Temporal-Geospatial Cooperative Visual Analysis

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***Abstract*— Given the diverse set of pervasive tracking technologies available, temporal-geospatial data is being collected at an unprecedented rate. However, the effective visualization and interpretation of this data remains elusive. Visualizations have focused on showing an object's location, however more complex inter-entity queries also need to be supported, e.g. "did X and Y meet, and if so, where and when?". We present Cooperative Visual Analysis, a combination of two novel visualizations, the Parallel Schedule View and the Braille Plot, working in synergy with a traditional 2D map. The Parallel Schedule View focuses on showing colocation (simultaneous or time separated), with the Braille Plot used to resolve position ambiguity and identify patterns and trends within a data trace (in addition to colocation). We present descriptions of each, and a user study showing support for these approaches. The study compared Cooperative Visual Analysis with a current approach, the Space Time Cube, and found the Cooperative Visual Analysis is an effective means for visualizing temporal-geospatial relationships in a data set, performing at or above the Space Time Cube, whilst being preferred by users.**

Keywords—Cooperative Visual Analysis; visualizaiton; temporal; geospatial; Braille plot; proximity;

I. Introduction

The ever-growing importance [1] and increasing collection [2] of temporal-geospatial data has introduced the challenge of developing effective visualizations to explore and better understand the data [3, 4]. Low accuracy technologies (e.g. WiFi) are abundant, but the reduced accuracy adds to the problem and has not addressed to date [4]. The visualizations presented in this paper improve previous methods to provide tools that help users understand and interpret temporal-geospatial data. Our approach is not a single solution for every temporal-geospatial data query, but it is an investigation into developing suitable visual analysis tools that expose patterns that are difficult to identify otherwise. We extend the suite of visualization tools for a subset of complex queries, such as "*did X and Y meet, and if so, where and when?*". We refer to these queries as *convergence* and *divergence* queries [4].

While automated analysis can help analyze datasets, the analysis is only as good as the parameters. As such, the use of effective visualizations allows analysts to instantly evaluate different aspects, enabling them to quickly and repeatedly query the data set, as opposed to repeatedly performing automated analysis with different parameters.

The need for visualization in such scenarios has continued the debate of 2D versus 3D approaches [5]. Approaches using a single representation show both time and location, with increased information density but reduced readability. To address this, approaches such as the Space Time Cube (STC) [6] enable using the Z-axis of the map to represent time. However, this new axis introduces loss of perspective and obfuscation, which require additional user operations to avoid. Cockburn and McKenzie [7] found in evaluations that as greater freedom to find items in the third dimension was given, performance deteriorated. The use of the Z-axis also limits the use of the visualization for existing domains where the Z-axis is already utilized (e.g. visualizing air traffic movement).

The Cooperative Visual Analysis (CVA) system addresses previous limitations, combining two complimentary visualizations, the Parallel Schedule View (PSV) and the Braille Plot, which work in synergy with a 2D map to support visual analysis. There are two time-based visualizations: the *PSV*, to explore the colocation of objects, and the *Braille Plot* (extending [4]), to explore the relative locations of objects, reduce uncertainty and identify patterns in the data. Both visualizations together enable data reconstruction from low accuracy data sources. The PSV and Braille are supported by a third visualization technique, a traditional map. Fig. 1 depicts the application we have developed showing a sample data set.

Our visualizations are validated with a user study, focusing on a set of higher level concepts, rather than single attributes of individual traces. We investigate the movement of, and interaction between, objects relative to a location of interest, the identification of idle periods, and periods of colocation. The contribution of this work is as follows:

1. The introduction of the PSV as means of visualizing colocation,
2. The adaptation and extension of the Braille Plot as an interactive means of exploring data, reducing error, and identifying patterns within it, and
3. A full user evaluation supporting their use.

The next section explores related work. Following this, we describe the two complimentary visualizations in detail, with the remainder of the paper describes the study and a discussion of the findings, followed by concluding remarks.

