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A Visual Analytics Framework for Microblog Data Analysis at Multiple Scales of Aggregation

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Abstract

Real-time microblogs can be utilized to provide situational awareness during emergency and disaster events. However, the utilization of these datasets requires the decision makers to perform their exploration and analysis across a range of data scales from local to global, while maintaining a cohesive thematic context of the transition between the different granularity levels. The exploration of different information dimensions at the varied data and human scales remains to be a non-trivial task. To this end, we present a visual analytics situational awareness environment that supports the real-time exploration of microblog data across multiple scales of analysis. We classify microblogs based on a fine-grained, crisis-related categorization approach, and visualize the spatiotemporal evolution of multiple categories by coupling a spatial lens with a glyph-based visual design. We propose a transparency-based spatial context preserving technique that maintains a smooth transition between different spatial scales. To evaluate our system, we conduct user studies and provide domain expert feedback.

Categories and Subject Descriptors (according to ACM CCS): I.3.3 [Computer Graphics]: Visual Analytics, Social Media Analysis, Disaster Management—

1 Introduction

Online microblogging platforms (e.g., Twitter, Instagram) not only provide social networking services, but also serve a prominent role in online news sharing and broadcasting [KLPM10]. In contrast to traditional news media outlets, these services reflect the way individuals think and act in the real world more quickly and comprehensively [SOM10]. An increasing number of microblogs are tagged with geographical and temporal information that further provide the potential to improve situational awareness during emergency and disaster management situations. People interact with others using social media to confirm and obtain additional information about the risks they face in emergency and disaster scenarios [oPRtAM13]. Furthermore, an American Red Cross survey reveals that two-thirds of their respondents would prefer having the response agencies regularly monitor social media in order to achieve a quick response in emergencies [Ame10]. Accordingly, the analysis of such datasets has the potential to improve the understanding of public response during these events, and can assist first responders and emergency management personnel in effectively dealing with both emerging and emergent situations.

The task of utilizing such microblog data for situational awareness requires these casual experts (experts in their respective domains, but not necessarily experts in data sciences) to understand the spatiotemporal scale dynamics of the data. Social media data are typically collected at a very fine geospatial scale/resolution (e.g., point locations), but the casual experts are usually responsible for gaining situational awareness of their environments at much coarser scales that can span across multiple levels of geospatial aggregations (e.g., precinct, city, state-wide). Accordingly, the problem of scale (from the data perspective) refers to choosing an appropriate data aggregation and granularity for conducting analysis. Human decision makers need to explore data under a variety of different data scales that directly reflect the problem domain and the domain specific questions being asked. However, while flexible navigation through the multiple scales is a necessity, it is also important for the casual experts to maintain a cohesive thematic context of the transition between the different granularity levels. It, therefore, becomes necessary to choose effective scales for analysis and design navigation methods that allow users to traverse through these scales, while preserving their context and minimizing the impedance mismatch between the data, problem, and the human decision maker scales [REE*09, MMT*14].

To this end, we propose a novel visual analytics environment that supports the analysis and exploration of emergency and disaster related spatiotemporal microblog datasets at multiple geospatial scales. Our system, as shown in Figure 1, utilizes a recently developed approach that provides microblog classification resources for information-specific categories related to the crisis social media data [TCV15]. Our system visualizes these categories and spatiotemporal crisis-related microblogs through interactive glyphs in a spatiotemporal context. The system also supports the visual preservation of spatial contexts when switching between different

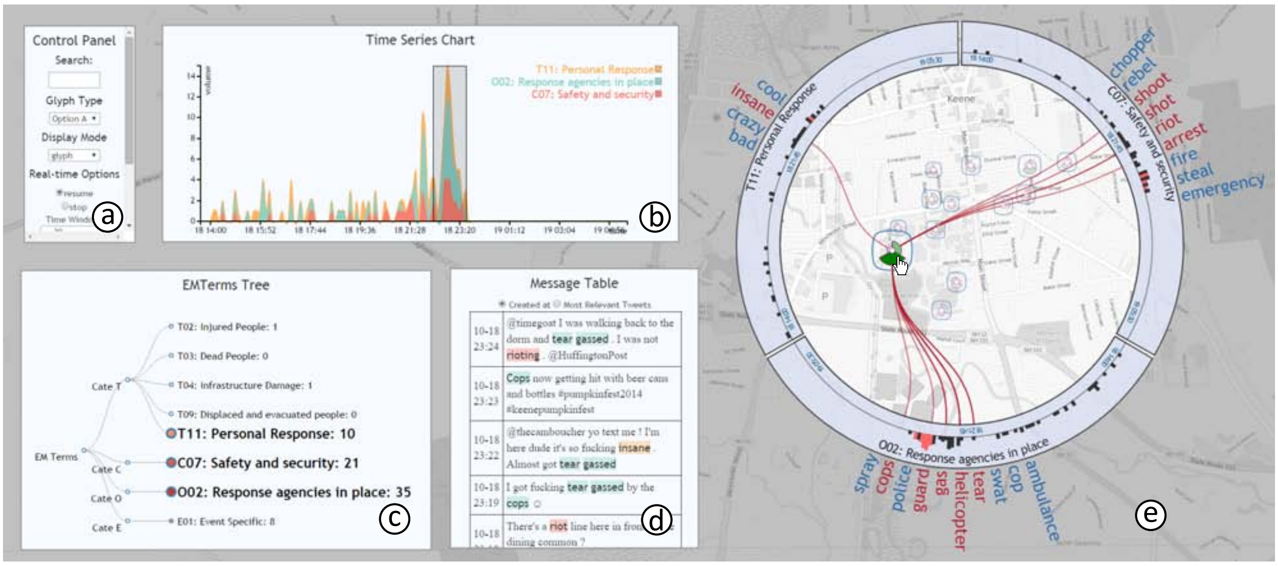

Figure 1: *An snapshot of our visual analytics system. (a) Control Panel; (b) Time-Series View; (c) Category Tree; (d) Message Table; (e) Map View. Hovering over a petal glyph (e) highlights the related keywords and connects to the corresponding keywords using threads.*

