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Context-Preserving Visual Analytics of Multi-Scale Spatial Aggregation.

Jiawei Zhang
Purdue University

CONTEXT-PRESERVING VISUAL ANALYTICS OF MULTI-SCALE SPATIAL AGGREGATION

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STATEMENT OF DISSERTATION APPROVAL

Dr. David Ebert, Chair

School of Electrical and Computer Engineering

Dr. Niklas Elmqvist

College of Information Studies, University of Maryland

Dr. Edward Delp

School of Electrical and Computer Engineering

Dr. Alex Quinn

School of Electrical and Computer Engineering

Approved by:

Dr. Venkataramanan (Ragu) Balakrishnan

Head of the Department Graduate Program

To my parents and girlfriend.

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ABSTRACT

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Spatial datasets (i.e., location-based social media, crime incident reports, and demographic data) often exhibit varied distribution patterns at multiple spatial scales. Examining these patterns across different scales enhances the understanding from global to local perspectives and offers new insights into the nature of various spatial phenomena. Conventional navigation techniques in such multi-scale data-rich spaces are often inefficient, require users to choose between an overview or detailed information, and do not support identifying spatial patterns at varying scales. In this work, we present a context-preserving visual analytics technique that aggregates spatial datasets into hierarchical clusters and visualizes the multi-scale aggregates in a single visual space. We design a boundary distortion algorithm to minimize the visual clutter caused by overlapping aggregates and explore visual encoding strategies including color, transparency, shading, and shapes, in order to illustrate the hierarchical and statistical patterns of the multi-scale aggregates. We also propose a transparency-based technique that maintains a smooth visual transition as the users navigate across adjacent scales. To further support effective semantic exploration in the multi-scale space, we design a set of text-based encoding and layout methods that draw textual labels along the boundary or filled within the aggregates. The text itself not only summarizes the semantics at each scale, but also indicates the spatial coverage of the aggregates and their hierarchical relationships. We demonstrate the effectiveness of the proposed approaches through real-world application examples and user studies.

1. INTRODUCTION

Spatial clustering is an important component of the spatial data mining field [1], which generally refers to approaches that group similar spatial data points into classes. Spatial clustering provides valuable insights into the spatial data distribution, characteristics of the individual groups, as well as trends and anomalies within the dataset.

The varying scale is an inherent property in spatial cluster analysis (e.g., [2–5]). Spatial datasets can be aggregated by varying granularity levels that are determined by a distance measure between pairwise data points in the clustering process. Accordingly, the clustering results often vary significantly across different scales. For example, Figure 1.1(a) shows an aggregated keywords visualization (Tag Map) on a geographical map. Zooming into the map shows lower-level sub-events [6]. Figure 1.1(b) shows different spatial clustering results at consecutive zoom levels. Large clusters at a higher zoom level split into multiple smaller ones at lower levels [7]. Figure 1.1(c) shows clustering results of spatial statistics under different geographical resolutions (left: county level, right: state level) [8].

Although the variation in scale provides a unique perspective to characterize the spatial data attributes [3], it also poses great challenges to casual experts in various fields where the multi-scale analysis is critical to their domain-specific tasks. On the one hand, the multi-scale analysis requires data aggregation at different levels, making the analysis space more complicated. On the other hand, since the analysis can produce different results at different scales, choosing the proper scale and interpreting the varying results become non-trivial tasks.

In this chapter, we first characterize the challenges of multiple spatial scales to solve interaction overload and cognitive overload in Section 1.1. Then we propose our visual analytics solutions to the above challenges in Section 1.2, and present

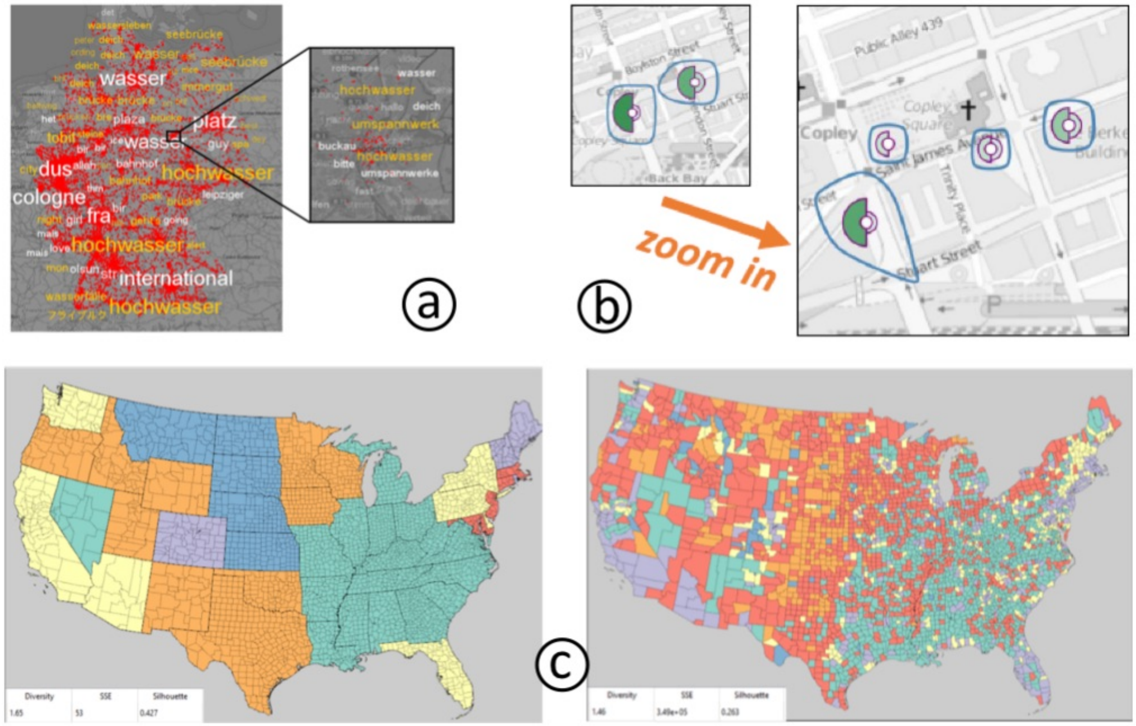


Fig. 1.1. Examples of multi-scale clustering: (a) Keywords are aggregated and displayed on the map. Zooming into the map shows low-level sub-events [6]. (b) Spatial clusters are visualized at consecutive zoom levels. Large clusters at a higher zoom level split into multiple smaller ones at a lower level [7]. (c) Clustering results of demographic statistics under different geographical resolutions (left: state level, right: county level) [8].

our thesis statement in Section 1.3. Finally, Section 1.4 provides an outline of the following chapters in this document.

1.1 The Challenges of Multiple Scales

Spatial scales typically range from an overview (the global view) to low-level details (individual data points). On the one hand, from a global perspective, the entire data are aggregated as a single object, which may provide overall summary information, but is too coarse-grained to reveal potential spatial patterns. On the other hand, from the detail perspective, each data point is regarded as one cluster, where no actual aggregation exists for analysis. Therefore, users have to identify the appropriate scale between these polar extremes that can best characterize the hidden spatial patterns.

Conventional navigation paradigms such as the zooming operation require the users to switch to individual scale in order to understand the analysis result at that scale, adding significant **interaction overload** to the analysis process. Moreover, in most multi-scale analysis scenarios, understanding how spatial attributes and patterns evolve across scales is critical. For example, crime in certain regions may be unnaturally high; however, this may be explained if local geospatial patterns (e.g., petty thefts at the mall) are analyzed. Hence, users require the ability to effectively correlate analytical results between different scales. With conventional navigation paradigms, users have to remember the analysis results at different scales during navigation. Mentally correlating those results further increases their **cognitive overload** in the analysis process.

1.2 A Context-Preserving Visual Analytics Solution

Having discussed the major challenges with multi-scale spatial aggregation, we now describe our visual analytics solutions that attempt to resolve the aforementioned challenges and facilitate more effective multi-scale navigation and exploration. The fundamental idea of our approaches focuses on preserving the context of different scales as users navigate across the multi-scale aggregation space. With these context-preserving approaches, users are able to simultaneously understand, correlate and compare the structure of the space at different levels without mentally memorizing the results. This can significantly reduce the cognitive overload. Meanwhile, since the context of other scales is preserved, users do not need to navigate to the corresponding scale. As such, the interaction overload is also reduced.

Our approaches have been guided by the hierarchical aggregation model [9] that consists of two primary stages: (1) Data space aggregation; (2) Simplified visual representations of aggregates in the visual space. First, we model the multi-scale spatial clusters as a hierarchical representation where each scale (zoom level) maps to a specific layer in the hierarchy (*data space aggregation*). Then we design a set of visual analytics techniques that present the hierarchical structure in the visual space and maintain the context at different spatial scales (*simplified visual representations of aggregates in visual space*).

We propose two context-preserving visual analytics components to support more effective multi-scale navigation and exploration. These two components can be seamlessly integrated to strengthen the context preservation. First, we propose a visual summarization method that combines the results of multiple spatial scales into a single visual display. We design a boundary distortion algorithm to minimize the visual clutter caused by overlapping aggregates. We also explore several visual encoding strategies to enhance the understanding of statistical and hierarchical relationships of aggregates and provide guidelines in terms of using different visual dimensions such as color, transparency, shading, and shapes for encoding multi-scale aggregates. To further support semantic exploration within the multi-scale space, we design a series of text-based encoding and layout methods such that the text itself not only summarizes the semantics at the individual scale, but also indicates the spatial coverage of the aggregates and their underlying hierarchical relationships. Second, we propose a transparency-based animated transition design that maintains a smooth and continuous transition when users switch to adjacent scales. This design has been motivated by the fade-in/fade-out transition in computer graphics research [10]. When users 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. Our proposed approaches have been evaluated through domain expert feedback and several controlled laboratory experiments. The results indicate that with these visualization and interaction designs, both interaction overload and cognitive overload are significantly reduced as users navigate, correlate, and explore the spatial aggregates at multiple spatial scales. Our techniques have also been integrated into several visual analytics systems to facilitate more effective exploration and analysis of spatial dataset including location-based social media data and crime report data.

1.3 Thesis Statement

The thesis statement of this dissertation is as follows:
Coupling multi-scale spatial aggregates in the same visual display enables users to perform analysis over the multi-scale hierarchy with higher accuracy and speed than conventional zooming techniques. Specifically, we claim:

- *Combining the boundaries of multi-scale aggregates into one visual space without visual occlusion and utilizing the boundaries to encode information (TopoGroups [11]) enable context preservation of the hierarchical and categorical information associated with spatial aggregates.*

- *Applying text-based encoding and layout methods to the multi-scale aggregates (TopoText [12]) helps preserve the context of semantic information across scales.*

- *The animated transition technique [7] supports users to maintain the context using a smooth and continuous visual transition when zooming between adjacent scales.*

The main contributions of this work include the following:

- Design of a visual analytics approach that couples multi-scale spatial aggregates into a single visual display in order to preserve the context of multi-scale navigation.

- Design of a boundary distortion algorithm in order to remove the visual clutter caused by overlapping aggregates.

- Design of a set of text-based encoding and layout strategies to facilitate semantic exploration within the multi-scale space.
- Evaluation of visual encoding strategies based on multiple visual dimensions including color, transparency, shading, and shapes, in order to study which designs to use depending on the complexity of the clustering hierarchy and the semantic information.
- Design and evaluation of a transparency-based spatial context preservation technique that maintains a continuous transition when switching between spatial granularity levels.
- Proposal of several glyph-based visualization techniques and evaluation of their efficacy in depicting the categorical distribution of spatial aggregates over the selected geospatial areas of interest.
- Design and implementation of several visual analytics systems that apply the context-preserving techniques to facilitate spatial data exploration at multiple scales, with an emphasis on location-based social media analysis and crime data analysis.

1.4 Outline

This document has been organized in the following chapters. Chapter 2 discusses the background and related work in this research domain. Chapter 3 describes the data aggregation and visual representation of the multi-scale spatial aggregation. Chapter 4 presents our context-preserving visualization that combines multi-scale aggregates in the same visual display. Chapter 5 presents our extension of the context-preserving technique that supports effective semantic visualization using text-based encoding strategies. Chapter 6 presents our transparency-based visual design that provides a smooth visual transition across adjacent scales. Finally, chapter 7 concludes this thesis and outlines the planned future work.

2. BACKGROUND AND RELATED WORK

To facilitate effective exploration of geospatial datasets at multiple spatial scales, researchers in the visual analytics field have proposed various visual and interaction methods. Conventionally, interactive maps allow users to explore geospatial datasets at multiple levels of aggregation by directly zooming in and out of a region of interest. As an intuitive approach, it has been used extensively in various visual analytics frameworks. However, there exist several limitations when utilizing interactive maps to support multi-scale analysis. On one hand, users need to switch between different spatial scales in order to observe the results at different scales, which adds a heavy interaction overload. On the other hand, since the map typically only visualizes the analysis results at the current scale, users can easily lose the semantic context of the previous scales as they interact across multiple scales.

