GeoGate: Correlating Geo-Temporal Datasets Using an Augmented Reality Space-Time Cube and Tangible Interactions

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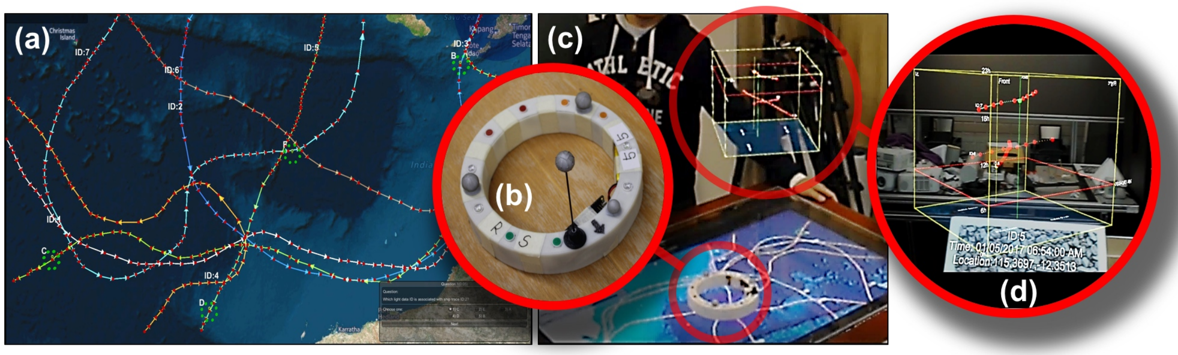

Figure 1: The GeoGate system supports visualization of complex trace datasets for verification and accuracy resolution. (a) Presents a traditional 2D desktop maritime visualization with multiple traces, (b) the ring-shaped tangible user interface, (c) the GeoGate system combining tangible interaction and Augmented Reality visualization, and (d) the user's view of the space-time cube.

Abstract

This paper introduces GeoGate, an Augmented Reality tabletop system that extends the Space-Time Cube and utilizes a ring-shaped tangible user interface to explore correlations between entities in multiple location datasets. We demonstrate GeoGate in the context of the maritime domain, where operators seek to find geo-temporal associations between trajectories recorded from a global positioning system, and light data extracted from night time satellite images. GeoGate utilizes a tabletop system displaying a traditional 2D map in conjunction with a Microsoft Hololens to present a single view of the data with a novel Augmented Reality extension of the Space-Time Cube. To validate GeoGate, we present the results of a user study comparing GeoGate with the existing 2D approach used in a normal desktop environment. The outcomes of the user study show that GeoGate's approach reduces mistakes in the interpretation of the correlations between various datasets, while the qualitative results show that such a system is preferable for the majority of geo-temporal maritime tasks compared.

Keywords: Augmented Reality, Space Time Cube, Multivariate Network Visualization, Multiple Data-sets, Maritime Visualization, Geo-visualization, Tangible User Interface, Tabletop.

Index Terms: H.1.2 [Information Systems]: User/Machine Systems—Human factors I.3.6 [Computer Graphics]: Methodology and Techniques—Interaction techniques

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1 Introduction

Maritime, amongst other organizations, utilize multiple spatial datasets to develop situational awareness of moving entities, whether for operation or surveillance needs. These three dimensional datasets (latitude, longitude, and time [31]) lead to the use of visualization techniques to better understand the data and the correlations between data sources [16]. However, the density of the data that emerges from using multiple datasets leads to greater complexity [36]. Further, this high complexity increases the difficulty in interpreting and understanding the information when using traditional visualizations on common desktop systems. The issue remains of how to effectively correlate multiple data sources for verification and accuracy resolution, as opposed to just supplementing one dataset with another.

Our work with a national geospatial agency focused around the verification of self-reported shipping location data generated by the beacon-based Automatic Identification System (AIS). Such data is provided to the public from a variety of sources (e.g. MarineTraffic [1]), however this data may be counterfeited for illicit purposes such as smuggling. While this data is public, it cannot be implicitly trusted given the self-reporting nature. The National Oceanic and Atmospheric Administration [2] provides satellite data showing night time light emissions from ships around the world. Using these two datasets, the self-reported AIS data can be validated by correlating it with the NOAA light data. This allows users to obtain more accurate trace/trajectory information of vessels (subject to variation between NOAA light snapshots). By comparing the datasets, we can highlight the anomalies that warrant further investigation or interception.

Although 2D geotemporal visualizations that use common trajectory representations are still regularly employed, the complexity of the information has increased, leading to additional uncertainty when correlating the various datasets [35]. Researchers studying geotemporal visualization have sought to understand the natural coexistence of space and time and how it can be visualized to reduce

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uncertainty [6, 7]. The Space-Time Cube (STC) is one such approach, using 3D to directly represent both 2D space and time [27]. Such techniques can illicit deeper insight into trajectory based data. However, many of these works depend on 3D projections onto 2D displays, which introduce occlusion, depth perception and spatial understanding issues. This paper explores extensions to the concept of STC as a new approach to overcome these limitations.

Given that Augmented Reality (AR) has been shown to overcome the occlusion and depth perception issues that projecting 3D on standard monitors incur [33], AR displays such as the Microsoft Hololens are a natural choice for visualizing STCs. Although current AR technologies suffer from a limited field-of-view and require visual guidance systems for virtual objects out of view [12], they do provide a novel platform for presenting spatial information and can be applied to extend the STC representation. Further, even with 3D display technology such as AR, the STC still requires techniques to filter large overlapping datasets in order to reduce complexity.

