Immersive Analytics of Dimensionally-Reduced Data Scatterplots

Jorge A. Wagner Filho*   Marina F. Rey†   Carla M.D.S. Freitas‡   Luciana Nedel§

Institute of Informatics
Federal University of Rio Grande do Sul

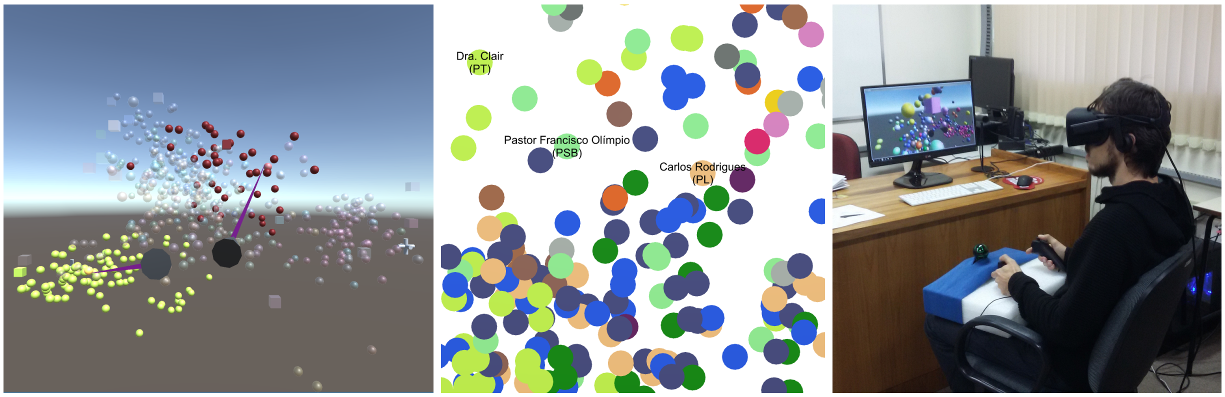


Figure 1: Alternative environments for the visualization of dimensionally reduced roll call voting data scatterplots: 3D (left) and 2D (center). The three dimensional environment can be explored either through non-immersive (traditional mouse and keyboard interaction) or immersive (HMD-based, with selection rays controlled by position-tracked hand controllers) setups. A comparative user study (right) was designed to evaluate the effect on accuracy in different tasks.

Abstract

In this work, we evaluate the use of an HMD-based Immersive Analytics approach to explore multidimensional data. Our main hypothesis is that the benefits obtained, such as a more natural interaction and an egocentric view of the data, besides the stereopsis, will be able to compensate the typical downsides of three dimensional visualization, enabling a better comprehension of distances and outliers. This hypothesis was tested through a case study with roll call analysis, using dimensionally-reduced voting data from the Brazilian Chamber of Deputies. A user study was conducted to allow a comparative analysis between the desktop-based 2D, desktop-based 3D and HMD-based 3D approaches. Results indicate advantages in accuracy in a point classification task with respect to the original dataset, as well as in distance perception and outlier identification tasks with respect to the principal components being visualized. The proposed immersive framework was also well rated in terms of user perception, with the best scores for accuracy and engagement.

Keywords: Immersive analytics, dimensionality reduction, 3D scatterplots, roll call analysis

Index Terms: H.5.1 [Information Interfaces and Presentation]: Multimedia Information Systems—Artificial, augmented, and virtual realities

1 Introduction

Over the past few decades, the visualization community has progressively explored the use of immersive displays and new interaction devices to enhance analytical reasoning. Recently, the term Immersive Analytics was coined [5] to specifically refer to this research topic and stimulate further studies. Even though immersive 3D visualizations present clear advantages for scientific spatial data, it still remains unclear, for example, if and how these technologies can be properly applied to visualize abstract information [9, 10].

In this work, we focus specifically on studying an HMD-based immersive environment for the exploration of abstract multidimensional information using dimensionality reduction techniques and 3D scatterplots. Dimensionality reduction (DR) methods are essential in order to analyse high dimensional or noisy data since these algorithms generate a more compact version of the information, yet maintaining the same characteristics of the original dataset [6].