In this chapter, we first discuss state-of-the-art visual analytics of multiple spatial scales. This part includes three aspects: multi-scale interactive navigation, multi-scale visual summary, and context-preserving approaches. Then we discuss research related to visualization of hierarchical and spatial aggregation. Final, we discuss text-based visualization techniques of spatial data, which motivates our work on text-based encoding and layout strategies for multi-scale semantic exploration.

2.1 Multi-Scale Navigation

The interactive map system is a common technique to support exploration of multi-scale spatial aggregation [13–16]. For example, Bosch et al. [13] propose a real-time visual analytics system, *Scatterblogs2*, which allow users to customize message classification and navigate across multiple spatial scales in order to discover events at different aggregation levels. Cho et al. [14] propose VAiRoma, a highly interactive spatiotemporal visual analysis system that explores major events in Roman history. Chang et al. [16] explicitly visualize the focal point of the viewer on top of the map surface in the 3D space, and allow the users to interactively change the position of the focal point in order to navigate across different scales. Furthermore, much research has been explored to investigate the effective navigation paradigms and commonly used navigation operations such as zooming and panning [17–19].

In order to reduce the interaction overload arisen in common map systems, and maintain the semantic context, researchers have proposed several frameworks that juxtapose multiple maps at different scales. In this way, users are able to visually compare the analysis results across different scales without the need to perform numerous zooming operations.

Ferreira et al. [20] develop an interactive system to visualize spatiotemporal distributions of birds. Their system provides multiple coordinated geographical map views to facilitate the effective visual comparison of different spatial regions across multiple scales. Javed et al. [21] propose a novel visual design named stack zooming. As users navigate on the map from higher to lower scales, the corresponding geographical visualizations stack on each other to indicate the hierarchical relationships across multiple scales. The idea of stack zooming has also been applied to time-series dataset to enhance the ability of multi-scale and multi-focus exploration [22].

Besides the common applied juxtaposition-based approach, Javed et al. [4] apply a gravity model to facilitate more effective multi-scale navigation especially in a huge navigation space. The approach constructs a gravity field based on points of interest in the visual space, which guides and speeds up the navigation to targeted regions. Zhao et al. [15] propose *TrailMap* that automatically generate implicit bookmarks for previously visited locations in a multi-scale map in order to allow users to review interaction history. The approach significantly reduces the overload caused by revisitation in the information-seeking process.

2.2 Multi-Scale Visual Summary

In contrast to the aforementioned interaction-based approaches, there also exist visual approaches that create summaries of the analysis results at multiple scales in a single visualization. This approach reduces the overload caused by jumping across different views for visual comparison. It also effectively maintains the context of exploration as the users are able to observe the multi-scale analysis results in a single visualization without the need to memorize the previous results.

Dykes and Brunsdon [23] propose the concept of geographically weighted interactive graphics (*geowigs*) that visualize the relationships between the statistics and the geographical attributes. Specifically, they propose *scalogram*, which combines the statistical results at different geographical scales in the same visualizations using a series of line charts and box-plot diagrams. Similarly, Turkay et al. [24] visualize the multivariate geographical dataset at different scales using a single chart, which they name an *attribute signature*. This technique summarizes the multi-scale statistical results in a static visualization that avoids the tedious zooming operations and meanwhile maintains the context of different scales. Goodwin et al. [25] propose a set of glyph-based design to encode the correlations of a given variable at different scales. The proposed glyphs provide an effective visual summary of statistics from global to local perspectives. They are then embedded into a matrix view to indicate the correlations of multiple variables. Delort [26] establishes a hierarchical clustering tree based on the spatial clustering results. The approach enables users to interactively select multiple cluster nodes at different levels (scales) that do not have parent-children relationships, and the map view visualizes the selected clusters using a voronoi partition. The visual clutter in the voronoi diagram is highly reduced as there exist no parent-children relationships among different cluster nodes. Rosenbaum et al. [27] apply a similar approach to exploring and comparing election results at different levels of administrative units (country, state, county, etc.).

2.3 Context-Preserving Visual Design

Overview+Detail and Focus+Context techniques [28] have been widely applied in the visualization field to provide efficient context preservation. Overview+detail separates the focus and context into separate views, while focus+context integrates the focus within the context, often by applying distortion such as fisheye distortion [29,30].

Most approaches that have been proposed in this domain can be related to one of these categories. For overview+detail paradigm [31–33], the aforementioned stack zooming technique [34] has been successfully applied to both time-series exploration as well as geographical navigation [21]. In terms of focus+context, Gutwin [35] improves fisheyes views by dynamically adjusting the distortion effect based on the movement of the cursor to allow users to more effectively target objects. Pietriga and Appert [36] explore and evaluate several visual attributes including transparency, distortion and time to control the transition between the context and the focus. The opacity of the context visualization gradually decreases as it approaches the center of the focus region, while the opacity of the focus increases accordingly. Furthermore, the distortion and transparency are achieved through a smooth transition instead of an abrupt change to provide context preservation.

Variants of fisheye techniques have been applied to various usage scenarios [37–40]. In the system diagram visualization, Cohe et al. [37] propose a topology-aware fisheye technique that integrates the focus+context visualization in the diagram, meanwhile maintains the readability of the diagram by utilizing the topology of the diagram. Sun et al. [40] distort and expand routes within a certain region of interest, and embed time-series visualization such as line charts or bar charts to reveal the temporal information within that region. Other related examples can be found in the survey paper by Tominski et al. [41].

2.4 Visualization of Hierarchical and Spatial Aggregation

Hierarchical datasets are common across various research fields and disciplines. Major visualization techniques for hierarchical structures includes node-link diagrams, space-filling visualization and hybrid techniques. In the node-link-based representations, the node usually represents an individual aggregate, and the link represents a parent-child relationship among different aggregates. Various visualization and layout methods have been proposed in this area, including orthogonal layout (dentrogram, icicle tree, etc.) [42–44] and radial layout [45, 46] visualized in either 2D or 3D space [47]. While node-link diagrams with a tree-like layout or radial layout naturally depict the hierarchical relationships of individual aggregates, it potentially produces visual overlapping [9] and the visual space is not fully utilized. In terms of the space-filling visualization, treemap-based approaches [48,49] have been largely explored and applied to various domains. This technique creates space-constrained hierarchical visualization by filling the space with nested rectangles. Each rectangle represents an individual aggregate, and sub-aggregates are embedded inside the parent rectangle. The size of the leaf nodes is proportional to a specific dimension corresponding to the aggregate. Furthermore, Demain and Fruchter [50] propose the nested treemap that adds padding to adjacent rectangles to emphasize the parent-child relationship. Lu and Fogarty [51] propose cascaded treemap, which further stacks child rectangles on top of the parent to produce a 3D visual effect and help users visually distinguish children and their parents. Blanch and Lecolinet [52] extend treemap to support multi-scale navigation by integrating zooming operations. Inspired by the aforementioned techniques, research has been also explored in terms of combining two techniques in order to fully take advantages of both approaches [53–55].

Previous research has explored to visualize the spatial aggregates on the geographical map at either a single scale or multiple scales. Typical visual representations include heat maps [56, 57], icons or glyphs [7, 58], grids [59], and Voronoi diagrams [26]. These methods have different advantages in terms of visualizing the single-scale clusters; however, they pose great challenges when applied to a multi-scale scenario. In particular, since the cluster at one scale can contain or overlap with another cluster at a different scale, the visual clutter generated by overlapping visualizations hinders effective visual perception and causes heavy cognitive overload. Hence, choosing the proper visual representation that can potentially reduce the overlapping issue is critical in a context-preserving approach.

2.5 Text-based Visualization Techniques for Spatial Data

Typical approaches to visualizing textual information extracted from spatial data visualize them in a view that is physically separate from, but linked to, the geographical space [7,60,61]. However, they usually require the users to switch between multiple views and perform additional interactions in order to correlate the spatial and textual dimensions, potentially adding to the cognitive load of the user. Research has explored combining text within the geographical space in order to reduce the overload. One common technique is Tag Maps [13, 62–65], a variant of tag clouds that appropriately positions the words on a map to indicate their geographical distribution and prominence. Other work also utilizes the spatial dimension for visualization, where the position of the textual features does not necessarily represent their geographic locations. For example, Nguyen et al. [66, 67] sort words based on the user-defined order and position the text on the map along the vertical skeleton of the geographical boundary. Brath and Banissi [68,69] extend common set visualization techniques [70] to coupling textual attributes.

Text-based design space involves a rich set of the visual attributes. Among them, position is probably the most critical aspect to consider as it potentially indicates the latent relationships among different text entities and can reflect other information dimensions when properly encoded. When positioning text, Spatial constraints commonly exist in various text-based visualizations. The most well-known technique, tag clouds [71], and its descendants [39, 65, 72–76], typically generate a compact and occlusion-free word layout in which the feasible position of the individual words is constrained by the existing words in the visual space. Other spatial constraints are defined based on the additional information dimensions associated with text, such as the geometric elements in either 2D or 3D space, where text labels provide supporting information. Wong et al. [77] combine text and visual elements (e.g., nodes and edges) in a graph in order to recycle the space resource and avoid visual clutter among multiple elements. Maharik et al. [78] propose digital micrograms that creates calligrams (text arranged to form a shape that illustrates its semantic meaning, which has been crafted by artists and poets even before the emergence of computer graphics) by calculating the vector fields for the graphical elements in the image in order to guide the text layout. Xu and Kaplan [79] introduce Calligraphic Packing, a technique that divides an image into segments and warps and fills letters into each segment. Afzal et al. [80] automate typographic maps [81], in which the text layout is constrained by the underlying geographical elements. Similarly, Godwin et al. [82] apply the typographic map to visualizing semantic topics extracted from social media [82]. Moreover, the spatial constraints commonly exist in various map design applications, where the label placement is carefully executed in order to indicate the feature locations and avoid potential ambiguity or contradiction [83–86].

3. MODELING AND VISUALIZING MULTI-SCALE SPATIAL AGGREGATION

Our technique consists of two major steps, following the hierarchical aggregation model proposed by Elmqvist and Fekete [9]. First, we model the multi-scale spatial clusters as a hierarchical representation, where each scale (zoom level) maps to a specific layer in the hierarchical structure. This step has been described as *data space aggregation* [9]. Second, we design our visual analytics approach that allows users to explore the spatial clusters both hierarchically and spatially, while maintaining the context of navigation at different spatial scales. This step has been described as *simplified visual representations of the aggregates in visual space* [9].

3.1 Data Space Aggregation: A Hierarchical Clustering Approach

Geospatial datasets are typically represented by latitude and longitude in a geographical coordinate system, and can be transformed into planar coordinates based on map projection methods. In our technique, the geo-spatial data points are projected into 2D screen space coordinates, where the clustering is performed. For the clustering procedure, we utilize the common algorithm where each data point only belongs to one cluster at a single scale, e.g., the DBSCAN [87] or the k-means algorithm. We also note that the clustering process maintains a consistent distance measure (Euclidean distance in screen space) across different spatial scales (zoom level). Under such conditions, geospatial data clustering highly depends on the spatial scales (zoom levels) of the geographical space. As the spatial scale varies from a higher (abstract) level to a lower (detailed) level, the screen space distance of any pair of geo-spatial points increases accordingly. Intuitively, the clusters at a higher

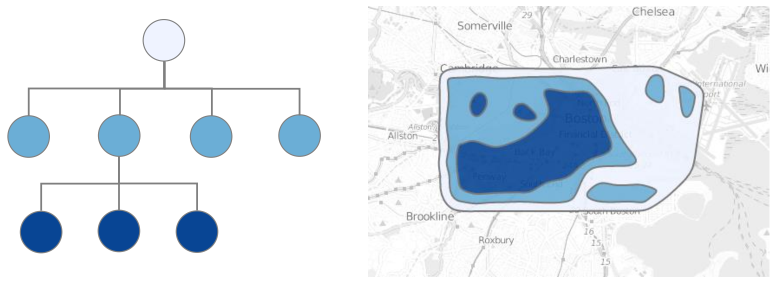


Fig. 3.1. The hierarchical (left) and the corresponding geospatial (right) representations of the multi-scale aggregates

level split into smaller ones at a lower level. Hence, the clusters at different spatial scales naturally form a hierarchical structure (dendrogram) as shown in Figure 3.1.

We represent the multi-scale aggregates using a tree structure that naturally depicts the hierarchical relationships of the clusters at different scales. In this hierarchy, nodes represent individual spatial clusters, while the edges represent the parent-child relationships of clusters at adjacent spatial scales. The clusters that are formed at the same spatial scales correspond to the nodes that have the same depth in the tree.

