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Why not both? – Combining 2D maps and 3D space-time cubes for human trajectory data visualization

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Throughout the years, researchers have tried to understand dynamics and general patterns associated with human movement, e.g. in the context of urban planning, to improve the lives of citizens. To do this, it is necessary to properly analyse the spatio-temporal and the thematic properties of their trajectory data. Thematic maps, particularly 2D maps and 3D space-time cubes (STCs), are among the most common approaches to analyse and visualize these data. Previous research attests to the usefulness of these visualization techniques in different types of tasks. However, it is unlikely that the analysis of trajectories will be always limited to a specific type of task, thus, motivating additional studies to evaluate the dis/advantages of combining both techniques, within the same view/interaction context.
In this paper, we address this specific challenge, by presenting a comparative study between three prototypes, one using a 2D map, one using a STC, and one combining both techniques, for the visualization of trajectories. Our results support previous studies' conclusions, by showing the advantages of 2D maps and STCs for spatial and spatio-temporal tasks, respectively. They also point out towards the advantages of using both techniques together, as users seem to prefer this alternative and are able to complete different types of tasks accurately, despite the increasing complexity of the visualization.

Spatio-temporal data, trajectories, information visualization, visual analytics, space-time cube, 2d map, usability

1. INTRODUCTION

The increasing popularity and accuracy of mobile computing technologies and global positioning systems has enabled a significant expansion, in terms of quantity and quality, on the amount of spatio-temporal information that is recorded, particularly human trajectory data (Lee and Krumm 2011). A relevant example of this growth pattern consists of the increasing use of *mobile exertion* applications, such as *Endomondo*[1], that allow sports practitioners, along several other types of users, that are often non-experts with data visualization or analysis, to record their movements in the form of spatial trajectories (Lee and Krumm 2011). Similarly, social networks or cellphone operators can record their users' locations, whenever they perform *relevant* actions (e.g. log-in, post a message, take a picture, or make a phone call), thus also contributing to the generation of spatial trajectories.

These trajectories are often represented as a temporally ordered sequence of location points, embedded with *thematic* information, either derived from the registered data (e.g. speed or transportation mode) or extracted from other datasets (e.g., events happening at specific locations). Consequently, the analysis of these components allows the extraction of valuable knowledge concerning activities and events in the observed world (Andrienko et al. 2010). However, due to the large dimensions associated with trajectory datasets, and the, sometimes, uncertain role of space, time, and thematic attributes in the data analysis, there are still open challenges in several research areas. These areas include, among others, visualization and human-computer interaction, that aim to understand how to better represent and enable the exploration/analysis of these data (Andrienko et al. 2010; Amini et al. 2015).

Due to the spatial characteristics associated with trajectory data, maps are often regarded as important tools for their visualization (Kraak 2008). Among other techniques, two-dimensional (2D)

[1] http://www.endomondo.com/

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static maps and three-dimensional (3D) space-time cubes (STC) are considered as viable approaches to visualize and analyse these data.

As such, the choice for an adequate visualization technique can be seen as an important, and sometimes *controversial*, challenge, since the results of previous studies suggest that each technique is more adequate than the other for specific types of visualization tasks (e.g., identify, compare, associate). Interestingly, despite some authors suggesting the interest of combining both techniques (Amini et al. 2015; Gonçalves et al. 2015), few studies have addressed this challenge, while those that did can be seen as somewhat focused in distinguishing the different components rather than exploring the actual consequences of their combination (Gonçalves et al. 2013; Kveladze et al. 2015).

In this paper, we aim to address those issues. We present a comparative study between three prototypes, one using a 2D map, one using a 3D STC, and one implementing both techniques. In particular, we aim to: i) expand the existent knowledge that distinguishes the benefits from using 2D maps compared to 3D STCs; ii) explore the dis/advantages of combining both techniques within the same view, comparatively to using them separately; iii) empirically validate the proposed features (e.g., control options) to help interacting with these techniques, taking into account the types of tasks a user might need to perform in order to achieve a given goal (Roth 2012); and iv) understand which strategies/methods non-expert users adopt to control the visualization and acquire information, alongside their performance and acceptance towards these alternatives. The remainder of this paper is organized as follows: the next section presents, in more detail, the main characteristics of 2D maps and 3D STCs. Then, the paper describes the prototypes developed in the context of this study, followed by the user study and results obtained with the prototypes. The paper concludes with a discussion of the results, and with ideas for future work.

2. CARTOGRAPHIC VISUALIZATION OF HUMAN TRAJECTORY DATA

Due to the spatial characteristics associated with trajectory data, maps are often considered important tools for visualizing human trajectories. More specifically, thematic maps are considered an effective and crucial means for summarizing and communicating complex georeferenced information (Kessler and Slocum 2011), and given their usefulness in supporting analysts to solve various spatial and temporal related problems, they are often used to support decision making (Kraak and Ormeling 2010).