geospatial granularity levels. This preservation is achieved through transparent transition of adjacent visualizations, so that analysts are able to maintain smooth and continuous spatial transition, as well as avoid abrupt changes caused by different zoom levels. Our system has been designed to support both retrospective and real-time analysis of the streaming microblog channels. Analysts can examine the different aspects of crisis events based on textual-level categorization, understand their geospatial and temporal evolution in real time, as well as iteratively explore and narrow down to critical knowledge for maintaining an effective situational awareness. The major contributions of this paper are as follows:

- We design a visual analytics environment for the retrospective and real-time exploration of categorical and spatiotemporal streaming microblog datasets across multiple scales of analysis.
- We systematically characterize the domain related challenges and user tasks in order to derive the design goals for our system.
- We propose and evaluate a transparency-based spatial context preservation technique that maintains a continuous transition when switching between spatial granularity levels.
- We provide several glyph-based visualization techniques and evaluate their efficacy in depicting the categorical distribution of microblog data over the selected geospatial areas of interest.

2 Related Work

In recent years, social media has gained much attention from researchers and practitioners as a new data source for improving situational awareness in crisis management situations (e.g., [SOM10]). In this section, we present related work in the areas of visual analytics for enhancing situational awareness using social media, context preserving, and exploring data at multiple scales.

2.1 Situational Awareness Using Social Media

There has been much work to understand disasters, victims, and their needs by collecting information about their surroundings from social media. Researchers have utilized several techniques to classify tweets into categories and to detect specific features using lexicon analysis, natural language processing, and machine learning techniques (e.g., [OCDV14, IEC*13, SRG15]). However, locating specific feature sets from the datasets is often insufficient in crisis management situations, and requires an interactive visual analytic approach to allow users to gain a situational awareness of their area of responsibility. ScatterBlogs2 [BTH*13] provides a way to train classifiers by learning historical tweets and loading the pre-trained classifiers to monitor and examine tweets related to events of interest. Chae et al. [CTJ*14] utilize multiple visualization techniques for spatiotemporal analysis in order to detect abnormal events using geo-tagged tweets during threats. Our system has been built using visual analytic principles that allow users to explore streaming social media data across multiple scales.

2.2 Context Preserving Data Navigation

Various techniques and approaches have been proposed to provide efficient context-preserving on top of "Overview+detail" and "Focus+Context" [CKB08]. Context-preserving techniques have commonly been realized by utilizing multi-screen space that creates several viewports for each scale and focus that can lose the intervening context [KH13]. In these situations, a new issue arises on how to best support human analysis when transitioning from one state to the other across multiple views. In order to resolve these issues, Gutwin [Gut02] presents a time-based transition technique that dynamically controls the time of magnification. Pietriga and Appert [PA08] show that this technique outperforms traditional magnifying glass and fisheye techniques. In this paper, we utilize a visual analytics approach to preserve the intervening geospatial context during transition between different zoom levels and across time steps using a new transparency-based technique that avoids separate views and occlusion. Our method is motivated by computer graphics animation research, and facilitates a smooth transition between the different spatial scales of the system.

2.3 Visual Analytics across Multiple Scales

Scale is an important factor in geographical analysis. The varying analysis results at different scales reflect the statistics of the dataset from global to local perspectives. Waqas et al. [JGE12] propose the stack zooming technique, which allows users to hierarchically explore the geographical regions of interest. Turkay et al. [TSH*14] visualize small multiple charts to provide a visual summary of different statistical variables under the varying levels of aggregation, which they named attribute signatures. Goodwin et al. [GDST16] propose a set of glyph-based design to encode the correlations of a given variable at different scales. The glyphs are then embedded into a matrix view to indicate the correlations of multiple variables. Compared to existing work, our proposed approach aims to help users maintain the context of the spatial clusters at different spatial scales when they perform zooming operations.

3 Domain Characterization

In this section, we discuss the requirements of the domain related tasks, characterize the main challenges domain experts face in their use of microblog data, and present abstractions of the tasks using visual analysis vocabularies [Mun09, SMM12]. This discussion has been motivated by conversations with our emergency and law enforcement partners responsible for mitigating and responding to disaster and emergency situations. These partners include a mid-sized U.S. law enforcement department that serves a population of 70,000 people and the U.S. Coast Guard. Our focus for these discussions was mainly with regard to monitoring for safety and security needs using microblog data.

3.1 Problem Formulation

Social media data typically tends to be large, multi-type, and multi-dimensional in nature and are generated from multiple sources at high velocities. Domain experts need effective retrieval and categorization pre-processing approaches to help them categorize and filter the streams, so that they can focus their analysis on relevant information. Conventional approaches, such as sentiment analysis [WLY*14] and topic modeling [XWW*13], have been typically focus on a coarse-grained categorization and only provide an overview of the situation. However, this approach can be ineffective in disaster management and emergency response situations where stakeholders are interested in different categories that are more related to their specific responsibilities (e.g., safety/security issues, injured people, services needed). Hence, there is a need for fine-grained, crisis-related categorization approach that is able to depict different aspects of crisis situations from microblogs.