The use of 3D scatterplots has been controversial since long before the first uses of immersion. In thesis, a 3D representation allows clearer spatial separation, reduced overplotting and faster construction of a mental model [12]. Nevertheless, challenges such as difficulty of navigation, perspective distortion, foreshortening and occlusion have led multiple researchers to dismiss its utility. The use of 3D scatterplots for the representation of dimensionally reduced data is particularly discussed in the literature. Adding an extra component could potentially reduce information loss in the process, but results of studies to quantify visual analysis gains have been contradictory [12, 23]. To the best of our knowledge, however, few authors have investigated how immersion and stereopsis may impact in these issues. Most of them have only provided preliminary results, based on technologies which have advanced enormously over the past few years [1, 7, 22]. Therefore, we believe that an updated and expanded investigation is needed to clarify this topic.

In this paper, we present initial findings of our research, resulting from a case study performed on multidimensional roll call voting open data from the Brazilian Chamber of Deputies. Voting data is an area of great interest both to political researchers and to the general community, and one where DR techniques have been applied extensively due to the nature of the data [2, 4, 16].

We hypothesise that the benefits provided by immersion, such as

*e-mail:jawfilho@inf.ufrgs.br
†e-mail:mfrey@inf.ufrgs.br
‡e-mail:carla@inf.ufrgs.br
§e-mail:nedel@inf.ufrgs.br

a more natural interaction and an egocentric view of the data [5], besides the stereopsis [14], will compensate the 3D challenges and provide an enhanced comprehension of distances and outliers in DR data (**H1**). We also expect the information gain in both 3D versions to enhance precision in distance perception and classification tasks (**H2**). The 2D version, on the other hand, is expected to be the quickest, given its inherent smaller cost for navigation and interaction (**H3**). These hypotheses were evaluated in a user study comparing a desktop-based 2D (*2D*), a desktop-based 3D (*3D*) and an HMD-based immersive 3D (*IM*) visualizations over a set of defined user tasks.

2 Related Work

In this work, we are concerned about immersion in HMD-based environments, considering the current technology provides adequate capabilities with accessible requirements, both in terms of cost and space, and its exploration in the Infovis literature is still incipient. Donalek et al. [9] presented a very interesting early work in this direction. They implemented iViz, a platform for visualization of multidimensional data using an Oculus Rift HMD and a Leap Motion sensor for interaction. In their application, up to 8 data dimensions are mapped to different attributes (such as size, colour and transparency) of the points in a 3D scatterplot.

The use of three dimensional representations, such as scatterplots, has been discussed for a long time in the literature. Some authors have investigated specifically the use of 3D scatterplots for visualization of dimensionally reduced data, but results have been mixed. Gracia et al. [12] performed an user study evaluating point classification, distance perception and outlier detection tasks, and also applied several quality loss metrics from previous literature to affirm the advantage of using the third dimension. Sedlmair et al. [23], on the other hand, performed a data study where two annotators evaluated around 800 scatterplots in relation to cluster separability, and concluded that the interactive 3D versions never outperformed the 2D scatterplots (individually or in matrixes), especially considering the added interaction cost.

Concerning immersive environments, Arms et al. [1] performed a comparative evaluation of the visualization of multidimensional data projected to two and three dimensions, achieving better cluster identification results in the virtual environment and serving as inspiration to our study. However, they explored a CAVE environment, and suffered from heavy technological limitations of the time, especially regarding interaction. Raja et al. [22] also explored the application of immersive VR to 3D scatterplots in a CAVE environment, observing favourable results when including large field-of-regard, head-tracking and stereopsis. Their user study, however, was very initial, with only four subjects. A later study with 32 users was performed with similar indications, but failed to present statistical significance [21]. Recently, Gray [13] also explored HMD-based 3D scatterplot navigation, contributing with a recommendation to include a reference plane and some illumination from above, for the sake of orientation.

We decided to employ a case study with roll call analysis after observing the frequent application of DR algorithms to this domain. A survey was presented by Spirling and McLean [24]. In a roll call voting, each legislator may answer “yes”, “no” or abstain to a given proposition. The collected data may then be tabulated as a matrix, and used to estimate the ideal point for each politician in a spectrum [4, 8]. The NOMINATE algorithms were designed specifically for this domain [20]. Classical, less-complex DR algorithms, however, have also been applied with substantial success, for example using open data from the European Parliament [2] and the US Senate [16]. Previous works have already explored the use of these techniques, especially PCA, for 2D visualization of the Brazilian Chamber of Deputies data [8, 18, 19], and were particularly used as references to our implementation.

