. Also, results in Task 3 evidence that Overlaid Trails is 1.59 faster than Animation. However, Task 8 shows evidence that Animation is 0.65 faster than Small Multiples. Furthermore, there is evidence that Overlaid Trails is more accurate only in Task 3 by 27.78% on average than Small Multiples and Animation. For Task 8, there is no evidence of differences in accuracy between conditions, the proportion of correct responses among participants being higher in Small Multiples (72.22%) than Overlaid Trails (61.11%) and Animation (50%). As for Task 9, the proportions of correct responses suggest high difficulty in tasks using Small Multiples (16.67%), followed by Animation (27.78%) and Overlaid Trails (33.33%).

Finding long trails (Tasks 5 and 11). Results report that participants were faster using Overlaid Trails (45.32s) than using Animation (21.49s) and Small Multiples (63.31s) for Task 5. There are no differences in completion time for Task 11. In Task 5, there is strong evidence that Small Multiples is more accurate than Animation both in the propor-

Figure 4.6 – Completion Time (seconds) and Proportion of Correct Responses (in %) for each task. S = Small Multiple, O = Overlaid Trails and A = Animation. In the first column, we represent tasks' features showing targets (red) and distractors (black). Arrows indicate starting and ending positions. Interpretation is also shown in red e.g., $-\Delta Y > +\Delta X$ means that the variation in Y-axis is decreasing and increasing on X-axis. The second and third columns show the means per visualization (left) and pairwise comparison (right). Evidence of differences is marked with *. Thick error bars represent 95% CIs, while thin error bars are conservative 99% (the further away from 1.0 for time ratio and 0 for proportion and the tighter the CI, the stronger the evidence).



Source: The author

tion of correct responses (33.33%) and correctness (50%). For Task 11, results suggest that participants had difficulties identifying all targets correctly without evidence of differences between conditions. Less than 17% of participants responded all correctly.

Finding reversals (Tasks 4 and 7). For Task 4, there is strong evidence that Overlaid Trails is faster than Small Multiples by 0.56 and than Animation by 1.93. For Task 7, there is no evidence of differences in completion time between conditions. The proportion of correct responses among participants is 100% in Task 4 using Overlaid Trails. Results suggest that Overlaid Trails is more accurate than Small Multiples by 5.56% and than Animation by 11.11%. On the other hand, the correct responses for Task 7 using Small Multiples is 100%, with strong evidence that Overlaid Trails and Animation are less accurate than Small Multiples by 5.56%. In Task 4, the mean partial correctness is also 100% using Overlaid Trails, with evidence of 11.11% difference for Small Multiples and 16.67% for Animation.

Finding small changes on overlaid points (Task 2). There is strong evidence that Animation is faster than Small Multiples by 0.59. Also, the proportion of correct responses among participants and partial correctness support our assumptions that there is evidence of Overlaid Trails being less accurate than Animation and Small Multiples (more than 55% of difference). There is no evidence of differences between Animation and Small Multiples.

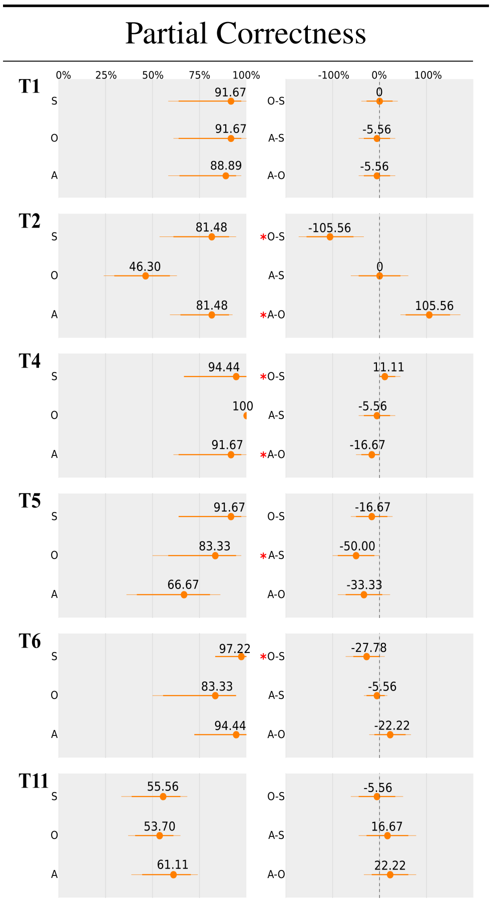
Finding similar trends (Task 10). There is no evidence of differences in completion time, although mean times are shorter for Overlaid Trails (70.00s), followed by Animation (82.04s) and Small Multiples (92.89s). Participants reported this task as the most difficult. Accuracy was less than 50%, and there is no evidence of differences between conditions.