3.2 Representation in Visual Space: A Boundary-Based Representation

Typical visual representations of spatial aggregates include heatmap, icons or glyphs, screen space grids, and Voronoi diagrams. These methods are commonly applied to visualize single-scale aggregates. However, in terms of the multi-scale aggregates, these methods usually generate visual clutter that hinders effective visual analytics of multi-scale aggregates.

To this end, the visualization for the multi-scale aggregation hierarchy in our technique adopts a boundary-based visual representation using an implicit curve for each aggregate in the hierarchy. The boundary represents the area occupied by the points of a specific aggregate. To generate the boundary of aggregates at a single scale, we follow the concept of concave hull in computational geometry [88, 89]. We first

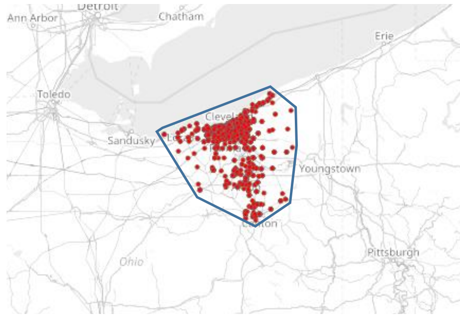


Fig. 3.2. The boundary-based representation of a spatial aggregate

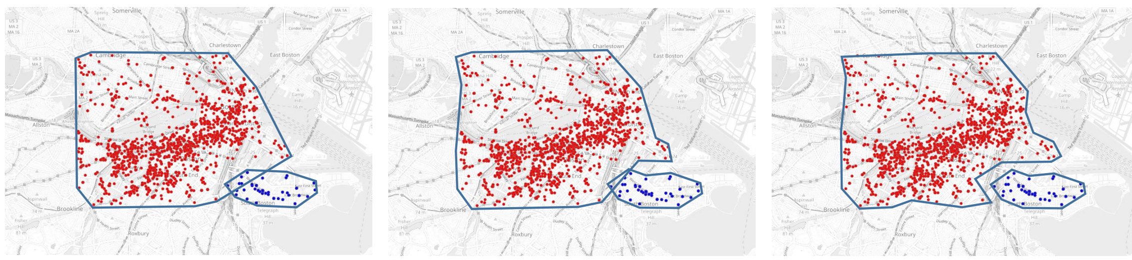


Fig. 3.3. The concavity of the polygons is iteratively adjusted to avoid overlap.

calculate the convex hulls for all aggregates at the current scale (Figure 3.2) and detect potential overlap among different convex hulls. If there exists an overlap between two hulls, we iteratively increase the concavity of the polygon until the overlap is removed (Figure 3.3), which results in a more generalized hull representation called alpha-hull [89] (or concave hull).

The major benefits of the boundary-based representation lie in three aspects, referring to the six guidelines G1 through G6 by Elmqvist and Fekete [9]. First, the boundary within the context of a geographical space naturally depicts the spatial scope of the aggregate, which is intuitive and interpretable to the users (*G2, G6*). Second, while the data points are typically represented as small circles, the implicit curve is easily distinguishable from the data items (*G4*). Third, since the visual space inside the boundary of the higher level clusters can be utilized to visualize the lower level clusters, the boundary-based representation produces minimum visual clutter (*G3*). The major limitation of this boundary-based representation is that it merely depicts the spatial coverage of the aggregate based on the outmost data points, lacking the ability to reveal more fine-grained information such as the point density within the aggregate (i.e., scatterplot, kernel density estimation). In essence, a trade-off exists between the visual simplicity and the visual budget available to individual aggregates. Since we attempt to combine the multi-scale aggregates in one visual space and avoid potential information overload to users, the visual simplicity is favored.

The boundary-based visual representation is the foundation of our context-preserving approach. On the one hand, since the boundary-based representation produces minimal visual clutter, we propose a novel design that combines multi-scale boundaries in the same visual display in order to maintain the context (more details in chapter 4). We note that there still exists overlapping between the aggregates that share a subset of data points. Thus we propose a boundary distortion algorithm to minimum the overlap. On the other hand, since the boundary naturally represents the spatial scope of the aggregate, we propose a novel animated transition design that provides a smooth visual transition instead of an abrupt change as the users navigate across adjacent scales (more details in chapter 6). Hence, as the users zoom in or out on the map, the boundaries at the previous scale fade out while the boundaries at the new scale fade in. During the transition, there exists a period of time when the boundaries at adjacent scales are visualized at the same time, thus effectively providing the context of previous aggregation level.

Table 3.1.: Design guidelines for information visualization of hierarchical aggregation [9].

Design Guideline	Description
G1: Entity Budget	Maintain a visual entity budget when rendering hierarchical aggregated visualizations
G2: Visual Summary	Visual aggregates should convey information about the underlying data
G3: Visual Simplicity	Design visual aggregates to have a clean and simple visual appearance
G4: Discriminability	Design visual aggregates to be easily distinguishable from visual data items
G5: Fidelity	Counteract fidelity problems in visual aggregates
G6: Interpretability	Aggregate items only so much so that the aggregation is still correctly interpretable within the visual mapping

4. VISUAL SUMMARIZATION OF MULTI-SCALE AGGREGATES IN A SINGLE VISUAL DISPLAY

In this chapter, we describe our novel visual summarization that combines multiple levels of the hierarchy at the same time to provide information about patterns at multiple scales of aggregation. The boundary of each cluster is modeled using an implicit curve that is distorted to reduce overlap between clusters at adjacent hierarchy levels. Our technique also allows for coupling navigation to the visual representation: double-clicking on a specific cluster automatically zooms and pans the viewport to fit the entire viewport to its extents.

The design space of our technique includes multiple visual encoding choices using color, transparency, shading, and shape for representing aggregation level, cluster contents, and statistical aspects of the spatial data. To determine the strengths and weaknesses of each visual encoding strategy, we conducted several controlled laboratory experiments where participants are asked to perform spatial analysis tasks under different visual encodings. Our results yield guidelines on which visual encodings to use depending on the user, task, and application. We also discuss ideas for how our technique can be extended with text visualization encoding to show terms, phrases, and topics for each cluster. The practical applications for our include geographic information systems (GIS), geospatial visual analytics, and online geographic services such as Google Maps, Bing Maps, and OpenStreetMap.

4.1 Visual Clutter Minimization of Multi-Scale Aggregates

When coupling multi-scale boundaries in the same visualization, there may exists overlapping between the aggregates that share a subset of data points, as shown in Figure 4.1(b). To minimize the overlap, we propose a bottom-up distortion algorithm

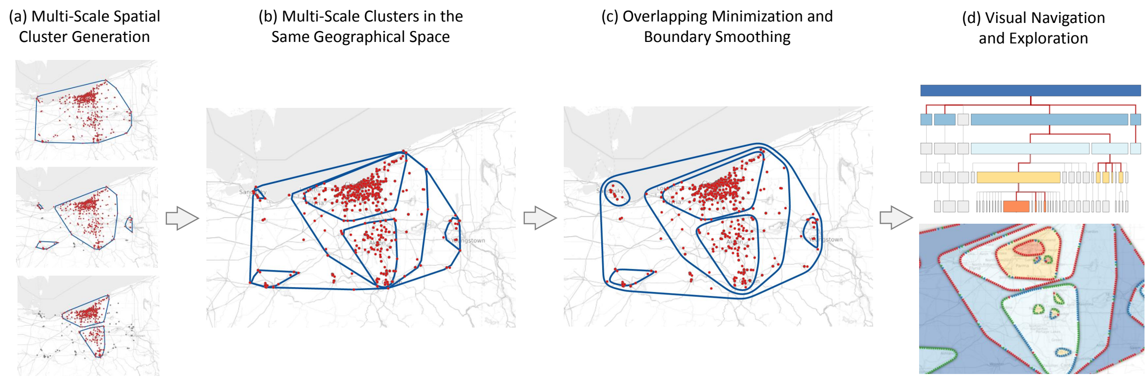


Fig. 4.1. Coupling the multi-scale spatial clusters into a single visual display.

toward effective overlap minimization of the multi-scale spatial boundaries (*G3, G5*). This is inspired by the nested treemap design that adds padding to adjacent rectangles in order to highlight the parent nodes in the hierarchy more effectively [50]. Figure 4.2 describes the detailed procedure of the overlapping minimization, which has been inspired by the force-directed drawing algorithm [90]. In essence, the force-directed layout simulates the repulsive forces among the visual elements and minimizes the energy of the entire system in order to reduce the visual overlapping. Instead of measuring the energy of the system, our algorithm traverses the hierarchy to the bottom level and for each non-leaf node, the algorithm simply repositions the control points of the boundary that overlap with its children for the sake of both an aesthetic visual result and performance efficiency.

4.2 Visual Encoding Design for Hierarchical and Statistical Information

In order to facilitate effective visual perception of the hierarchical and statistical information of the geographical aggregates, Our technique provides a set of visual encoding strategies combining different perceptual dimensions including color, transparency, shading, and shapes. The strategies have been applied to the inner area

Algorithm 1: Minimizing the boundary overlap between the parent and its children.

```
function minimizeOverlap (polygon pp, polygon[] cp);
Input   : The boundary polygon pp of the parent, and the array cp containing
          the boundary polygon for each child.
Output  : The updated boundary polygon of the parent.
begin
    /* detect overlapping vertices in pp                    */
    olPts ⟵ ∅;
    for p ∈ pp do
        minDist ⟵ Infinity;
        for poly ∈ cp do
            minDist = min(minDist, distPointPoly(p, poly));
        end
        if minDist < THRESHOLD then
            arrayPush(olPts, p);
        end
    end
    /* inflate the entire polygon of pp                     */
    newPP ⟵ inflatePolygon(pp, SPACING);
    /* partially utilize the inflation result               */
    for p ∈ newPP do
        minDist ⟵ min(distance between p and vertices in olPts);
        if minDist <= SPACING then
            arrayPush(pp, p);
        end
    end
    /* update pp based on newly added vertices              */
    pp ⟵ verticesToPoly(pp);
end
```

Fig. 4.2. The proposed overlap minimization algorithm

of the aggregates as well as the boundary, which is inspired by Bristle Maps [91, 92] where map features (roads, subway line, city blocks, etc.) are associated with visual elements—bristles—in order to visually encode the multivariate information in the geographical region of interest. Typically, we aim to convey both univariate and multivariate attributes of the spatial aggregates through our visual design.

Univariate Attributes

Examples of univariate attributes of the aggregates include the volume of data points, size of the geographical area, scale of aggregation (zoom level), quantitative measure of relevance to a domain-specific category or topic, etc. We encode this type of attribute using either the color of the inner area of the cluster, or the width/color of the boundary. For example, Figure 4.3 illustrates a pipeline of encoding the scale of the individual clusters by rendering the inner area based on a divergent color scheme. In this case, dark blue represents the abstract level while dark red represents the detailed level. Clusters of the same color indicate that they are generated at the same level. Different color schemes such as sequential or qualitative schemes can also be applied here. In order to evaluate whether the color encoding strategy can enhance the understanding of hierarchical relationships of multi-scale boundaries in the geographical space, and which color scheme achieves the best result, we conducted a user study. The detailed evaluation design and results are discussed in the evaluation section.

In addition to filling the color, we also apply the halo effect on the boundary of the clusters, as shown in Figure 4.3(c), in order to visually indicate the sidedness of the boundary [93]. The halo is only rendered at one side of the boundary (outer side of the cluster) in order to provide a visual cue in terms of which side of the boundary belongs to the cluster. The halo effect is especially helpful when the user zooms into a certain level where only the partial cluster is visualized in the viewport (Figure 4.3(d) and Figure 4.3(e)).

Multivariate Attributes

Examples of the multivariate attribute include distribution of different categories, etc. Visualization of the categorical information helps users understand the quantitative distribution of different categories, and further identify trending and abnormal categories across the geographical region of interest. In the context of the multi-scale clusters, this is especially helpful in terms of revealing the evolution of categorical distribution across different scales.

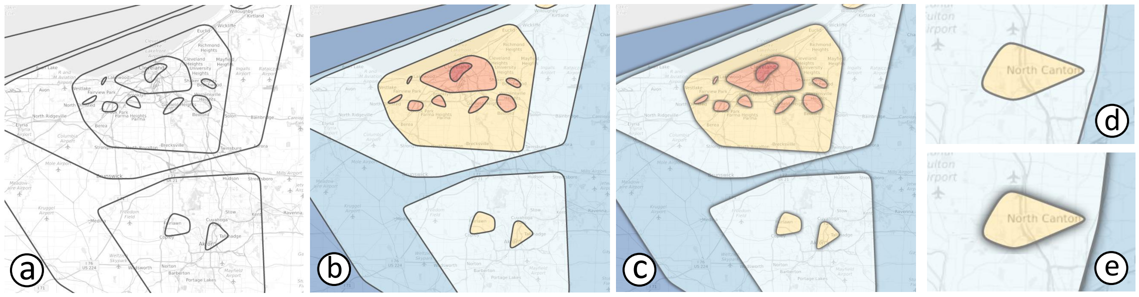


Fig. 4.3. The visual encoding strategy that illustrates the aggregation level of the multi-scale clusters. (a) The boundaries are visualized using a single color; (b) The area inside the clusters is filled based on a divergent color scheme from blue (abstract level) to red (detailed level); (c) The halo is rendered along the boundary in order to help distinguish the sidedness of the boundary. The comparison of the visualization without halo (d) and with halo (e) is shown. With halo, it is easier for the user to determine which side of the boundary belongs to this cluster.

