Geovisual Analytics & the Science of Interaction: A Case Study

Robert E. Roth and Alan M. MacEachren

Abstract—Among the most pressing research and development challenges facing geovisual analytics is the establishment of a science of interaction that will inform the design of visual interfaces to computational methods. The most promising work on interaction to date has attempted to identify and articulate the fundamental interaction primitives that define the complete design space for the user experience. In this paper, we report on an interaction study leveraging a three-stage interaction primitive taxonomy in order to investigate how variations in interaction primitive combinations impact broader interaction strategies. *GeoVISTA CrimeViz*—a geovisual analytics application developed in partnership with the Harrisburg Police Department—was leveraged as a living laboratory for examining the nature of interaction strategies. Ten law enforcement officers with the Harrisburg Police Department completed a set of fifteen benchmark tasks while their interactions were logged. Experimental results suggested that use of the interface increases as the user objective increases in sophistication. Results also confirmed Shneiderman's visual information seeking mantra as the primary interaction strategy during visual exploration and analysis. Further, consistently successful and suboptimal interaction strategies were summarized and articulated as interaction personas, allowing for the establishment of interface design recommendations for promoting positive personas and avoiding negative ones.

Index Terms—geovisual analytics, science of interaction, interaction primitives, interaction strategies, interaction personas

1 INTRODUCTION

Geovisual analytics at its core requires a synergistic relationship between humans and machines. Geovisual analytics differs from prior research approaches to cartography and visualization in its focus on the human reasoning faculties needed to build evidence and generate actionable knowledge about complex problems [1]. However, the complexity of the problem at hand—and the datasets collected about said problem—too often surpass human cognitive limits. As a result, geovisual analytics also differs from prior research approaches in its application of sophisticated statistical and computational techniques to extract relevant insights from voluminous datasets [2]. In this way, the machine scales the human to meet the complexity of the problem.

In the following, we treat neither the human nor the machine in isolation, but rather approach the 'glue' that makes their synergy possible: the visual interface. The design and development of map-based interfaces that are both useful and usable is tantamount to successful geovisual analytics, as it is through the interface that insights are shared between human and machine. Our research contributes to an emerging ***science of interaction*** that spans the related fields of human-computer interaction, information visualization, and usability engineering [3]. Importantly, Thomas et al. [4: p76] include "the creation of a new interaction to support visual analytics" among the core set of research and development initiatives facing visual analytics.

Existing research on interaction to date has attempted to describe the complete interaction solution space by reducing the interaction process into its smallest structural constituents, resulting in taxonomies of ***interaction primitives*** [5]. Such interaction primitives are the conceptual parallel to the visual variables in representation design [6], and therefore serve as a foundational framework for the science of interaction. However, there is relatively minimal research leveraging the interaction primitives to track and assess competing ***interaction strategies***, or sequences of interaction primitives applied to complete an exploratory or analytical task [7]. By relating successful or suboptimal interaction strategies to their constituent interaction primitives, the ultimate promise of a science of interaction may be realized: empirically-derived and broadly-generalizable design and use guidelines for visual interfaces.

To this end, we conducted an interaction study with a geovisual analytics application called *GeoVISTA CrimeViz* using the interaction primitives as the theoretical unpinning for evaluating user interaction strategies with the application. *GeoVISTA CrimeViz* (Fig. 1) is a collaborative project between the Penn State GeoVISTA Center and the Harrisburg (Pennsylvania, USA) Bureau of Police. There is great and largely untapped potential for geovisual analytics to support the functions of policing and public safety. Law enforcement personnel simply call the *hypotheses* generated from visual exploration and analysis by a different name: *hunches*. The *GeoVISTA CrimeViz* application enables law enforcement officers to build complex queries of their crime incident database in space, time, and attribute and to generate flexible aggregates of the query results for display in linked map and timeline visualizations. Ultimately, law enforcement officers can drill-down into potential incidents of interest, building evidence for solving past crimes and generating actionable knowledge for preventing future ones.