GeoGate focused on addressing the question of *how can we reduce the complexity of multiple datasets in geotemporal visualization and the resulting uncertainty present in 2D visualization?* As such, we present one approach for correlating multiple data points for geotemporal visualization. GeoGate uses AR to present an extended STC suited to verification and accuracy resolution using multiple datasets. We employ a ring-shaped tabletop Tangible User Interface (TUI) to support user interaction, facilitating spatial exploration and induces a natural collaborative environment to support discussion [47]. The ring-shaped TUI is used as a direct interface for the AR content, allowing users to control the AR content without having to change their focus, whilst allowing other users to manipulate the system at the same time as a discussion environment. We enhance the tabletop display with contextual AR information, that goes beyond the typical 3D functionality [14, 15].

The contributions of this paper are:

- Extending the STC with AR to addresses the complexity of correlating multiple datasets,
- a five-view enhancement of the STC which shows the multiple views of the STC simultaneously in "wings" around the STC,
- a novel TUI that enables continuity and interaction between STC and tabletop data whilst acting as a physical filter for data selection, and
- an integrated tabletop system linking the above features.

The following section introduces previous work related to this study, followed by a detailed description of GeoGate. The remaining sections present an evaluation of GeoGate's functionality through a user study focused on finding correlations between two datasets, whilst reducing complexity and uncertainty. We then present a discussion of the study outcomes and final section provides concluding remarks and future directions for research.

2 Related Work

In this section we review previous research, primarily from the maritime domain, on using multiple geotemporal datasets, and review techniques for representing and exploring geotemporal data.

2.1 Multiple Datasets

In examining vessel movement data for national security, Kazemi, et al. provided a framework for creating the *Open Data Anomaly Detection System (ODADS)* for detecting abnormal events in the perspective of maritime security for example smuggling activities [29], albeit from a data-analysis perspective. Similar in goal, but differing in approach, Rhodes, et al. and Bomberger, et al. studied the maritime domain awareness to detect abnormal ship activity using a *fuzzy ARTMAP neural network classifier* [11, 39]. In a more primitive fashion, Willems, et al. and Scheepens, et al. used sea lanes and anchor zones from historical trajectory data, and expressed the density fields in height map format [9, 40, 41, 50]. Such analysis is not limited to paths, but also the types of vessels [19]. As a study of similar patterns in movement datasets, Bak et al. [9] proposed a method for the scalability of geotemporal encounters using real-world datasets from urban public transportation. Whilst prior work has looked at examining multiple data sets for detecting abnormal actions, they rely on a certain element of repeated action, which is not always the case for vessels, especially in the non-commercial domain.

2.2 Geotemporal Visualization

Existing maritime AIS visualization is commonly expressed in 2D, as overcoming the 3D drawbacks (e.g. occlusion and extra animations like rotation, zoom in and out [26]) is challenging, however the choice of 2D vs 3D is not mutually exclusive. Hybrid 2D/3D visualizations have been demonstrated that express space, time, and attributes of trajectory data [46] and spatial-temporal narratives [18]. When considering uncertainty, human in the loop uncertainty resolution has been explored for passive sonar trajactories [17]. As a space-time cube specialized in maritime surveillance, Delmar and Virrantaus presented an algorithm for representing the space-time density of trajectories using a space-time cube (aquarium) and the 3D kernel density [20]. They described the two directions of maritime research as: (1) a situation-oriented space-centric approach using direction and speed, and (2) a trajectory-oriented space-centric approach using position and time. Our work focuses on the latter.

While Shneiderman's mantra [42] provides the initial motivation for focus-plus-context visualization, the visualization of big data is now an issue. Previous works [21–23] have presented a visualization called "Sampling Lens" for the visualization of high density multivariate data. Using a technique similar to filtering, the works examined identifying the correlations between data sets. Tominski et al. [44] presented a visualization that extended wide area information *(Fisheye Tree Views)* into a ring-shaped focus (lenses) from the original focus plus context theory [45]. Kruger et al. [30] demonstrated *TrajectoryLenses* to show the filtering of trajectories within a defined circle as the area of interest. GeoGate also uses the same method, filtering the trace information and light data rendered on a map to those within a selected circle, and transmits that data to the *HoloLens* to render in STC represented by AR.

In using the STC, Andrienko et al. [4, 5] introduced various spatial and temporal positions and movement directions methods to express movement events (m-events) on geographic maps. In order to pre-filter such data, Enguehard et al. [24, 25] proposed a hybrid geotemporal filtering system and behavioral change point analysis system, which is compared with the conventional vessel monitoring systems for the visualization of fish trap management. In looking at the visualization of collocation amongst entities, Walsh et al. [49] represented the parallel schedule view and the "braille" scatterplot in 2D along with an optional STC. They used the braille plot in 2D to show the distance of an object relative to two locations of interest (e.g. work and home), since extended with tangibles [48].

2.3 AR-based Tabletops and TUIs

As new AR, Tabletop and TUI hardware devices are becoming available we are seeing new interfaces emerge to leverage their new capabilities. In designing GeoGate, we investigated the use of tangible interactions as a means of enabling natural interaction that supported use in control room environments, e.g. being collaborative, tabletop-based, and accessible for novice.

Of particular interest was Bach et al. [8], who performed a study comparing the benefits of AR visualization using head-mounted displays (HMD), tablets, and traditional desktop displays. The results showed promise for both HMD and tablet, however both are subject to their own issues. Participants disliked the mismatch between interaction and perception when using tablet-based AR, an issue the HMD resolves. Whilst the HMD was not best for manipulation, it did aid comprehension, however the Bach et al. believe training would improve users' manipulation capabilities.

Whilst previous works have examined the use of 3D space for exploring 3D data with a tablet/phone [10, 13, 32], we sought to utilize a tangible input. Terrenghi et al. [43] compared physical and digital interaction on interactive surfaces, noting that physical metaphors encourage manipulation, in our case, encouraging the physical exploration of the space by moving the GeoGate TUI to select different regions. This is supported by Raynal et al. [38], who demonstrated that tangible interaction is better for more difficult exploration tasks. However, tangibles can make selection of specific points difficult.