Although other visualization techniques, usually based on charts, may be used instead to convey information regarding trajectory data, their isolated use is often not recommended, due to their inadequacy in representing georeferenced information (Kraak and Ormeling 2010; Andrienko et al. 2011). Nevertheless, these methods can still be used alongside map visualization techniques, as a means of providing additional points of view over the data. An example of those techniques are time-graphs, which consist of line-graphs that represent variations of attribute values in time (Andrienko and Andrienko 2013). In addition, due to the high complexity of the visualizations, it is often necessary to mediate the interaction between the user and a map with some sort of computational device, therefore, making the ability to interact with the visualization and the data critical for geovisual analysis (Roth 2013).

Overall, 2D static maps are one of the most common techniques used to represent georeferenced information and, by generalization, trajectory data. Typically, these techniques take advantage of the manipulation of the visual variables of graphical elements, like the colour, size, or transparency of points, lines, and/or areas, to convey different types of information present in the dataset (e.g. speed, or altitude) (Kraak and Ormeling 2010; Bertin 1967). The most simple and recognizable approach to represent trajectory data consists in the use of lines over the map plane, usually to depict the evolution of the position of one or several objects, or the use of differently shaped symbols, to represent, for instance, different spatial or spatio-temporal events (e.g. a traffic accident). On the other hand, when the dataset is too big/complex and/or the target users have some experience in data analysis, more complex approaches can be used, including coloured tables over a trajectory to represent the evolution of thematic attributes through space and time (Andrienko et al. 2013), or density maps to show the concentration of movers and/or events in space (Scheepens et al. 2011). However, despite their common use, 2D maps tend to undermine the representation of the temporal information present on trajectory datasets. To better convey the existence of time in 2D maps, previous works have proposed, among others, the use of: visual variables, like transparency, to emphasize more recent events (Booker et al. 2007); textual timestamps, to explicitly show the time when an object passed through a landmark (Kjellin et al. 2010); or additional views displaying temporal-based information, for instance, in the form of graphs (Andrienko et al. 2013), inside or outside the map.

On the other hand, following the advances in computer graphics, 3D visualizations are continuously being presented as a promising way to represent complex information (Kjellin et al. 2010). More specifically, in the context of trajectory data visualization, space-time cubes (STCs) allow the representation of both spatial and temporal information within a 3D cube, typically by using the $x - y$ axes to represent spatial information, while the $z-$axis represents time (Hägerstrand 1970). Similarly to 2D maps, trajectory data information can be conveyed through the use of a sequence of symbols, graphically encoded to represent thematic information. However, using the third dimension to convey temporal information minimizes the 2D map's inadequacy in representing time (by itself), allowing other visual variables to be used for representing other thematic attributes, which would likely be used to represent time in a 2D map (Kjellin et al. 2010), and allowing the representation of several layers of information, each one defined as a plane along the $z-$axis (Tominski et al. 2005; Thakur and Hanson 2010; Tominski et al. 2012). Nevertheless, given their 3D characteristics, STCs may be affected by human perceptual issues (Seipel 2013), which in turn has fostered some discussion regarding the actual usefulness of 3D, comparing to 2D visualizations.

Previous studies have tried to compare and/or analyse the dis/advantages of these techniques. Overall, existing results suggest that 2D visualizations are better for relative positioning and location-based tasks (John et al. 2001; Goncalves et al. 2014), and are an adequate choice in tasks that deal with metric properties (Kjellin et al. 2010). On the other hand, 3D visualizations and STCs provide a better understanding of shapes and patterns in the data (John et al. 2001; Goncalves et al. 2014), are an adequate choice in tasks dealing with ordered properties (Kjellin et al. 2010), and may help users solving tasks with more certainty on their decisions (Seipel 2013; Kveladze et al. 2015). However, previous studies have also reported some complaints of visual discomfort when using 3D visualizations (Seipel 2013), and have suggested that STCs are less scalable than 2D approaches (Willems et al. 2011). This is due to the visual occlusion and the 3D perspective issues caused when larger amounts of information are displayed, which may increase the difficulty in visualizing and understanding the data. Consequently, STCs (and 3D visualizations as a whole) are dependent on effective interaction techniques that support an easy and adequate change of the point of view within the data (Kjellin et al. 2010) and/or improve the users' spatial/geographical awareness (Gonçalves et al. 2015).

As suggested by the literature, despite their flaws, both techniques have important roles in different tasks. However, the analysis of trajectory data may not be focused in just one type of task. This makes the choice for an adequate visualization technique an important challenge, and suggests the need for studying and quantifying the advantages of combining both types of techniques (Amini et al. 2015; Gonçalves et al. 2015; Kveladze et al. 2015). Gonçalves et al. (2015) present an alternative for the STC technique, by using a parallel 2D map overview to the STC, as a means to improve user performance in location-based tasks. Their results suggest both a higher accuracy in complex tasks and a higher subjective preference comparatively to purely 3D STCs. The authors also report the participants' interest towards more control and a more relevant role in the interaction process with the 2D map overview. In addition, Gonçalves et al. (2015) and Kveladze et al. (2015) refer the possibility to alternate between a 2D map and a 3D STC, either by changing the STC's temporal granularity or selecting a menu option, respectively. Based on the analysis of interviews, Kveladze et al. (2015) also report that both domain and non-domain experts were receptive towards this feature, regardless of how much they actually used it.