Casual experts also need the ability to explore the microblog streams at different scales of space, time, and data categorizations for maintaining situational awareness. Most previous work in spatial and temporal aggregation creates abrupt changes in results that hinder the analysts' frame of reference as they rapidly navigate across these various scales of space, time, and categories. This contextual/frame of reference cross-scale problem is challenging and has only been an active area of research in other navigation and analysis contexts [JGE12]. There is a need for maintaining a thematic context upon transitioning between different granularity levels for the exploration and analysis tasks. In this paper, we primarily focus on addressing these issues in terms of the spatial dimension.

The high velocity of streaming social media data poses yet another challenge. As new data arrives over time, the data visualization needs to update in order to present the newly arrived and analyzed data. However, the transition between the new state and the old state of the visualization has the potential to disrupt the ongoing analysis as the new data may have different spatial distributions. It becomes necessary to factor in for and provide visual cues for transition between the different states of the system over time for the analysts to maintain a thematic context.

3.2 Design Goals

During our discussions with the casual experts in the disaster and emergency management domain, we noted that they had several commonalities in their real time monitoring tasks. Their analysis typically began with developing a set of microblog keyword classifiers that pertain to the crisis situations or major events that fall in their areas of responsibility. Various types of tasks were then performed in the information-foraging loop [PC05] to gain a situational awareness, including investigation of quantitative (TQ), temporal (TT), spatial (TS), and real-time (TR) aspects of the data, along with the ability to analyze spatial clusters (TC) and raw data (TRD). Details on these tasks have been provided in Table 1. Based on the aforementioned challenges and domain characterization, we derive the major design goals of our visual analytics system.

- G1 **Navigate Through Multiple Dimensions (Spatial, Temporal, and Categorical) Across Scales [TQ, TT, TS, TC, TF]:** The system should allow the navigation through information space by casually specifying query parameters of spatial, temporal, and categorical dimensions across multiple scales [DCCW08].
- G2 **Facilitate Exploration of Categorical Data in the Spatiotemporal Context [TT, TS, TC]:** The visualization should reflect the evolution of multiple categorical data dimensions within the context of both space and time.
- G3 **Maintain Spatial Context Across Scales [TS, TC]:** The system should provide a smooth and context preserving transition that highlights the changes across different scales.
- G4 **Preserve Spatial Context for Streaming Data [TS, TR]:** The visualizations should accommodate new data streams and maintain the analysts' context between the data states.
- G5 **Summarize as well as Access Raw Data [TQ, TRD]:** The system should allow analysts to have access to both summarized and original data for further investigation.

4 Microblog Exploration at Multiple Scales of Aggregation

Our system, described in Section 4.2, is comprised of several linked views that enable exploration and analysis of microblog data at multiple geospatial scales. We utilize a microblog classification scheme [TCV15] that reduces the complexity of the analysis space by automatically classifying the data into appropriate disaster and emergency categories (Section 4.1). Our system has been designed to allow users to visualize the microblog streaming data in an interactive environment, with the ability for them to filter the data based on their categories of interest. In addition to choosing from the pre-populated disaster and emergency classifiers, users can also interactively create their own classifier categories in our system. Our system also provides the ability to perform retrospective analysis of historical events for both investigative analysis and proactive planning and management preparedness of future events.

Task Type	Problems in tasks	System Tasks
TQ (Quantitative)	What is the volume of the messages related to the different crisis-related categories? When and where is the message posted? Who posts the message?	Show the volume of messages and prominent keywords for a specific category. Show who talks about the keywords, the location, and timestamp of the messages.
TT (Temporal)	How does a specific category evolve over time? When does the temporal peak occur? Do the peaks of different categories occur simultaneously?	Show the temporal evolution of the overall messages and specific categories.
TS (Spatial)	What is the spatial distribution of different categories? Where are the spatial clusters? Are those clusters located in the same region?	Visualize spatial clusters on the map and show the spatial distribution of the selected categories.
TR (Real-time)	Which crisis-related topics/keywords are trending at the moment? Where are they located in the geographical region?	Provide the analysts with real-time updates based on a sliding time window in order to reflect the latest data states.
TC (Clusters)	Does the visualization/analysis change at different spatial scales (e.g., state, county, city block, street)?	Allow the analysts to navigate across multiple spatial scales, and to preserve context when they zoom in/out on the map.
TF (Filtering)	How can one narrow down to specific time ranges, geographical regions (e.g., areas of responsibility), and categories of interest?	Allow the analysts to interactively specify query parameters in the spatial, temporal and categorical dimensions.
TRD (Raw Data)	What is the actual content of the message? Among a large set of messages, which ones best characterize the event/topic?	Identify the most representative messages and avoid duplicate ones. Show the content of the messages of interest.

Table 1: *Problem and task characterization [Mun09, SMM12] for visual microblog data exploration.*

4.1 Pre-Processing and Categorization of Crisis Microblogs

In order to make sense of the microblogs data during emergency and disaster events, the effective retrieval of crisis-related messages is critical during pre-processing. We utilize a newly developed terminological resource that is especially designed for crisis-related microblogs [TCV15]. This resource contains around 7,000 crisis-related phrases used in Twitter that fall into 23 categories from 3 major sources, as shown in Figure 1c. This resource has been developed for use by practitioners to search for and drill down into relevant messages in crisis and emergency situations.

Although this resource provides a fine-grained categorization that covers various aspects of crisis situations, the included phrases extracted from the original texts are extremely sensitive to the writing style of the individual who posted that message. To overcome this limitation, we identify the major textual features from the phrases based on natural language analysis of the microblogs. We first generate the part-of-speech tags for each word in the phrase [GSO*11]. We then remove stop words and extract *verbs*, *nouns*, and *hashtags* as major features. We notice, however, that in some cases the extracted nouns and verbs may not have explicit semantic relationships. Therefore, we utilize the semantic role labeling method [DK15] to identify the *primary predicate* of the sentence and associated *object/subject*, based on which we remove irrelevant verbs and nouns. The features retained after this processing pipeline are used for the categorization within our system.