Nilsson et al. [34] worked across police and military domains in crisis management by using tabletop system, a geographical map, and AR. They evaluated a multi-user AR application in which professionals working in different fields can work in the same place with the same goal of helping people in emergency situations. Given the such environments predisposition for collaboration, Ulbricht et al. [47] implemented tangible AR (TAR) on a tabletop, combining TUI and AR using ARToolKit markers as part of a gaming system.

Izadi, et al. [28] introduced a new type of interactive tabletop technology based on a switchable projection screen, which can be made diffuse/transparent under electronic manipulation devices with an easy to understand the internal configuration of objects. GeoGate extended their *"beyond the display"* idea and focused on information visualization extending from the ring-shaped TUI (See Fig. 1).

3 GEOGATE

The creation of GeoGate was motivated by two questions. The first fundamental question was: how can we reduce the complexity of visualizing multiple geotemporal datasets and reduce the uncertainty that traditional 2D projection introduces? The second question was: which tools are appropriate to support these visualizations? These questions were identified through early workshops with industry experts in the maritime domain, who presented this scenario as an active research problem, inspiring GeoGate's development. The first data set they use is self-reported AIS trajectory generated by the vessel's positioning system, and includes other information (e.g. bearing, velocity) and the meta-data associated with it (e.g. ID, timestamp). GeoGate combines this trajectory information with NOAA satellite image data showing the location of vessels based on the light points they emit at the time image was captured. This data is presented using: 1) an AR implementation STC, enhanced with "wings" showing alternative viewports, 2) a ring-shaped tangible for direct and natural interaction, and 3) a tabletop display showing a traditional map view used for exploration. In the remainder of this section, we discuss each of these aspects respectively.

3.1 Enhanced Augmented Reality Space Time Cube

We provide an enhanced STC using the Microsoft HoloLens, in conjunction with a tabletop system (Fig. 1). The STC displays the trajectory data in 3D space. Using the vertical axis, latitude and longitude can be represented over time, such that early measurements appear at the bottom of the cube while later measurements rise in the cube (or the opposite). By utilizing AR, we are able to represent the STC in the context of a digital tabletop map while also avoiding the typical limitations of 3D rendering (e.g. occlusion), as such technology has been shown to overcome some of the limitations of 3D on standard monitors [8].

On the tabletop display, the trajectory data is presented by a group of nodes and edges, where a red circle represents each node, and colored arrows represent each edge. The light data is presented by individual green spherical nodes for the individual time and position values. A HoloLens worn by the user shows the same trajectory and light data as a virtual STC hovering over the tabletop (see Fig. 2).

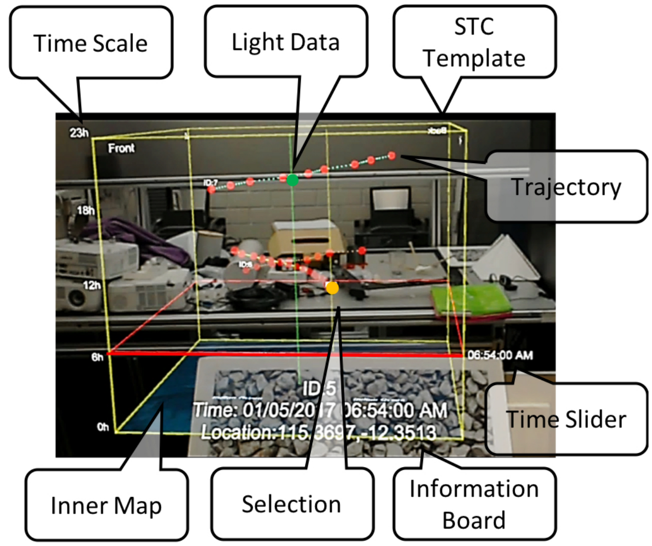

Figure 2: The Configuration of AR STC in GeoGate.

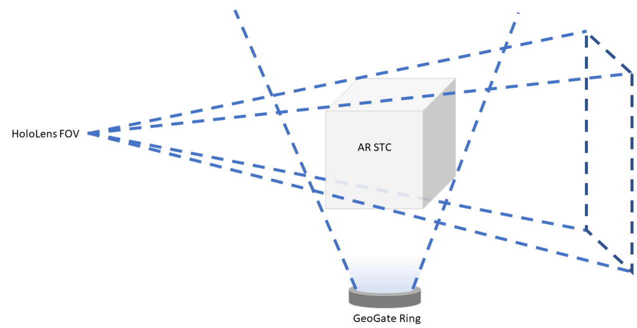

Figure 3: The size of the STC was designed to fit within both the field of view of the Hololens, whilst also appearing to be extending out from the GeoGate's selection area.

The position and functions (e.g. rotating and zooming) of the STC are manipulated using the ring-shaped TUI (see Fig. 4). The selected field of view can be manually adjusted with a zoom interaction, using two buttons on the top of the ring. In addition to the STC trajectories and light points, the AR view consists of a time scale, an AR version of the map, and metadata about the currently selected data point (see Fig. 2). The edges of the STC are rendered as yellow lines, with the colors of the trajectories and points the same colors as the information in the tabletop. As time progresses (from bottom to top), the direction of trajectories naturally moves up.

The size of the STC has been designed to take into consideration the horizontal and vertical field of view of the HoloLens viewport and assumes arms-length interaction (see Fig. 3). The STC renders regions within the TUI circle, and is scaled to a larger visual size. The STC represents 24 hours of data by default.

Given the field of view of the Hololens, the TUI allows the user to select a region of interest on the map by placing the GeoGate around that location. This limit naturally reduces the user's expectation of a wider field of view, given the implicit link between the size of the tangible and the graphics rendered to the user. The shape/size of the the input device naturally limits the expected size/shape of the output representation.