Despite the existing work addressing these challenges, we argue that more studies must be conducted in order to empirically validate and expand on the existing knowledge, and to understand/quantify if and how the combination of these techniques affects user interaction. In the next section, we describe three prototypes used in the a comparative study aiming to address these challenges.

3. VISUALIZATION PROTOTYPES

We developed and compared three prototypes integrating different map techniques (Figure 1 a, b, and c) that supported the visualization of pickup/dropoff locations of 10 taxis, selected randomly, for the duration of one month (Jan, 2013), based on a sub-set of the data made available by the Taxi and Limousine Commission of New York City.

Despite their differences, all prototypes are composed by six main components with similar functions. The first component, the control panel (Figure 1d) allows the selection of the data to visualize, through various filters. These include temporal filters to select the time period (days and hours) of movement and thematic filters that allow the selection of data based on the maximum/minimum trip time, distances, number of passengers, profit obtained, payment types, and the taxi and/or driver identification. The second component (Figure 1e), the representation panel,

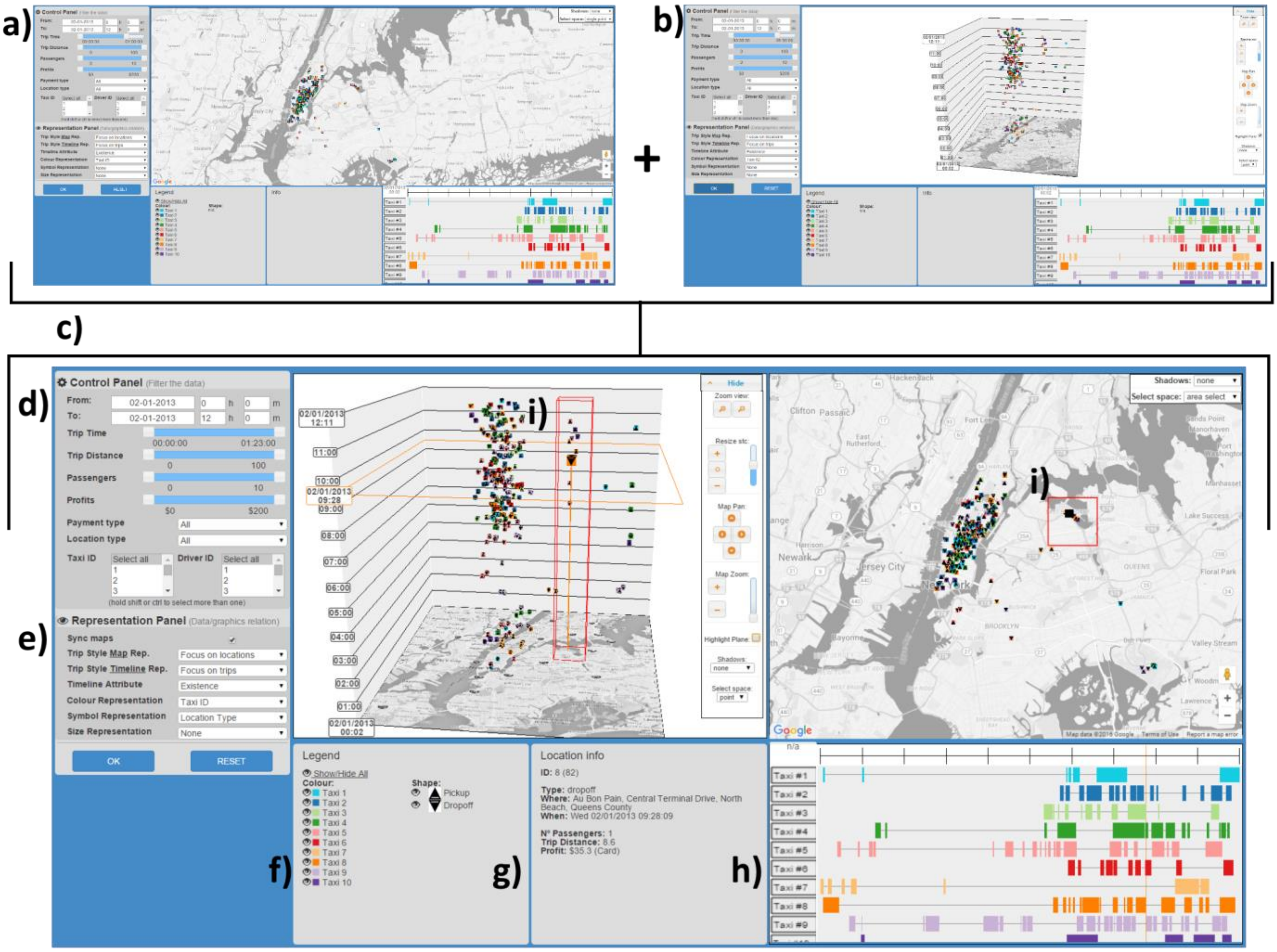

Figure 1: *Prototypes used for the study: a) 2D map prototype; b) STC prototype; c) 2D map + STC prototype d) Control panel; e) Representation panel; f) Legend; g) Information panel; h) Timeline; i) Spatial highlight reflected in both maps*

