Ground Control: Leveraging the User's Spatial Position as an Input Modality in an Embodied Immersive Analysis Use Case

Christopher Katins
christopher.katins@hu-berlin.de
HU Berlin
Berlin, Germany

Thorben Grodon
thorben.grodon@student.hu-berlin.de
HU Berlin
Berlin, Germany

Katja Chen
chenkatj@hu-berlin.de
HU Berlin
Berlin, Germany

Thomas Kosch
thomas.kosch@hu-berlin.de
HU Berlin
Berlin, Germany

ABSTRACT

Extended Reality (XR) has already enabled sophisticated implementations of immersive visualizations, providing a more intuitive and engaging way of analyzing data. Yet, the user interaction with such immersive visualizations remains challenging, often relying on hand tracking or additional devices. We introduce a novel XR prototype that leverages the concept of embodied exploration, allowing users to interact with an exemplary visualization directly through their spatial position within the room relative to the displayed data. This approach eliminates the need for handheld controllers, offering a more intuitive engagement with the visualization. Our preliminary evaluation with twelve participants reveals a general preference for using XR for immersive visualizations compared to PC and paper-based versions. We suggest further research into non-standard interaction and exploration modalities for data analysis applications using XR, potentially offering new possibilities for engaging interactions with data.

CCS CONCEPTS

• **Human-centered computing → Mixed / augmented reality**; **Interaction techniques**; **Visual analytics**.

KEYWORDS

Extended Reality, Immersive Analytics, Embodied, Interaction

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1 INTRODUCTION AND BACKGROUND

Analyzing data, from initial parsing to unraveling correlations, causations, and connections, is challenging. Visual analysis, a field dedicated to enhancing our comprehension of data through innovative and interactive interfaces and visualizations [6], is one among several approaches seeking to assist humans herein. Since its inception nearly 20 years ago, the research has changed immensely as the readily available commercial off-the-shelf devices have steadily advanced in recent decades. While these emerging technologies empower designers to create novel visualizations and interfaces, the relevance of human factors persists, perhaps even more so in recent times, with both technologies [1] and data sets (i.e., big data [3]) becoming more and more complex.

In 2004, Tory and Möller noted that "interacting with 3D visualizations can be challenging because mapping movements of a 2D mouse to actions in 3D space is not straightforward" [24]. A decade later, emerging technologies such as Extended Reality (XR) have introduced a new domain within visual analysis known as Immersive Analysis (IA). These new technologies enable the visualization of 3D data in a real-world three-dimensional environment, making it feasible for the user to fully immerse themselves in the data at hand. Yet, the interfaces of these implementations often still depend on controllers, gestures, or voice commands that require initial comprehension themselves. While the issue of mapping 2D mouse movement does not explicitly exist with XR devices anymore, interaction within IA is still hard.

A systematic review by Saffo et al. in 2023 finds eleven contributions regarding Embodied Exploration, therein characterized as spatial visualizations that allow user interactions in a natural way [21]. One recent example of an Embodied Exploration implementation is Imaxes by Cordeil et al. [4]. The application allows a straightforward analysis of multivariate data and its correlations by representing each variable as a distinct virtual object before the user. However, multivariate data is not the only data type to be considered for IA. In a 2019 survey on the current research corpus on IA by Fonnet et al. [7, Table 1], the relevant literature is categorized based on Shneiderman's taxonomy [23]. Here, spatial data type visualization emerges as a prevalent theme, with a substantial portion of references visualizing either spatial or spatiotemporal data. Of those, most publications propose to encode the data using its position in comparison to its visual or auditory presentation. One such example is superimposing data elements onto maps [5, 8, 18], with GeoVisor by Billow et al. [2] being one such instance where a map-like visualization was developed.

One way of interacting with IA visualizations is by navigation [7, Table 2], defined by Fonnet et al. as "interactions that alter the viewpoint of the user". This navigation can be achieved in different ways, ranging from inherently intuitive interaction metaphors like walking and flying to teleporting or moving the surroundings around while the user stays stationary. Interactions with these systems are predominantly facilitated by controller input or through head tracking, which most current immersive technology devices (e.g., Microsoft HoloLens 2[1], Meta Quest Pro[2]) incorporate as well. Ready et al. implemented both view-based and controller-based movement in their IA prototype [19], noting that many participants had difficulty with the controllers.