4.2 Visual Analytics Environment

Our system is developed based on the server-client architecture. The back-end server was developed using python and we use Apache Sol as the back-end database. The front-end interface is purely web-based and was developed based on several javascript libraries including D3JS, OpenLayers and AngularJS.

Our system contains several coordinated views that support the navigation of different information dimensions. The views are intelligently linked through a rich set of interactions. The map view serves as the base layer of our interface and enables users to gain an overview of the microblogs over the different data categories across multiple geospatial scales, and streaming data states, while maintaining a spatial context across the multiple scales through intuitive interaction and transition methods. The analysts can freely reposition any of the other views of the system if they overlap with the region they intend to explore in the map view. The main components for our system are described in detail below.

4.2.1 Category Tree Visualization

Our system utilizes a tree structure to depict the organization of the different categories (Figure 1c). Each leaf node in the tree represents an individual category, and the color of the node encodes the corresponding microblog volume of the messages based on a sequential color scheme from orange to red [Col16] (G1). The name of the category and the volume of microblogs are also visualized next to the node (G1). This view provides the analysts with an overview of the distribution of different categories for the selected geospatial and temporal range. Hence, analysts can identify and select the significant categories they intend to further investigate (G1, G2). Upon selection, the corresponding node and label are highlighted to reflect being selected.

4.2.2 Time-Series View

The time-series view (Figure 1b) shows the temporal evolution of the different categories selected by the user (G1, G2). This view supports both line chart and stacked bar chart visualizations. Furthermore, users can draw a time window of an arbitrary duration within the time series view to filter the data, and further drag the window to scroll across time (G1). During real-time analysis, the analysts can specify a fixed-length time window. As the new data comes, the time window moves forward to show the real-time updates of the data streams (G4).

4.2.3 Message Table

The message table (Figure 1d) visualizes the detailed messages, including the user name, timestamp, and message text (G5). In the text field, the keywords relevant to the corresponding categories are highlighted using a consistent color scheme across the multiple views. The message table also supports sorting based on different criteria (e.g., time, message length, user influence). This view provides a summarization function [HCB*12] that identifies the representative microblogs in order to allow the analysts to quickly access the most critical information in a timely manner (G5).

Figure 2: *Coupling spatial lens with petal glyphs.*

4.2.4 Map View

The main view of the system consists of an interactive geographic map (Figure 1e) that allows the exploration of the spatiotemporal and categorical dimensions of microblog data through the combination of a spatial lens and petal glyph visualizations. Details on the design of the spatial lens and the petal glyphs are presented in Section 4.3. Besides the spatial lens and the petal visualization, the map view also supports point-based and heat map visualizations to show the geospatial distribution of the microblog data. The map view provides a rich set of interactions that allow the analysts to navigate, filter, highlight and drill down, the details of which are also discussed in Section 4.3.

4.3 Multiple-Category Visualization in the Context of Space and Time

Visualizing spatiotemporal and multi-categorical microblog data is a non-trivial task that requires an intelligent visual combination of multiple information dimensions and also techniques that avoid visual complexity. In this work, we consider *geospace* as the major visualization dimension since the geographical location is the most important aspect in terms of providing situational awareness for disaster managers and emergency responders. Thus, an interactive map visualization serves as the primary workspace for the domain experts to perform analysis and exploration of the social media data. Within the geographical view, we reveal the multi-categorical and spatiotemporal aspects of the data with a compact design where we couple an interactive spatial lens with a petal-like visualization [LWC*14, KAW*14] (as shown in Figure 2).

4.3.1 Seeing the Big Picture: The Spatial Lens.

The spatial lens is drawn on the geographical map, as shown in Figure 2. This lens is segmented into evenly spaced sectors that correspond to the categories selected by the analysts (Section 4.2.1). The inner ring of the spatial lens embeds a time series view [ZCB11] for the corresponding category (Figure 2a), along with keywords extracted from the microblogs for the category (Figure 2b) (G2) [CGS*11]. These provide analysts with an overview of the categorical and temporal dimensions within the spatial context. Furthermore, when the analysts zoom or pan the underlying map view, the system automatically performs spatial filtering based on the current scope of the lens (G1). The linked time-series charts and the keywords of the spatial lens automatically update to reflect the change in the map view. The size and position of the spatial lens is fixed in order to maintain the context of the exploration.

4.3.2 Examining Categorical Dimension in Space and Time: Petal Glyph.

Dense microblog clusters in space or time typically tend to draw the attention of emergency management personnel because of the intensity of relevant activity. To help analysts better understand the volume of the categories within different geospatial clusters, we apply a petal-based glyph visualization on the geographical map to visually summarize the multi-categorical information dimension.

The design of the petal glyph consists of two parts: the outer petals and the inner circle (Figure 2c). The layout of the outer petals correspond to the layout of categories in the perimeter of the spatial lens. The size and color of each petal doubly encodes the volume of microblogs related to the corresponding category for the geospatial cluster (G2). We note that the inner circle can be used to further encode other attributes of the cluster (e.g., overall volume, aggregated sentiment score). Considering that the size of petals can be very small in some cases due to sparse data distribution, the inner circle has a fixed size across all glyphs in order to facilitate the visual recognition across different petal visualizations.