4.4.3 Interaction Results

Since participants can combine navigation and other interaction techniques (Section 4.2.3), their behavior in each scene offers insights into their preferences. Figure 4.8 shows the distribution of task time per interaction technique. Participants' heads were tracked during the entire experiment, and translating and rotating camera refer to head movements. We sampled every 2 seconds and determined a threshold of 0.1m for translation and 30° for rotation.

Results suggest that participants interacted more in the Small Multiples scene, where the design and the composite interactions over grid and cells induced the longest times. Interaction time was similar between Overlaid Trails and *Mixed scene*, while

Figure 4.7 – Partial Correctness (in %) for each task with multiple answers: mean correctness (left) and pairwise comparisons for each visualization (right). S = Small Multiple, O = Overlaid Trails and A = Animation. Evidence of differences are marked with *. Thick error bars represent 95% Bootstrap CIs, while thin error bars are conservative 99% (the further away from 0 and the tighter the CI, the stronger the evidence).

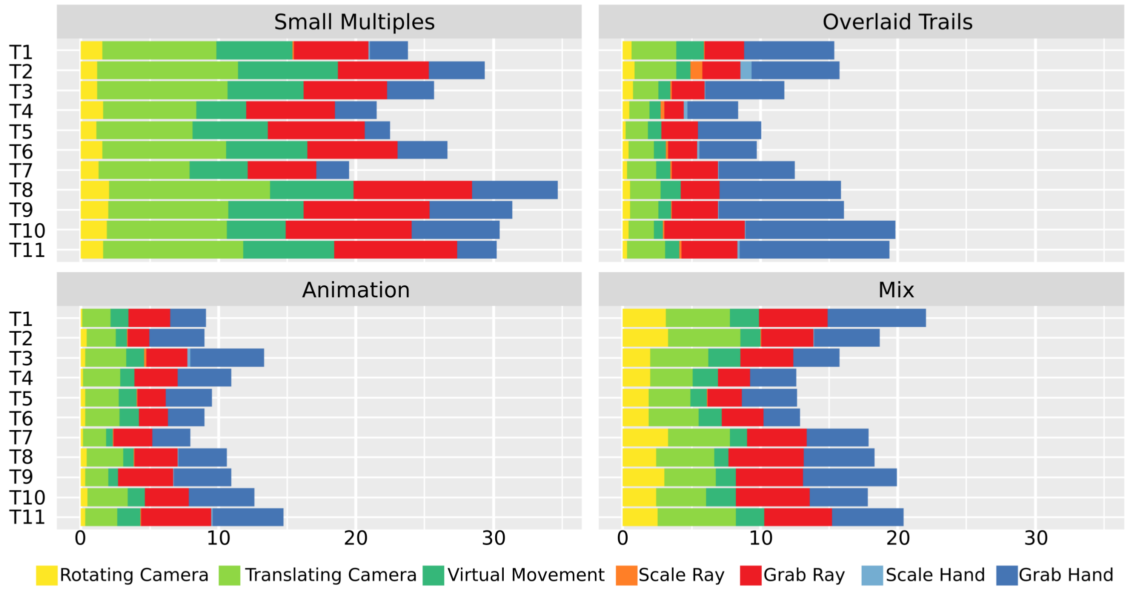


Source: The author

Mixed scene resulted in longer navigation times due to multiple visualizations, and the participants interacted more, grabbing Overlaid Trails using Virtual Hand. The Animation scene shows the lowest interactivity since the participants only follow the points transition during the automated loop.