3 Methodology

3.1 Data collection and processing

In this work, we visualize open roll call voting data from the Brazilian Chamber of Deputies. This dataset is particularly interesting for visualization tasks because, unlike in the United States or most European countries, Brazil’s political system is composed by more than 30 different political parties with very fuzzy ideological borders. From this dataset, we extracted information about the votes of each deputy, the official vote instruction given by each party represented in the Chamber, as well as those by the government and opposition leaders. We selected four different four-year legislatures from the Brazilian Congress: 52nd (451 roll calls), 53rd (619 roll calls), 54th (428 roll calls) and 55th (493 roll calls). Since it is common for deputies to leave their seats during the term, we avoid calculating positions for deputies with very few votes by following the approach of De Borja et al. [8] and selecting only the most present 513 (the official number of seats) in a legislature.

For each dataset, we construct a voting matrix where all deputies, parties, government and opposition are represented by M lines, and roll calls are represented by N columns. Each (i,j) cell is then attributed a value depending on the ith deputy or party vote on the jth roll call: -1 for “no”, 1 for “yes” or 0 for abstention or absence. Principal Component Analysis (PCA) by Singular Value Decomposition [11] is then applied to this matrix, resulting in $min(N,M)$ principal components. For visualization purposes, only the first two or three are considered.

3.2 Virtual environments implementation

We implemented two different virtual environments (VEs) using the Unity engine, for 2 and 3 dimensional visualization of DR scatterplots (see Fig. 1). The 3D version can be explored either through desktop-based or HMD-based setups. All VEs explore the same visual encodings (colours for political parties and shape for different categories of points - deputies, parties or blocks). They also all offer the same set of possible interactions: a user may click a point to show/hide its name and may highlight the whole party of any point in order to inspect its relative position. All versions also support the simultaneous selection of up to two parties for comparison (see Fig. 1 left). The setups differ, however, in the forms of navigation and interaction. While in *2D* the user may zoom in/out and pan the screen, in both 3D versions he may navigate freely in all directions. The 3D versions also include a ground and sky background and illumination from above for orientation purposes [13].

In both desktop-based VEs, controls were implemented using only mouse and keyboard, as in a traditional data analysis setup. In *IM*, our implementation choice in order to provide a more natural and immersive interaction was to use two selection rays, which are controlled by two position-tracked Razer Hydra controllers. This environment is explored through an Oculus Rift CV1 HMD, with the user seated in a swivel chair (see Fig. 1 right). Several guidelines were employed in order to minimize possible discomfort and simulator sickness: the speed of movement is slow and constant; user control of the camera is maximized; no ground was included to avoid uncomfortable rapid ground plane changes; and adequate hardware was employed to minimize latency and lag. In the event of teleportation to a new position, such as in the beginning of a task, a camera fade is also applied [25].

3.3 User tasks

The following user tasks were designed to evaluate our set of hypotheses and, in our opinion, constitute a representative subset of the typical tasks of a data analysis in this specific domain.

Selection of closest deputy. In this distance perception task, the user is requested to select the closest deputy to a blinking one. The 3D setups have the advantage of including an extra PCA component, which should be able to allow distances to be represented more accurately. However, without careful inspection, perspective distortion and occlusion may lead to incorrect perceptions.

Selection of closest party. In this more difficult variation of the previous task (since deputies are usually positioned between multiple parties), the user is requested to select the closest party to a blinking deputy. It can also be seen as a point classification task, where the user is reclassifying deputies in parties according to vote coherence.

Identification of party outlier. In this task, the user must identify the member of a specific blinking party which is furthest located from the official party position. The party highlight feature allows this inspection to be done easily.

Comparison of two parties. The user is requested to compare two blinking parties and indicate the one where deputies are more loyal to the party position. We expect *IM* to benefit from its more natural interface in this task (highlighting one party with each hand).

3.4 Evaluation

Our user tasks were applied to a population composed of 20 subjects (18-44 years old, 70% male, 25% female, 5% other), recruited on the University campus. 75% of the participants reported at least average previous experience with first person games, but only 25% with HMDs.