allows users to associate a given set of thematic attributes to different visual variables (colour, shape, and size), in the map(s) visualization(s) and in the timeline (explained below). In particular, users can use colour to represent the taxi/driver ids, the time periods of the day (i.e., four categories, each defined by a period of six hours), the location type (pickup or dropoff), or the payment type (money or credit card). On the other hand, a point shape can be used to represent the time period of the day and the location or payment types. The visual variable size can be used to represent the number of passengers, the distance, time, or the profit associated to each trip. The higher the value of the attribute, the larger/wider the points/lines used to represent the data. The third component (Figure 1f) consists of a legend, that describes the meaning of the visual variables being used, and allows to quickly show/hide sub-sets of the data associated to those variables. The fourth component (Figure 1g) is used to display all data associated with a location or trip selected in the visualizations, i.e., the name of the locations, the date when the location was visited, and thematic information regarding the number of passengers, the duration, the distance, and the profit associated to the trip.

The fifth component (Figure 1h), the timeline, consists of a point/line chart focused on displaying data from a temporal perspective. By default, this view is composed by several rows, each one representing the movement data of one taxi, containing various icons distributed horizontally, to indicate the moments in time in which movement was detected. Through the representation panel, it is possible to select other thematic attributes, such as the number of passengers, distance, time, or profit related to a trip, and visualize their evolution through time, in an alternative timeline view (Figures 2 a and b). We added this component into the prototypes for two main reasons: on one hand, it provides an additional point of view over the information; on the other hand, to support the acquisition of relevant results, it is fundamental to ensure that the prototypes being used are *informationally equivalent* (i.e., it is possible to extract similar information from the different prototypes), therefore making it necessary to compensate the limitations in the 2D map when representing time.

The last component consists of the map visualization technique, which, depending on the prototype used, can either be a 2D map, a 3D STC, or a visualization with both techniques displayed in parallel (Figures 1 a, b, and c, respectively). As previously mentioned, this study is focused on non-experienced users in terms of trajectory visualization and analysis. As such, we opted for data representations that should be simple to use and to understand. In all cases, the pickup/dropoff locations are represented with points, whose colour, shape, and size are changed according to the attributes chosen in the representation panel. Using the representation panel, these points can also be connected with lines, to better illustrate the sequence of locations visited.

Both the 2D map and the 3D STC provide common interaction techniques based on panning and zooming, through the use of the mouse and/or additional controls located at the edges of the views. In particular, the STC allows the user to rotate the visualization along any of its axes (by mouse dragging) and to rescale its height (with a slider), therefore enabling users to, respectively, change the point of view, and to manipulate the temporal granularity of the data. Users are also able to select an additional map plane that could be placed anywhere along the STC's height (by hovering in it), as a means to improve spatial awareness (Kraak 2003). Additionally, both visualizations allow drawing areas, by double-clicking in the map. These can be used as references when analysing the data or when changing the map view through panning and/or zooming operations. Moreover, as usual in applications with multiple views, the selection of information in any of the map views or the timeline highlights the correspondent data element in the other views. Similarly, as a means to further emphasize the combination of the studied techniques, in the prototype combining the 2D map with the 3D STC, any change made to one map is immediately reflected in the other. Namely, panning/zooming the map or drawing a reference area will cause the other map to be panned/zoomed or have a reference area drawn into the correspondent geographical area (Figure 1i). This synchronization can also be de/activated through the representation panel.

4. USER STUDY

The following section describes the comparative user study conducted with the previously described prototypes. In particular, with this experiment we

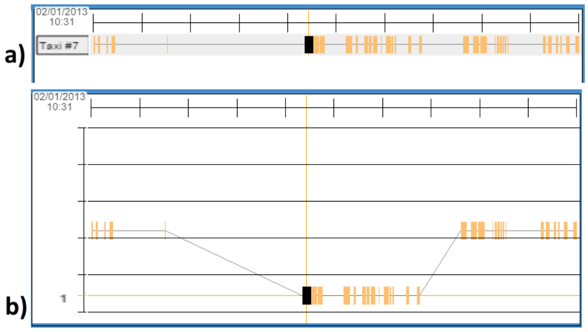

Figure 2: *Alternative timeline views (with the data of one taxi) a) Each* block *represents a period of time in which a trip occurred; b) similar to a) but the y-axis is used to represent the number of passengers per trip.*

aimed to: i) identify strategies that users may adopt to obtain spatial and/or temporal information when using a 2D map and an STC; ii) identify possible techniques that may improve the interaction with these visualizations; and iii) assess the users experience with those methods, while empirically comparing them, to better understand the role of each method in the different tasks, as well as the dis/advantages of each prototype over the others.