Figure 4.8 also shows that participants used more the grab interaction in Overlaid scene than others. The overlaying trails and points lead the participants to make rotations using virtual hand more than with the ray casting. Targeting 3D small points (Figure 4.1) at a distance using ray is difficult; for this reason, participants preferred to interact with shelves and cells using rays and virtual hands to choose responses. Rotating camera is mostly used in the *mixed scene* because participants checked the points selected across coordinated visualizations, resulting in more confidence (Figure 4.9). Scale interaction

Figure 4.8 – Distribution of task time per interactions for each task in each scene condition, where time (x-axis) is in minutes. Each interaction technique is encoded in a different color.



Source: The author

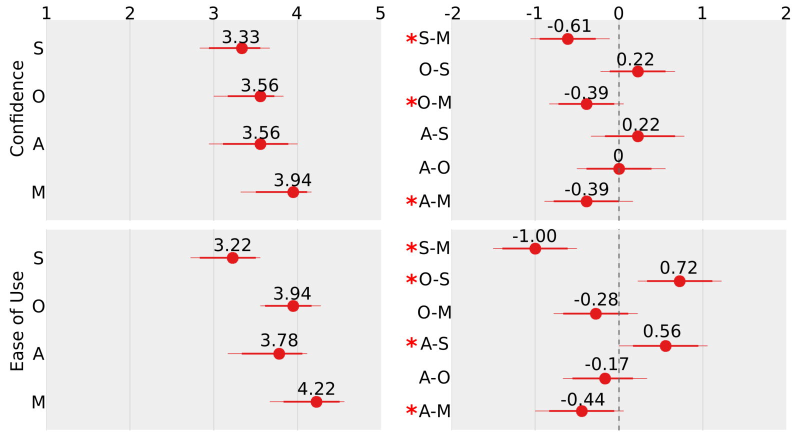
times are short (<0.9m using finger and <0.6m using ray by task), practically indistinguishable. Overlaid Trails is the most scaled among all scenes, and participants scaled this chart more for finding **small changes on overlaid points** (Task 2). Furthermore, **comparing two dimensions** tasks present different results between them in *mixed scene*, while Task 1 was the most interactive of all, Task 6 was one of the lesser ones. Also, Task 7 had the lowest interactivity for Animation and Small Multiples, while Task 4 had the lowest for Overlaid Trails and Mixed scene.

4.4.4 Results from Questionnaires

4.4.4.1 Self-reported confidence and ease of use

The participants were asked about their confidence in the responses and the visualization's ease of use after each scene during the experiment. The mean ratings along with CIs on a Likert scale from 1 (low) to 5 (high) concerning these measures are shown in Figure 4.9. Participants reported they were more confident in their responses in the *mixed scene* than in single-technique scenes (Animation, Overlaid Trails, and Small Multiples). Regarding the ease of use, *mixed scene* was also the most well-rated, followed by Overlaid Trails and Animation. Small Multiples is the less rated with strong evidence that the overload of interactions contributed to these results.

Figure 4.9 – Subjective results rating from 1 (low) to 5 (high) for S = Small Multiple, O = Overlaid Trails, A = Animation and M = Mixed scene. Evidence of differences are marked with *. Thick error bars represent 95% CIs, while thin error bars are conservative 99% (the further away from 0 and the tighter the CI, the stronger the evidence).



Source:The author

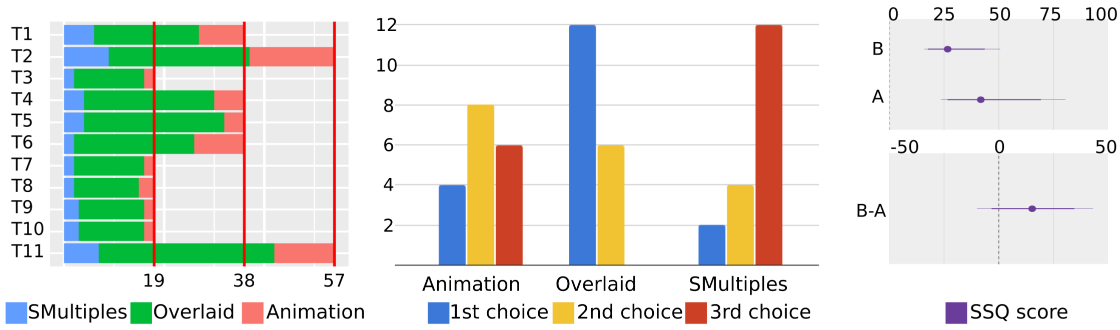
Figure 4.10-left shows the distribution of response points across different visualizations. Some participants selected the response in different visualizations more than one time. We report the last selection as the answer with the most confidence. It is clear that Overlaid Trails is the visual technique with more preference. We were surprised to see the choice of the Overlaid Trails technique in Task 2 because the overlaying trails + points would induce to prefer the other techniques.