Instead of using controllers, some recent publications focus on body tracking as a way to interact in XR. The most recent literature review to date [21] finds three distinct contributions that use body tracking as the main input modality [15, 17, 25]. However, many current prototypes make implicit use of the user's position for their visualizations, like the TimeTables prototype, which is a tabletop-based system where users can move around and "jump into" surrounding visualizations [27]. In comparison, further publications look into how data can be visualized in the active working environment [9–11, 14] or during transportation [13, 20]. Notably, Zheng et al. present an in-situ visualization to aid workers in agriculture [28].

2 INITIAL DESIGN CONSIDERATIONS AND IMPLEMENTATION

Inspired by recent map-based visualizations like "Tilt Map" [26] and the insight that embodied interactions can enhance both learning and engangement [16], we opted for implementing an Embodied Exploration prototype for location-based data. For this work, we chose to use energy trade data within the European Union for the visualization. This dataset was selected due to its high complexity, representing a typical example where identifying an effective visualization method can be challenging. All data is sourced from the Eurostat energy database, officially supplied by the European Union free of charge[3].

The prototype was designed for the Meta Quest Pro, using its ability to blend virtual and real-world environments through its pass-through feature. Central to the prototype is a room-scale map of the European Union projected onto the floor. This map is designed to fill as much of the available room space as possible and remains stationary. Across this map, energy trades between EU countries are represented by rounded lines, stretching from one country to another. These lines are transparent to avoid visual clutter but become prominently highlighted in bright red when the user stands over the corresponding country. The thickness of these lines varies proportionally with the volume of energy traded, offering a visual representation of the quantity of energy movement between nations. This design allows users to walk through the data, gaining insights through physical exploration and spatial positioning within the visualization.

[1]https://www.microsoft.com/en-us/hololens, last accessed on 2024-01-25.
[2]https://www.meta.com/en/quest/quest-pro, last accessed on 2024-01-25.
[3]https://ec.europa.eu/eurostat/web/energy/database, last accessed on 2024-01-25.

3 METHODOLOGY

Following the development of the XR prototype, an initial participant study was carried out for evaluation. The same visualization was developed for a desktop PC with a computer mouse, and paper-based printouts for all countries were created. These variants are explained further in Section 3.1. Then, the following study was conducted, trying to assess the two hypotheses:

- **H1** Users perform better at post-study quizzes about the data at hand when using the immersive analysis visualization than PC- and paper-based visualizations.
- **H2** Users find the immersive analysis visualization more engaging and prefer it over the PC- and paper-based visualizations.

3.1 Independent Variable: Visualization Modality

Our study focused on visualization as a single independent variable with three distinct levels, each representing a different medium through which the same visualization was presented. As previously described, the first level involved our XR prototype, where participants interacted with the visualization using their spatial position as the only input modality. The view of one participant looking at the XR visualization can be seen in Figure 1a. The second level used the same application but presented it on a PC instead. In this scenario, participants interacted with the visualization via a mouse, offering a more traditional, non-immersive approach to the data analysis. By hovering over a country, its energy trade for the year of the data would be highlighted, analogous to positioning oneself on it in the XR variant. The third and final level diverged from digital mediums, presenting the data in a printed format. For this level, we prepared a small booklet that detailed the different energy trades per country. This tangible format starkly contrasted the immersive and PC-based variants, serving as a baseline to compare the effectiveness and user experience across different media for presenting essentially the same data.

3.2 Dependent Variables: UEQ, Quizzes, and Interviews

To determine the different variants' subjective impressions, we employed the User Experience Questionnaire (UEQ) [22] for each level. To evaluate the participants' comprehension and retention of the information presented, we administered a quiz focused on the data visualized during the interaction. This quiz aimed to objectively measure the effectiveness of our prototype in conveying complex information. Each quiz consisted of six multiple-answer questions (e.g., *"To which country did Germany export the most electricity to [this year]? Netherlands, Austria, France, or Poland?"*) of varying difficulty. Finally, we conducted a short semi-structured interview with each participant at the end of their session to gather qualitative insights into the user's experience and general thoughts about the different visualizations.

(a) A capture of the Immersive Analysis app. Italy is currently selected as the participant is standing closest to this country, making its data highlighted.

(b) A photo of the PC application in use. It is the same application as in 1a, but it is displayed on a PC instead, and the user interacts with a common mouse.