Based on the characteristics of the techniques and the objectives of the experiment, our hypothesis were the following:

(H1) We expected a more significant preference towards the prototype combining the 2D map and the STC visualizations. Despite the visual similarities with the other prototypes, and the redundancy of the data displayed (same data in two similar maps), this prototype still provides more choices, to the participants, in terms of visualization and interaction, which may, in turn, affect their preferences.

(H2) We expected a higher performance (i.e., efficiency, and effectiveness) and a more significant usage of the 2D map in location-based tasks. This hypothesis is supported by the results of previous studies that point out towards the more advantageous use of 2D maps for these types of tasks, in addition to the fact that 2D maps are widely known/used visualization techniques, even by users with no experience.

(H3) We expected a higher performance with the STC in tasks that require the analysis of the data's temporal component. Although the 2D map prototype provides also temporal information, through the use of the timeline component, the participants need to change their focus between the two different views, which, in turn, may affect their analysis. On the other hand, the STC combines spatial and temporal components within the same view, expectedly allowing for an easier analysis.

Due to the novelty and exploratory nature of this study, we recruited a total of 30 participants, aged between 19 and 40 (Av: 25.6, SD: 4.9). All participants were knowledgeable with computer applications for the visualization of geo-referred information and the search of directions towards specific points of interest, such as Google Maps, as well with applications that use 3D visualizations to convey or manipulate information, like Google Earth, design applications, such as Blender, or various games. Out of all participants, four mentioned that despite being knowledgeable, they were not fully comfortable with 3D graphic applications. Finally, no participant was familiarized with New York's geography, nor had any significant experience with spatio-temporal nor trajectory data analysis.

4.1. Experimental Design

To test our hypotheses, the participants performed two tasks, *identify* and *compare*, which are based on the most common types of cartographic visualization objectives described in the literature (Roth 2012). Each task was subdivided into two categories: *spatial* and *spatio-temporal*, depending on the main types of constraints associated with the task. This division was decided due to the fact that 2D maps and 3D STCs differ mostly in how temporal information is presented, which in turn, may affect how the data is analysed. Consequently, this results into four types of tasks, described as follows: **Spatial identification** – required participants to identify information (e.g. *point of interest or taxi/driver id*) in which one or several taxis performed a certain action (e.g. *drop a passenger*), based on a spatial restriction (e.g. *which drivers dropped passengers outside of New York?*); **Spatio-temporal identification** – required participants to identify information based on a spatio-temporal constraint (e.g. *in a certain day, which driver was the first dropping a passenger outside of New York?*); **Spatial comparison** – required participants to analyse relations/similarities/differences between data elements based on a spatial constraint (e.g. *which driver covered a wider geographical area?* or *which points of interest were the most visited?*); and **Spatio-temporal comparison** – required participants to analyse relations/similarities/differences between data elements based on a spatio-temporal constraint (e.g. *which taxi had the most service in New York during a given time period?* or *in which time periods was a given location the most visited?*).

In addition, we considered two independent variables for this experiment: Visualization technique (*Vt*), with three levels, 2D map, STC, and 2D map + STC; and number of taxis/trajectories (*Nt*), with two levels, 1 and 10. We consider this last variable, and its values, necessary to a complete analysis, given the existence of previous results that suggest the STC's low scalability (Scheepens et al. 2012; Demsar and Virrantaus 2010).

The experiment followed a *within subjects* design and all participants carried out each task individually, in a controlled environment. At the beginning of the experiment, the participants were briefed about the objectives of the study and the types of visualization techniques. After that, they viewed a demonstration of the prototypes and were asked to interact with them. Before carrying out the tasks, the participants were also encouraged to clarify any doubts.

After the training phase, the participants were asked to perform the four tasks, first the identification, then the comparison tasks, due to expected higher difficulty in comparison tasks and due to the fact that, in order to compare information, the user will usually need to identify it first. Nevertheless, to mitigate sequence effects, the order in which the independent variables and the type of task (spatial or spatio-temporal) were presented was counterbalanced based on a *latin-square* design. As a result, each participant performed a total of 24 trials: 4 tasks x 3 *Vt* x 2 *Nt*.

To measure our results and assess our hypothesis, we considered the following dependent variables: (i) subjective preferences: at the end of each task, the participants were asked to rate each prototype on a 10 point Likert scale; (ii) task accuracy: each task was rated on a 0 to 5 scale, based on the correction and detail of the answers given by the participants; (iii) task completion time: from the moment the participant started the task until the final answer was provided; (iv) number of actions performed: these included map and/or view panning/zooming operations, rescaling the STC's height, or highlighting information. (v) component usage (for the third prototype): ratio between the total number of actions and the number of actions on each visualization component (2D map, STC, or timeline).