1. Related Work

The amount of temporal-geospatial data being generated is increasing every day, creating issues often dealt with under the umbrella of "big data" as the "five Vs" of big data [8] (previously the "three Vs" [9]). Although the visualization of space and time are still open research problems [1, 10, 11], many solutions are focused solely on representing a single object. Users are needing to analyze spatial relationships between multiple objects (a higher level problem [12]), and not just a

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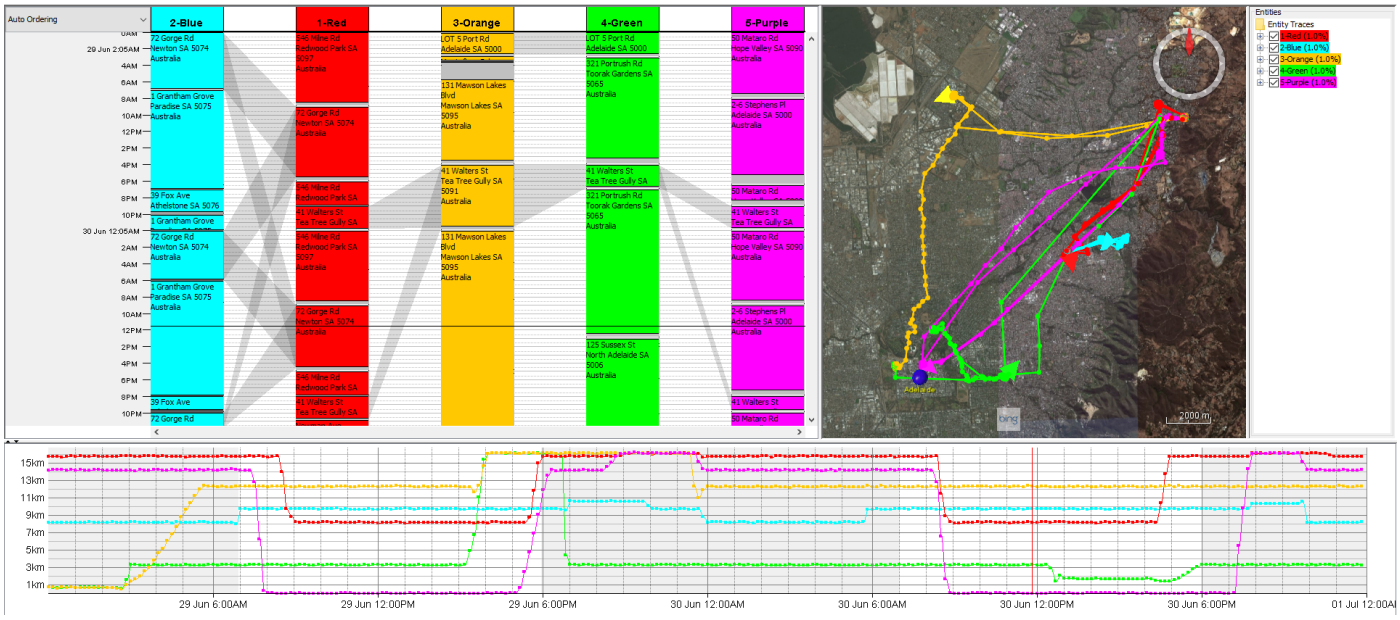

Fig. 1. The Cooperative Visual Analysis user interface showing sample data for five entities, with the PSV in the upper-left panel, the panel on the upper right is the 2D map, and the panel on the bottom is the Braille Plot.

Single trace [3]. This is compounded by the data type being visualized, including movements of vehicles [13], vessels [14], or crime [15], or even object-agnostic events such as data from environment sensors [4, 16].

When exploring the types of queries for temporal-geospatial data sets, Bertin, et al. [17] noted there are as many questions as there are components in a data set, which can be grouped into levels based on referring to a single element, a group or the whole. Peuquet [18] identified three components of data: space (where), time (when) and objects (what).

Although solutions such as STC exist, 2D map visualizations have been the primary method of visualizing an object's trace across a map [3], with four types of 2D maps identified [16]. As such, researchers have continued to investigate appropriate ways to integrate time into these visualizations [19], and evaluate their effectiveness [20].

Aigner, et al. [21] provided a survey of current approaches for visualizing time-orientated data, breaking them down into different categories of approaches, looking at time, data, and representation as criteria. Noting that there is no single 'best' representation for data, different views are dedicated to different types of analysis. In particular, multiple views can be useful for analyzing time-orientated data. Graphics generated are not static, but are continuously reconstructed until the underlying relationships between the data becomes apparent [17].

The inclusion of a third dimension of time for a corresponding latitude and longitude led to the STC [6] and subsequent implementations [22, 23]. This approach utilizes the third dimension above the map (Z Axis) to represent time for the data points. This has also been extended show individual events [24] (a third level question as defined by [16]), as well as the ability to extract 'stories' based on abstractions of the data [25].