2 BACKGROUND

Contemporary research on the science of interaction recognizes a fundamental distinction between ***interactions***, or the overarching action-response sequence between a human and a machine, and ***interfaces***, or the specific tools developed to support the interaction in a digital environment [8]. In both the academy and industry, it is increasingly common to refer to this distinction as user experience (UX) design versus user interface (UI) design [9]. By considering the complete user experience, Norman [10] segments a single interaction (physical or virtual) into a series of seven ***stages***: (1) forming the goal, (2) forming the intention, (3) specifying an action, (4) executing an action, (5) perceiving the state of the system, (6) interpreting the state of the system, and (7) evaluating the outcome.

Theoretically, a unique taxonomy of interaction primitives can be assembled at each of Norman's [10] stages of interaction in order to articulate, and ultimately to account for, the complete UX design space. In past work, we found that most existing taxonomies of interaction primitives align primarily with one of three of these stages [5, 11]. First, many taxonomies enumerate user ***objectives***, or close-ended tasks that can be completed with a visualization. Objective taxonomies align closely with the second stage of interaction, forming the intention. A second approach is to compartmentalize primitives according to interface ***operators***, or the generic kinds of functionality that can be implemented in an interface. Operator taxonomies align closely with the third stage of interaction, specifying an action. The final approach lists primitives according to characteristics of the interaction ***operand***, or the recipient of the interaction. In geovisual analytics, the operand

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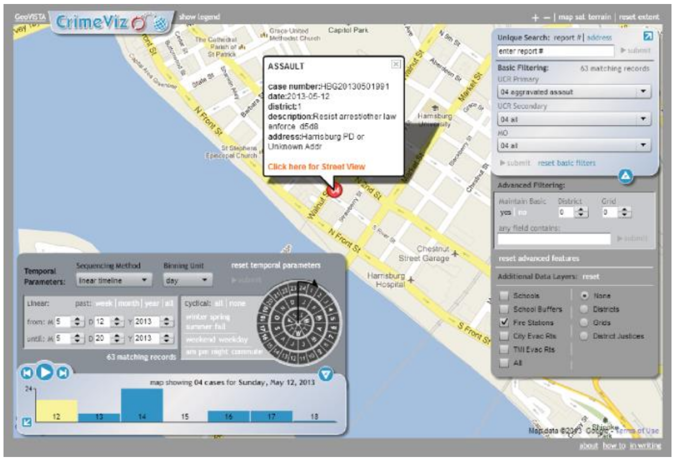

Fig 1. GeoVISTA CrimeViz (http://www.geovista.psu.edu/CrimeViz)

often is the map itself, or the object being manipulated between the fourth (executing an action) and fifth (perceiving the state of the system) stages of interaction. Importantly, objective and operand combinations describe ***benchmark tasks*** for geovisual analytics, as they define both the user's intention in manipulating the visualization and the aspect of the visualization to be manipulated.

In order to produce a 'composite' taxonomy of interaction primitives, the first author completed a card sorting study requiring participants to organize example statements derived from both literature and practice on cartography and geovisual analytics [12]. Table 1 lists and defines the resulting primitives, organized according to objective, operator, and operand. We used the three-stage taxonomy of interaction primitives described in Table 2 to inform the interaction study with *GeoVISTA CrimeViz*, given that this taxonomy is specific to map-based visualization and therefore geovisual analytics. In total, 8 of the 12 operators were implemented in *GeoVISTA CrimeViz* and interaction with all three operands was supported (see Table 3 for a description of the supported operator-operand combinations).

An ***interaction study*** is a method that requires participants to complete a set of benchmark tasks with an interface in a controlled setting while their interactions are captured in an interaction log [13]. Our research builds upon a small set of interaction studies reported in the cartography and geovisual analytics literature, including MacEachren et al. [14], Andrienko et al. [15], Edsall [7], and Robinson [16, 17]. Purpose-driven interaction primitive taxonomies were developed as part of each of these interaction studies in order to analyze the collected interaction logs. Thus, these studies provide important examples of employing an interaction primitive taxonomy (primarily operator-based taxonomies) to codify user interactions to the end both of improving the evaluated interface as well as identifying prototypically successful interaction strategies that may be generalizable beyond the evaluated interface. The applied and basic insights generated from each interaction study were used to inform the design of the interaction study on *GeoVISTA CrimeViz*.