4.2. Results

The following section describes the results obtained in the study, particularly, focusing on the most statistically significant ones and those close to be considered as such (i.e. with a *low p*-value). For simplicity, the remainder of the paper will address the prototypes that implement the 2D map, the STC, and the combination of both techniques as *2DM*, *STC*, and *3VC*, respectively. We will also address the *identification* and *comparison* tasks as *id* and *cp*, respectively.

Table 1: *Mean participants' results in terms of a) subjective preferences, b) task accuracy, c) task completion time, d) number of interactive actions, e) percentage of component used in* Vt(3VC) *– Sp and SpT stand for spatial and spatio-temporal tasks, respectively*

	Identify (id)				**Compare (cp)**			
a) Preferences [0-10]	**Sp**		**SpT**		**Sp**		**SpT**	
2DM	7.97		7.20		7.40		6.77	
STC	5.40		6.10		6.27		6.83	
3VC	7.97		8.23		8.03		8.20	
b) Accuracy [0-5]	**Sp Nt(1)**	**Sp Nt(10)**	**SpT Nt(1)**	**SpT Nt(10)**	**Sp Nt(1)**	**Sp Nt(10)**	**SpT Nt(1)**	**SpT Nt(10)**
2DM	4.67	4.20	4.17	3.07	4.60	4.00	4.13	3.73
STC	4.73	3.80	4.53	4.17	4.73	3.83	4.53	4.37
3VC	4.77	4.27	4.40	4.00	4.60	4.00	4.43	4.40
c) Time (sec)								
2DM	96.23	120.85	103.53	183.55	71.52	117.32	112.33	144.23
STC	142.13	262.80	106.62	230.23	70.85	171.75	139.33	131.33
3VC	143.62	155.43	104.80	174.42	76.70	130.57	130.52	107.72
d) N° Actions								
2DM	18.43	40.43	21.87	45.37	21.60	41.07	22.80	29.50
STC	55.03	93.03	46.83	105.43	32.67	71.00	90.80	71.90
3VC	51.80	71.10	43.83	92.47	33.27	60.53	29.50	59.03
e) Comp. use (%)								
2DM	57.23	54.77	21.19	27.56	41.45	52.51	17.81	19.08
STC	25.42	12.42	39.73	49.07	15.03	15.60	47.51	51.62
Timeline	14.64	6.25	28.78	11.23	3.43	5.47	25.65	21.26

4.2.1. Subjective preferences

To analyse the differences in terms of subjective preferences, we applied a Friedman's test, followed by a Wilcoxon Signed Rank test, with a Bonferroni correction, for pairwise comparisons (see Table 1 a). Significant differences were detected in all tasks (*spatial id*: $X^2(3) = 38.697$, $p < 0.001$; *spatial cp*: $X^2(3) = 25.59$, $p < 0.001$; *spatio-temporal id*: $X^2(3) = 28.625$, $p < 0.001$; and *spatio-temporal cp*: $X^2(3) = 19.049, p < 0.001$). For **spatial tasks**, the results revealed a lower preference towards *Vt(STC)* (versus *Vt(2DM)*, *id*: $Z = -4.24$, $p < 0.001$ and *cp*: $Z = -3.30$, $p = 0.001$; versus *Vt(3VC)*, *id*: $Z = -4.32, p < 0.001$ and *cp*: $Z = -3.64$, $p < 0.001$). For **spatio-temporal tasks**, the results revealed a higher preference towards *Vt(3VC)* (versus *Vt(2DM)*, *id*: $Z = -3.02$, $p = 0.003$ and *cp*: $Z = -3.38$, $p = 0.001$; versus *Vt(STC)*, *id*: $Z = -4.58$, $p < 0.001$ and *cp*: $Z = -3.64$, $p < 0.001$).

4.2.2. Accuracy

A similar procedure was used to compare the differences in terms of accuracy (see Table 1 b). Significant differences were detected in all tasks (*spatial id*: $X^2(5) = 31.16$, $p < 0.001$; *spatial cp*: $X^2(5) = 51.38$, $p < 0.001$; *spatio-temporal id*: $X^2(5) = 34.37$, $p < 0.001$; and *spatio-temporal cp*: $X^2(5) = 19.20, p = 0.002$). More specifically, in **spatial tasks**, the results suggest a lower accuracy in conditions with more trajectories, *Nt(10)*, comparatively to just one, *Nt(1)*, when using *Vt(STC)* (*id*: $Z = -3.33$, $p = 0.001$; *cp*: $Z = -3.03$, $p = 0.002$). In the **spatio-temporal tasks**, however, the results suggest a lower accuracy with *Vt(2DM)* (versus *Vt(STC)*, *id*: $Z = -2.63$, $p = 0.009$ and *cp*: $Z = -2.37$, $p = 0.018$; versus *Vt(3VC)*, *id*: $Z = -2.66$, $p = 0.008$; *cp*: $Z = -2.62$, $p = 0.009$).