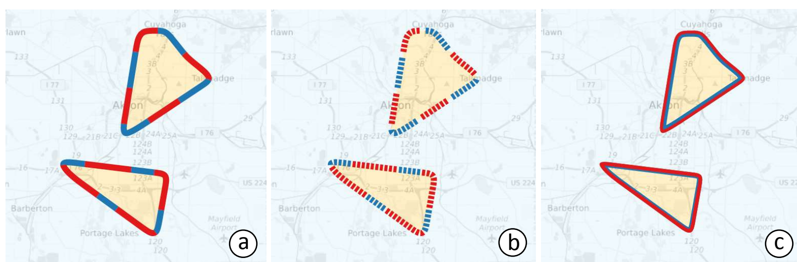


Fig. 4.4. Encoding categorical information on the boundary of the cluster. (a): Continuous colored segments; (b): Discrete colored dashes; (c): Stacked Lines.

Our technique provides three boundary-based encoding strategies to convey the categorical distribution of the individual aggregates (*G2*), as Figure 4.4 shows. In all three designs, each color corresponds to a specific category:

- **Continuous colored segments**: Figure 4.4(a) shows line segments being used as the major visual element to convey the quantity of categories. The length of the colored segment is in proportion to the quantity of the corresponding category. Segments repeat to fill the entire boundary.

- **Discrete colored dashes**: Figure 4.4(b) shows a sequence of dashes being used to convey the quantity of categories. The number of colored dashes in each sequence is in proportion to the quantity of the corresponding category. Sequences repeat to fill the entire boundary. In other words, in this design, we choose the dash as the visual element instead of circle or other similar shapes for the sake of visual discrimination between aggregates and data items (*G4*).

- **Stacked Lines**: Figure 4.4(c) shows the entire boundary line of the cluster being used to convey the quantity of categories. The width of the boundary lines is in proportion to the quantity of the corresponding category. The lines for different categories are stacked next to each other.

We note that for both the continuous colored segments and discrete colored dashes, we fill the entire boundary of the clusters by concatenating the segments or dash sequences repetitively along the boundary. The rationale behind such a design is that the repetitive patterns avoid misleading the users in terms of interpreting the categorical information (Figure 4.5(b)). Without the repetitive patterns, the visual designs can convey the wrong categorical information particularly when only a partial cluster is shown in the viewport (Figure 4.5(a)).

4.3 Interaction and Interface Design

Our technique consists of two visual and interactive dialogs: an interactive map view that visualizes the multi-scale aggregates within the same geographical display, and a tree view that illustrates the hierarchical relationships of the multi-scale aggregates. These two dialogs are coordinated and seamlessly integrated when the users navigate across different scales.

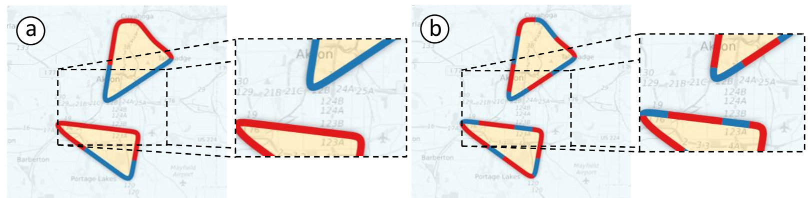


Fig. 4.5. Without the repeating patterns (a), the visualization may convey the wrong categorical information when only the partial cluster is in the viewport. This visual confusion can be avoided by introducing the repeating patterns (b).

General Navigation: The interactive map view allows the users to navigate across different spatial scales through common zooming operations. Each time the user zooms in or out, the map navigates to either the higher or lower adjacent level, respectively. our technique visualizes the multi-scale spatial aggregates that are visible or partially visible in the map viewport. Aggregates that occupy too small screen space (i.e., less than 100 pixels) are not rendered (*G1*). Furthermore, as [9] suggests, our technique provides a configurable parameter S that restricts the number of adjacent scales to visualize (*G1*) in order to avoid computational performance issue and potential overload on the user. For example, if the user navigates to zoom level 10, with $S = 2$, then only the levels from 8 to 12 are visualized. After a visual inspection of the results, we found $S = 2$ to produce reasonable results with respect to performance and readability.

Muti-Scale Navigation through Selecting Targets: our technique supports simple yet intuitive interaction features that allow users to navigate across multiple levels. As the user double-clicks on a target aggregate, the map automatically pans to the target aggregate and zooms in to fit its extent. With such a design, the conventional navigation paradigm that requires multiple panning and zooming operations is simplified by a single and intuitive interaction that significantly alleviates the interaction overload. Furthermore, by double-clicking on the region outside the target aggregate, our technique automatically resets the view back to the previous geographical space.

Exploring the Hierarchy — The Tree View: The tree view in our technique illustrates the multi-scale hierarchy by utilizing both a dendrogram and a node-link diagram. The dendrogram representation illustrates the information of scale, as the nodes of the same scale are aligned based on the same vertical offset (Figure 4.1(d)). However, this may cause significant visual clutter when the number of nodes is large. To manage this, our technique provides a complementary node-link representation that fully utilizes the two dimensional space. The node-link diagram simply regards the hierarchical structure as a graph rendered using a force-directed layout (Figure 4.1(d)). The user can toggle between the two views in the control panel.

The tree view is coordinated with the geographical view through the *brushing and linking* paradigm. As the user navigates on the map, the aggregates that are visible in the geographical space are highlighted in the tree view. With this design, while the user may focus on exploring at the deep level on the map, the tree view is able to provide a context of the entire structure to the user. When the user selects one or more nodes in the tree view, the corresponding aggregates in the geographical space highlight accordingly.

The tree view supports a rich set of interaction features that allows users to select, filter, sort, and highlight the multi-scale aggregates. This view also supports filtering based on the properties of the aggregates such as geographical size, data volume, and density. The user can filter to show only a subtree by specifying a node as the root of that subtree. The view supports sorting the children (from left to right) of each tree node based on the aforementioned properties.

Details-on-Demand: our technique supports easy access to details-on-demand of the raw data items. When the user right-clicks on the specific aggregate and selects the relevant option, the data items that belong to this aggregate are shown on the map as circles. Simultaneously, a separate message table shows the semantic content of those data items in a list. In the scenario of categorical information exploration, the table highlights the keywords relevant to different categories based on the same color scheme.

4.4 Implementation Details

The implementation of our technique consists of a multiple layered SVG canvas. The map layer stays at the bottom of the hierarchy, and provides a visualization of map tiles and interactive navigation. On top of the map layer is the visualization layer, which is the primary workspace for rendering various visual elements including boundaries, halos, categorical encoding designs, text, etc. The toolbox layer stays on the top of the hierarchy, showing interactive menus and the toolbar.

To achieve the visual effects that are presented in this work Our technique applies the cardinal spline interpolation (D3.line.interpolate) to smooth the boundary of the spatial aggregates. In order to fill color inside the boundary, the SVG <mask> command is used to create masks according to the boundary of the inner children aggregates in order to avoid rendering those areas.

Our technique achieves the shadow (halo) effect by initiating a SVG filter (<filter>) and associates a Gaussian blur (<feGaussianBlur>) to the filter. The size of the shadow is controlled by the standard deviation (<stdDeviation>) of the Gaussian blur. A higher SD value results in a larger shadow in screen space. The SD value in our technique is set as 5, which achieves a satisfactory visual effect.

Our technique utilizes SVG dash styling to render colored line segments (each line segment is regarded as a long dash) and dash sequences along the boundary. Specifically, the <stroke-dasharray> attribute defines the patterns and gaps of the dash styling, and the <stroke-dashoffset> attribute controls the offset where the pattern begins. In order to visualize multiple categories, Our technique pre-calculates the dash patterns and offset for each category based on the categorical distribution, and then renders them iteratively.

4.5 Evaluation

Our technique combines spatial clusters at different scales into the same geographical space to maintain hierarchical context: when the users focus on aggregation at a specific scale, the visualizations at adjacent scales are maintained in the same visual display without additional navigation to those scales. Since our technique models and visualizes the hierarchical spatial aggregates as well as provides visual encoding strategies to indicate the categorical information related to individual aggregates, we conducted two independent user studies to investigate the effectiveness of different visual encoding choices in terms of conveying the hierarchical and categorical information at different scales.

4.5.1 Participants and Apparatus

We recruited 20 participants (age range of 19 to 28, 7 female, 13 male) for the first user study, and 20 participants (age range of 22 to 36, 6 female, 14 male) for the second user study. Most participants were students and staff from our college of engineering, who have some basic understanding of the concepts being tested (e.g., spatial clustering, hierarchical structures). The participants were paid $5 for participation in one study. The experiments were conducted on a windows-based computer with a 30-inch Dell monitor. The interface for the main visualization occupied an area of 1600x1600 pixels.

4.5.2 Procedure

The two studies were conducted independently and had similar procedures. At the start of the study, the investigator asked the participants to sign a consent form and introduced the research background and the different visualization designs. Then the investigator provided a training session and presented sample questions covering major visual designs and task types to familiarize the participants with the tasks. In order to ensure that they did not have any difficulty or misunderstanding, the participants were provided with the correct answer and were asked to raise any questions or concerns to the investigator during the training. The accuracy and the completion time for each trial were recorded. After each study, the participants were asked to complete an online demographic survey.

4.5.3 User Study 1: Encoding the Hierarchical Information

This experiment evaluated the efficacy of color and different color schemes in terms of conveying the hierarchical structure of the spatial aggregates within the geographical space.

Techniques and Task Design

In this experiment, we utilized four different visual encoding strategies (visualization technique V) in the experiment:

NoC Only the boundaries of the clusters are visualized. No color is rendered inside the cluster.

SEQ A sequential color scheme is used to indicate the scale of aggregates. In our technique, blue is used as the main hue. Lighter colors represent higher scales (abstract level), and darker colors represent lower scales (detailed level).

B-R A blue-red color scheme is used to indicate the scale of aggregates, which starts from blue (higher scales), transitions to yellow (middle scales), and ends at red (lower scales).

QT A qualitative color scheme is used to indicate the scale.

We developed two classes of typical tasks. The first class investigated the participants' performance in terms of visual comparison between scales of individual aggregates (TSC). A typical task of this class highlights two aggregates denoted as A and B, and the participants are asked to decide which one is at a higher (or lower)

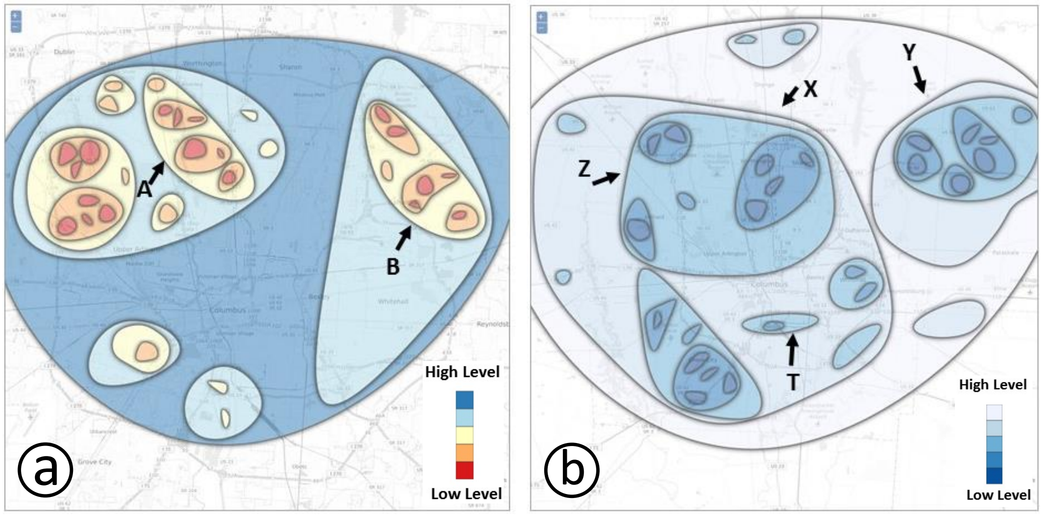
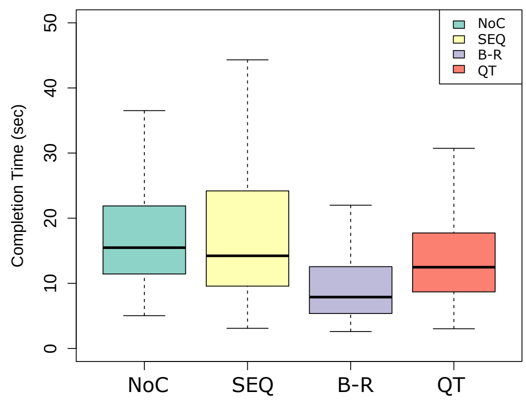


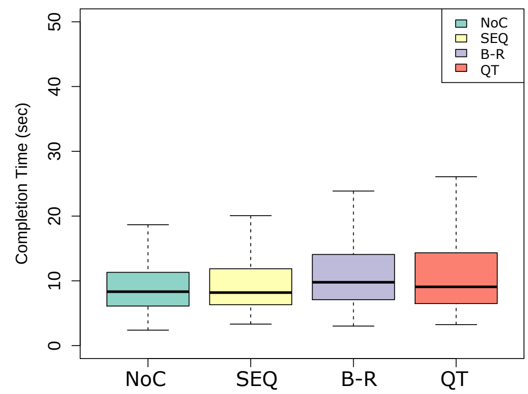
Fig. 4.6. Task design in Study 1: (a) Comparing scales of aggregation (TSC); (b) Identifying parent-children relationships (TPC).

level (Figure 4.6(a)). The second class of tasks evaluated the participants' understanding in terms of parent-child relationships among aggregates at different scales (TPC). A typical task of this class specified a cluster denoted as T, and highlighted a set of clusters denoted as X, Y, Z. The participants were asked to decide which cluster among X, Y and Z contains T in the visualization (Figure 4.6(b)).