Amini, et al. [3] focused on comparing and contrasting the approaches for visualizing movement data in 2D and 3D. They developed and evaluated their own space-time visualizer as an experimental testbed based on the STC concept. Amini et al. also presented a taxonomy for classifying questions about movement-based data sets (building on previous work [17, 18]). They classified questions based on the known or unknown value, and singular or plural references for times, objects of interest, and spatial positioning.

A similar study to our investigation (Kristensson et al. [26]) compared the STC against a baseline 2D representation, finding that for simple questions, error rates were lower for the 2D view, however for more complex questions that required an understanding of the overall structure of the data set, the STC was superior.

Andrienko and Andrienko [27] categorized the visualization of movement from a different perspective, instead of looking at the visualization itself, they examined what the user was interested in. By focusing on whether the user was examining trajectories, detecting movement characteristics, analyzing all movement, or the interactions between objects, they presented a survey of visual analytics approaches for movement data.

Utilizing a timeline representation, but augmented with a map, Thudt, et al. [28] showed small snippets of an object's idle location on a map, placed alongside each other. The size of the map fragment shown on the timeline is representative of the object's idle duration at that location. While this is effective in showing the movement of a single object as a function of time, it does not support the effective identification of interactions between objects shown on the map.

Crnovrsanin, et al. [4] presented line graphs for proxemic visualization (entity movement relative to a location). A similar concept was also presented by [29], however only visualized proximity to a "starting point", e.g. for animal migration. However, no formal evaluation was performed in either. Our work not only provides an evaluation validating of this approach, but also presents an extended version for the

reduction of error in data sets as well as pattern identification.. Another more recent approach combining both space and time, however focusing for groups of entities, was presented in [30]. While visualizing temporal data, van Wijk and Van Selow [31] utilized familiar metaphors and layouts from everyday calendars to layout data. This involved both using a 3D representation for data and time as the X and Y axes, and some custom data value as Z, as well as traditional calendar month views view with color coding.

Again in the case of visualizing only temporal data, Reinders, et al. [32] presented a method for tracking features, and associated events for those features, using a modified line-graph, showing time across the X-axis, with features such as birth, death, merging, and splitting showing through the line plot itself. While not spatial, it presented a novel approach for showing temporal events in an intuitive fashion.

2. Cooperative Visual Analysis

Our approach, Cooperative Visual Analysis, is designed to use complimentary views, separating the visualizations of data from an object's geospatial location, and multiple objects' location or colocations, see Fig. 1. We isolate the time dimension from the geospatial view that it traditionally omitted or displayed along another axis. We are particularly interested in queries relating to identifying multiple unknown objects, at multiple unknown points in time, at multiple unknown locations [3].

The first visualization we present is a modification of the traditional linear schedule view to support additional functions, known as the *Parallel Schedule View*. The second is an extension of [4] for proxemic visualization that we refer to as the *Braille Plot.* To support typical geospatial exploration, a standard map representation is also presented. To support the quick navigation through data sets, regardless of the temporal period being visualized, the visualizations support zooming to reduce/increase the scale and temporal density per-pixel. As such, selection and navigation of time is provided by means of an interactive time slider using the Braille Plot as an effective means of navigation [3]. This section concludes with an example use case describing the PSV and Braille Plot visualizations.

A. Parallel Schedule View

The PSV utilizes the schedule representation for a series events, as is familiar to users from calendar-focused applications, such as Microsoft Outlook. Two approaches are presented. One is object-focused (top-left panel in Fig. 1), with each column representing an object, and entries within each column representing each objects' idle location over time. The second representation is location-focused, with columns representing single and objects as entries in the columns moving between them as the objects move from one location to another.

In addition to the familiar appointment-entry view, we use the design parameter of parallel plot lines from Parallel Coordinate Plots (PCP) [33]. Each plot line links schedule objects and entries for the same location/object, allowing the user to easily view which other objects have visited that same location, either at the same time, or different. Hovering over an entry or plot line highlights the other plot lines for the same location, allowing the user to quickly identify the links between different objects. The width of the plot line linking the entries in each column (either becoming wider/thinner, or the same) can be an indicator of the relative duration of the column entries being linked (subject to skewed plot lines).

1) Advantages

Whilst not representing the spatial location of an object over time, the PSV is effective in communicating when distinct events are occurring (as a normal schedule does) and also the interaction between multiple collocated events over time. As such, the PSV represents idle periods for each object. Representing an object's movement between idle periods is relegated to the Braille Plot or map.

One of the benefits of the STC is in identifying stops and returns along the same path [34]. PSV has these benefits, as when combined with the normal 2D map representation, the user easily identifies traces and stops for an individual. The can also identify the locations where stops occurred, and relate them between multiple objects in the scenario, but without the interaction overhead required for 3D manipulation.