4.2.3. Task completion times

To compare the differences in terms of the task completion times (see Table 1 c), we applied a repeated measures ANOVA, followed by Bonferroni tests, for pairwise comparisons. In both **spatial tasks**, significant effects were found in ***Nt*** (*id*: $F(1, 29) = 15.61$, $p < 0.001$, *cp*: $F(1, 29) = 44.51$, $p < 0.001$), in ***Vt*** (*id*: $F(2, 53) = 10.71, p < 0.001$, *cp*: $F(2, 58) = 3.040$, $p = 0.05$), and in both factors (*id*: $F(2, 51) = 15.61$, $p < 0.001$, *cp*: $F(2, 43) = 44.51$, $p = 0.014$). In the **spatio-temporal identification task**, the tests also revealed a significant effect from ***Nt*** ($F(1, 29) = 56.9$, $p < 0.001$) and ***Vt*** ($F(2, 53) = 3.43$, $p = 0.043$). For **spatial tasks**, pairwise comparison tests revealed overall faster completion times with *Vt(2DM)* comparatively to *Vt(STC)* ($p \leq 0.048$) and, overall, longer times with more trajectories (*Nt(1)* < *Nt(10)*). On the other hand, no significant differences were detected in the **spatio-temporal comparison task**.

4.2.4. Number of interactive actions

A similar procedure was applied to analyse the differences in terms of the *number of interactive actions* conducted in each task (see Table 1 d). In both **identification tasks** and in the **spatial comparison task**, similar differences were detected. The results reveal a significant effect from ***Nt***, where a higher number of actions was conducted in *Nt(10)* conditions (*spatial id*: $F(1, 29) = 4.94$, $p < 0.001$; *spatio-temporal id*: $F(1, 29) = 24.88$, $p < 0.001$; *spatial cp*:

$F(1, 29) = 14.48, p = 0.001$). A significant effect was also found on ***Vt*** (*spatial id*: $F(1.7, 49.2) = 8.74$, $p < 0.001$; *spatio-temporal id*: $F(1.9, 55) = 8.20$, $p = 0.001$; *spatial cp*: $F(1.6, 48.9) = 4.05$, $p = 0.03$). Pairwise comparison tests revealed that a lower number of actions was conducted with *Vt(2DM)* comparatively to the other techniques ($p \leq 0.049$). In the **spatio-temporal comparison task**, a significant effect of ***Vt*** was found over the results ($F(1.4, 42.87) = 5.32$, $p = 0.015$). Pairwise comparison tests revealed, again, a significantly lower number of actions with *Vt(2DM)* comparatively to *Vt(3VC)* ($p = 0.019$).

4.2.5. Components used

To compare the differences in terms of the components used in *Vt(3VC)* (see Table 1 e), we applied an ANOVA test, followed by a Bonferroni test, for pairwise comparisons, over each task condition. Significant differences were detected in both **spatial tasks** ($F(2, 84) \geq 6.14$, $p \leq 0.003$ for all conditions). Participants used the 2D map component more often that the STC and timeline components ($p \leq 0.003$ for all conditions). Significant differences were also detected in both **spatio-temporal tasks** ($F(2, 84) \geq 3.71$, $p \leq 0.048$ for all conditions). However, the results reveal a more frequent use of the STC component over the 2D map and the timeline components ($p \leq 0.049$).

5. DISCUSSION

Overall, the results obtained in this experiment not only allow us to discuss our hypotheses, but they also support the results of previous studies, and highlight relevant aspects regarding the techniques and how users interact with them.

We consider that the results support our first hypothesis (H1: higher preference towards *Vt(3VC)*). Throughout the study, the participants have shown a higher preference towards *Vt(2DM)* and *Vt(3VC)*; however, although no significant differences were found between these two prototypes in *spatial* tasks, in *spatio-temporal* tasks *Vt(3VC)* was the preferred prototype. Participants commented that using the 2D map helps overcoming the STC's limitations when analysing spatial information. Other participants also praised *Vt(3VC)* for providing more choices to analyse and/or confirm information. Another positive aspect mentioned consisted of the synchronization between the two maps, which allowed users to easily change the focus from one view to the other.

On the other hand, the results partially support our second hypothesis (H2: *Vt(2DM)* better in spatial tasks). Analysing the task completion times and the number of actions in spatial tasks allows us to conclude that the participants were generally faster and performed a smaller number of actions to complete the tasks; however, no significant results were found in terms of accuracy. These results are worth mentioning, specially when associated with the subjective preferences registered. Despite the significant preference towards *Vt(2DM)*, the participants were still able to complete the tasks as accurately with *Vt(STC)*.

We consider that the results also support our third hypothesis (H3: *Vt(STC)* better in spatio-temporal tasks). As in the previous case, the participants performed more actions to complete the tasks with *Vt(STC)*. However, comparatively to *Vt(2DM)*, they were, generally, more accurate, in both spatio-temporal tasks (even if not by a large margin), while not significantly slower as in spatial tasks. Analysing these results with the participants' preferences shows that, despite no differences being found between *Vt(STC)* and *Vt(3VC)*, in terms of completion times, number of actions, or accuracy, they still preferred *Vt(3VC)*.