Each participant experimented all techniques in a within-subjects protocol. The order of application was varied to minimize the learning bias. To avoid the use of previously viewed information, the dataset visualized in each technique was also rotated, varying between 52nd, 53rd and 54th legislatures (all technique-dataset combinations were also executed evenly). The 55th legislature dataset was used in order to familiarize the participants with the controls before each technique, when they could navigate for as long as they required. Every task described in Sect. 3.3 was performed five times in a row with different parameters of varying difficulty levels, and users were always asked to be precise. After each technique, subjective opinion questionnaires were applied, including SUS questions [3]. SSQ [17] was applied pre and post VR exposure to evaluate eventual well-being effects. In the end, users were allowed to compare all the techniques according to different criteria. The complete experiment took approximately 45 minutes.

4 Results

4.1 Time and accuracy

The results obtained for the dependent variables time and accuracy are shown in Fig. 2. Asterisks indicate the occurrence of statistically significant differences between groups in a task. Since we were not able to verify normality under Shapiro-Wilk tests, we opted to execute non-parametric Friedman tests. Post-hoc tests are implemented using the Wilcoxon-Nemenyi-McDonald-Thompson test [15], and the significant pairwise differences, when found, are indicated with red lines. Errors correspond to the Euclidean distances between the users' answers and the correct ones – or the difference in average distances per party in the comparison task –, and were evaluated both considering the complete set of principal components and the three ones being visualized.

Noticeably, when we consider distances in the original dataset, the party classification task was the only one where *IM* obtained a statistically significant advantage ($p = 0.004$) in conveying more accurate information, as expected in our hypothesis H1. Nevertheless, we also expected that distance perception and outlier identification tasks would follow this same behaviour. In the former, average errors were indeed smaller in both 3D versions (in conformity with our hypothesis H2), but without significance ($p = 0.5$ in the Friedman test). In the latter, results were very similar ($p = 0.7$). We attribute this to the very high dimensionality (between 450 and 620 dimensions) of the datasets employed in our case study, which made it very difficult for the distances between individual deputies to be accurately represented in only two or three dimensions. While evaluating the errors considering only the first three PCA components, however, we observe that the performance was actually improved in the immersive scenario, with statistical differences between *2D* and *IM* in the first three tasks ($p = 0.00006$, 0.0003 and 0.03, respectively). Trends of smaller errors are also observed when comparing *3D* and *IM*. In the first task, the average error in meters was reduced from 1.26 in *2D* to 0.55 in *3D* and 0.16 in *IM*. We believe this is an indication of the advantage of the immersive approach for this kind of task as well, especially when dealing with datasets which can be more satisfactorily represented in detail in three dimensions.

The party comparison task, not shown in this paper due to space constraints, failed to present significant differences in both analyses ($p = 0.08$ and 0.54, respectively), actually showing trends of larger errors in *IM*. We believe this task was better suited by the orthographic data overview provided in *2D*, and the less intuitive interaction was compensated by the users previous experience with mouse and keyboard interfaces.

Fig. 2 (a) confirmed our expectations in relation to task elapsed time, with *2D* always being the quickest (H3). Comparing *3D* and *IM*, results were generally similar, without significance in the post-hoc test in any task.