Being able to analyze the data we have is just as important as being able to realize its limitations and data we do not have. To address this, each column contains horizontal lines marking when a data point is present (visible in the top of the orange column in Fig. 1). Gaps without lines indicate gaps in the data set for that object.

1) Limitations

Three limitations of this approach are identified. The first is the lack of scaling beyond a limited set of objects (8-10 depending on screen dimensions and resolution). However, the focus of our work was on small teams/groups of objects (8-10 objects). The second limitation is the impact of cross-column plots, i.e. a plot line linking two non-neighboring columns. To counter the second limitation, the ordering of the columns is brute forced for minimal linking between non-neighboring columns. The third limitation is it relies on idle periods already having been detected (or detected using algorithms). Offset errors in the location data will make the automatic clustering of data points difficult. As such, the Braille Plot technique provides a useful mechanism for this, as discussed later. Future work could seek to automate this process.

B. Braille Plot

The Braille Plot extends Crnovrsanin et al.'s technique [4], and focuses on spreading temporal data over a linear view (using time as the unique dimension and overloading the location). While the PSV represents the collocation over time of multiple objects, the PSV relies on the data set already having been isolated into a series of discrete visits to each location. We would like to view the movements of an object relative to a given location (or two) or another object. The Braille Plot addresses these requirements. This section describes an extended one-point version of the Braille Plot (as described by [4]), and a new two-point version of the visualization.

1) One-Point Braille

The Braille Plot visualizes the proximity of each object from a given location (Fig. 3) or specified object (set by a right-click menu), and works as a component of an interactive system, as opposed to a static image as was the case in [4]. The X-axis represents time with the distance of an object from the selected location shown along the Y-axis, increasing bottom-to-top. Similar approaches have been used to show temporal distribution [35]. In cases where data is missing or the temporal resolution being visualized is greater than that supported by the data, the Braille interpolates between the last and next known locations of the object, showing this interpolated (i.e. estimated location) as a hollow marker on the plot, a new feature compared to [4].

When viewing the Braille relative to a location, if objects meet at that location, their plots will appear to intertwine on the bottom of plot (as both objects are 0m from that location). However, if they meet at a location other than the selected one, their markers will still intertwine, albeit further up the Y-axis based on the distance of the location (where convergence occurred) from the location of interest. If viewing the position of objects relative to the dynamic location of another object of interest, any colocation will be illustrated with markers entangling on the bottom of the plot.

The Braille provides two distinct advantages over viewing the same data set on a map not identified by [4]. Viewing data with large margins of error causes problems for interpreting that data, especially when combined with the fact that any repeated travel by objects over a given path will be hidden/obscured for the user. For example, Fig. 2 shows an object making five visits to two locations, however the five visits are indistinguishable within the two clusters.

Fig. 2. Showing trace data with 5km error for a single object over five visits to two locations.

However, viewing that same data in the Braille Plot (Fig. 3) easily identifies the five distinct stops at the two locations. This is the same problem the STC addresses, however as the Braille is in 2D it does not suffer the associated perspective issues the STC has in 3D or the increase 3D manipulation overhead. In addition, the day/night shading on the timeline assists in identifying when each visit occurred.

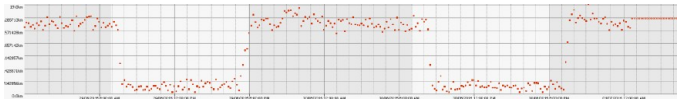

Fig. 3. Showing the five easily identifiable stops across two destinations for the same object as shown in Fig. 2., with distance from location of interest increasing up the Y-axis and time (including highlighted overnight periods) across X.

a) Limitations

As we are visualizing proximity alone, if multiple objects are equidistant from the Braille centroid, but not at the same location, their plots will intertwine, making it appear as if the objects met at that time, even when they did not. To address this, the user may employ the map to confirm colocation. Our implementation of the Braille Plot provides a world-in-miniature map above the mouse cursor on the Braille, showing the location of each object, preventing the user from having to adjust their primary map's field of view.

2) Two-Point Braille

The two-point Braille (Fig. 4), a new approach over [4], enables the user to visualize the movement of an object relative to two locations of interest, for example where an object might spend the majority of their day versus the majority of their night. The two locations are shown as the top and bottom of the plot. Ideally, users would travel *as a bird flies* in a direct path between two locations A and B, shown in Fig. 5 as $\overrightarrow{A\,B}$ Depending on the time spent at each location, this would generate a pattern with a similar appearance to a sine wave.