(c) A printout of the energy trade data of France of the paper-based variant. The visualization is still the same, but all countries are printed separately.

Figure 1: The three variants of the visualization for the study yield the three levels of the independent variable. Here, they are shown in use during one participant's run.

3.3 Procedure

The study employed a counterbalanced within-subjects design, ensuring each participant experienced all three independent variable levels. Furthermore, datasets of different years were used to combat learning effects. Participants were briefed about the general procedure and study conditions at the outset and consented. The study was conducted in a well-lit, spacious room, allowing freedom of movement when using the XR prototype. Participants had the opportunity to familiarize themselves with the Meta Quest Pro headset beforehand using apps unrelated to the study. This introductory phase included an explanation of the device and the test environment. Before engaging with the actual data visualization, participants were allowed to walk around a faux data set within the XR environment, hoping to mitigate any learning effects. They then interacted with the visualizations through each medium, with a maximum allotted 10 minutes per level. However, participants could choose to finish earlier if they felt ready. Participants completed the UEQ after each level to record their subjective experience. They then took the quizzes and were allowed to take a short break before proceeding to the next level. Upon completion of all three levels, a short semi-structured interview was conducted with each participant.

3.4 Participants

A total of twelve participants (eight male, four female) took part, aged between 17 and 35 years ($\bar{x}$ = 25, s = 4.67). No compensation was offered for participation, and participants were primarily recruited through word-of-mouth. Three participants stated that they had some moderate experience with XR devices before and two more indicated that they had extensively used XR devices before (> 20 hours).

4 DATA ANALYSIS & RESULTS

Compared to the UEQ benchmark [22], the prototype ranks above average for pragmatic quality ($\bar{x}$ = 1.35, s = 0.64) and excellent for both hedonic quality ($\bar{x}$ = 2.1, s = 0.5) and its overall rating ($\bar{x}$ = 1.73, s = 0.5). Both the results of the subscales and the UEQ as a whole were further analyzed with a Repeated Measures ANOVA, showing significant differences between the prototype and both the PC ($t(11) = 3.9,\ p_{\text{holm}} < .01$) and the paper-based variant ($t(11) = 15.93,\ p_{\text{holm}} < .001$) for the complete UEQ. While there is a difference between the pragmatic subscale when comparing XR and paper-based version ($t(11) = 3.77,\ p_{\text{holm}} < .01$), no such significance could be noted when comparing the XR to the PC version ($t(11) = -0.95,\ p_{\text{holm}} > .05$). Lastly, all three post hoc comparisons of the variants' hedonic measures were significant, most notably the XR-paper ($t(11) = -10.7,\ p_{\text{holm}} < .001$) and the XR-PC ($t(11) = -5.14,\ p_{\text{holm}} < .001$) tests. These results are also visualized in Figure 2.

For the results of the quizzes, a Friedman test yielded no significant differences between the variants ($\chi^2(2) = 1.33,\ p > .05$), making post hoc tests superfluous. Participants scored roughly between 60 % and 70 % of all achievable points for XR ($\bar{x}$ = 4.25, s = 1.54), PC ($\bar{x}$ = 5.08, s = 1.0), and paper-based variant ($\bar{x}$ = 4.83, s = 0.83).

In the closing questionnaire and semi-structured interviews, participants unanimously agreed that the XR prototype was intuitive and easy to use. A third (n = 4) thought the prototype was the visualization that made it easiest to analyze and learn the data, half (n = 6) thought the PC application was better in this regard, and the remaining two were in favor of the paper-based variant. Most (n = 10) participants voted for the prototype to be the most fun visualization to interact with, none regarded the paper-based visualization as the most fun. In the end, the participants were undecided about not having to (or being able to) use a controller or