4.4.4.2 Secondary measures results

The System Usability Score (SUS) of the VR system (including tutorial, training, and experimental session) was calculated from UMUX-lite (LEWIS; UTESCH; MAHER, 2013) and ranged from 60.82 to 87.90 (M = 74.66, SD = 6.75), which corresponds to "Good"(BANGOR; KORTUM; MILLER, 2009). Also, the long duration of the experiment demanded to analyze sickness incidences. The pre and post-VR Simulator Sickness scores widely adopted in VR researches (Bimberg; Weissker; Kulik, 2020) measured through SSQ showed that there is no evidence of differences. Furthermore, we calculated the average delta 4.06, which is considered negligible (KENNEDY et al., 2003).

Finally, participants rated the visualization technique preference (Figure 4.10-Center). Most participants rated Overlaid as their first choice (66.66%), followed by Animation (33.33%). Only two participants rated Small Multiples as their first choice.

Figure 4.10 – (Left) Distribution of answers across the different visualizations in Mixed Scene, number of task's answers limited by red line. (Center) Distribution of rating choice across the different visualization techniques. (Right-up) Mean Cybersickness score evaluated before (B) and after (A) the experiment. (Right-down) Pairwise comparisons, where thick error bars represent 95% CIs, while thin error bars are conservative 99%.



Source: The author

4.5 Discussion

Given the lack of studies about the effectiveness of animation techniques for exploring data visualization in immersive environments, our study compared 3 different scatterplot variants (Animation, Overlaid Trails, and Small Multiples) for analyzing trends in immersive environments. We replicated the majority of features from Brehmer et al.'s and Robertson et al.'s studies (BREHMER et al., 2019; ROBERTSON et al., 2008), which focused on mobile phones and large displays settings. Given the differences between our design and theirs, the results cannot be directly compared, but we discuss our findings in the light of their results when possible.

4.5.1 Contrasting Tasks

The Overlaid Trails showed completion time faster overall, followed by Animation and Small Multiples, with results statistically different from previous studies where Animation was the slowest. The accuracy was task-dependent: results from tasks requiring the analyses of three dimensions were less accurate. Also, for 3D tasks, there is insufficient evidence of differences across visualizations, contrasting with 1D-2D tasks, which showed differences. Notoriously, Small Multiples had disadvantages in our experiment. The desire to provide the same interaction techniques in each visualization produced an overload for Small Multiples, and consequently, long time to perform the tasks and a low score in the subjective questionnaires.

As for individual tasks, Animation was faster only in 2 tasks, while Small Multiples was slower in 6 tasks. Tasks 1 and 6 were the easiest ones (**Comparing two dimensions**), with Task 1 showing a ceiling effect. Brehmer et al.'s study also had a ceiling effect for Task 6 but not for Task 1. We infer that our immersive design helped to identify targets from their distractors in slope comparison. Results from **finding trend in two dimensions** showed task dependency: for Task 3, Overlaid Trails was the most accurate, while in Task 8, Small Multiples was the more accurate, opposite to Task 9, where the accuracy was low. These results contrast with Brehmer et al.'s findings. We infer that distinguishing a "slight movement" from distractors in 3D visualizations was more difficult to perceive, possibly due to depth. As for finding **long trails**, Task 5 showed Small Multiples as the most accurate, similar to Brehmer et al. However, Task 11 involves comparing three dimensions, where the participants suffered to complete all three responses correctly. We noted that the participants did not measure the length of reversal trails, which was probably the most important reason that the results had insufficient evidence of differences. Participants were most accurate for the tasks of finding **reversal trails** (Task 4 and 7), similar to Brehmer et al.'s study. The behavior of targets and distractors moving in the same direction initially but later moving in a markedly different direction is easily perceived in 3D charts. For the task of finding **small change on overlaid points**, Overlaid Trails is less accurate as we expected. Similar accuracy is obtained between Animation and Small Multiples: the accuracy proportion was larger than half, different from Brehmer et al. We infer that immersive environments improve identifying trends on overlaid points. Finding **similar trends** involved three dimensions and was the most difficult. Participants lost trails' tracking, and although we decided to ask for similar changes to avoid overload of conditions, some of them commented confusion about the “similar change” expression. The poor performance of three-dimensional trend tasks entails the need for finding better interaction techniques.