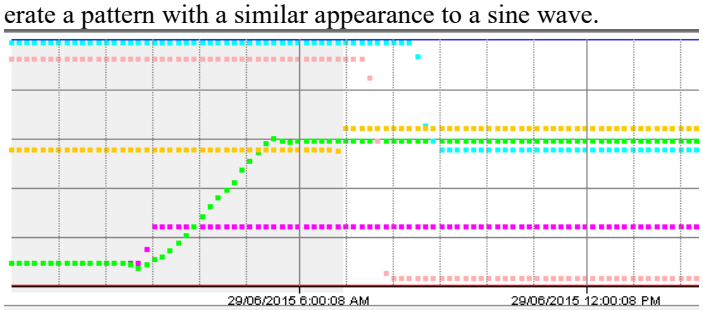

Fig. 4. Two-Point Braille Plot showing the distance of an object relative to two locations located as the bottom and top of the plot for a perfect data set (no error).

Outside of that ideal case, data points can be located 'inside' A and B (P1), or 'outside' A and B (P2). To map both of these cases to a single value to be charted on the braille, we measure and sum the length of each vector from the data point to each location (i.e. $\overrightarrow{A\,P1} + \overrightarrow{B\,P1}$) and divide by the length either vector (depending on which location is plotted on the top or bottom of the graph), giving a value 0 to 1 inclusive. For example, if we had A on the bottom on the Braille graph, we can calculate the position of any data point at time t with (1) as follows:

$$V_t = (\overrightarrow{A\,P1} + \overrightarrow{B\,P1}) \,/\, \overrightarrow{A\,P1} \qquad (1)$$

As the tracked object moves between the two locations, a pattern similar to a sine wave should occur given any regularity

in movements (e.g. work week movements). Any change from this pattern results in a 'splinter' off that wave, indicating a change in behavior from the object's normal routine.

In summary, the advantage of the Braille Plot is that it enables the user only to focus on an object relative to a location (or two) over time, rather than focus on the path the object over time.

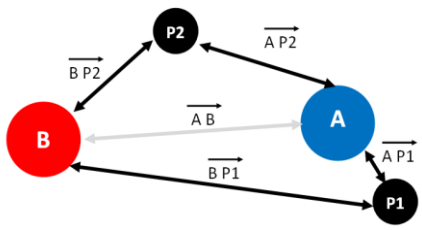

Fig. 5. Calculating the relative position of two data points (P1, P2) between two locations A and B.

C. Example Use

As previously mentioned, the PSV communicates convergence for idle periods, whereas the Braille is used for identifying not only those idle periods of possible convergence, but also the movements in between. Geolocation is performed using the traditional 2D map (showing the direction entities are moving based on their current and subsequent locations). Switching between object and location-centric PSV representations, and between one and two-point Braille views is via right click on the respective control. The remainder of this section describes a simple use case, and how the three views work in synergy to help the user.

Loaded data sets can have mixed levels of error. For low amounts of error, thresholds can be set to allow the system to identify idle periods within a trace based on low movement. When loading in data with significant amounts of error (which prevents the system from automatically identifying when each object was idle given certain thresholds), the user can manually identify and select periods of time where the object was idle in the Braille plot (as shown in Fig. 4) and average the object's location over the period (a right click operation), manually adjusting the location as required by hovering overing the data point on the map and right clicking on the desired/corrected location. Repeating this process for each idle period will populate the PSV with idle periods for each entity, and also create the associated entries and links between those entries for colocation, allowing the user to see which entities have visited the same location. Given the PSV, Braille and map view are coordinated, hovering over or selecting a period of time on either the PSV or Braille also selects/highlights the corresponding point on time on all three views (data points on the map change color). As the user hover over different periods of time on any control, markers on the map move around to represent each object's location at the selected point in time. Entities are represented by an arrow that points towards the location of the next data point.

We see the application of CVA to datasets where relative positioning is important, for example logistics where the position and idle time of delivery trucks relative to the base station. CVA can be applied to data sets similar to those presented in [4], including animal migration patterns and movement of people or vehicles.

3. User Study Evaluation

To assess the effectiveness of the PSV and Braille representations, we performed a user evaluation following [3]. The study compared a system with the PSV, Braille, and traditional 2D map view (referred hereafter as the Cooperative Visual Analysis system, or CVA), shown in Fig. 1, to a custom implementation of the STC. Participants were presented with data sets and asked multiple-choice questions. Our hypotheses were as follows:

- H1: Participants answer questions with the CVA visualization in less time than the STC.
- H2: Participants answer questions with the CVA visualization in less attempts than the STC.
- H3: Participants prefer the CVA over the STC.