3 METHODS

We purposively sampled ten participants from the Harrisburg Bureau of Police to participate in the interaction study using *GeoVISTA CrimeViz* as a 'living laboratory'. The primary criteria for participation in the interaction study included work responsibilities that are supported by *GeoVISTA CrimeViz* and general familiarity with the *GeoVISTA CrimeViz* application. The participant sample therefore was characterized by high levels of user expertise and motivation. The sample size of n=10 aligns with expert involvement in the interaction studies reviewed above [7, 14-17], which range from n=6 to n=10 experts.

Table 1. Interaction Primitives

Objectives	
Identify	examine and understand a single feature
Compare	determine the similarities and differences between two features
Rank	determine the order or relative position of two or more features
Associate	determine the relationship between two or more features
Delineate	organize features into a logical structure
Operators	
Reexpress	set or change the visual isomorph used in the representation or information views linked to the representation
Arrange	manipulate the layout of a visual isomorph when multiple, typically linked visually isomorphic views are provided
Sequence	generate an ordered set of related representations
Resymbolize	set or change the design parameters of a representation form without changing the represented features or the representation form itself
Overlay	adjust the feature types included in the representation
Reproject	set or change the projection used to transform the information to a two-dimensional screen
Pan	change the center of the representation
Zoom	change the scale and/or resolution of the representation
Filter	alter the representation, and information views linked to the representation, to indicate features that meet one or a set of user-defined conditions
Search	alter the representation, and information views linked to the representation, to indicate a particular feature of interest
Retrieve	request specific details about a feature or features of interest
Calculate	derive new information about a feature or features of interest
Operands	
Space-Alone	interact only with the geographic component of the representation
Attributes-in-Space	interact with the temporal component of the representation to understand how a dynamic geographic phenomenon acts over time
Space-in-Time	interact with the attribute component of the representation to understand how one or several characteristics of a geographic phenomenon varies across space

We conducted the interaction study in a private room used for depositions and interrogations in the Harrisburg Police Headquarters. We configured a simple usability laboratory in the interview room, which consisted of a laptop computer that we used during testing and an external monitor, keyboard, and mouse that the participant used during testing. A duplicate display of *GeoVISTA CrimeViz* was shown on both the laptop and external monitor, and the investigators each had control over the application through our respective input devices. We logged the interactions with *GeoVISTA CrimeViz* using Camtasia Studio, a video recording application that records screen interactions; we captured audio backups of the sessions using a voice recorder.

Following an initial exploration period, we required participants to answer a set of 15 close-ended questions using *GeoVISTA CrimeViz*. The questions were based on objective-operand benchmark tasks (Table 1), with one question generated for each objective (*identify*, *compare*, *rank*, *associate*, and *delineate*) and operand (*space-alone*, *attributes-in-space*, *space-in-time*) pairing. Before testing began, we first administered a pilot study with two additional stakeholders at the Harrisburg Bureau of Police in order to revise questions that were unclear or poorly worded, that potentially had more than one correct or partially correct answer, and that had answers that participants would be able to recall from experience without first interacting with *GeoVISTA CrimeViz*.

During the interaction study, we read each question aloud and then handed a print of the question to the participant for reference. The order of the questions was randomized, with no two participants receiving the same question order. Unlike the exploration period, we did not allow participants to ask for clarification about *GeoVISTA CrimeViz* while completing the benchmark tasks. Once the participants believed they had found the answer to the question, we instructed participants to state it aloud for the audio recording. We provided participants a maximum of three minutes to answer each question in order to ensure the set of 15 questions was completed in 45 minutes or less; only four of the total 150 task (15 questions by 10 participants) exceeded the three minute limit, with all participants completing the formal testing component of the cartographic interaction study in 20-25 minutes. After an answer was verbalized for a question, or after the three minute time limit expired, we refreshed the browser containing *GeoVISTA CrimeViz* to force the participant to start from the default overview when answering the subsequent question.