4.5.2 Implications from Design

The design of effective visualizations for immersive environments still requires experimental studies. In comparison to previous studies (ROBERTSON et al., 2008; BREHMER et al., 2019), where the visualizations have similar designs, ours differ. While Animation and Overlaid Trails have a similar design by the space volume, the shelf structure of Small Multiples demands small markers, and one can interact either within the cell or shelf, which resulted in notable differences in the subjective preferences and completion time. In addition, the major problem lies in the cell comparison; when the participants took far to view all the shelves, the trail thickness was not distinguishable. Consequently, they demanded more effort navigating. Figure 4.8 shows the translating camera and virtual movement are notably higher on Small Multiples than others. Nonetheless, Small Multiples allowed properly to find trends in each scene despite demanding the longest interaction times. Accuracy results did not differ greatly from the other techniques. Also, it shows notable advantages on finding **small change on overlaid points** and absolute accuracy on finding **reversal trails** using two dimensions.

When comparing Animation and Overlaid Trails, the continuous animation loop resulted in participants taking more time than with Overlaid Trails. The difficulty of tracking points probably required more attention, and therefore participants preferred the static version (Figure 4.10-left) and found it easier to use (Figure 4.9-bottom). It is worth noting that the interaction techniques differ from Robertson et al.'s experiment, where participants could use a time slider control and performed better in Animation than in static charts (Overlaid Trails and Small Multiples).

Regarding trails, thickness is important to achieve good performance. We observed some participants had difficulties following the trail when they were far from the scene. Small Multiples design has this problem, and also reading the axis labels demanded more interaction. Some participants wanted to interact with the trails, similar to the transition detail when the bubble moves. Also, they commented on the interest of observing the details on a specific point of the trail.

The *Mixed scene* was considered the most engaging and accurate visualization. We left this scene out of our quantitative analyses because it was performed after the three other scenes and might have a learning effect. However, the SUS score, confidence results (Figure 4.9), and comments from the participants demonstrate that our multiple visualizations design does not lead to cognitive overload (BALDONADO; WOODRUFF; KUCHINSKY, 2000). A typical user behavior we observed was the validation of the response using other techniques. Participants used commonly Overlaid Trails to select the data (Figure 4.10) but made a previous verification of their choice with the other views. This finding opens opportunities to novel strategies to support tasks that demand multiple views, how to combine them in an immersive environment, and different ways of controlling multiple interactions and navigation techniques (CHEN et al., 2020; ROBERTS et al., 2021).

Concerning interaction, our experiment would not have been successful without the multiple interactive techniques we implemented. The ray and virtual hand modes operated harmoniously throughout the experiment, the same for the navigation techniques. We observed the finger gesture to switch mode was quickly assimilated by participants. Also, each action shared the same button distribution in the two modes (Figure 4.2), which afforded intuitive learning.

Indeed, long-term experimental produces fatigue implications on virtual environments (MURATA; MIYOSHI, 2000). We tried to avoid such implications affecting the results, inviting participants to rest at the end of each scene. Only four out of 18 participants decided not to rest; they had previous experience using VR devices. In addition, our study did not prevent the experiment from being carried out either standing or sitting because previous works (MURATA; MIYOSHI, 2000) concluded that some hours of immersion in a VR environment reduce postural control psychologically and physiologically. Finally, we were not notified of any high implications during the experiment, validating our design experiment, this being represented on the Cybersickness score (Section 4.4.4.2).