A. Participants

Twelve people participated in the study recruited through email or social networking. Participants were compensated $25.00.

B. Apparatus

The study used an Intel Core i7 5930K CPU with dual nVidia 980TI graphics cards running in SLI mode for a single 1920x1080 pixel display on a Dell P2415Q 24inch monitor.

C. Data Sets

Following [3], seven artificial data sets were generated for three objects over a 48-hour period (one set was used for training). Data sets were generated with up to 100m of off-set error.

D. Questions

Six questions were created of medium-to-high complexity (defined by [3]). Questions were designed to focus on the movement of objects relative to a location of interest, identifying periods where they were idle, and periods of colocation. [3] encoded each query as a combination of o – object, t – time, and x – location with two attributes: 1) u – unknown or k - known and 2) s – single or p plural, we assign a primitive number system, assigning values 0-3 for object, time, and location. Adding the value for each column gives us an approximate indicator of a question's complexity (0-9).

Seven variations of these six questions, referencing different objects, locations, or times, were then generated to create seven data sets (one used for training). In order to ask questions relating to locations on the map, a single 'location of interest' was defined as the center of the CBD as denoted by a blue marker on the map. The core questions and categorization of those questions were as follows:

Q1. Which object(s) have all been in the selected area at the same time? [o:u.p.; t:u.p.; x:k.s., complexity 6)

Q2. When did at least three objects met at any time or location? [o:u.p.; t:u.s.; x:u.p., complexity 7)

Q3. How many times has the red object been within 6km of the selected location? [o:k.s.; t:u.p.; x:k.s., complexity 3)
Q4. What is the closest the red and orange objects have ever been to each other? [o:k.p.; t:u.p.; x:u.p., complexity 8)
Q5. How many times has the blue object been idle for more than two hours? [o:k.s.; t:u.p.; x:u.p., complexity level 6)
Q6. Which object has been idle at any location for at least 4 hours? [o:u.s.; t:u.s.; x: u.p., complexity level 4)

E. Design

The independent variables (factors and levels) examined were as follows:

Factor	Levels
Visualization	Cooperative Visual Analysis (CVA), Space Time Cube (STC)
Question	1, 2, 3, 4, 5, 6

Dependent measures were total completion time and number of errors. The experiment was a $2\,(visualization) \times 6\,(question)$ repeated measures. All participants were tested on all levels. All conditions were presented in random order.

1) Data Collection

The data recorded for each task included the time in milliseconds to when they selected the correct answer. The total number of errors made were also recorded. Errors are defined as the number of attempts made, including the correct selection. The range of errors was 1-3 inclusive.

F. Procedure

Following the reading of the information sheet and consent approval, participants were seated in front of CVA. Reading from a script, the PSV and Braille were explained. Instructions on how to navigate the map control was also provided (panning, zooming, and scrolling), with a reference sheet provided. After the PSV and Braille visualizations were described, participants ran through a training data set, using variations of the same six questions previously described. For any question, participants could attempt it three times. If on the third attempt the answer was still incorrect, the participant was moved the next question. Training was then repeated for STC.

Following the STC training set, participants answered the sets of six questions, alternating between CVA, and the STC approach. The ordering of the visualizations, the data sets, questions and multiple choice answers were all randomized.

At the start of each question, all views in the respective system would be reset, and everything on the screen blocked except for the question to be answered by a single button. Upon clicking that button, the possible answers, along with the rest of the GUI and associated visualizations were displayed. Users were timed from when they clicked the button, negating any time required for reading the question. In total, there were two visualizations (CVA/STC) multiplied by three data sets per visualization (ignoring training) multiplied by six questions per set = 36 questions multiplied by 12 participants = 432 trials.

4. User Study Results

This section describes the results of the experiment. Unless otherwise stated, Analysis of Variance (ANOVA) models were used in order to determine significance. Mauchly's test was used to determine whether sphericity had been violated. Where sphericity had been violated, degrees of freedom were corrected using Greenhouse-Geisser estimates. A Bonferroni correction was employed for all post hoc analysis. Statistical significance is set at $\alpha = 0.05$. The positively skewed completion times were corrected via a square-root transformation resulting in distributions being close to normal. Completion time and error values greater than three standard deviations away from the mean were removed from the data. Uncompleted attempts (three incorrect selections) were removed from the data. In total, 29 out of the 432 (6.7%) data points were removed from the analysis. The empirical results relating to the mean total completion time and the number of errors are presented here.