We controlled the difficulty level D of each trial based on the complexity of the cluster hierarchy. The hierarchy complexity is defined based on two parameters: the height (or depth) of the hierarchy (L), and the average number of children for each non-leaf node (C). Moreover, we define three difficulty levels: *easy* ($L \in \{3,4\}; C = 2$), *middle* ($L \in \{6,7\}; C = 4$), *hard* ($L \in \{9,10\}; C = 6$). Each trial consists of a multiple-choice question along with the visualization. The four techniques were presented in a counter-balanced order. The whole study consisted of 4 (technique) $\times$ 2 (task type) $\times$ 3 (complexity of hierarchy) $\times$ 2 (repetition) $= 48$ trials.



(a) Completion Time (TSC)



(b) Completion Time (TPC)

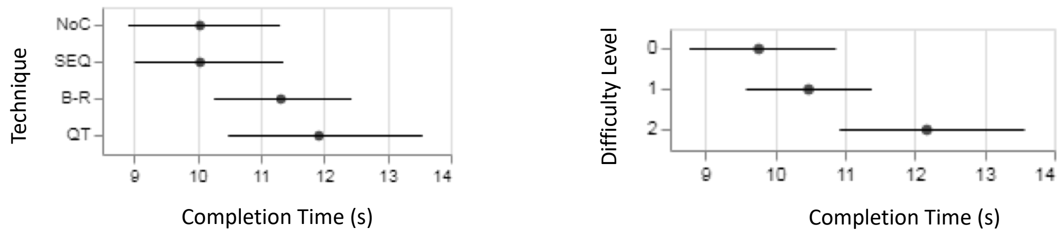
Fig. 4.7. Completion time for the two task types in Study 1. Color encoding the areas helps identify the scale of aggregation (a), but not the parent-child relationships (b). The box plots display the distribution of results based on the five number summary: minimum, first quartile, median, third quartile, and maximum.

Results and Observations

The accuracy was quite high (average of 96.04%) across all visualization techniques for both tasks. Since there was no time limit for the tasks, the users were able to correctly identify the hierarchy of the spatial aggregates shown.

The completion time for the type 1 task (TSC) is shown in Figure 4.7(a). The results have been analyzed based on a repeated-measure analysis of variance (assumptions met). Visualization technique V had a significant main effect on completion time ($F(3, 57) = 27.12$, $p < .0001$). Pairwise comparison between visualization techniques using a Tukey HSD showed that all pairs have statistical significance ($p < .05$), except for the pair of no color (NoC) and sequential scheme (SEQ). As expected, the difficulty level D had a significant main effect on completion time as well ($F(2, 38) = 48.54$, $p < .0001$). Furthermore, there was a significant interaction effect between visualization technique V and difficulty level D on completion time ($F(6, 114) = 6.60$, $p < .0001$) We also calculated the 95% confidence interval of the mean value based on

(a) Evaluation results of task type 1



(b) Evaluation results of task type 2

Fig. 4.8. Evaluation results of the two task types in Study 1 based on the bootstrapping method.

the bootstrapping method [94] (the number of iterations equals 1000), and examined the result based on the overlap-test [95] and t-test [96]. As shown in Figure 4.8(a), the sequential scheme (SEQ) has the highest completion time (mean: 19.70 seconds), followed by no color (NoC) (mean: 18.14 seconds), then the qualitative scheme (QT) (mean: 14.47 seconds), and finally the blue-red scheme (B-R) (mean: 10.20 seconds). The difficulty level also showed statistical significance (easy, middle, and hard). The blue-red color scheme had the lowest completion time and showed statistical significance. This can be explained by noting that this scheme consists of different hues diverging from the middle, making the encoding space a bit larger while retaining a step to step relationship between the shades at each level. The qualitative color scheme follows the blue-red scheme in completion time. This scheme facilitates the user tracing across multiple scales since equal levels are quickly identifiable by their color, and adjacent levels are also easily distinguishable. The sequential color scheme and no color scheme had the longest completion time. This can be explained by noting the sequential color scheme is based on a single hue, and requires a higher cognitive load for a user to identify the equal levels between very similar shades of the same color. Similarly, without rendering color in the aggregates, users have to identify the scales purely based on the nested boundaries, which adds to the cognitive overload. Based on the post-experiment survey, users seem to prefer the blue-red color scheme: one user commented: "I liked the contours with the blue-red color as it is the easiest to view and decreases my response time to answer."

The completion time for the type 2 task (TPC) is shown in Figure 4.7(b). Based on a repeated-measure analysis of variance, visualization type V had a significant main effect on completion time ($F(3, 57) = 2.87$, $p < .05$). However, for pairwise comparisons using a Tukey HSD, only no color (NoC) vs qualitative scheme (QT) and sequential scheme (SEQ) vs qualitative scheme (QT) were marginally significant (p ¡ .05). Similarly, we calculated the 95% confidence interval of the mean value based on the bootstrapping method [94] (the number of iterations equals 1000), and examined the result based on the overlap-test [95] and t-test [96]. As shown in Figure 4.8(b), the difference between the completion time for each technique (Figure 4.7(b)) was relatively small and showed no statistical significance (QT: 11.92 seconds, B-R: 11.32 seconds, SEQ: 10.05 seconds and NoC: 10.04 seconds). The difficulty level showed statistical significance between the easy level and the hard level.

This can be explained by the fact that although color changes across scale, there is little color diversity among different sub-groups of aggregates. As users are not able to intuitively identify these differences with the help of color, color may be of limited benefit in identifying the parent-child relationship.

Our guidelines for color encoding the multi-scale aggregates in order to convey hierarchical information are summarized in two aspects. First, color encoding the areas of multi-scale aggregates helps to identify the aggregation level. We found that a blue-red (or similar) color scheme is most effective toward this end. Second, while encoding the areas of multi-scale aggregates can assist identification of the aggregation level, it does not fully convey the parent-child relationships. Additional encoding

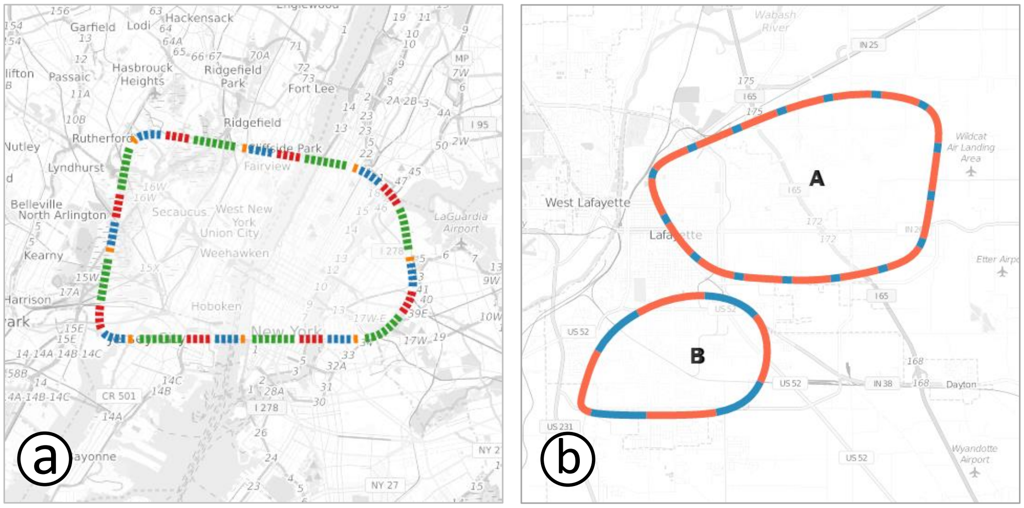


Fig. 4.9. Task design in Study 2: Comparing categories within one aggregate (a) and across multiple aggregates (b).

or interaction designs are required, such as providing different sub-clusters with individualized color encoding or highlighting sub-clusters when a parent is selected.

4.5.4 User Study 2: Encoding Categories on the Boundary

This section describes the experiment that evaluates the design alternatives in our technique that encodes categorical information at individual aggregates.

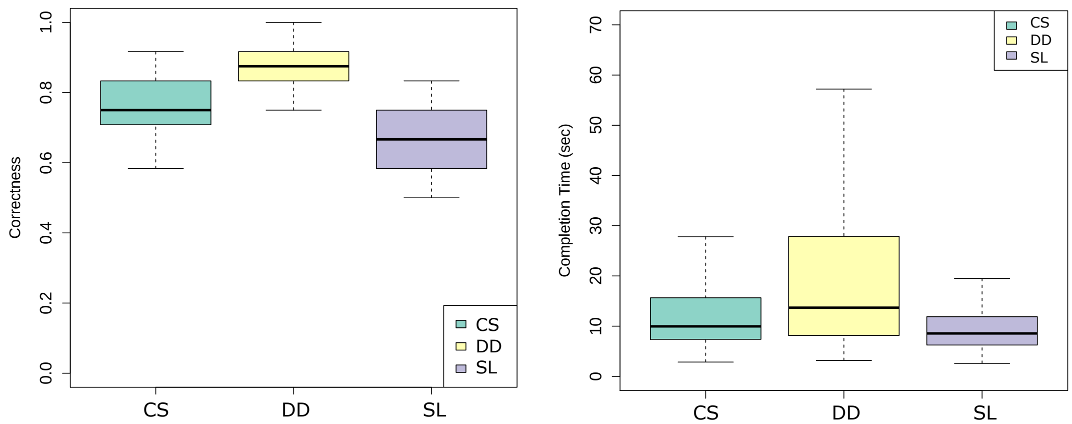
Techniques and Task Design

In this experiment, we evaluated three design choices (visualization technique V) (Figure 4.4) for encoding categorical information on the boundary of the spatial aggregates: continuous colored segments (CS), discrete colored dashes (DD) and stacked lines (SL). Two types of tasks were involved in the experiment. For the first type of task, the participants were shown a single aggregate on the map, with the boundary being visualized according to an underlying categorical distribution (category set denoted as $S = \{C1, C2, C3...\}$). The participants were asked to identify the category that has the highest/lowest volume within category set S in the visualization (Figure 4.9(a)). For the second type of task, the participants were shown two aggregates denoted as A and B on the map, with the boundaries being visualized according to two different categorical distribution of the same category set: with one category denoted as $C1$ highlighted, the participants were asked to determine in which cluster (A or B) the category $C1$ is more prominent (has a higher proportion among all categories) (Figure 4.9(b)). For each type of task, the same visual design was applied to all the aggregates. The different categories were visualized based on a qualitative color scheme, appropriately adjusted so that when concatenating segments of different colors or stacking lines of different colors, the adjacent colors were easily distinguishable. Although the proposed designs are applied to multi-scale aggregates, the scale itself has a minimum effect on the visual perception of categories. Hence, we limit this study to a single scale to emphasize the impact of comparing categories within and across different aggregates.

We controlled the difficulty level D of each trial based on the size of the category set (2 and 4). Each trial consisted of a multiple-choice question along with the visualization. The three techniques were presented in a counter-balanced order. The whole study consisted of 3 (technique) $\times$ 2 (task type) $\times$ 2 (difficulty level) $\times$ 3 (repetition) = 36 trials.