To generate the spatial clusters, we apply the DBSCAN algorithm [EpKSX96] on the geo-tagged data points in the current scope of the lens and at the current zoom level. Next, for each cluster, we calculate its corresponding convex hull and render the petal glyph at the centroid of the convex hull. Since the spatial clustering is dependent on the current spatial scale, analysts are able to interactively examine the categorical distribution of clusters at different granularity levels. The convex hull is also drawn on the map view to indicate the geospatial range of the clusters during the transition between the different geospatial scales (Section 4.4).

In order to further investigate certain clusters, the analysts can specify the spatial clusters through a single mouse click or a polygon selection. Specifically, if the analyst hovers over a cluster of interest, the system generates a set of threads that connects the petals to the relevant keywords in the perimeter of the lens (Figure 1e). The related keywords and time-series in the spatial lens are also highlighted to depict the keywords that correspond to the highlighted cluster (G2). Such an interaction design provides analysts with a quick visual summary of a geospatial cluster of interest and provides them with a situational awareness of the local regions of interest. Furthermore, when the analysts click a certain sector or keyword in the spatial lens, the relevant geospatial clusters are also highlighted to reflect the selection. Finally, when the analysts click on a petal or the central node of the glyph, the message table (Figure 1d) updates to show the detailed messages of the corresponding category or the overall cluster, respectively.

We also provide users with two alternatives to the main petal glyph design (shown in Figure 4). The design shown in Figure 4b uses only color to encode the volume of each category. The size of the petals are the same across all the glyphs. The color of the inner circle encodes the overall volume of this cluster. Figure 4c is similar to that of Figure 4b; however, the overall volume of this cluster is encoded using the size of the pie instead of the inner circle. We conducted a user study to assess the efficacy of these techniques in conveying the data (Section 6.1). Our study shows that the petal glyph design is the most effective in conveying the information. Accordingly, we select this design as the default view in our system.

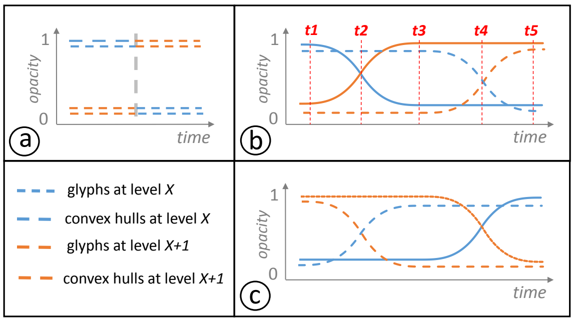

Figure 3: *Conventional transition: Zooming in (a). The animated transition: Zooming in (b), Zooming out (c).*

Figure 4: *(a): The design of the petal glyph. Two design alternatives are presented in (b) and (c).*

4.4 Preserving Spatial Context at the Same Scale and Across Multiple Scales

In most of the current map-based visualization systems, when analysts reach a new spatial scale by performing zoom operations, the visualizations at the previous scale are immediately replaced by the new visualization under the current scale. While this kind of interaction scheme is applied universally, it poses a challenge for analysts to mentally connect the results at the different scales.

Animated transition techniques are commonly applied to provide a smooth change between different visualization states. Existing work typically applies animated transition between different representations of the dataset [HR07], perspectives of the user [EDF08], and positions and layout of the visual elements [DRRD12, BPF14]. Different from the aforementioned work, we aim to provide a smooth transition between data states(spatial clusters in our context) at different spatial scales (level of aggregation). The transition should not only provide a smooth change between different visualizations, but also help users mentally connect visual elements (spatial clusters) at different spatial scales.

To this end, we introduce a new transparency-based technique that fades the results of the different scales concurrently. Our approach is motivated by the ease-in/ease-out effects traditionally applied in animation in computer graphics research [Par12]. When the analysts zoom in or out to a new scale, the visualization at the old scale fades out while the visualization at the new scale fades in. This provides a smooth visual transition along the analysts' interaction process (G3). In our system, we apply the cubic function to achieve the ease-in/ease-out effects, as shown in Figures 3b and c.

Our approach couples the rendering of the convex hull of the clusters with the petal glyph, which forms a two-stage combined transition [HR07], as shown in the timeline in Figure 3. Here, we assume that level X stands for a higher (abstract) zoom level, while Level $X+1$ represents a lower (detailed) zoom level. The intuition behind such a design is that the convex hulls can facilitate the context preservation since it indicates the spatial scope of the corresponding glyph. We note that X is not a fixed or predefined value. It represents any zoom levels that are involved in the analysis process in general. In our system, the users can toggle the spatial context preserving technique on or off. We describe the details of the two-stage transitions below. The combined transitions are slightly different between the zoom in and zoom out operations:

Zooming in: As shown in Figure 3b and Figure 5, when the analyst zooms in on the map (Figure 5(t1)), the glyphs in Level X fade out while the glyphs in Level $X+1$ fade in (Figure 5(t2)). The convex hulls in Level X then fade out, while those in Level $X+1$ fade in (Figures 5(t4 and t5)). During this process, the glyphs at the lower level are shown, meanwhile the convex hulls at the higher level still keep visible to maintain the spatial scope of the corresponding glyphs at the higher level (Figure 5(t3)).

Zooming out: As Figure 3c shows, the convex hulls in Level $X+1$ fade out, while the convex hulls in Level X fade in. Then the glyphs in Level $X+1$ fade out, while those in Level X fade in. The convex hull of the higher level are visualized before the glyphs at the lower level fade out. Similarly, the convex hulls of the higher level are visualized before the glyphs at the lower level fade out.