A. Completion Time

The mean time taken to answer the questions correctly across all conditions was 42.34 seconds (SD 28.61). Analysis revealed a significant effect on visualization $F_{(1,11)} = 5.119$, $p < 0.05$ on mean completion time. The mean time taken to identify and select the correct answer using the CVA visualization was 35.69 seconds (SD 16.60) which performed significantly faster than the STC visualization, reporting a mean time of 48.99 seconds (SD 35.68). Question type was found to significantly affect completion time $F_{(2.518,27.701)} = 13.669$, $p < 0.05$. In addition, a significant interaction between visualization and question type $F_{(2.244,24.682)} = 4.168$, $p < 0.05$ was also found. Fig. 6 depicts the mean completion time for each question and visualization technique. Participants performed comparably when undertaking questions one, two and three; the difference between visualization styles was not significant.

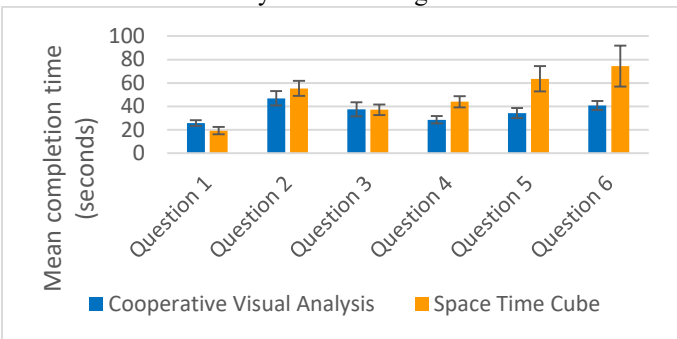

Fig. 6. Mean completion time for each question and visualization technique (including standard error bars).

When undertaking question four, on average, participants were significantly faster using the CVA visualization (M = 28.63, SE = 3.19) than when using STC (M = 44.05, SE = 4.81), t(11) = -2.523, p < 0.05, r = 0.61. Participants were significantly faster using the CVA visualization (M = 34.40, SE = 4.31) than when using STC (M = 63.62, SE = 10.84) when answering question five, t(11) = -2.412, p < 0.05, r = 0.59. For question six, participants were noticeably faster using CVA (M = 40.74, SE = 3.82) than when STC (M = 74.33, SE = 17.50). Interestingly, this difference was not significant t(11) = -2.157, p = 0.054; however, it does represent a large sized effect r = 0.55.

B. Number of Errors

Across all conditions, the mean total number of errors was 1.33 (SD 0.34). Visualization did not affect the measure of mean error rate ($F_{(1,11)} = 0.085$, $p > 0.05$). The number of errors made was comparable between the CVA (M = 1.32, SD = 0.31) and STC (M = 1.34, SD = 0.36). Question type significantly affected mean error rate $F_{(5,55)} = 5.429$, $p < 0.05$. An interaction between visualization and question type was not found ($F_{(5,55)} = 2.334$, $p > 0.05$). Fig. 7 depicts the number of errors made for each question using the different visualization techniques. Question five reports the largest disparity of errors (although not significant).

C. Participant Survey and Qualitative Results

Participants were required to complete an exit questionnaire where they were asked to rate the visualization technique on a five-point scale in terms of ease of use (scale of 1 being very easy to use and 5 being very hard). The mean rating across all questions for the CVA visualization was 1.75 (SD 0.86), while the STC was 3.44 (SD 1.10). Table 1 summarizes the median values, along with Wilcoxon Signed-Rank Test results.

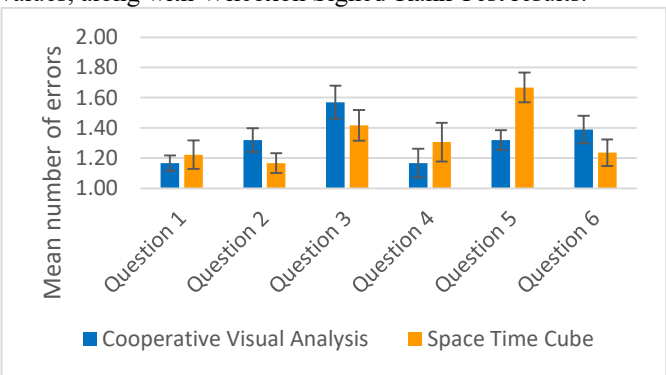

Fig. 7. Mean number of errors for each question and visualization technique (including standard error bars).