Results and Observations

The results of accuracy is shown in Figure 4.10(a). The results have been analyzed based on the linear regression (glimmix) with the assumptions satisfied. Visualization technique V had a significant main effect on completion time ($F(2, 38) = 10.76$, $p < .0001$). Pairwise comparison between visualization techniques using a Tukey HSD showed that all pairs had statistical significance ($p < .05$). As expected, difficulty level D had a significant main effect on completion time ($F(1, 19) = 45.11$, $p <$



(a) Accuracy (b) Completion Time

Fig. 4.10. Accuracy and completion time for Study 2. Among the three design alternatives, the discrete dash design achieves the highest accuracy (a) and meanwhile requires the longest time (b). The box plots display the distribution of results based on the five number summary: minimum, first quartile, median, third quartile, and maximum.

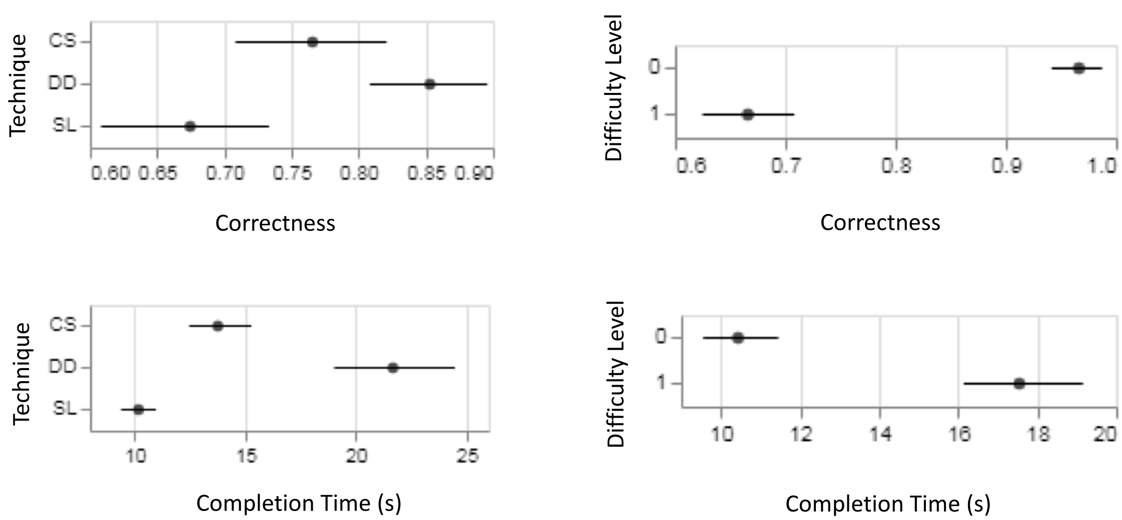


Fig. 4.11. Evaluation results of the accuracy and completion time in Study 2 based on the bootstrapping method.

.0001). We also calculated the 95% confidence interval of the mean value based on the bootstrapping method [94] (the number of iterations equals 1000), and examined the result based on the overlap-test [95] and t-test [96]. As shown in Figure 4.11(top), the discrete dashes (DD) had the highest accuracy (average: 85%), followed by continuous segments (CS) (average: 77%) and stacked lines (SL) (average: 67%). The difficulty level showed statistical significance (easy and hard). The results reflect that calculating the number of dashes is more accurate than visually comparing the length of different segments, especially when the difference between the values is small. Furthermore, stacked lines was the least effective as the visualization budget (the entire width of lines) is too limited to visually reflect the variation of different values.

In terms of the completion time (Figure 4.10(b)), visualization technique V had a significant main effect on completion time ($F(2, 38) = 47.08$, $p < .0001$). Pairwise comparison between visualization techniques using a Tukey HSD showed that all pairs have statistical significance ($p < .05$). As expected, difficulty level D had a significant main effect on completion time as well ($F(1, 19) = 45.88$, $p < .0001$). According to the bootstrapping results (Figure 4.11(bottom)), the participants spent significantly longer time on the discrete dashes (DD) (21.55 seconds) than continuous segments (CS) (13.79 seconds) and stacked lines (SL) (10.19 seconds). The difficulty level showed statistical significance as well (easy and hard). The results indicate that although DD achieves the highest accuracy, it requires a longer time for the users to count the number of dashes in each category for comparison. In terms of visual perception, the number of visual units in this design is the largest, requiring a longer time for the users to perceive. When the length of the boundary is large, or the size of the dash is small, this can potentially result in a larger number of dashes and overload the users.

Our guidelines for encoding categories on the boundary are summarized in the following two aspects. First, the discrete dash design is the most effective in terms of the accuracy. This is useful in analyses where comparison accuracy is critical, and the quantitative difference between categories are potentially not obvious. Second,

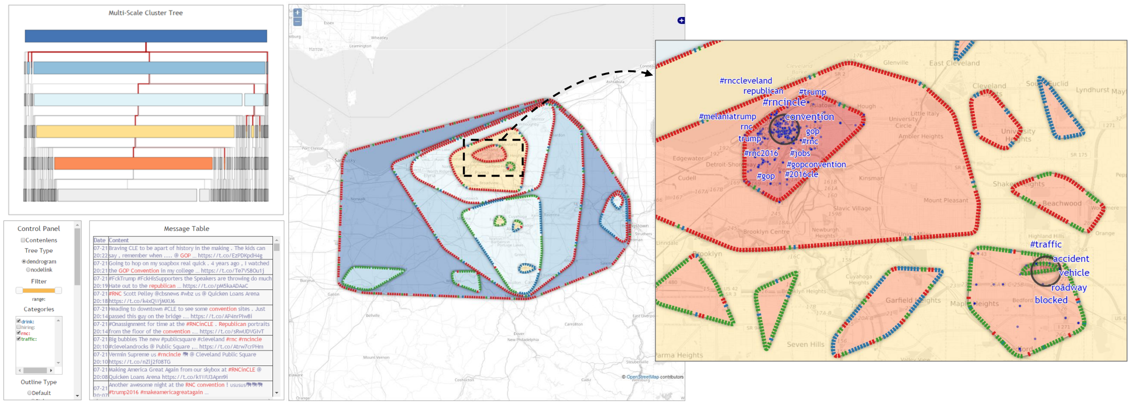


Fig. 4.12. Overview of our context-preserving visual analytics framework

the continuous segment design should be used for analyses where speed is favored over accuracy, as the discrete dash design may overload users in extreme cases.

4.5.5 Experimental Results in Practice

Analyzing geolocated tweets collected during the Republican National Convention in July 2016 (8839 tweets) illustrate the use and benefit of these designs in our technique, as shown in Figure 4.12. We started by extracting the major topics that were trending during the event using LDA topic modeling. The top four topics include jobs and hiring (*hiring*, *job*, *career*, *retail*), RNC-related (*#rncincle*, *trump*, *#rnc*, *republican*), traffic and accident (*accident*, *blocked*, *traffic*, *vehicle*), and drinking and entertainment (*drinking*, *show*, *beer*, *drunk*). Since most of the job-related tweets are online advertisement, the user can filter out that topic, and generate the multi-scale clusters based on the other three topics. The topical distribution is visualized using the discrete colored dashes, as shown in Figure 4.12(left). The user clearly notices that while most of the tweets are related to RNC at an abstract scale (the major color in the outward cluster is red), as she investigates lower levels, the clusters within Cleveland are more related to RNC topics, while in the nearby cities more tweets relate to traffic (green) and entertainment (blue). Therefore, the multi-scale context preserving visualization provides a comprehensive picture in terms of how the different topics are correlated with the clusters at different spatial scales, and how they evolve from the overview level to the detailed level.

The user further zooms into the city of Cleveland and explores the semantic information of those three topics. The user chooses to visualize the keywords of the highest frequency in the clusters. As Figure 4.12(right) shows, a large cluster appears around the downtown Cleveland that contains a set of RNC-related keywords, including *#rncincle*, *#2016cle*, *#gopconvention*, etc., which indicates that the convention has become a hot topic around this region. Interestingly, the user also identifies that drinking and traffic related tweets form several clusters around the suburban regions (Figure 4.12(right)). The semantic visualization allows the user to make sense of the trending semantic knowledge at clusters of different spatial scales. Therefore the visual outcome effectively preserves the semantic context at overview levels, and highlights the regions of interest at the detailed levels.

Focusing on the RNC topic, she further extracts the more fine-grained topics related to protest and response agency. She focuses on the downtown area and visualizes the related clusters. Interestingly, she finds that the two topics have a very similar spatial distribution. Several relevant keywords appear, including *protester*, *arrested*, *#antitrump*, *#notrump*, *swat*, *police*, *gun*, etc. Further navigating from the city level to the street level, she easily identifies several clusters with relatively high data volume located around the Public Square, the RNC Arena, and the streets in between.

4.6 Discussion

Our technique applies a boundary distortion algorithm in order to minimize overlapping of the multi-scale aggregated visualizations (Figure 4.2). While the spatial boundaries of overlapping aggregates are distorted, it has a minimal effect in terms of lowering the fidelity (*G5*) and interpretability (*G6*) of the boundary representation, since the proposed bottom-up distortion approach enlarges the parent boundary that overlaps with its children. Hence, the data points that belong to a specific aggregate are guaranteed to stay in the boundary of the same aggregate after the distortion is applied. However, we note that this method can potentially distort and exaggerate the geospatial boundary results and provide misleading results to the users. Accordingly, we plan to investigate the effects of this distortion on the interpretability of the geospatial accuracy of the results from our technique.

Our technique summarizes the categorical information along the boundary based on various visual designs, and fills the boundary with repetitive patterns. Since the visualization is presented within a geographical context, the users may associate the categorical information with the geographic information in the background. Unfortunately, the users may have the wrong interpretation that the visualization represents the local statistics near the boundary. We note that this is a limitation of this current design, and preventing this requires clear explanation or training to the users before they use the system. Future work could address this design limitation by encoding the locality of information into the boundary itself. For example, categorical data points could be projected to the nearest point on the cluster boundary, which would reduce potential errors over larger areas, and indicate the spatial distribution of the categorical information contained within.

Although our technique combines and visualizes multiple scales in the same display, the user may only focus on a specific scale (i.e., the current zoom level). Other scales are used to provide contextual information. A potential improvement might be to allocate more visualization budget (screen space) to the level on which one is focusing. This can be achieved by adding a weight parameter to the distortion algorithm so that boundaries of adjacent scales are shifted with larger offsets. This could provide an opportunity to encode more information within the chosen scale, perhaps layering different techniques on top of one another. For example, a semi-transparent sedimentation layer as a background would allow for users to quickly understand the categorical distribution while still being able to add other information relevant to the analysis space.

We note that although our approach provides users with a configurable parameter S to restrict the number of adjacent scales visible from the current scale, further evaluations are required to explore the scalability of our approach. The number of scales visible on the map increases as S is increased that can introduce potential visual clutter issues on the map. This also makes it difficult for users to visualize the underlying map due to occlusion. We leave these evaluations as future work.

As a future extension, we would like to extend our technique to visualize the semantic knowledge underlying the multi-scale aggregates. The prominent terms or phrases extracted from the content associated with the data items can be embedded within the aggregates, in order to maintain the semantic context across different scales. A potential issue associated with this text-based visualization is that some keywords that are of lower significance may have a longer length; thus, occupy more space and unduly draw the users' attention. A potential solution for this might be to dynamically adjust the font weight (thickness) in order to make the important words stand out.

4.7 Conclusion

Our primary contribution in this work is a novel context-preserving visualization and navigation technique for representing discrete spatial data as hierarchically clustered shapes. We have adopted a boundary-based visual representation for multi-scale aggregates and coupled them in a single visual display for context preservation.

A polygon distortion algorithm has been designed to remove the overlap between aggregates and allow users to easily identify the structure of the hierarchy.

We have described appropriate interaction designs including smoothly navigating in the cluster hierarchy. We have also explored the design space of different visual encodings for the boundaries and contents of each shape using multiple visual channels including color, transparency, shading and labels. Our experiments yielded guidelines on optimal visual encoding strategies for conveying hierarchical and categorical information of multi-scale aggregates.

5. TEXT-BASED TECHNIQUES FOR MULTI-SCALE AGGREGATES

In this chapter, we present TopoText [12], a technique extended based on the TopoGroups technique that has been described in chapter 4. Although TopoGroups visualizes the statistical or categorical information associated with individual aggregates and enables the users to compare and correlate them within a multi-scale space, exploring textual information aggregated at multiple scales in TopoGroups and other visual analytics techniques (e.g., tagmap in Figure 5.1) is inefficient because the displayed text changes at different spatial scales, requiring the users to switch between scales and mentally remember the multi-scale results.