In Fig. 2, the light data is shown as a green sphere, trajectory

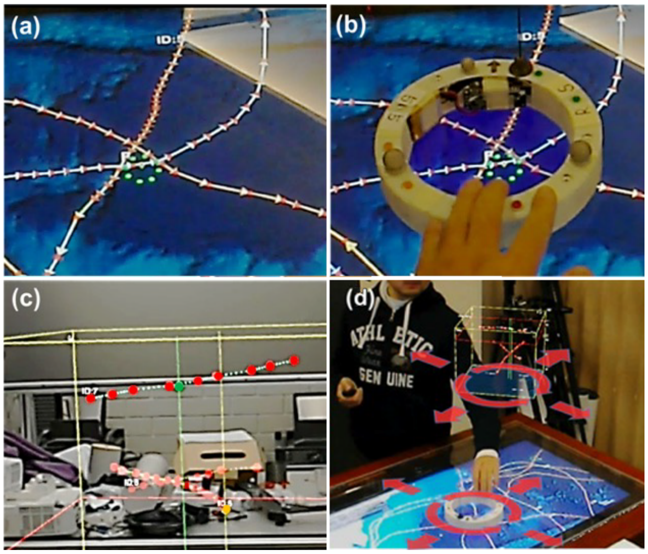

Figure 4: GeoGate visualization strategy: (a) 2D parts of maps that have difficult to interpret data set associations, (b) TUI focuses on difficult areas, (c) STC supports time and space in different dimensions to separate the data, and (d) user navigates the space using the TUI.

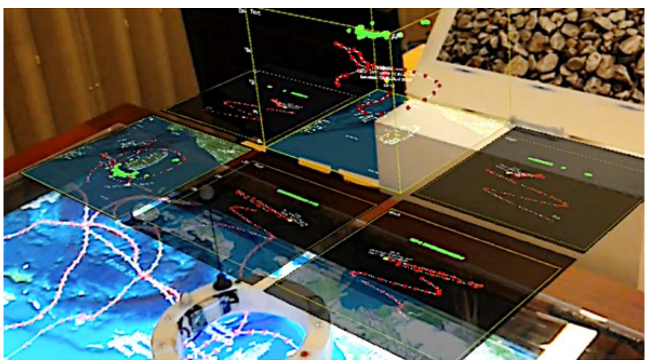

Figure 5: The STC with wings unfolded. Each view represents a side of the STC oriented toward the user. Counter clockwise, the views are left, top, front, back, and right.

information as red spheres, and the selected trajectory data point is shown as a yellow sphere. The information board shows details of the nodes of the selected trajectory, vessel ID, latitude and longitude, and timestamp. When choosing a node on a ships trajectory (described later), a horizontal red line appears around the outside faces of the STC cube, lining up alongside the time slider labels, showing the associated time information of the node.

The small colored spheres on the trajectory show the exact 3D location (latitude, longitude, and time) of the data points, with edges drawn between them. The distance between nodes indicates the movement speed of vessels. Luminosity is used to represent the distance between the light data points (i.e. the green sphere) and the trajectory data points. A bright red color represents trajectory points close to the light data, while dark tones represent trajectory points far from the light data. If the trajectory does not have light data, it is rendered in black.

3.1.1 Space Time Cube Wings

Given the view-management overheads that can be associated with 3D visualization, we found ourselves often needing rapidly rotate the TUI to view the STC from different sides when examining the data. To reduce this view management, we added a mode to extend the STC with five *wings*, showing the view of each side (left, right, front, back and top) of the STC cube presented in a grid layout around the STC itself (see Fig. 5). Each view is oriented towards the user. This allows the user to "view" the STC from all sides simultaneously, without physically moving their bodies. Each view presents the view the user would see if viewing the STC from that side. This extension of the STC is enabled by the extra physical space afforded by AR. Without the wings, the STC is presented above the tangible ring, as a direct extrapolation of the selected area on the table. Given the size of the wings, they necessitate that the STC be locked in place above the middle of the tabletop, ensuring adequate visibility. However, this aspect does allow the user's view to remain fixed on a single location as they move the TUI to explore.

3.2 Tangible Ring Controller

GeoGate uses a ring-shaped tangible as a physical bridge (i.e. a *Gate*) to connect the tabletop and hologram. We use the natural affordances of tangible to provide users with a direct method for manipulating focus-plus-context, whilst also allowing the user to rotate the STC view, and perform unary options using physical buttons on the top of the ring. For our implementation, only two buttons were used to zoom the map. The 2D tabletop map provides *context* and the HoloLens view provides *focus* for detail information at a particular location on the map [37]. A visual association between the TUI and map is reinforced with the ring casting a *digital shadow* onto the tabletop. This allows the user to pick the ring up, and still see the outline of it on the tabletop display.

Despite the "real world" presence associated with AR content, AR can limit the user in how they can interact with the data. For example, the HoloLens falls back to simple click+drag operations using pinching. From our experience, such operations are not without significant overhead on the user, especially given imperfect hand tracking. One of the core benefits of the tangible is its affordance for direct manipulation; the user can remain focused on the AR content of the STC while moving the tangible controller to update the AR view (Fig. 4, d). By leveraging the direct and natural affordances of the input device, we lower the input overhead, whilst creating a direct link between input and output.

The tangible controller and interactions went through several revisions. We explored the different uses of the controller, such as using the rotation of the controller for navigating the selected time, as well as using it to control the zoom of the selected area. These initial functions motivated the ring shaped design, as it supports continuous rotation with no inherent "direction". In practice, we found such an interaction was slower to perform than anticipated. Prior to the development of the wings, we also found through testing that users needed to be able to orient the STC independent of their viewpoint in order to view the trajectories from different angles, necessitating this as the rotation function. While a square tangible would align better with the STC, the ring design remains a hold-over from these early design iterations.