Table 1. Median ease of use values for each question and visualization technique; Wilcoxon Signed-Rank Test.

	CVA Ease of Use (Median)	**STC Ease of Use** (Median)	**Wilcoxon Signed-Rank Test**
Q1	1.5	2.5	z=-1.542, p>0.05, r=-0.31
Q2	2	3	z=-1.930, p=0.054, r=-0.39
Q3	1	4	z=-2.262, p<0.05, r=-0.46
Q4	1	4	z=-2.853, p<0.05, r=-0.58
Q5	2	4	z=-2.976, p<0.05, r=-0.61
Q6	2	3.5	z=-2.836, p<0.05, r=-0.59

Participants found visualization techniques for questions one and two comparable for ease of use. CVA outperformed STC in questions three, four, five and six with participants reporting that the CVA was easier to use than STC.

Participants were asked which visualization they preferred for each question (Fig. 8), with CVA being the preferred method.

Participants were also asked which visualization technique was preferred overall; 11 of 12 preferred CVA.

Participants found the Braille useful for measuring relative distances. They also found the alternative views useful, noting the appeal of the 2D presentation of information.

1) Written Comments

It was noted that by using the PSV and Braille's strong points, they gained a simpler expression of the same information, reducing map use. The use of an actual timeline to represent movements was reported by multiple participants as being the preferred method for representing temporal data.

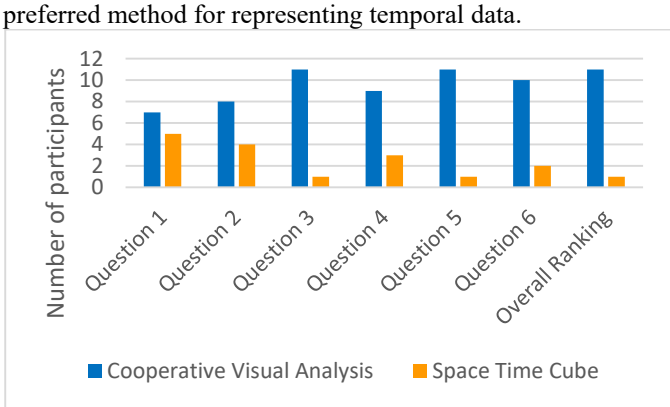

Fig. 8. Visualization style preferred for each question.

D. Discussion

The evaluation of any visualization will be heavily influenced by the focus of the questions used to evaluate it [3]. As such, the questions we selected were designed to evaluate the effectiveness of representing colocation, divergence, and idle periods of time, and higher complexity questions compared to previous evaluations of the STC. Given the STC approach has been shown to be superior in previous studies, there is no reason why the PSV, Braille, and STC cannot be used in conjunction with each other, leveraging the advantages of each. The 2D digital map in CVA could be replaced with the STC, as suggested by [3] and [26].

Significant results were found for questions four and five, with participants performing faster using CVA (H1). CVA performed faster in question six (although not significant). Whilst significant results were found for two questions, participants did prefer CVA, specifically for questions three, four, five and six (H3). In addition, participants overwhelmingly preferred the CVA overall for selecting a single system to use (H3). The analysis showed no significant difference between the two visualizations in error rate (H2).

In our use case where the domain of questions focuses on the interactions between objects, rather than the attributes of individual objects, we have shown that our representations are superior for specific types of question and preferred by users.

5. Conclusion

In this paper we presented two novel visualizations, the Parallel Schedule View and the Braille Plot as two approaches that work in synergy for visualizing temporal-geospatial relationships within and between objects in a data set. The PSV is

used to identify periods where objects are idle and visualize any colocation amongst those idle periods. Similarly, the one-point Braille Plot is used to visualize idle periods and proximity, as well as to reduce the impact of a large amount of error within the data set and supporting the identification of multiple visits to the same location. The two-point Braille can also be used to identify movements between two locations of interest, and divergence from that pattern.

As previously mentioned, future work might include incorporating the STC into the combined system to leverage the best benefits of each view, possibly being able to switch between the traditional 2D map representation when viewing from above, and then transitioning to a 3D representation when the user views the data set on the map from the side.

Whilst proxemic visualization has been previously presented, we extended it with new functionality, and presented the first formal evaluation. In addition, we presented the PSV as a complimentary tool. Following the results of the user study, it is clear that both the PSV and Braille Plots provide an effective approach for visualizing temporal-geospatial relationships within and between objects in a data set, performing at or above the STC, whilst being preferred by users to existing approaches.

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