TopoText extends TopoGroups to tackle the challenges of visualizing text at multiple scales. Inspired by the typographic maps [80,81], TopoText utilizes the occlusion-free property and employs textual labels as its primary visualization entity to reduce visual complexity. Although the design space of the text-based visualization is broad and consists of multiple perceptual channels (color, size, density, position, shading, etc.), employing too many attributes may easily increase visual complexity and overload readers. Thus, we tailored a hierarchical aggregation and visualization model [9] to develop design goals for a multi-scale text exploration technique. Then we identified a subset of perceptual channels for text rendering that meet the design goals (consideration space), proposed appropriate design choices and rejected bad ones at the design time (proposal space). Finally, we evaluated the efficacy of the design candidates in a user study setup (selected solution) [97].

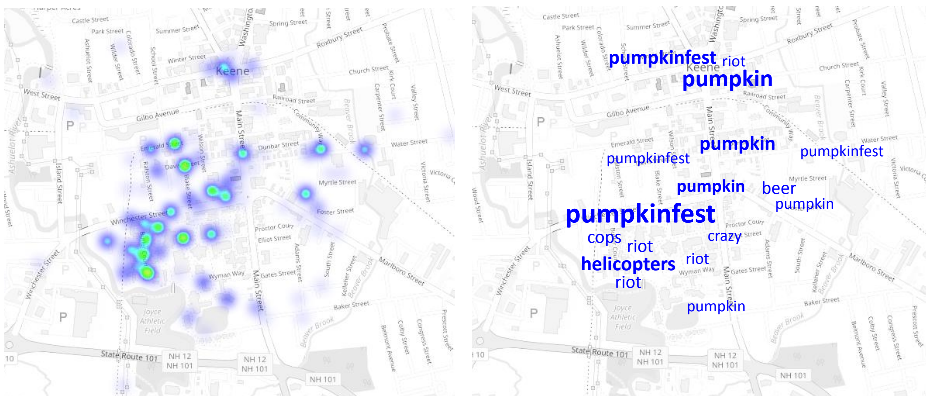


Fig. 5.1. A heat map (left) reflects the spatial data distribution but does not support exploring the textual information. A tag map (right) depicts the major keywords at different regions at the current spatial scale, but does not indicate the variation of the text data across multiple scales. (The same data are visualized by TopoText and shown in Figure 5.3.)

5.1 Design Process

Our primary design principle is consistent with the concept of the geographical mashup [65] by regarding textual information as a secondary information dimension overlaid on the primary geographical dimension. Doing so visually indicates the correlation between these two dimensions and provides contextual information of the spatial patterns. This can also reduce the overload caused by switching to separate views with textual information. Below, we detail our design goals regarding text data exploration of multi-scale spatial data. They are mainly extended from a hierarchical aggregation model for information visualization [9].

Entity Budget (G1): The entity budget for the text data is proportional to the budget for the aggregate since the text labels are visually associated with the geographic location of the corresponding aggregate. Hence, an aggregate with larger/smaller spatial coverage (not necessarily a larger/smaller number of data points) has a correspondingly larger/smaller visualization budget for the text. Aggregates that are too tiny (e.g., occupy less than 5∗5 pixels in the screen space) or outside the viewport are not visualized.

Visual Summary (G2): The accuracy of the textual information presented at a single scale should be compromised or at least not prioritized. Hence, for each scale we should show a coarse-grained summary instead of details. One should not expect that a visualization design shows the entire multi-scale hierarchy while being able to depict the fine-grained information at each individual scale (e.g., tag map).

Visual Simplicity (G3): The amount of the textual information presented at a single scale should be limited. In order words, the representation should be simple and clean in order to avoid generating visual complexity. G2 and G3 constraint the textual information at a single scale in order to express the textual information at multiple scales succinctly and avoid overloading the users. These two principles are especially critical within the domain of the text-based visualization since the design space of text is complicated and can easily involve design choices that confuse or overload readers. Hence, a reasonable design should identify a small and optimal set of orthogonal visual channels and establish a reasonable mapping between them and the data dimensions that need to be conveyed.

Discriminability (G4): This refers to the capability of visually distinguishing between the aggregate and data items. The data items (e.g., the geospatial data points) are usually represented as simple dots or more complex glyphs on the geographical map. Therefore, the visual entity of the aggregate—the text label—is easily distinguishable from the data item and does not require additional decoration as suggested in the model [9] to facilitate visual discrimination.

Fidelity (G5): The fidelity issue is often involved in visualizing aggregates. Since only a summary of the entire textual features is visualized (G2), the readers may have a biased interpretation on the textual information associated with the aggregate. Furthermore, this issue also exists in text visualization due to inappropriate encoding choices. For example, when the font size is fixed, a longer length keyword typically occupies more screen space, which can visually mislead its importance value and introduce perceptual bias [98]. Hence, text encodings should be carefully executed in order to prevent visual confusion. In essence, a trade-off between these potentially contradictory principles needs to be considered.

Interpretability (G6): Inappropriate text visualization methods may also hamper its interpretability. For example, a radial layout of a set of text should make necessary adjustment to avoid rendering the text upside-down [7,99]; Rendering a word sequence along a curve with sharp angles may result in distorted letters and inconsistent spacing between them [77, 78, 80]. A reasonable design should avoid such flaws related to the low-level visual attributes.

Fig. 5.2. Design alternatives for visualizing the text data on a single aggregate. (a): The text labels are placed along the boundary; (b): The text labels are filled within the area of the aggregate; (c): The space-filling visualization is enhanced by applying a transparency gradient on the text labels; (d): The text labels that are close to the boundary are placed inside the aggregate.

5.1.1 Visualizing the Text Data: A Single Aggregate

An aggregate is the basic element in the multi-scale aggregation hierarchy, which can be visually represented as a node in the dendrogram representation (Figure 3.1). TopoText creates four primary design alternatives for showing text of a single aggregate as described below (Figure 5.2). These approaches solely rely on appropriate text encoding and layout to indicate both the textual information and the geographic characteristic of the aggregate.

S-bd **S**ingle-scale **b**oun**d**ary-based visualization: The text labels are placed along the boundary (Figure 5.2(a)). Particularly, TopoText identifies sharp angles along the boundary and divides it into segments accordingly. This ensures that the segments have low curvature without any sharp change in direction. The text labels are then placed within the segment with potential distortion avoided [78] (G6).

S-sp **S**ingle-scale **sp**ace-filling visualization: The text labels are filled within the area of the aggregate based on the sweep line approach in order to fully utilize the inner space (Figure 5.2(b)). The text labels are clipped based on the boundary to visually indicate the shape of the aggregate. The direction of the text layout is determined by the direction of the diameter (the longest axis) of the polygon instead of a fixed direction (e.g., a horizontal layout) to avoid generating short and fragmented text lines that are hard to interpret [78] (G6). The vertical and horizontal spacing between adjacent text labels within one aggregate is set as a constant value in order to provide a simple and clean visual effect.

S-tsp **S**ingle-scale **t**ranslucent **sp**ace-filling visualization: When the aggregate occupies a relatively large space on the screen, directly applying the space-filling method (S-sp) can result in a large number of the text labels visible, potentially overloading the users. To this end, we apply a transparency gradient to the visualization such that the labels close to the boundary have a higher opacity value while those close to the aggregate's center have a lower opacity value (Figure 5.2(c)). A cubic function is used in the transparency gradient to enhance the visual perception of the boundary.

S-bh **S**ingle-scale **b**oundary-space **h**ybrid visualization: The text layout strategy in this design is similar to the space-filling visualization (S-sp), except that only the text labels that are close to the boundary are visualized to visually indicate the boundary shape (Figure 5.2(d)). The distance measure is based on the Euclidean distance between the center point of the text labels and the edge of the polygon that is the closest to the center point.

We note that in the four proposed design choices the position of the text is determined based on the available space resource of the aggregate and does not reflect the spatial distribution of the keywords within the aggregate (G2 and G3). Furthermore, the text labels in an aggregate have a fixed font size. The rationale behind these designs is that we aim to provide a visual semantic summary that doesn't cause potential information overload by employing too many visual channels (G2). The color of the text can be used to encode information such as topics, sentiment, etc., and TopoText allows the users to change the setting interactively.

5.1.2 Visualizing the Text Data: Multi-Scale Aggregates

As the multi-scale aggregates introduce more complexity to the visualization space, an effective visual representation should be free of visual occlusion and constrain the number of the visual elements presented to the user. We enumerate a set of potential design candidates by extending the single-scale design choices (Section 5.1.1) to the multi-scale aggregates. Then we identify the potential limitations in each design, perform appropriate refinement and propose the satisfying solutions that are listed below [97]. The visualization results of these solutions are shown in Figure 5.3.

M-bd **M**ulti-scale **b**oundary-**d**ominant visualization: The boundary-based technique (S-bd) is applied to the multi-scale aggregates that are not at the lowest aggregation level (Figure 5.3(a)). Since the lowest-level aggregates do not have children in their inner space, the space-filling visualization (S-sp) is applied to them in order to improve the space resource utilization (Figure 5.4(a)). This

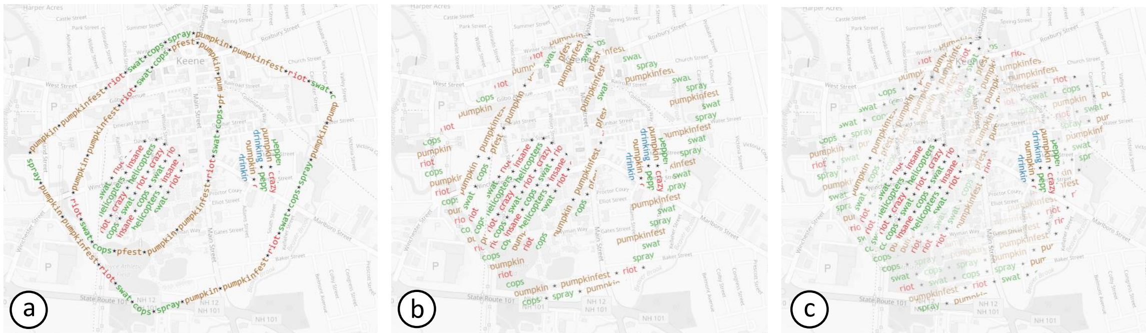


Fig. 5.3. TopoText showing the prominent topics (encoded by color) at different spatial scales on social media around the city of Keene in the state of New Hampshire, during the Pumpkin Festival riots in 2014. TopoText creates novel text-based visualizations to couple the multi-level textual information in the same visual display for context preservation. (a): The multi-scale boundary-dominant visualization; (b): The multi-scale boundary-space hybrid visualization; (c): The multi-scale space-dominant visualization.)

approach generates an occlusion-free visual result by taking advantage of the proper spacing between the boundaries [11].

M-bh **M**ulti-scale **b**oundary-space **h**ybrid visualization: The hybrid visualization (S-bh) is applied to the multi-scale aggregates that are not at the lowest aggregation level (Figure 5.3(b)). o avoid visual clutter generated by the overlapping aggregates (typically the aggregates that have a parent-children relationship), the child aggregate is visualized on top of the parent aggregate such that the parent's area that is covered by the child is invisible to the user. Because the direction of text is dependent on the diameter of the aggregate, this variation in the direction makes it easier for users to distinguish the adjacent aggregates [80]. Furthermore, the text labels at a higher (abstract) level are more transparent and sparse while those at a lower (detail) level are more opaque and dense [100]. Similar to M-bd, the space-filling technique is applied to the lowest-level aggregates.

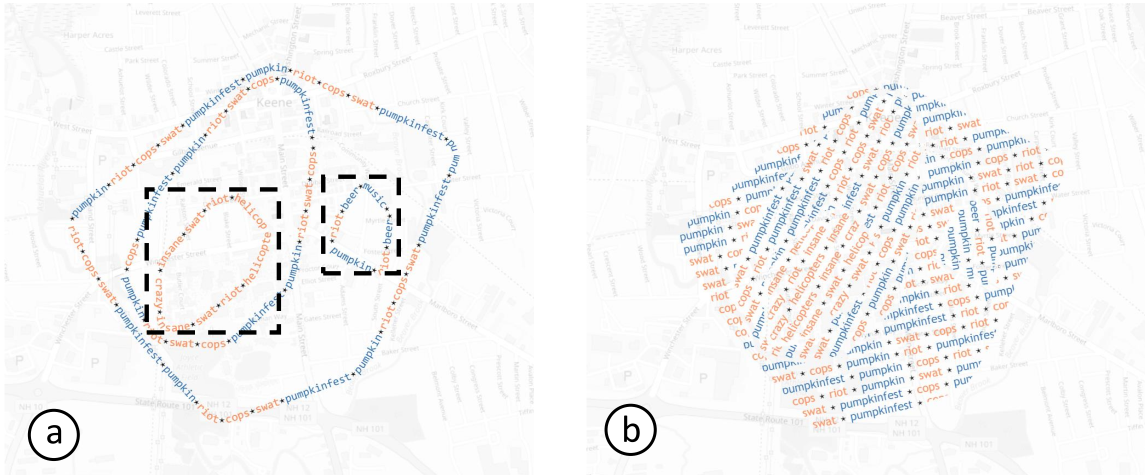


Fig. 5.4. (a): Applying the boundary-based visualization (S-bd) to the multi-scale aggregates. The space utilization of this design can be improved by filling the text labels in the lowest-level aggregates (shown in the black rectangles). (b): Applying the space-filling visualization (S-sp) to the multi-scale aggregates. Since the number of the text labels in the visualization can potentially be large, this design may add significant visual overload to the user.