4 Results

We analyzed the interaction logs in two stages. In the first stage, we calculated descriptive statistics on the interaction primitives in aggregate form in order to draw broad connections across objectives, operators, and operands. Table 2 provides descriptive statistics across objective-operand pairings based on metrics recommended by Sweeney et al. [18]. Participants performed well overall, answering 123 of the 150 total questions correctly (82%). The high accuracy rating perhaps is a reflection on the high levels of user expertise and motivation, as well as the opening exploration session. On average, participants required 1:00 (one minute) and employed 3.4 different operators a total of 7.4 times to answer each question.

The Table 2 metrics indicate an increasing level of difficulty in objectives (*identify→>compare→rank→associate→delineate*) that reflects a previously hypothesized continuum in cognitive sophistication [19]. The *identify* objective (i.e., the least sophisticated) required the least amount of time overall (0:31) and the fewest operators per benchmark task (3.1). Conversely, the *delineate* objective (i.e., the most sophisticated) required the most amount of time overall (1:27) and the most operators per benchmark task (9.8); the *delineate* objective also resulted in the most incorrect answers (only 67% accuracy).

Regarding the operand component of the benchmark tasks, participants most easily responded to questions regarding the *space-alone* operand; this finding holds across all five metrics. Summary metrics regarding the *attributes-in-space* and *space-in-time* operands were similar, with participants requiring slightly more time to respond to questions including the *attribute-in-space* operand and slightly more frequent and diverse operators to respond to questions including the *space-in-time* operand. Interestingly, participants only had problems answering questions about the *attribute-in-space* operand within the allotted three minute time limit, but were considerably less accurate in their responses to questions about the *space-in-time* operand.

Table 3 provides descriptive statistics across operator-operand pairings. *Retrieve* was the most frequently and extensively applied operator (frequency=395, extensiveness=71%), followed by *filter* (frequency=240, extensiveness=60%) and *zoom* (frequency=127, extensiveness=44%) respectively; no other operators were used in more than one-third of the 150 interaction strategies. Such a reliance on *retrieve*, *filter*, and *zoom* suggests that Shneiderman's [20] visual information seeking mantra (overview first, zoom and filter, then details on demand) was the primary participant interaction strategy.

Regarding operands, participants least commonly interacted with the *space-alone* operand (frequency=175, extensive=33%). Further, several of the interfaces provided to manipulate the *space-alone* operand were ignored altogether (e.g., *search* and *overlay* by *space-alone*). Because a map first and foremost is a spatial representation supporting many spatial tasks without digital interaction, interfaces for manipulating the attribute and temporal components of a dataset may be more important in geovisual analytics than those manipulating the spatial components, somewhat paradoxically so.

Table 2. Interactions by Objective & Operand Pairings (A=Percent Completed, B=Percent Correct, C=Average Time, D=Frequency of Operators, E=Diversity of Operators)

Objective-Operand	A	B	C	D	E
All Identify	**100%**	**87%**	**0:31**	**3.1**	**2.1**
Space-Alone	100%	100%	0:18	1.3	1.2
Attributes-in-Space	100%	100%	0:32	1.6	1.5
Space-in-Time	100%	60%	0:43	6.5	3.6
All Compare	**100%**	**83%**	**0:58**	**7.4**	**2.7**
Space-Alone	100%	90%	0:25	7.6	3.0
Attributes-in-Space	100%	100%	0:57	3.5	1.6
Space-in-Time	100%	60%	1:32	11.2	3.4
All Rank	**97%**	**93%**	**0:56**	**9.1**	**4.3**
Space-Alone	100%	90%	0:42	8.9	3.9
Attributes-in-Space	90%	100%	1:11	11.2	5.1
Space-in-Time	100%	90%	0:53	7.1	3.8
All Associate	**100%**	**80%**	**1:06**	**7.6**	**3.2**
Space-Alone	100%	100%	0:18	3.0	1.6
Attributes-in-Space	100%	80%	1:24	10.5	5.0
Space-in-Time	100%	60%	1:36	9.2	3.4
All Delineate	**90%**	**67%**	**1:27**	**9.8**	**4.6**
Space-Alone	100%	90%	1:08	8.8	4.8
Attributes-in-Space	70%	30%	2:13	13.6	4.9
Space-in-Time	100%	80%	1:02	7.0	4.2
All Space-Alone	**100%**	**94%**	**0:34**	**5.9**	**2.9**
All Attributes-in-Space	**92%**	**82%**	**1:16**	**8.1**	**3.5**
All Space-in-Time	**100%**	**70%**	**1:09**	**8.2**	**3.7**
Total	**97%**	**82%**	**1:00**	**7.4**	**3.4**