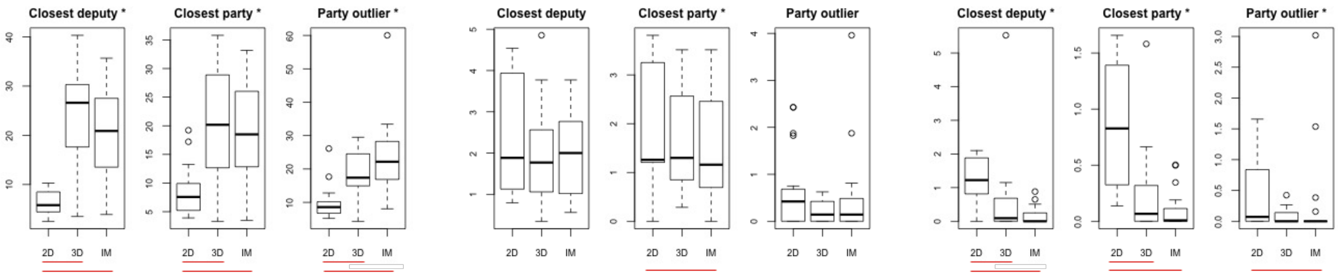
4.2 Navigation behaviour

The average distance travelled by the users in the three dimensional virtual space (in meters) was also one of the variables we observed in this study. The first three tasks presented statistically significant differences when comparing *3D* and *IM* (under paired Wilcoxon signed-rank tests), even after we discounted the 6 meters difference from the closer starting position in the immersive version (implemented to minimize movement in VR and take advantage of its larger field of view). Distances travelled in *3D* were, on average, 52% longer than in *IM*. This indicates a possible reduction in the effort to establish distances and depths in *IM*. Navigation was also perceived to be considerably more related to accuracy in *3D* than in *IM* in some tasks. Notably, in the classification one, the Pearson correlation between distance travelled and error (w.r.t the components shown) was of -0.81 in *3D*, compared to -0.32 in *IM*. Fig. 3 illustrates this difference in behaviour by contrasting the trajectories (seen from above) of five users who classified correctly a specific deputy in *3D* with five who did the same in *IM*. While users in *IM* tend to get closer to the deputy point before deciding their answer, users in *3D* present a pattern of more distant and lateral observation. We believe this may be a consequence of the difference in depth cues available: stereopsis and motion parallax.

4.3 User perception

The user experience post-test questions indicated that participants believed *2D* to be quicker (85%) and more intuitive (55%), while *IM* was more engaging (85%) and accurate (55%). Comparing the scores from the SUS questionnaire, *2D* was the best evaluated (83.1), followed by *IM* (68.3) and finally *3D* (61.3). We believe these results derive in part from the familiarity of 2D visualizations with mouse and keyboard interfaces and the users' lack of experience to navigate 3D environments using HMDs. Nevertheless, they still mostly felt the immersive setup to be more accurate and engaging for the tasks performed, indicating that the depth perception made the chore seem easier and more interesting to complete.

The level of discomfort observed in *IM* was not significant, with an average increase of the SSQ score of only 121.03 points. Moreover, only 25% of the participants had a considerable decrease in their general well-being, while 20% actually reported an improvement in their mental state.



(a) Time elapsed (b) Avg. error (w.r.t. original dataset) (c) Avg. error (w.r.t. 3 principal components)

Figure 2: Results observed for time (a) and two assessments of error (b,c). Asterisks and red lines indicate occurrence of statistical significance.

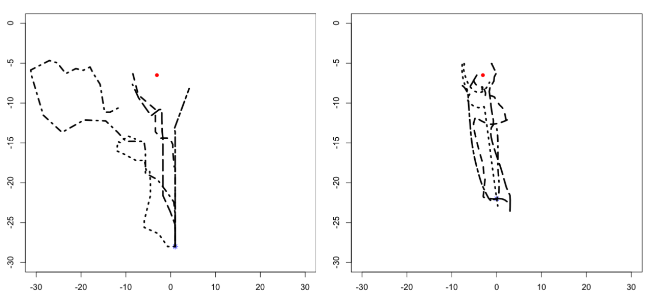


Figure 3: Different navigation behaviours observed between users in *3D* (left) and *IM* (right) when classifying the deputy marked in red.

5 Conclusion

In this paper, we presented initial findings of our research into 3D DR data scatterplots, a topic we believe deserves more attention in the ever-growing Immersive Analytics community. A comparative within-subjects user study was applied to 20 participants, who were subjected to a desktop-based 2D, a desktop-based 3D and an immersive HMD-based 3D voting data visualization approaches, and asked to perform different tasks. We observed that the classification accuracy was statistically greater in the immersive approach. Distance perception and outlier identification, despite not achieving statistical significance when considering the complete dataset, were also improved with respect to the principal components being shown, what we believe also indicates possible benefits when experimenting with other datasets that can be more precisely represented in three dimensions. Considering the subjective results, users still perceived the 2D technique to be more intuitive and faster. Nevertheless, the immersive technique surpassed the desktop-based 3D in every aspect, and exceeded all techniques when compared by perceived engagement and accuracy. We are currently analysing the data collected during the experiments, and trying to identify the different users behaviours and their relation with each of the proposed setups. We also intend to improve the immersive setup considering the subjective feedback obtained from the user tests, and perform new user studies using different datasets and DR techniques.

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