3.3 Tabletop Display

The tabletop display renders satellite imagery of the region and a traditional 2D view of the trajectory data that experts would be immediately familiar with. GeoGate employs a tabletop display to support extraction, understanding, and collaborative learning [33]. Furthermore, large tabletops are already well utilized in the maritime domain to arrange maps and plot trajectories. This familiarity, coupled with the physical size afforded by a tabletop display, makes the tabletop visualization an ideal method for providing a situational overview of the data. In addition, the use of the TUI necessitates a physical surface not just to rest it on, but given we use the TUI for selecting regions of interest, the relative positioning of the STC

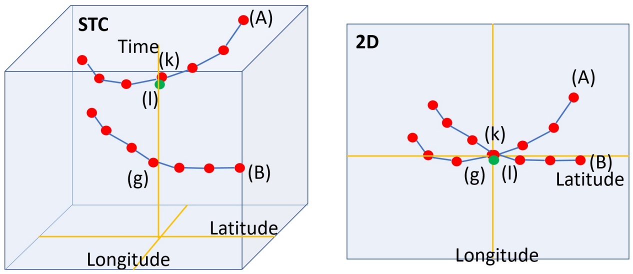

Figure 6: Two tracks of AIS data with a single light point. The light point appears to be associated with both tracks (the tracks cross near the light point) on the 2D display, but only one track has the same time as the light point. STC view is shown as left and 2D view right.

with the digital display to which it relates becomes crucial, with a tabletop being a straightforward approach to supporting such an interaction.

4 Example Use Case

To explore GeoGate in more detail, we present a potential use case demonstrating the system. Fig. 6 shows a moderately complex scenario with two crossing trajectories but a single light data point. The nodes (k), (g) and (l) in 2D look like they are correlated with each other. However, the 3D view indicates that (l) and (k) are related to each other, and (g) is data from an earlier point in time. In exploring this data, the user would move the TUI over the trajectory intersection (e.g. **??**b), displaying that data in the STC view. The user continues to move the TUI to follow the trace, but does so whilst fixated on the STC. The limited selection area of the GeoGate TUI, defined as the area within the ring, means its physical size serves as a filter for what data to explore in AR. Given the size of the STC was defined by the field of view of the HoloLens, and the size of the TUI selection area, the user can ensure that whatever area has been selected using the TUI will easily be visible using the headset. This shows one of the advantages of using something like the STC and TUI with the HoloLens, as we can leverage the limitations of each Fig. 3. Depending on the user's perspective, the light data point (l) may still appear to intersect the top-most point of the (B) trajectory. By looking outside of the STC onto the wings (e.g. Fig. 5), the user can quickly identify that *from all angles* l is actually associated with (A), negating any impact of the 3D projection.

5 Architecture and Technical Implementation

GeoGate's tabletop is a $116 \times 84 \times 97$ cm table with an inlaid 42 inch 1920×1080 display. A fiducial marker is positioned behind the tabletop to calibrate the tabletop to the HoloLens using Vuforia. Natural Point OptiTrack cameras are mounted around the tabletop in an external frame to track the tangible controller. Inside the tangible controller, we used an Adafruit WICED WiFi Feather (STM32F205 with Cypress WICED WiFi shield) to connect to the buttons on the TUI to the rest of the system. This was powered by a 3.7v 500mAh lithium ion polymer battery. All the buttons were connected to the Feather board and transfer messages over WiFi.

The PC driving GeoGate's tabletop acts as the server, with the HoloLens and TUI controller connecting as clients. All trajectories and light data are sent from the server over UDP (given we care about the most recent action, dropped packets are ignored). The data transmitted from the server includes trajectory data, light data, STC position and rotation values (obtained from the OptiTrack), and TUI button events. Whilst only one Hololens was used for development, the system actually supports multiple HoloLens devices, and theoretically, multiple GeoGate tangibles as well, opening up possibilities for shared experiences collaboration.

Figure 7: Showing the physical devices (a), 2D desktop condition (b), pointer (c), and response keypad (d).

6 Evaluation

We conducted a study comparing GeoGate with the existing 2D desktop approach used in traditional vessel movement visualization with standard inputs (mouse and keyboard with traditional monitor). Whilst the 2D condition could have been run on the same tabletop display, keyboard and mouse inputs are not ideally designed for such a configuration. As such, we used the desktop setup in the 2D condition to avoid biasing the task. We did not incorporate a tablet based AR condition, given that users experience a "mismatch between interaction and perception" for such a setup [8].

The hypotheses for the study were as follows:

H1: **Speed** — GeoGate will be as fast or faster for understanding the geotemporal movements of multiple objects compared to a traditional 2D Desktop system.

H2: **Accuracy** — GeoGate increases accuracy when correlating geotemporal movements of multiple objects compared to a traditional 2D Desktop system.

We required multiple datasets consisting of various situations and complexities. Two different types of data were created: trajectories for vessel movements (red spheres and edges) and light data (green sphere in STC, green pin in 2D). Our evaluation used four maps over three geographical regions. Map A was used for training before starting the actual task. Map A consisted of three trajectories and two pieces of light data. Maps B, C, and D consisted of seven trajectories and six pieces of light data.

6.1 Apparatus

We used a 23 inch in monitor display with a resolution of 1920×1080 for the 2D condition (Desktop) (Fig. 7). Both the GeoGate and 2D Desktop condition used the same computer: an Intel Core i7 59030K CPU and a NVidia 980TI graphics card.

The GeoGate system used a Logitech R400 Laser Pointer, for selecting individual points on a trace), and a Targus numeric keypad for responding to multiple choice questions. The laser pointer buttons previous (left) and next (right) were employed in the study to navigate the selected data point on a trajectory. The selection of such an input device may appear counter intuitive, however it allows users to navigate the dataset without having to maintain their arms on the tabletop, allowing them to stand naturally while still exploring individual data points. The TUI buttons on the device were not used outside of zoom, as following initial trials they were found to be awkward to use given the ambiguous orientation of the ring itself, and thus the ambiguous role of the buttons that prevents the user from clicking a button without first shifting their focus to the button. We hope to find an improved method in future work.