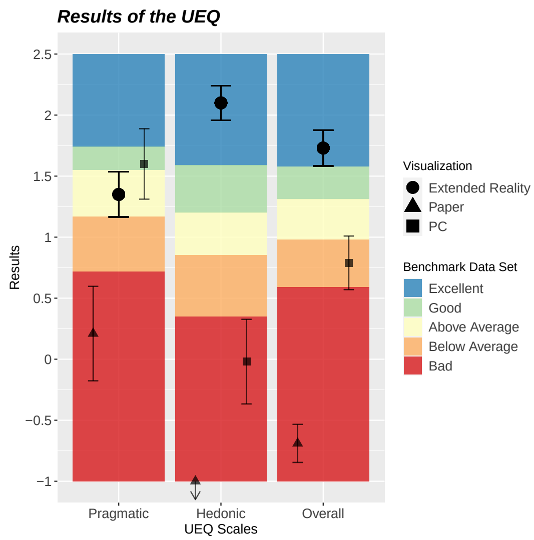

Figure 2: UEQ results of the study. The XR visualization has the highest overall and hedonic rating, while the pragmatic evaluation is comparable between XR and PC-based visualization. The paper version performs worst in all comparisons. Error bars indicate the standard error.

gestures to interact with the XR visualization, which was helpful for focusing on the task at hand. This resulted in an even split of agreement and disagreement. Next to map-based data analysis, other potential use cases for such a hands-free interaction were multivariate and time-based data sets, architecture and 3D modeling fields, education/learning, and collaborative XR environments. Some participants ($n = 3$) mentioned that continuously looking down hurt their necks as the Meta Quest Pro is still quite heavy.

5 DISCUSSION

The results from our initial participant study present a mixed picture. The participants seemed to comprehend and retain a similar amount of information compared to more traditional modalities, as evidenced by the comparable points achieved in the quizzes. With this, **H1** has to be dismissed. Having the information displayed in the room around them and requiring them to actively move around did not appear to significantly impact the final results. These quizzes did not appear to be excessively challenging nor too easy, with participants, on average, scoring around two-thirds of the available points. However, the influence of the specific data and question type used herein remains unclear. Most real-life applications of IA do not necessitate a test or quiz at the end, except perhaps in educational settings. Finding correlations in complex data sets is also a different task than remembering relationships between countries and their respective energy trades.

While the final scores weren't significantly influenced by the modality used, each variant's perceived usefulness (pragmatic subscale of the UEQ) is notable. Only the paper-based variant was rated poorly in terms of this quality compared to the UEQ benchmark standards.

As anticipated, the hedonic quality of the XR prototype significantly surpasses that of the other two modalities, a result likely influenced by the novelty of both the device and the interaction modality itself. While paper-based visualizations are not to be dismissed entirely, in this specific use case, the ability to swiftly switch between countries explains the preference for these modalities in terms of efficiency and ergonomic experience.

Despite the higher hedonic quality of the XR prototype, most participants still favored the simplicity and familiarity of the PC interface for data analysis. Even though the XR prototype offers a more engaging and enjoyable experience, the ease and practicality of traditional computer interfaces currently appeal more to tasks requiring detailed analysis. Therefore, **H2** only holds true in parts. While most participants found the prototype more engaging, from a truly task-based point of view, a majority would still prefer the PC variant.

5.1 Limitations and Future Work

For future studies, it is beneficial to identify and utilize a different dependent variable that better captures the user's understanding, engagement, and concerns when using IA with data [12]. Such a variable could provide a more accurate measure of the effectiveness of a new interaction modality in IA for real-world scenarios beyond the controlled testing environment. Conducting a longer-term study to observe user preferences over time could also be insightful. It would be particularly interesting to see which modality users prefer when given the freedom to switch between the XR and PC versions at will. Such a study could reveal deeper insights into long-term user engagement and the practicality of different modalities in IA. Our study's biggest limitation is the specific data set used. Switching between different data sets could offer significant benefits in future research. Exploring a variety of data visualizations could also help us better understand how different interaction modalities and mediums influence users.

6 CONCLUSION

In this work we present an XR prototype that allows users to interact with a complex data set through an IA implementation that allows interaction without gestures or controllers using the spatial position of the user as the only input modality. Our findings indicate that while this new method does not necessarily enhance the user's ability to remember or understand the data compared to traditional methods, it introduces a unique and engaging way of interacting with complex datasets. The XR prototype, with its emphasis on Embodied Exploration, notably excels in terms of user experience, particularly in its hedonic qualities, as compared to the more conventional PC and paper-based modalities. With this, we aim to contribute to the ongoing discourse about Embodied Exploration and other novel interaction modalities in the field of IA. Though there remains a considerable amount of work to be done in designing and implementing IA applications that are accessible and applicable in real-life scenarios, using embodied interaction methods shows the potential to establish intuitive interactions that keeps users engaged.

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