Additionally, in order to maintain the context for streaming data, we apply a similar technique where the previous visuals on the map fade out, while the new visuals fade in (G4). This is performed after every t minutes (i.e., refresh rate of the system), after which the system pulls new data from the data server for the previous time window of T minutes. We set t to 5 minutes and T to 10 minutes by default, and provide users with control over these parameters.

5 Case Studies

We present case studies to demonstrate our work in this section.

5.1 Boston Marathon Bombing

The Boston Marathon is the oldest annual marathon and remains one of the largest athletic events in the world. On April 15, 2013, two bombs exploded near the finish line during the event at 2:49 pm EDT that killed 3 and injured about 260 people. In this section, we demonstrate our work by utilizing Twitter data surrounding the Boston Marathon bombing event (Figure 6). In order to demonstrate our system from the perspective of real-time analysis, we replay the event and Twitter stream to simulate the interactive analysis process utilizing the streaming data. For reference, we have highlighted the location of where the bombs exploded on the map in the figures. In this hypothetical scenario presented, we assume that an emergency response manager is interested in the *injured people*, *response agencies in place*, *infrastructure damage*, and *safety and security* categories (Figure 6) for his analysis of the event. Note that although the case study we've presented focuses on only these particular categories, the system allows users to interactively select, remove, or modify any of the categories on demand.

Figure 6(A) shows a snapshot of the map view of our system 30 minutes after the explosions. The emergency manager initially monitors the Twitter traffic at the city level. After a few moments,

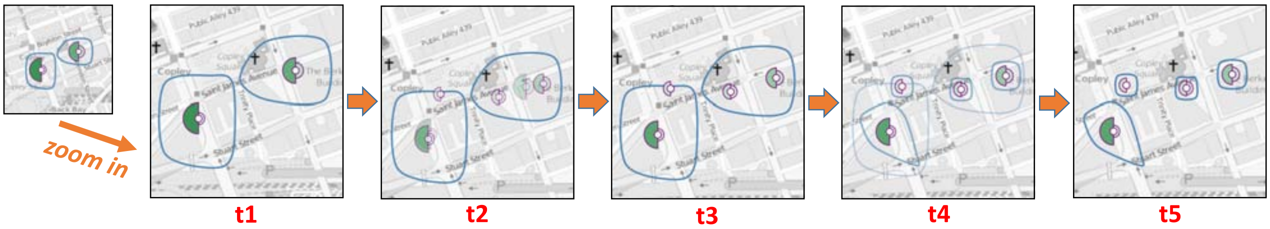

Figure 5: *An example of the animated transition in a zooming-in scenario. The transition states correspond to the timestamps in Figure 3b.*

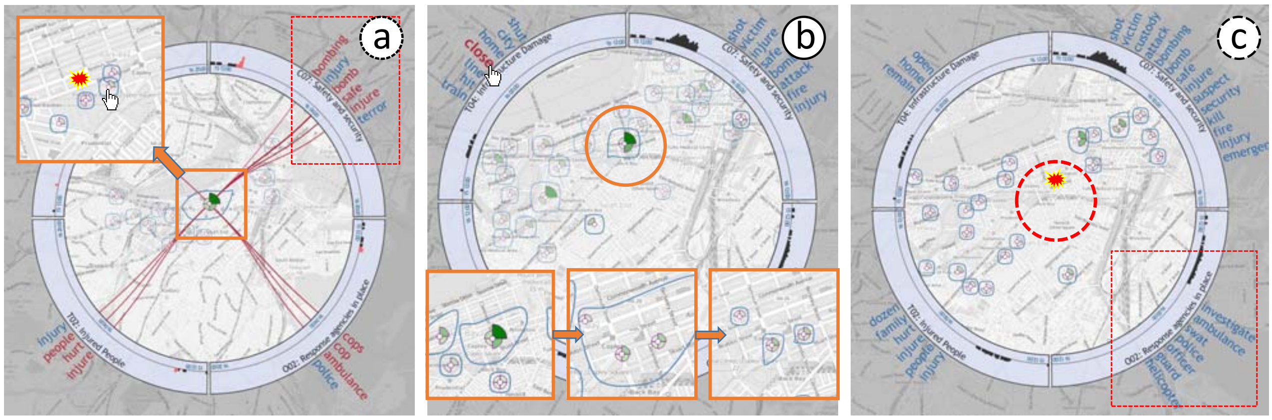

Figure 6: *Demonstration of our system using the Boston Marathon bombings incident. Screenshots of our system after 30 minutes (A), 1 hour (B), and 2 hours (C) of the bombings are shown.*

he notices a spike in Twitter activity related to disaster and emergency management on the map, with the *safety and security* category taking prominence around certain regions. He also notes that the major keywords that are trending in the spatial lens, include the words *bomb*, *safe*, and *injure*. He then focuses on a huge cluster located around the downtown area and zooms in. The system provides a smooth transition between the abstract and detailed aggregation levels in order to maintain a visual continuity. With the help of the context preserving transition, it is readily apparent that this large cluster splits into a few smaller ones near the marathon's finish line. He then clicks on the corresponding petal at this location and finds a few tweets that mention a bomb has just exploded.

After nearly 1 hour, the manager notes that more clusters are beginning to appear in neighboring regions. While the *safety and security* related category still remains the most prominent, the other selected categories start to gain prevalence ex post facto (e.g., *injured people*, *response agencies in place*, *infrastructure damage*). The manager hovers on a few keywords including *shut*, *close* and *train* in the *infrastructure damage* category. The system highlights the corresponding clusters in the map view, as shown in Figure 6(B). By further examining the clusters at the finer spatial granularity, the manager realizes that transportation logistics including the airport and the subway are shut down by law enforcement.