6.2 Task and Questions

We followed Amini et al. [3] in considering the time and accuracy of task completion using multiple choice questions on data sets of varying defined difficulties. We created five questions as either easy, medium, and hard difficulty based on the number of trajectory and light data points (see Table 1). The difficulty of the association between data types was classified based on whether one trajectory was associated with one location of the satellite light data, whether there were no light data, or whether there was several trajectories associated with one location of light data. Questions were generated to interpret the trajectories/light data used in the task, based on searching the ID, longitude, and/or latitude on the screen (see Table 2). Participants answered the questions as multiple choice, with a maximum of three incorrect attempts before being moved to the next question. Participants entered the questions via the keypad.

The task given to all participants was to answer the questions displayed on the bottom right of the screen as accurately and as quickly as possible. The multiple choice questions were shown in the question box at the lower right of the respective display, one at a time. Participants explored the geographic maps to find the answer to the questions. In the Desktop condition, this information is obtained from the mouse tooltip. In GeoGate, the information is gained by using 2D maps that are browsed with the tabletop and the control of the holographic STC and TUI.

6.3 Experimental Design & Measures

The experiment was designed as a full factorial within-participants study, with participants completing repeated trials that covered all system conditions and questions. Each question was repeated three times using three different maps. The experimental design was 2 (systems) $\times$ 5 (questions) $\times$ 3 (maps). The ordering of the visualizations, maps, questions, and option answers were counter-balanced.

We recorded three dependent variables from the trials:

- *Task Completion Time*: the total seconds it took to complete the trial.
- *Trial Attempt Error*: the number of attempts made to complete the trial (successful or otherwise). Participants were allowed three attempts before being moved to the next question. As a result, the minimum value was 1 and the maximum value was 4 (representing that they never answered correctly).
- *Task Failure*: whether the question was answered correctly within the maximum of three attempts.

For observational purposes, we recorded a measure of *activity*, as well as survey results for ease of use and system preferences after each condition. Activity was measured as the ratio of time spent moving (either the tangible or the mouse depending on the condition) to idle time, captured at an accuracy of 0.5 seconds.

Table 1: Attributes that define the difficulty of task questions

		Easy	Medium	Hard
Association	**Trajectory Data**	Single	Single	Multiple
	Light Data	Single	Single or Nothing	Single

Table 2: The five question types and related difficulties.

No	Purpose	Example	Difficulty
1	Find a trace ID	Which ship's trace ID is associated with light data ID: C?	Easy
2	Find a trace ID from a specific location	Which ship's trace ID is associated with light data location: 104.26112991, -16.87405205?	Medium
3	Find a trace ID without light data	Which ship's trace ID does not have light data at all?	Medium
4	Find a closest one among multiple trajectories	Which ship's trace ID is closest with light data ID: F?	Hard
5	Find light data	Which light data ID is associated with ship trace ID: 1?	Easy

6.4 Procedure

The study consisted of four phases: (1) introduction, (2) training, (3) main task, (4) exit survey and debrief, lasting $\tilde{4}$5–60 minutes/participant. During the introduction in Phase 1, participants read the information sheet and gave consent. Participants were then seated at a desk. Reading from a script, the experimenter explained the tasks and systems, with a reference sheet given to participants to explain the details of the information on the maps. Next, the additional components of GeoGate (keypad, remote controller, and HoloLens) were explained. In Phase 2, participants ran through a training map (map A) for both conditions. Participants the performed the trials in Phase 3, alternating between conditions. After each block of trials, the participant was provided an ease of use and preference survey. At the end of all the trials (Phase 4), participants completed an exit survey to provide additional comments and observations.

6.5 Participants

Twenty four participants (21 male, 3 female) were recruited from the PhD student body of the university or via social networks (21 from within the School of Information Technology and Mathematical Sciences). Participants were between 21 and 63 years of age ($M = 32.9, SD = 9.02$). No participants had previous experience with geotemporal information visualizations. Two participants were left handed and 22 were right handed. For 3D gaming experience, 17 participants reported being familiar with 3D gaming environments.

7 Results

This section describes the results of study. Analysis of task completion time, attempts and failures are presented, followed by observations on interaction and qualitative feedback. We used an alpha value of 0.05 for all statistical tests.

7.1 Task Completion Time

Mean task times per question are shown in Fig. 8. A linear mixed effects model was conducted to examine differences in task completion time. The model was specified with fixed effects of system, question, and map, and full-factorial interaction effects. A random effect of the participant was specified on the intercept.

The model revealed significant main effect of system ($\chi^2(1) = 280.73, p < 0.001$) and question ($\chi^2(4) = 14.67, p < 0.001$). No main effect was found for map type. The model revealed a system $\times$ question interaction effect, ($\chi^2(4) = 81.16, p < 0.001$). Considering the interaction effect, we performed post hoc pairwise comparisons of questions and system using the Tukey HSD test. The post-hoc test showed that GeoGate ($M = 84.24, SD = 66.84$) was significantly

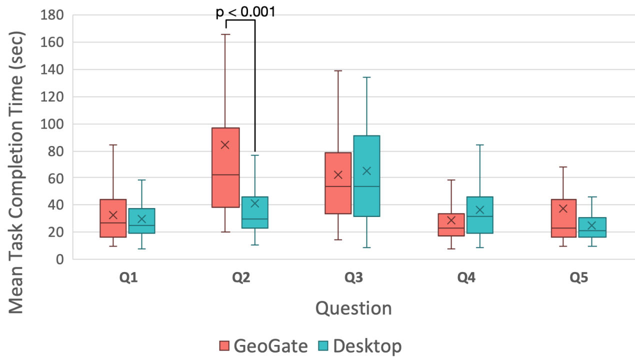

Figure 8: Box plots of the task completion time per question. GeoGate was found to be significantly slower than Desktop for Q2. The mean is represented by the cross marker.