5 CONCLUSIONS AND FUTURE WORK

In this work, in an effort to address some of the challenges of Immersive Analytics reported in Table 2.1, we developed and evaluated an approach for interacting with multiple coordinated views that shows 3D visualizations in immersive environments. Our approach uses a virtual cube as a 3D-WIMP version – we call it *Space*, for encapsulating each view, and two modes of interaction with the views: the *macro* mode for interacting with the Spaces, and the *micro* mode for interacting with the data displayed in the Space. Also, we improved the approach including two strategies: virtual hand and ray casting, which allow near and far interaction, respectively. Additionally, we included a walk and virtual navigation highly recommended in VR applications. As reported in this dissertation, we proceeded in two phases:

1. First, we explored multiple coordinated three-dimensional views, assessing performance during composed tasks, usability, interaction techniques, and interaction modes (Chapter 3, (QUIJANO-CHAVEZ; NEDEL; FREITAS, 2021a)). During that phase, we designed the main idea of our approach where the user can grab, move and clone any virtual cube containers ($Spaces$) with visualizations inside them, allowing composite patterns.

2. Secondly, we applied the knowledge obtained from the first phase to improve our approach and assess the effectiveness of three 3D scatterplot variants (Animation, Overlaid Trails, and Small Multiples) for analyzing trends in immersive environments (Chapter 4, (QUIJANO-CHAVEZ; NEDEL; FREITAS, submitted).

The development of the $Spaces$ approach required us to address several aspects, which we did based on previous studies:

1. Developing techniques for using multiple views in VR is a challenge because they require more complex control of interaction techniques (KNUDSEN; CARPENDALE, 2017).

2. There is a need for interaction methods capable of achieving the functionalities of the predominant WIMP (windows, icons, menus, pointer) used for visual analysis tasks (LEE et al., 2012).

3. Some experiments performed with FiberClay (HURTER et al., 2019) for exploring trajectories allowed the authors to report suggestions for improving the user expe-

rience in VR environments with multiple views, such as: avoid 2D graphical user interface components, limit the number of interaction modes, facilitate the navigation, and preferential use of one primary view.

4. Another studies, like the one by Yang et al. (2020), suggested the implementation of multiple navigation methods to suit different room sizes, allowing smooth experimentation remotely.

5. Wagner, Stuerzlinger and Nedel (2021) showed that integrating different modes of interaction (far and near) are not only helpful but necessary for IA to overcome the limitations of specific input methods.

Furthermore, in our second user experiment, we extended a sequel of studies about the performance between animated and static 2D scatterplot variants in large and small displays for analyzing trends. Besides 3D visualizations, our experiment design included features for far and near interactions and walk and virtual navigation for comparison tasks, different from previous works. Also, we designed a fourth scene to evaluate multiple views for trend analysis scenarios. Our findings show the value of interaction due to the potential insights it brings into the users' decisions.

5.1 Future work

Research on immersive interactive visualization is still an emerging field. As future work, we would like to conduct an extensive experimental study involving a more complex use case involving different visualization techniques and employing the overloading and integration CVVs patterns with the support of expert participants. Considering that expert users in visualization are not necessarily familiar with immersive VR and the use of the proprioception in virtual environments, we will also extend the training to motivate them better to explore the real environment and their body movements.

Moreover, since we extended the Small Multiples study by Liu et al. (2020) using it in our mixed scene, future work can evaluate animated small multiples. Furthermore, future studies could include interactive tools for annotating visualizations since this would facilitate identifying trends that involve 3D comparisons. Also, tools for scrolling time while keeping track of data points would help to identify trends in large datasets.

Finally, we encourage more studies of alternative proposals to our approach that provide more results that can be used as baselines and cover more visual analytics studies.

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APPENDIX A — UMA ABORDAGEM IMERSIVA PARA EXPLORAR MÚLTIPLAS VISUALIZAÇÕES 3D COORDENADAS EM AMBIENTES VIRTUAIS IMERSIVOS

A.1 Introdução

A quantidade de dados gerados constantemente excede nossa capacidade de analisá-los. Visual Analytics (VA) visa ajudar a atender a necessidade de técnicas flexíveis, precisas e diretas para tais tarefas de análise (THOMAS; COOK, 2005). Esta área é baseada em visualização de informação onde podemos encontrar visualizações mostradas em telas convencionais (por exemplo, monitores, telas grandes, telefones celulares, etc.) que são amplamente utilizadas no dia-a-dia. Também as visualizações podem ser exibidas em tecnologias imersivas como os head-mounted displays (HMDs) que permite interagir em ambientes de realidade virtual e aumentada (VR/AR). Essas tecnologias imersivas fornecem uma experiência diferente, pois permitem que os analistas fiquem imersos nos dados (MOH, 2018) permitindo experiencias mais reais.