Figure 6(C) shows a snapshot of the system 2 hours after the explosions. The manager easily discovers from the map view that no tweets are posted near the location of the bombing. This result is to be expected, as law enforcement cleared the area immediately surrounding the explosions. The manager also notices that more keywords related to the *response agencies in place* category appear in the spatial lens, such as *swat*, *investigate* and *helicopter*. This further reflects the priority of the emergency responders shifts from response to investigation after the bombing.

5.2 Keene Pumpkin Festival Riot

In October 2014, riots occurred in Keene, NH when the city was holding its annual pumpkin festival. Here, we assume that an emergency response manager is monitoring for the following categories during the event: *personal response*, *response agencies in place*, and *safety and security* (Figure 1). She monitors the microblog stream data based on a sliding window of 90 minutes and notices a spike related to the *safety and security* category and the *response agency in place* category in the time-series view (Figure 1(b)). The category tree also highlights the prominence of these specified categories (Figure 1(c)). The analyst further examines the map view and identifies a large spatial cluster near Keene State College (Figure 1(e)). She zooms into a detailed view and hovers over the cluster in the lens, and notes that the keywords *riot*, *arrest*, and *helicopter* are highlighted. She also notes that law enforcement used tear gas to subdue the rioters (the *response agency in place* category in Figure 1(e)). During this time, the microblog users express their negative attitude towards the law enforcement actions (as noted from the keywords in the *personal response* category in Figure 1(e)). Thus, the system provides an increased situational awareness for safety and security relevant incidents during the event.

6 Evaluation

We conducted two independent user studies to evaluate our petal-based visual design and the animated transition technique, which are described in Section 6.1 and Section 6.2. We also interviewed domain experts and present their feedback in Section 6.3.

6.1 User Study: Petal-Based Glyph Design

The key visual component of our system that allows analysts to understand the distribution of multiple categories of the spatial clusters over geospace is the petal glyph. In our study, we investigated which design is most effective to present the categorical information among our three alternatives (Section 4.3.2). Specifically, we were interested in the following aspects: (1) Which design is the best for visualizing the value of the individual category (i.e., individual petal)? (2) Which design is the best for visualizing the value of the aggregated categories (i.e., the overall glyph)?

6.1.1 Setup

We recruited 20 participants (age range of 20 and 46) from various backgrounds for our study. Each participant was paid $5 and spent an average of 15 minutes on the experiment. Participants were provided with an introduction of the three different design choices and a short training session, followed by 21 multiple-choice questions with 7 questions for each visual design (the questions were randomly ordered). For each question, the participants were shown one or two glyphs on the map view. Three types of questions were asked during the experiment: (1) For two petals in the same cluster, which one represents a higher value? (2) For two petals in two different clusters, which one represents a higher value? (3) For two clusters, which one represents a higher overall value?

We recorded the correctness and elapsed time for each question. In this post-experiment survey, we also asked the participants to select the best/worst design for visualizing the value of an individual category (petal) or the aggregated cluster (the overall glyph).

6.1.2 Results

Figure 7 shows the accuracy and completion time of the three visual designs. Based on the accuracy results (Figure 7a), we find that Design A (Figure 4a) has the highest accuracy (89.3% on average), followed by Design C (Figure 4c) (70% on average). Design B (Figure 4b) has the lowest accuracy (45.7% on average). In terms of the task completion time, we find no significant differences among the three designs. Most of time spans were between 6 and 12 seconds.

In the post-experiment survey, 15 participants (75%) agreed that Design A was the best to visualize an individual category. Many participants reported that introducing the size to encode the values helped them differentiate the adjacent petals more easily. Some participants also mentioned that they had difficulty in differentiating subtle color changes in Design B, since the petal color was being affected by the color of the inner circle or the color of the adjacent petals. In terms of the overall glyph, 10 participants (50%) found that Design C (Figure 4c) was the best for encoding the overall area since they did not need to mentally sum up all the petals (Design A), and the outer petal colors can also effect the perception of the inner circle (Design B).

6.2 User Study: The Animated Transition Technique

A key component of our system that allows analysts to better explore the spatial clusters at different scales is the animated transition technique. In order to evaluate the efficacy of this technique,

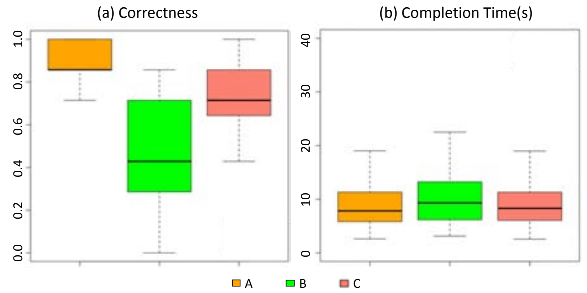

Figure 7: *The evaluation results of different petal designs.*

we investigated whether conventional zooming or the proposed animated transition technique is more effective to help users maintain the spatial context when they navigate through multiple scales.

6.2.1 Setup

We recruited 20 participants (age range of 23 and 30) for this study. The experimental setup was similar to our previous study described in Section 6.1.1. We asked the participants 20 Yes-No based questions, where the system randomly applied either the conventional zooming or the proposed animated transition technique for each question. The duration of the animated transition was set to be 3 seconds. The participants were shown several clusters on the map, and could zoom in/out by only one level (i.e., only two zoom levels were provided). They were asked whether a highlighted cluster (pointed to by a black arrow) at one level belonged to another highlighted cluster at the next level (either at a zoomed in or out level). The participants were allowed to zoom in/out multiple times. We recorded the correctness, elapsed time, and the number of zooming operations for each question.