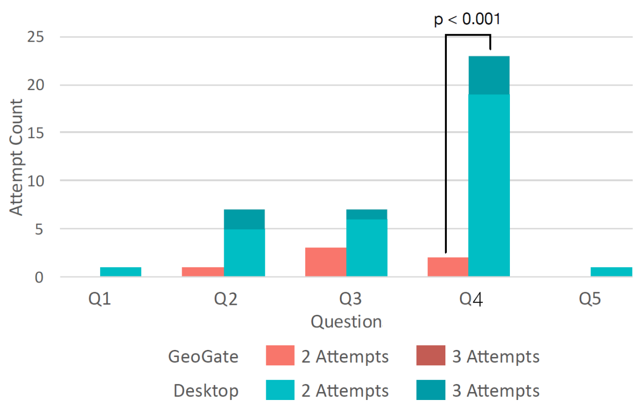

Figure 9: Number of consecutive attempts per question.

slower than the desktop system ($M = 40.94, SD = 30.73$) for Question 2 ($p < 0.001$). All other questions were not significant. These results suggest that an aspect of the task in Question 2 makes answering it take longer using GeoGate than Desktop when compared to the other questions. We explore this in the discussion section.

7.2 Trial Attempt Error

The number of repeated trail attempts were recorded as errors (Fig. 9). We conducted paired-samples t-tests to compare the trial attempts errors between GeoGate and Desktop for each question. There was a significant difference in Question 4, with GeoGate ($M = 1.02, SD = 0.09$) having significantly less errors that the Desktop ($M = 1.37, SD = 0.37$) condition; $t(23) = -4.26, p < 0.001$. All other comparisons were not significant.

7.3 Task Failure

If a participant incorrectly answered a question three times, that question was marked as failed. We found that failures were observed only for the desktop conditions. One failure for Q2, one failure for Q3, and four failures for Q4 (which was incidentally rated as a "difficult" task). Although too few failures were recorded for meaningful analysis, it should be noted that no failures were recorded for GeoGate in any question.

7.4 Activity

We conducted a paired-samples t-test to compare the activity between in the GeoGate and Desktop conditions. There was a significant difference in scores for activity for GeoGate ($M = 0.33, SD = 0.096$) and Desktop ($M = 0.74, SD = 0.022$) conditions; $t(23) = -5.65,\ p < 0.001$.

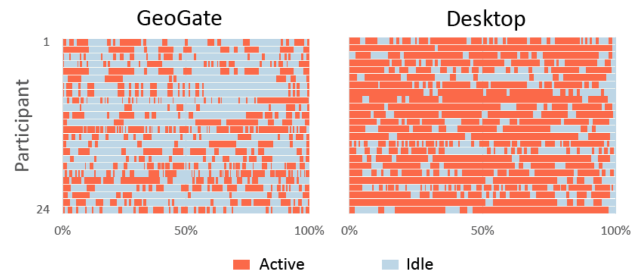

Figure 10: The activity patterns of GeoGate versus Desktop systems. GeoGate shows significantly less activity, suggesting that a majority of participant's time is spent interpreting the STC data rather than moving their focus in a search pattern.

Fig. 10 shows the distinct differences in active versus idle usage patterns between the systems across all tasks. Actions shorter than one second were removed to reduce noise. The same pattern is also seen in both A, B and C maps. We interpreted this to mean that GeoGate spends more time analyzing the visualization than checking information, i.e. using the tooltip. We also interpreted this to mean that the 2D Desktop system needs more user interaction compared to GeoGate, i.e. mouse movement.

7.5 Survey

After each question, participants were asked to answer a subjective questionnaire reporting ease of use and preferences. First, participants rated ease of use for each system on a five-point Likert scale (scale of 1 = very easy to use to 5 = very hard) (see Fig. 11). The mean rating across all questions for the GeoGate visualization was 2.19 ($SD = 1.20$), while Desktop was 2.88 ($SD = 0.99$).

Wilcoxon signed rank tests were used to compare ease of use. Participants rated GeoGate as significantly easier to use than Desktop for Question 1 ($T = 5.0, z = -3.814, p < 0.001$), Question 4 ($T = 21.5, z = -3.166, p = 0.002$), and Question 5 ($T = 23.0, z = -3.165, p = 0.002$). Desktop was reported as significantly easier than GeoGate only in Question 2 ($T = 47.5, z = -2.207, p = 0.027$). No significant difference was found for Question 3. Preferences for ease of use are shown in Fig. 11.

In the user preference questionnaire (Fig. 12), participants were

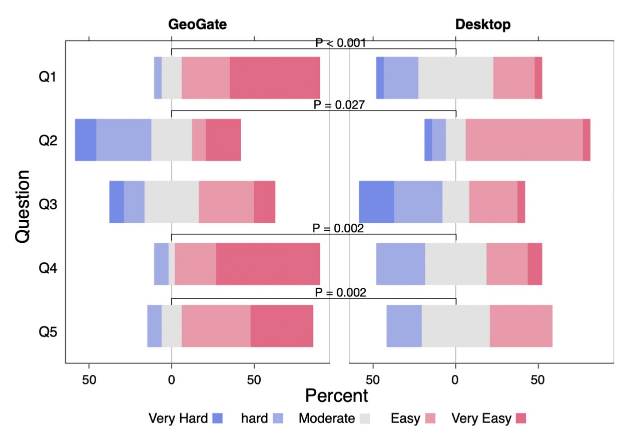

Figure 11: Ease of use results reported for each question. GeoGate was reported to be easier than Desktop for Q1, Q4, and Q5. Desktop was consider easier only for Q2.

asked to report which system they preferred for each question. The participants preferred GeoGate for all questions except Question 2. During the exit survey, participants were asked to select their overall preference for "practical use" and "enjoyment". For these questions, participants overall preferred GeoGate (Fig. 12).