Por outro lado, visualizações de dados em 3D podem oferecer vantagens em diversos contextos, especialmente quando a análise de dados requer a compreensão da estrutura geométrica tridimensional de objetos ou sua localização em cenas 3D (MUNZNER, 2014). Os estudos de visualizações 3D em ambientes imersivos constituem a emergente área denominada de Immersive Analytics (CHANDLER et al., 2015).

A complexidade e o volume dos dados tornam mais difícil o desenho de representações visuais e motivam o uso de múltiplas vistas (BALDONADO; WOODRUFF; KUCHINSKY, 2000). Dependendo dos dados, o uso de múltiplas visualizações 2D em monitores convencionais pode exigir o uso de configurações mais complexas como, por exemplo, os wall-displays, formados por múltiplas telas. Enquanto as visualizações 3D, as configurações convencionais pode não garantir uma ferramenta útil. Estudos anteriores em múltiplas visualizações 3D mostraram que as interações em monitores convencionais não atendem aos critérios de usabilidade (SANTOS; GROS, 2002). Essa falta de usabilidade pode ser superada se a exploração dos dados acontecer em ambientes imersivos, onde o usuário tem um grau extra de liberdade (GREFFARD; PICAROUGNE; KUNTZ, 2014).

Dada a motivação, o trabalho teve como objetivo geral desenvolver e avaliar uma abordagem útil para interagir com múltiplas visualizações coordenadas que exibem visualizações 3D. Nossa técnica usa um cubo virtual como uma versão WIMP 3D, denominada $Space$ e inspirada no trabalho de Mahmood et al. (2018), para encapsular cada visualização e oferece dois modos de interação: o modo *macro*, para interagir com os $Spaces$, e o modo *micro* para interagir com os dados exibidos em cada $Space$.

A.2 Trabalhos Relacionados

Há um conjunto grande de trabalhos relevantes relacionados ao trabalho, começando com os estudos em Immersive Analytics (ENS et al., 2021; CRUZ-NEIRA; SANDIN; DEFANTI, 1993; FEBRETTI et al., 2013; BACH et al., 2017; CORDEIL et al., 2016; FONNET; PRIé, 2021), seguido por Multiple Coordinated Views (ROBERTS, 2007; BALDONADO; WOODRUFF; KUCHINSKY, 2000; SANDSTROM; HENZE; LEVIT, 2003; SCHERR, 2008; JAVED; ELMQVIST, 2012a) e seu uso em ambientes imersivos (KNUDSEN; CARPENDALE, 2017), usando wall-displays (FEBRETTI et al., 2014; LANGNER; KISTER; DACHSELT, 2019; SU; PERRY; DASARI, 2019) ou tecnologias totalmente imersivas AR/VR (MAHMOOD et al., 2018; CORDEIL et al., 2017; BATCH et al., 2019; JOHNSON et al., 2019; LIU et al., 2020; PROUZEAU et al., 2019b; SATRIADI et al., 2020; LEE et al., 2021).

Esses trabalhos nos motivaram a descobrir a idéia central de pesquisa. Além disso, para fornecer compatibilidade com qualquer técnica de visualização, decidimos explorar a análise de tendências em séries temporais, porque é uma aplicação relevante e ainda não estudada na área de Immersive Analytics. Assim, foi dada seqüência a dois estudos encontrados na literatura que exploram variantes de scatterplots para análise de tendência (ROBERTSON et al., 2008; BREHMER et al., 2019). Foram estudadas as variantes de scatterplot existentes usadas em Immersive Analytics (ONORATI et al., 2018; BACH et al., 2017; CORDEIL et al., 2017; FONNET et al., 2018; WAGNER-FILHO et al., 2018; PROUZEAU et al., 2019a; YANG et al., 2020), e a visualização de tendências em ambientes imersivos (CORDEIL et al., 2017; BATCH et al., 2019; KLOIBER et al., 2020).

