Do 3D Visualizations Fail? An Empirical Discussion on 2D and 3D Representations of the Spatio-temporal Data

Erdem Kaya* M. Tolga Eren† Candemir Doger‡ Selim S. Balcisoy§

Sabanci University

1 Introduction

In this work, we investigate whether well-known aspects of 2D and 3D representations are also valid in spatio-temporal visualization. To support our findings, we conducted an experiment with highly representative scenarios and tasks that could be used in spatio-temporal data analysis.

The main contribution of this work is a novel empirical study leading to the conclusion that 3D visualizations should be considered as a valid option in spatio-temporal data visualizations. To our knowledge, this is the first work providing evidence opposing the findings of the previous research against 3D techniques on this domain.

A particular kind of visualization technique is not completely advantageous compared to others as suggested by previous work [2, 1, 4, 5, 3]. On the contrary, 2D and 3D visualizations seem to be counterparts completing each other. The advantages of 2D representations over 3D for various kinds of data seems to be well-accepted to the extend which might mislead to the understanding that 3D has more drawbacks than 2D in spatio-temporal visualization. Based on our study and [3], it appears to be the fact that there is enough evidence to reject the idea that 3D visualization should only be considered as secondary option in the visualization of spatio-temporal data.

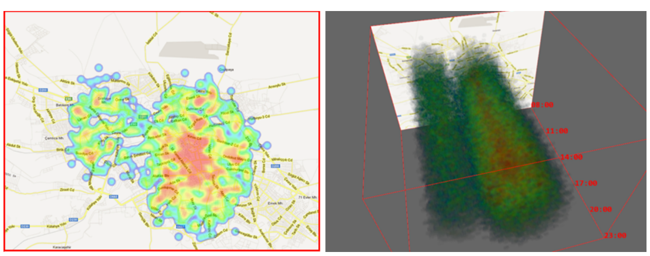

Figure 1: Views from our experimental tool showing the 2D and 3D representations of spatio-temporal data from a commercial friend finder application: 2D density map (on the left) and 3D density cube (on the right). Note that the third dimension for the density cube is time.

2 Methodology

Before designing our evaluation methodology, we have interviewed system administrators from a Location Based Services (LBS) company and identified most likely scenarios based on which we performed a laboratory experiment to compare density map and density cube techniques from *time* (to complete the tasks) and *correctness* perspectives.

The geographic data employed in our study comprises approximately 2.5 millions spatial event records with geographic coordinates with GPS-accuracy as well as a seconds-precision timestamp. To represent the data in 2D and 3D representations in the experiment, density map and density cube techniques were implemented.

2.1 Experimental Design

We designed a within-subject experiment with a single independent factor (Type of the visualization technique: Density map vs. Density cube). To better simulate the cases that might exist in real world situations, five most possible scenarios were prepared. As implied by the design of the experiment, each participant viewed the same scenario twice with different visualization technique. To prevent possible learning affects, *twin datasets*, each coupled with a single scenario, has been generated. The orders of dataset and technique were stratified such that each group of participants viewed scenarios with a specific order of dataset and visualization technique as demonstrated in Figure 2.

2.2 Tasks and Scenarios

Scenarios included situations such as the usage of the application in a downtown area where the usage rate reaches a peek at times closer to the end of the workday. Service failures and unexpected situations (e.g. sudden increase and decrease) in suburban areas have also been included in the scenarios.

As illustrated in Figure 2, each run of the experiment was comprised of 10 tasks, each of which is a combination of a scenario, an accompanying dataset, and the technique to visualize the dataset. The dataset and the accompanying visualization technique that will be used for a given task was determined according to the experiment groups. In each task, users where asked 4 or 5 questions measuring the capability of users to detect minimum and maximum points in a given time frame, trends lying on the data, and comparisons of various aspects of the data. According to the typology of Andrienko et al. [1], our minimum-maximum, comparison, and trend questions correspond to inverse comparison, direct comparison, and pattern identification, respectively, task groups.

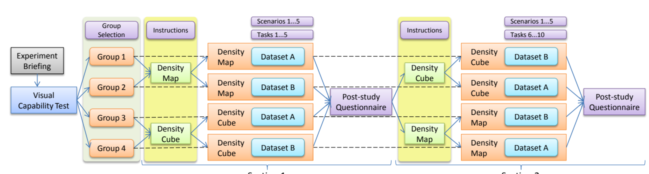

Figure 2: Experiment Conduct Flow

3 Results and Discussion

The total time spent on each technique showed that neither technique assisted participants in solving the tasks in less time than the other technique did. However, a notable exception occurred for

*e-mail: erdemkaya@sabanciuniv.edu
†e-mail:mustafae@sabanciuniv.edu
‡e-mail:cdoger@sabanciuniv.edu
§e-mail:balcisoy@sabanciuniv.edu

the minimum-maximum questions of the second scenario, $t(12) = 1.862$, $p < .1$, where the density cube technique ($M = 18.95, SD = 14.85$) outperformed the density map technique ($M = 35.58, SD = 31.2$). Another exceptional case existed for the comparison questions of the fifth scenario, $t(12) = 1.861, p < .1$, where the density map technique ($M = 25.72, SD = 11.07$) aided users to better compare the usage rates than the density cube technique did ($M = 37.97, SD = 21.33$).

We also found out that participants were able to answer both trend ($t(12) = 2.215, p < .05$) and comparison ($t(12) = 3.482, p < .01$) questions more correctly when they viewed the data with density map technique. However, there was no significant difference between the correctness measures of the two visualization techniques ($t(12) = 1.443, p > .1$) for minimum-maximum question type.