Table 3. Interactions by Operator & Operand Pairings (A=Frequency of Operators, B=Extensiveness across Benchmark Tasks)

Operator-Operand	Frequency	Extensiveness
All Reexpress	**78**	**33%**
Space-in-Time	78	33%
All Sequence	**32**	**9%**
Space-in-Time	32	9%
All Overlay	**57**	**31%**
Space-Alone	0	0%
Attributes-in-Space	57	31%
All Pan	**121**	**27%**
Space-Alone	81	19%
Space-in-Time	40	11%
All Zoom	**127**	**44%**
Space-Alone	82	26%
Space-in-Time	45	23%
All Filter	**240**	**60%**
Space-Alone	12	8%
Attributes-in-Space	90	21%
Space-in-Time	138	49%
All Search	**42**	**19%**
Space-Alone	0	0%
Attributes-in-Space	42	19%
All Retrieve	**395**	**71%**
Attributes-in-Space	185	39%
Space-in-Time	210	39%
All Space-Alone	**175**	**33%**
All Attributes-in-Space	**248**	**78%**
All Space-in-Time	**543**	**63%**
Total	**1092**	**100%**

In the second stage of analysis, we created timeline graphics representing the interaction logs in order to interpret individual interaction strategies and compare competing interaction strategies [21]. Through qualitative interpretation of the interaction logs, we were able to identify six ***interaction personas*** that characterized chronic issues in applying operators suboptimally that occurred across participants and across benchmark tasks:

1. ***blind-sequencer*****:** interaction behavior in which rapid application of the *sequence* operator results in the user missing spatiotemporal patterns depicted in the map view;
2. ***excessive-filterer*****:** interaction behavior in which the *filter* operator is unnecessarily applied as part of routine use with the application (i.e., while following the visual information seeking mantra), negatively impacting productivity due to the computing time and cognitive workload required to process the *filter* result;
3. ***lost-browser*****:** interaction behavior in which the *zoom* and *pan* operators are applied in rapid succession, indicating that the user is disoriented by the current map view;
4. ***mistaken-reexpresser*****:** interaction behavior in which the *reexpress* operator is applied to generate an inappropriate representation for the user objective, leading to misinterpretation of the provided visualization;
5. ***uninformed-zoomer*****:** interaction behavior in which the *zoom* operator is applied without the proper context provided by the *overlay* operator, resulting in user confusion about what he or she is viewing;
6. ***unsure-retriever*****:** a persona indicating interaction behavior in which the *retrieve* operator is applied in rapid succession, suggesting a time in which the user does not know how the *filter* tools support proper refinement of the mapped features.

There are equivalent positive interaction personas performed during successful interaction strategies that represent the inverse of the associated negative personas.

5 Conclusion

In this paper, we reported on an interaction study using the *GeoVISTA CrimeViz* geovisual analytics application as a ‘living laboratory’ to understand the association between interaction primitives and interaction strategies. The experimental results revealed several broad insights towards this research goal, including an increased use of the interface as the objective increases in sophistication and the common (although at times suboptimal) completion of Shneiderman’s [20] visual information seeking mantra using *filter*, *zoom*, and *retrieve*. The identification and tracking of interaction personas appears to be a particularly promising way of relating interaction primitives to interaction strategies, as suboptimal interaction primitive combinations can be suppressed in the design of the geovisual analytics application. Additional research is needed to further tease out the consequential relationships of interaction primitive pairings on the success of interaction strategies and to account for the identified interaction personas in geovisual analytics tools and techniques.

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