A.3 Uma abordagem imersiva para explorar múltiplas visualizações 3D coordenadas

Num primeiro estudo apresentamos nossa abordagem para exibir múltiplas visualizações coordenadas que contém visualizações 3D. A abordagem usa um cubo virtual, uma versão WIMP 3D, chamada *Space*. Dado que WIMPs 3D semelhantes podem também ser exibidas em monitores 2D, neste primeiro estudo desenvolvemos uma versão similar em *desktop* para compará-la com nossa abordagem de *Spaces* em VR. Formulamos hipóteses inspiradas nos problemas descritos nos estudos de múltiplas visões coordenadas relatados na literatura. Em seguida, conduzimos um estudo de usuário com 19 participantes. Nossos resultados mostram que a versão Desktop não é significativamente melhor do que a versão VR em termos de tempo e precisão, apesar de usar a abordagem FPS padrão com teclado e mouse. Múltiplas visualizações 3D de dados não são normalmente usadas em versões Desktop, e esse pode ser o motivo dos resultados não significativos. Os resultados subjetivos mostram que nossa abordagem em VR é significativamente melhor do que a versão Desktop. Inferimos que os participantes não são capazes de explorar múltiplas visualizações 3D com dispositivos de interação comuns em desktop.

A.4 Comparando Variantes de scatterplots para Visualização de Tendências Temporais em Ambientes Virtuais Imersivos

Nesse segundo estudo avaliamos a eficácia das variantes scatterplots 3D em tarefas de análise de tendências usando realidade virtual e interação 3D. A abordagem *Space* foi melhorada para incluir interações adicionais com diferentes técnicas de visualização. As técnicas de visualização utilizadas são Small Multiples, Overlaid Trails (versões estáticas) e Animation (versão animada). Independentemente da diversidade de contextos em que elas foram comparadas em *displays* 2D, não encontramos na literatura estudos sobre a eficácia dessas técnicas em ambientes imersivos. Então, conduzimos um estudo com usuários comparando a execução de tarefas específicas com cada técnica de visualização em relação ao tempo, precisão e preferências subjetivas. Além disso, incluímos uma cena com todas as três técnicas de visualização como a última fase do experimento para analisar as escolhas e preferências do usuário. Os resultados mostram que Overlaid Trails apresentam o melhor desempenho geral. No entanto, a precisão depende da tarefa e quando a tarefa requer análise de tendência usando as três dimensões, a precisão é inferior. Nossos resultados também mostram o valor da interação devido aos $insights$ proporcionados pela interação nas decisões dos usuários.

A.5 Conclusão e Trabalhos Futuros

Neste trabalho, em um esforço para explorar os desafios de sistemas de $ImmersiveAnalytics$, o objetivo foi desenvolver e avaliar uma abordagem útil para interagir com múltiplas visualizações coordenadas que mostram visualizações 3D e ambientes imersivos. Conforme relatado, procedemos em duas fases:

1. Em primeiro lugar, exploramos múltiplas visualizações coordenadas tridimensionais, avaliando o desempenho durante tarefas compostas, usabilidade, técnicas de interação e modos de interação. Durante essa fase, foi desenvolvida a ideia principal da abordagem onde o usuário pode pegar as visualizações dentro de um contêiner ($Space$), permitindo padrões de visualizações coordenadas compostas (CCVs).

2. e, em segundo lugar, aplicamos o conhecimento produzido na primeira fase para melhorar a abordagem, incluindo outras técnicas de interação, e avaliar a eficácia de três variantes de scatterplots 3D (Animation, Overlaid Trails e Small Multiples) para analisar tendências em ambientes imersivos.

Como trabalhos futuros, seria interessante realizar um extenso estudo experimental envolvendo um caso de uso mais complexo com diferentes técnicas de visualização e empregando outros padrões de CCVs com a participação de especialistas de domínio.

Adicionalmente, como estendemos o estudo de Small Multiples de Liu et al. (2020), trabalhos futuros podem avaliar Small Multiples animados. Além disso, estudos futuros podem incluir ferramentas interativas para anotações dentro das visualizações, pois isso facilitaria a identificação de tendências que envolvem comparações em 3D. Também, ferramentas para filtrar períodos de tempo nas visualizações de séries temporais ajudariam a identificar tendências em grandes conjuntos de dados.

Finalmente, são necessárias propostas alternativas de visualizações coordenadas em ambientes imersivos que forneçam resultados que possam ser usados como linhas de base para outros estudos em $ImmersiveAnalytics$.