It is also important to notice that, in addition to the type of task, increasing the number of trajectories (*Nt*) had also an effect on the interaction with the techniques, particularly in terms of task completion time and number of actions performed. However, in terms of accuracy, these effects were most noticeable in *Vt(STC)* for spatial tasks and in *Vt(2DM)* for spatio-temporal identification tasks.

In general, the results of this study point towards the superiority of *Vt(3VC)*. By one hand, analysing the accuracy in the various tasks shows that, at worst, this prototype is as useful as the better technique from *Vt(2DM)* and *Vt(STC)*. Moreover, the analysis of the component usage on *Vt(3VC)* (Table 1e) reveals the different behaviours adopted in the different tasks. In particular, in spatial tasks, participants focused on the 2D map component to complete the tasks, while in the spatio-temporal tasks they focused on the STC and, sometimes, the timeline component. This suggests the interest of having both techniques available to the user in scenarios where the focus of the task may vary between spatial and temporal information. On the other hand, combining both techniques should increase the complexity of the visualization, which may require users to perform more actions to successfully analyse information and complete a given task. Despite that, as evidenced by the results, users may still feel more comfortable with this approach, comparatively to visualizing just one of the techniques, which may minimize the effects of the additional complexity.

Throughout the study, the participants have also made relevant comments about the individual techniques. Regarding *Vt(2DM)*, some participants admitted that their preference towards this technique was, in part, based on their familiarity with it. They also commented that it was more difficult to work with this technique when temporal information was necessary, consequently commenting positively the existence of the timeline component and its usefulness for these tasks.

Regarding *Vt(STC)*, despite the complaints about the difficulties in dealing with the third dimension, often due to perspective issues, the participants have praised the additional map plane, that could be placed anywhere along the STC's height, and the possibility to highlight a specific geographical area. Participants have mentioned that the later feature was more helpful in *Vt(STC)* than in *Vt(2DM)* and aided them to understand the geographical area and how the information is distributed. Some participants also shown their appreciation towards this functionality in *Vt(3VC)*, when they would draw an area in the 2D map component and analyse the correspondent area in the STC.

In addition, participants have also mentioned the usefulness of the temporal granularity controls that allowed them to visualize with more detail variations of information in close periods of time and, for some participants, to *convert* the 3D STC into a 2D map. In fact, we detected similar strategies from the participants when using *STC* to those described by Gonçalves et al. (2015). Namely, to improve their spatial/geographical awareness, the participants have tried to minimize the third dimension aspect from the STC by looking at the data from a *bird's eye perspective* or by reducing the STC's height to its minimum, simulating a 2D map. These results require further investigation and suggest the interest in comparing different approaches to combine 2D map and STC visualizations, like those present in this study, with *Vt(3VC)*, and in Kveladze et al. (2015), by switching between the techniques.

Finally, the participants also appreciated the representation panel options, that allowed them to customize how the information should be displayed. They commented that it was both useful in highlighting information they thought as relevant for the analysis and that it made them feel in control over the interaction.

6. CONCLUSIONS AND FUTURE WORK

This paper reports on a comparative user study between three prototypes for the visualization of trajectory data: one based of the 2D map technique (2DM), another based of the space-time cube technique (STC), and the third using both techniques together (3VC). The study took into consideration tasks with different constraints (spatio and spatio-temporal information) and numbers of trajectories (one or ten) for non-experienced users.

The results suggest that, compared to the STC in spatial tasks, the 2DM is preferred and better, in terms of completion time and number of actions. In addition, compared to the 2DM, the STC is not preferred, but it is better in terms of accuracy, in spatio-temporal tasks. On the other hand, the results suggest the advantages in using 3VC. Although comparable to the STC, in terms of completion time and number of actions performed, this technique was never significantly outperformed by any other in terms of accuracy nor subjective preferences. In addition, participants adopted different strategies in the tasks, focused on the specific components from the 3VC, which supports the advantages of using this approach in scenarios where it is necessary to analyse spatial and temporal information.

Test participants have also voiced their concerns regarding the difficulty felt when analysing spatial data in the STC and temporal data in the 2DM. However, they praised several complementary features on both prototypes, namely, the timeline component, which improves the visualization with the 2DM and area highlights, the auxiliary moveable geographical planes, and the temporal granularity controls on the STC, which minimize the difficulties in analysing spatial information and support the analysis of spatio-temporal information.

As future work, we propose to continue studying these issues, in particular, the analysis of the types of strategies adopted with the different visualizations and their possible effects on user performance. In addition, we suggest the study and comparison of alternatives for the combination of the 2D map and STC techniques, in particular, the comparison between a visualization such as the one described in this study (3VC), that presented both techniques simultaneously to the user, and one as suggested by Kveladze et al. (2015) that displays only one technique, but allows its conversion into the other. Moreover, we suggest the study of the effects of the combination of other cartographic visualization techniques, including animated and/or small-multiple maps.

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