8 Discussion

We had two hypotheses. Hypothesis H1 was that GeoGate would be as fast or faster than Desktop for completing common tasks. Second, hypothesis H2 was that GeoGate can complete given tasks more accurately than Desktop.

H1 was not supported by task completion time results. We observed an interaction effect that caused GeoGate to take significantly longer than Desktop for Question 2. However, there was no significant difference between GeoGate and Desktop for the other questions. Investigating Question 2, participants were asked to firstly find light data associated with a particular latitude and longitude, and secondly, associate a ship ID to the light data. Since the second part of the task is encapsulated in Question 1 (where performance times were comparable), we surmise that the difficulty arises from the first part of the question. These results suggest identifying particular datapoints from a latitude and longitude is a significantly more difficult task using GeoGate. This is supported in observations of the system, where participants had to move the tangible and click through the data points to identify a latitude and longitude. In future work, we suggest that techniques for quickly identifying latitude and longitudes should be introduced into GeoGate.

H2 is supported by the results of the trial attempt errors. GeoGate had significantly less errors for both Question 2 and Question 4 (being of medium and hard difficulty respectively). Even with the support of brushing with tooltips in the Desktop system, participants were more likely to incorrectly infer answers when presented with complex data in the Desktop system. This result is especially interesting in light of the findings of the task completion time. Question 2 took significantly longer using GeoGate ($M = 84.24, SD = 66.84$) compared to Desktop ($M = 40.94, SD = 30.73$), however there were significantly less attempts.

Of particular interest was Task Failure, as GeoGate had no failed trials, but the Desktop trial failures directly reflected the question difficulty: none for easy questions, one each for the medium questions, and four for the hard questions. This is interesting given one can infer the difficulty directly from the failure rate. This means whilst the question difficuly had some impact on users for the Desktop condition, it did not affect their ability to answer it in GeoGate. Trial failure is especially interesting given the multiple choice nature of the questions, as three attempts from five options

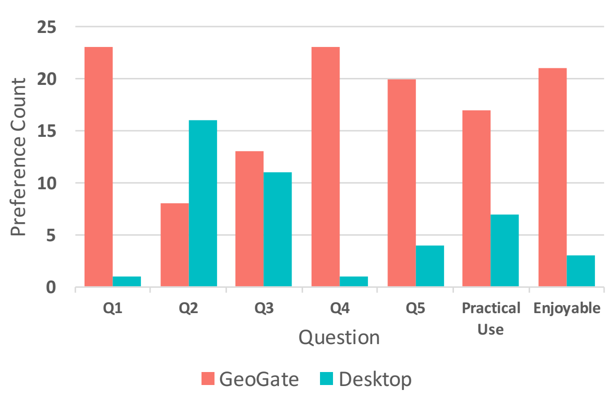

Figure 12: After each question block, participants were asked to select which system they preferred. Post-experiment, participants also reported which system they preferred for "Practical Use" and "Enjoyment".

The ease of use and system preference surveys collected qualitative feedback of the system. Participants rated GeoGate as easier to use in Questions 1, 4, and 5. Only in Question 2 did participants rate Desktop as easier to use, reflecting the findings from the task completion time results. Similarly, participants preferred GeoGate overall for all questions except Question 2. One particpant commented that "rotating the view and having an [extra] dimension to view the data gave a better insight into the association between light data." When discussing the GeoGate tangible, a participant noted that "[it was] very easy to move, easy to pin point the location".

Given the numerous differences between GeoGate and the Desktop, it is difficult to attribute the results to a single factor or design, such as 2D vs. 3D space, AR, tangible input, and display size. Despite design decisions made to minimize impact (e.g. the size of the STC, size of labels, etc.), the limited FOV and resolution of the Hololens may have also impacted on the results. Whilst testing each of these changes in isolation is non-trivial in effort, we believe this study represents a first step into evaluating the GeoGate version of a STC. Future studies are required for a better understanding of the factors affecting user performance when using GeoGate.

9 Conclusion

In this paper, we presented GeoGate, a novel geotemporal visualization system for exploring relationships between objects in multiple geotemporal datasets. GeoGate explored how to collate multiple geotemporal datasets using visualization, whilst reducing and the uncertainty that exists when the same data is presented in 2D. As a result, we developed an AR STC, incorporating novel wings to reduce user effort in manipulating the viewport, paired with a novel ring-shaped TUI as the primary method of interaction. The TUI allowed users to focus on the AR content, whilst actively filtering/navigating the dataset to select different geographic areas.

We evaluated GeoGate in a user study comparing it against a traditional 2D desktop environment, showing GeoGate was as or more accurate for the questions we asked, supporting hypothesis H2. In addressing the speed of the system (H1), GeoGate was as fast as the 2D desktop condition for all questions except question two. As previously discussed, this indicates that a certain element of question two is not fully supported by GeoGate in its current form. Our observation is that the seek action to retrieve data by longitude and latitude is inadequate. When addressed, we expect GeoGate to be equally as fast as existing method for all question types. In addition, we observed that users spent less time moving the focus with GeoGate than Desktop. Interestingly, for questions of medium or hard difficulty, participants failed the to get the correct answer five times using Desktop, despite it not occurring once with GeoGate. Despite the similar performance for the majority of questions, users preferred using GeoGate over the existing Desktop condition.

This work was presented within the maritime domain, taking inspiration from a real use case. However other applications exist, such as general surveillance and logistics. In addition, as a tabletop system, GeoGate supports collaboration implicitly, allowing multiple users to potentially explore the same space, using their own or shared TUIs. Future work will examine how to share the AR visualization, and how to apply this approach to support other fields.

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