Question Type	Visualization Technique	Means and Standard Deviations	Significance Levels
Trend	Density Map	M=74.62, SD=12.66	t(12) = 2.215, p* < .05
	Density Cube	M=59.23, SD=21.78	
Minimum-Maximum	Density Map	M=70.00, SD=19.15	t(12) = 1.443, p > .1
	Density Cube	M=58.46, SD=18.64	
Comparison	Density Map	M=80.00, SD=20.00	t(12) = 3.482, p** < .01
	Density Cube	M=58.46, SD=20.75	

Figure 3: Statistical results for analysis of overall correctness measure for each question type: A zero value means that all users answered the questions wrong, where a value of 100 demonstrates the opposite. Participants answered the questions more accurately when they viewed the data with density map animation technique for trend and comparison question types. Please note that p values for trend and comparison questions are significant.

Listing the benefits and drawbacks of 2D and 3D representations for each kind of data and task is out of scope of this work. We believe that there exists enough evidence in order to argue that 3D representations in the visualization of spatio-temporal data should remain as a valid option as 2D representations are accepted to be by the existing literature. This is to say that, some common and well-known drawbacks of 3D visualizations seems not to be significantly present when the spatial and temporal data is to be analyzed. Even more, 3D representations of spatial and temporal activities can aid the users perform significantly better in particular tasks where 2D representations accepted as the de facto leading option [3].

During the experiments, users tend to model the data in their mind as a whole rather than interpreting data in smaller chunks, causing them to browse through all data as fast as possible. The "computational offload" that occurs during the holistic observation of the data assists the completion of the comparison tasks in less time [2, 5]. According to the previous work along with our findings, the holistic overview capability of 3D representations suggested in these studies seems to be valid also for the spatio-temporal data visualization.

In their experimental study, Hicks et al. [2] reported that 3D representations poorly performed in terms of overall task completion time compared to 2D graph. However, in our experiment, we were not able to observe any significant superiority of 2D representation over 3D in terms of overall task completion time. The scenario-wise task completion times of the two representations also were not significantly different. The fact that 2D representation were not able to outperform 3D could potentially be due to the higher dimensionality of our spatio-temporal data compared to 2D temporal data used in [2]. Contrarily to the previous findings favoring 2D representations in data analysis [2, 5, 3], we could rarely observe the significant superiority of the 2D representation in terms of either time or accuracy during our experiment.

As Hicks et al. reported, 3D plot of the temporal data facilitates convenience and accuracy with the undirected comparison tasks [2]. Nevertheless, we did not observe similar results in our experiments where our participants were able to make more accurate inferences with density map technique (our 2D implementation). Locating minimum or maximum usage rates (inverse comparison task) with 3D representation has been a challenging task due to occlusion as reported by both our participants and the experiment results. The density map technique allowed our users to delve into the details of the data and draw more accurate conclusions opposed to the 3D representation leading us to the inference that the occlusion problem inherent in 3D visualizations is more apparent when the data is spatio-temporal.

Another difficulty with 3D visualization is complexity of making accurate size estimate due to the perspective forshortening [4, 6]. Heights and widths that are at different distances from the user complicates comparing patterns as suggested by [7]. Our participants were able to locate trends significantly more accurately with the 2D representation. This result is inline with [7, 6, 1] suggesting that the perspective projection effect in 3D representation is also a deterious effect in the visualization of spatio-temporal data.

Subtle regular patterns might aid revealing invaluable inferences with prominent importance to the analysts. As suggested by our results and those of [2], 3D techniques might better unveil subtly changing patterns over time. However, the choice of 3D technique is of importance since not all kinds of 3D representations could aid the detection of regular patterns without introducing occlusion.

4 Conclusion

Some of the inferences previously made about the 2D and 3D representations seem to be failing for the visualization of the spatio-temporal data. Due to its intrinsic properties, given the findings of our experiment, analysis of spatio-temporal data requires reconsideration of the widely accepted properties of 2D and 3D representations. Nevertheless, more research has to be done to investigate how and in which tasks 2D and 3D representations are effective.

References

[1] N. Andrienko and G. Andrienko. *Exploratory analysis of spatial and temporal data*. Springer Berlin, Germany, 2006.

[2] M. Hicks, C. O'Malley, S. Nichols, and B. Anderson. Comparison of 2d and 3d representations for visualising telecommunication usage. *Behaviour & Information Technology*, 22(3):185–201, 2003.

[3] A. Kjellin, L. W. Pettersson, S. Seipel, and M. Lind. Evaluating 2d and 3d visualizations of spatiotemporal information. *ACM Transactions on Applied Perception (TAP)*, 7(3):19, 2010.

[4] T. Munzner. Process and pitfalls in writing information visualization research papers. In *Information visualization*, pages 134–153. Springer, 2008.

[5] G. Robertson, R. Fernandez, D. Fisher, B. Lee, and J. Stasko. Effectiveness of animation in trend visualization. *Visualization and Computer Graphics, IEEE Transactions on*, 14(6):1325–1332, 2008.

[6] M. Tory, A. E. Kirkpatrick, M. S. Atkins, and T. Moller. Visualization task performance with 2d, 3d, and combination displays. *Visualization and Computer Graphics, IEEE Transactions on*, 12(1):2–13, 2006.

[7] C. Ware. *Information visualization: perception for design*. Elsevier, 2012.