6.2.2 Results

Figure 8 shows the results of conventional zooming and the animated transition technique. Based on the accuracy results (Figure 8a), we find that the animated transition technique had higher accuracy (90% on average) than conventional zooming (80% on average) ($p < 0.05$). We also find that participants performed fewer zooming interactions when they used the animated transition technique (2 on average) versus conventional zooming (3 on average) (Figure 8c) ($p < 0.0001$). For task completion time, they spent an average time of 18.7 seconds with conventional zooming versus an average of 20.7 seconds with animated transition ($p < 0.05$) (Figure 8b). These results show that although the animated transition takes slightly longer, it attains higher accuracy with lower interaction overload, as compared to conventional zooming. We also notice that the accuracy in both cases are relatively high. We believe this is because that since our visualizations are based on the geographical map, the users utilize the map features (e.g., roads, buildings) to preserve the context across different scales, particularly in the conventional zooming scenario.

In the post-experiment survey, 16 participants (80%) agreed that the animated transition technique was more effective in helping to maintain a spatial context when they navigate across the different spatial scales. Many participants reported that this design reveals the relationships of the spatial clusters at the consecutive zoom levels through the smooth visual change. As one participant noted,

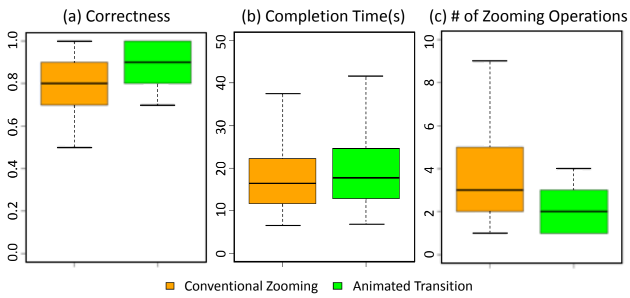

Figure 8: *Evaluation results: Conventional zooming vs. animated transition.*

the animated transition technique makes it easy to identify which clusters get merged when zooming out, and know where a cluster gets dispersed when zooming in. 4 participants preferred the conventional zooming techniques. Their major reason was being habituated to the conventional technique. One participant also suggested that it would be an interesting topic to evaluate how different time spans influence the performance of the animated transition.

6.3 Domain Expert Feedback

Our system was assessed by seven analysts at one of our partner law enforcement agencies. The analysts stressed the need for such a system that enables them to quickly gain situational awareness from social media channels for their areas of responsibility (AOR). They especially liked that the system provided them with a quick overview of their AOR for their emergency management, safety, security, and crisis related needs, while allowing them to drill down to specific regions of interest on demand (TS). They welcomed the fact that the map view was the main prominent view in our system (TS). They liked that the system provided preset classifiers for crisis and emergency management, with the ability to modify the keywords and create new keyword categories on demand (TF).

The analysts had positive feedback for the spatial lens feature of the system. They liked that the lens was segmented into sectors based on their selected categories, and had time series views within corresponding arcs that showed their evolution over time (TT) (Figure 2a). They did note, however, that the spatial lens became crowded as more category dimensions were added (more than approximately 8-10 categories). They noted that this made it difficult to visually relate the inner glyph visualizations to their corresponding topic categories. This highlights an important limitation of our system. Although the interactive thread visualizations (Figure 1e) have been designed to mitigate for this concern, the scalability of our spatial lens/petal glyph visualization in terms of the maximum number of categories that are discernible remains to be tested. We leave this as future work.

The analysts also had positive feedback regarding the petal view visualizations of the system. One analyst remarked that he especially liked the interactive thread visualizations and how the keywords on the outer periphery of the corresponding topic were highlighted with this interaction (TQ). This provided him with a quick way to discern which keywords were trending for his region of interest. He further advocated that the system should allow them to go in the reverse direction where they could hover over the keywords of the outer spatial lens and have threads lead into the corresponding inner petal glyphs on the map. We leave adding this feature into our system as future work. Furthermore, they suggested that the font size of the keywords of the spatial lens be used to encode their frequency (as in a traditional word cloud). We agree with this suggestion, and leave this task for the future as well. From the three petal view visualizations supported in our system (Figure 4), they preferred the petal glyph visualization (Figure 4a). We note that this is in line with the results obtained from our user study.

With regards to our context preserving approach across the different scales (Section 5), they noted that the animated transitions made it easy for them to mentally connect the petal glyphs across the different levels (TC). They also found the convex hull visualization (Figure 5) to be important to connect the petal glyphs to their respective geospatial regions (TC). Finally, they noted that the animated transitions between the visualization states in streaming mode helped them maintain a visual continuity between the states (TR). This feature, in addition to the ability to scroll across time using the interactive time series view, enabled them to perform both real time and retrospective analysis for their AOR (TT, TR).

7 Conclusion and Future Work

In this work, we have presented our visual analytics framework for improving situational awareness across multiple geospatial scales by utilizing microblog data. Our work focuses on the problem of multiscale analysis of geospatial data by performing analysis at appropriate data aggregations and granularity. We identify the major limitations of existing systems and identify design goals for our system. Our system provides a flexible navigation technique to maintain a cohesive thematic context of the transition between the different geospatial granularity levels and streaming data states. Our system has been designed in close collaboration with our law enforcement and emergency management partners, and is comprised of several coordinated views that support the navigation across different information dimensions.

Our future work includes expanding on the other facets of the problems of scale, including temporal, spatiotemporal, multidimensional data, user, and problem scales. We plan on investigating the temporal evolution of (possibly non-static) spatial data clusters. This remains to be a challenging task, and requires further research from the visual analytics community. Finally, we plan on factoring in the influence and correlations among the different spatiotemporal attributes in order to explore causal relationships for further improving situational awareness.

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