M-sp **M**ulti-scale **sp**ace-dominant visualization: he translucent space-filling visualization (S-tsp) is applied to the multi-scale aggregates that are not at the lowest aggregation level (Figure 5.3(c)). imply applying the space-filling technique (S-sp) may produce significant information overload (Figure 5.4(b)). Similar to M-bh, the opacity and density of the text increases from the higher-level aggregates to the lower-level ones. Similarly, the space-filling technique is applied to the lowest-level aggregates.

We have conducted a user study to evaluate the efficacy of the aforementioned design choices in conveying the textual information of the multi-scale aggregates while retaining the geographical and hierarchical relationships of these aggregates. he results are reported in the evaluation section. We also note that additional visual attributes besides the textual features can be integrated to encode different information dimensions. For example, the background color of an aggregate can be used to encode the data density or the aggregation level [11] (Figure 5.7). A blue-red scheme is applied in TopoText by default. But more color schemes are supported to account for personal preferences and accommodate color blindness. When the aggregate's background is rendered, TopoText chooses a color scheme that has high contrast with the text color for the purpose of better readability. TopoText also applies the halo effect on the boundary of the aggregate in order to produce a visual effect that the child aggregates stack on top of their parents, thus enhancing the perception of the aggregates' hierarchy [11] (Figure 5.7 and Figure 5.8). The users can toggle the halo on or off in the interface of TopoText.

5.1.3 Interaction and Interface Design

The interface of TopoText mainly consists of a geographic map view that visualizes the multi-scale text data (Figure 5.7(b)) and a tree view that overviews the multi-scale hierarchy (Figure 5.7(a)). The map view visualizes the aggregates that intersect with the current viewport and occupy a reasonable amount of screen space, e.g., more than 100 pixels (G1). As the user navigates to different regions and scales on the map, the nodes (aggregates) that are visible in the viewport are highlighted in the tree view accordingly. When a node of interest in the tree view is selected, the map smoothly zooms and pans to center the corresponding aggregate in the viewport. The two coordinated views enable the users to navigate to different scales and details on the map while being able to maintain the context of the entire analysis space.

When the text-based techniques are applied to the aggregates that have a limited visual budget (e.g., the aggregate occupies a relatively small region), the text labels may be partially visible to the users and thus hamper information fidelity (G5) or interpretability (G6). In these cases, TopoText utilizes a set of boundary-based encoding strategies from TopoGroups [11] that typically visualize a sequence of colored segments or colored dashes on the boundary to summarize relevant information, such as the volume of the messages corresponding to the different topics (the aggregate B in Figure 5.7(b)).

Given a limited spatial visualization budget for an aggregate, TopoText provides common methods to determine the top K representative keywords to visualize, which includes term and inverse document frequency (TF-IDF), latent Dirichlet allocation (LDA), and lexicon-based matching, and supports the users to toggle between different options and adjust the value of K. Furthermore, as the user hovers over a specific textual feature in the aggregate or searches for a keyword in the control panel, the aggregates that contain the same feature highlight accordingly (Figure 5.7(e)).

As TopoText visualizes a summary of the textual information, a detail-on-demand interaction design is supported to enable quick access to detailed information that is not presented in the current visualization. When the user specifies an aggregate, the child aggregates inside it fade out and the space-filling technique (S-sp) is applied to the aggregate for the purpose of fully utilizing the inner space to present textual features. Moreover, when the user performs a scrolling operation on the aggregate, the textual labels dynamically move up or down depending on the scrolling direction, thus presenting the previously invisible text to the user [67].

5.2 Implementation Details

TopoText is implemented based on a two-layered SVG canvas using *D3* [101]. A map layer (OpenStreetMap) provides a gray-scale geographic context at the bottom of the canvas. The visualization layer stays on top of the map and renders text labels, aggregate boundaries and halos.

To position text labels along the boundary (Figure 5.2(a)), TopoText divides aggregate boundaries into segments of low curvature and renders the text using the `<textPath>` element. When the labels are visualized on the path iteratively, the `<startOffset>` attribute is used to define the position of the label and updated accordingly that guides the layout of the label to be rendered next. To fill the text inside an aggregate (Figure 5.2(b)), TopoText identifies the diameter of the polygon and calculates the bounding box in parallel with the diameter. TopoText then positions the text labels inside the bounding box using the `<transform>` attribute such that the orientation of text is in parallel with the diameter. An `<clipPath>` element is initialized based on the aggregate boundary and forces the rendering to be masked against the boundary.

TopoText implements the transparency gradient (Figure 5.2(c)) using the SVG element `<linearGradient>`. The gradient vector is calculated based on the relative position of the text labels and the center of the polygon and is specified using the `<x>` and `<y>` attributes associated with the `<linearGradient>`. The `<stop>` element and its `<offset>` attribute are used to define the ramp of the opacity value to use on a gradient. As only a linear gradient is supported in the SVG, we sample multiple points along the gradient vector to approximate a higher-order gradient such as a quadratic or cubic function. We found 5 points to produce a visually appealing effect given the fact that the text labels have relatively short lengths.

5.3 Evaluation

To evaluate TopoText, we focus on the two major aspects that are typically involved in the multi-scale analysis and text analysis tasks. (1) How effective does the technique express the textual information related to the multi-scale aggregates? (2) How effective does the technique reveal the geographic characteristics of the multi-scale aggregates and their relationships in the hierarchy?

5.3.1 Participants, Apparatus and Procedure

16 participants (4 female, 12 male, age range of 24 to 30) were recruited in the first study, and 14 participants (7 female, 7 male, age range of 22 to 64) were recruited in the second study. Most of the participants were students and staff from an engineering college and had some basic understanding of geographic applications, data clustering and data visualization. The entire study lasted around 30 minutes and each participant was paid $5 for participation in one study. We used a Dell monitor with a 1920×1080 resolution to present the system interface and the task description. The major visualization occupies an area of 1024×1024 within the screen space.

The procedures for the two studies were similar but were conducted independently. The investigator introduced the participant to the research background as well as the visualization techniques that were being tested. Then a training session was conducted to allow the participants to get familiar with the designs and the tasks. Special characters or symbols that appeared in the text-based visualization were also explained at this stage to avoid causing potential confusion to the participants (e.g., the hash ("#") or the AT ("@") symbol in a tweet). For the study that tests the textual information, the investigator also presented the participants a list of keywords that would be shown in the tasks, which familiarized the participants with the text content. The participants were asked to raise any questions during the training session. The main study included a set of multiple-choice questions which were answered afterwards. The accuracy and the completion time were recorded for each trial. The

Table 5.1.: The analytical task design in the user studies.

User Study	Highlighted entity in the visualization	Analytical task	Task taxonomy
Study 1: Semantics (text)	Multiple aggregates $\{A,B,C\}$	Identify the one in $\{A,B,C\}$ that contains a target keyword	Locate, search
	One aggregate A and multiple aggregates $\{X,Y,Z\}$	Identify the one in $\{X,Y,Z\}$ that has one or more keywords in common with A	Compare, correlate
Study 2: Hierarchy	Multiple aggregates $\{A,B,C\}$	Identify the one in $\{A,B,C\}$ that is at a higher (lower) aggregation level	Rank, compare
	One aggregate A and multiple aggregates $\{X,Y,Z\}$	Identify the one in $\{X,Y,Z\}$ that is a child of A	Locate, compare

participants ended the study by finishing all the trials and filling in a post-experiment survey.

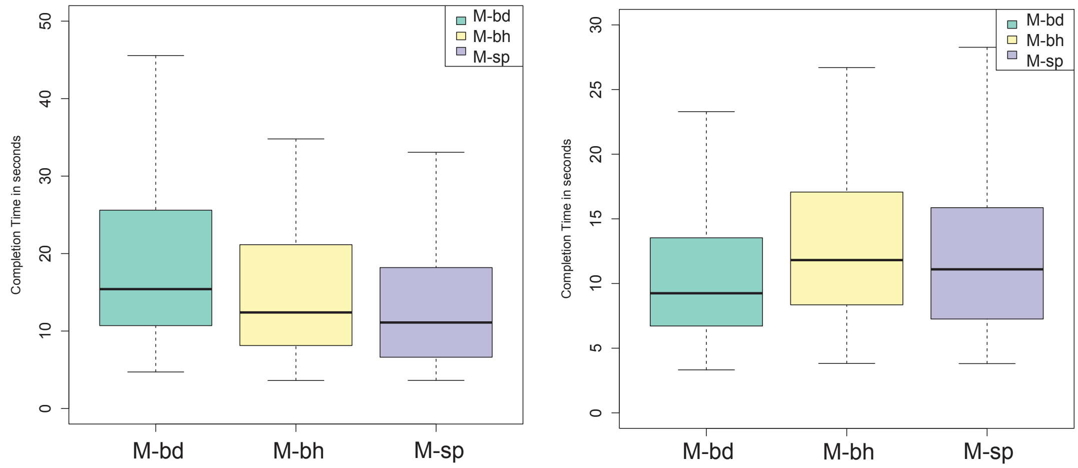
5.3.2 Techniques and Task Design

The techniques being evaluated in the two studies included the three multi-scale techniques: the boundary-dominant visualization (M-bd), the boundary-space hybrid visualization (M-bh), and the space-dominant visualization (M-sp). In order to focus on typography-based design choices (i.e., involving only text in the visualization and varying the visual attributes associated with text labels to generate design alternatives) and reduce the complexity of the evaluation process, the user studies did not involve additional visual channels such as the background color of the aggregate or the halo effect along the boundary. For the same reason, we did not design and involve a baseline technique (i.e., the TopoGroups technique combined with a word cloud visualization to show semantic content) for comparison. We note that these are potential limitations of the evaluation and we leave them as future work.

Inspired by previous research on representative analytical tasks regarding geospatial exploratory analysis [102–104], we involved four types of tasks in the two studies (Table 5.1). The first two tasks evaluated the capability of the technique to convey textual information (Study 1). The last two investigated the effectiveness of the technique to convey geographic and hierarchical relationships among the aggregates (Study 2). The first user study (the textual dimension) involves spatial tasks related to *locating*, *searching*, *comparing*, and *correlating*. The second user study (the geographical dimension) involves spatial tasks related to *ranking*, *comparing*, and *locating*. The task design of the second study was mainly inspired by the previous study that tested how effective users understand the hierarchical information of the multi-scale structure (Section 4.5.3). These tasks focus on the essential properties of a hierarchical structure: the level of the individual element within the hierarchical and the parent-child relationships of multiple elements within the hierarchy. Understanding this hierarchical structure is important to users because it helps them establish an explicit connection among spatial aggregates at different scales, thus enabling more effective navigation and exploration across scales.

For each trial, a static image was shown to the participant, in which one of the techniques being tested was applied to visualize the textual information of the multi-scale aggregates (similar to Figure 5.3). As Table 5.1 shows, specific aggregates related to the task were highlighted in the image using a black arrow and an upper case letter, such as X, Y, Z. The participants were asked to read the image, perform the corresponding task, and choose an answer from a list of options. For example, in the first task, three aggregates labeled as A, B and C are highlighted to the participant, and they are asked to find the aggregate that contains a target keyword W in the image. As a control variable, the color of the text labels in the image remains a constant value. We use synthetic data in the two studies.

For Study 1, we controlled the difficulty level D of each trial based on the complexity of the textual information, which can be quantified based on the number of distinct keywords for each aggregate shown in the visualization (we use 2, 4 and 8



(a) Completion Time (Study 1)

(b) Completion Time (Study 2)

Fig. 5.5. The distribution of completion time for the two studies. Left: The space-dominant technique (M-sp) was the most effective for understanding the textual information visually. Right: The participants spent the least time identifying the aggregates' hierarchy based on the boundary-dominant technique (M-bd). The box plots display the distribution of results based on the five number summary: minimum, first quartile, median, third quartile, and maximum.

in the study). The three techniques were presented in a counter-balanced order to prevent potential bias. The entire study consists of 3 (technique) $\times$ 2 (task type) $\times$ 3 (difficulty level) $\times$ 2 (repetition) = 36 trials. For Study 2, we controlled the difficulty level D of each trial based on the complexity of the hierarchy, which is quantified based on the number of scales in the hierarchy, or the depth of the hierarchy (we use 2, 4 and 6 in the study) Similarly, the three techniques were presented in a counter-balanced order to prevent potential bias. The entire study consists of 3 (technique) $\times$ 2 (task type) $\times$ 3 (difficulty level) $\times$ 2 (repetition) = 36 trials.

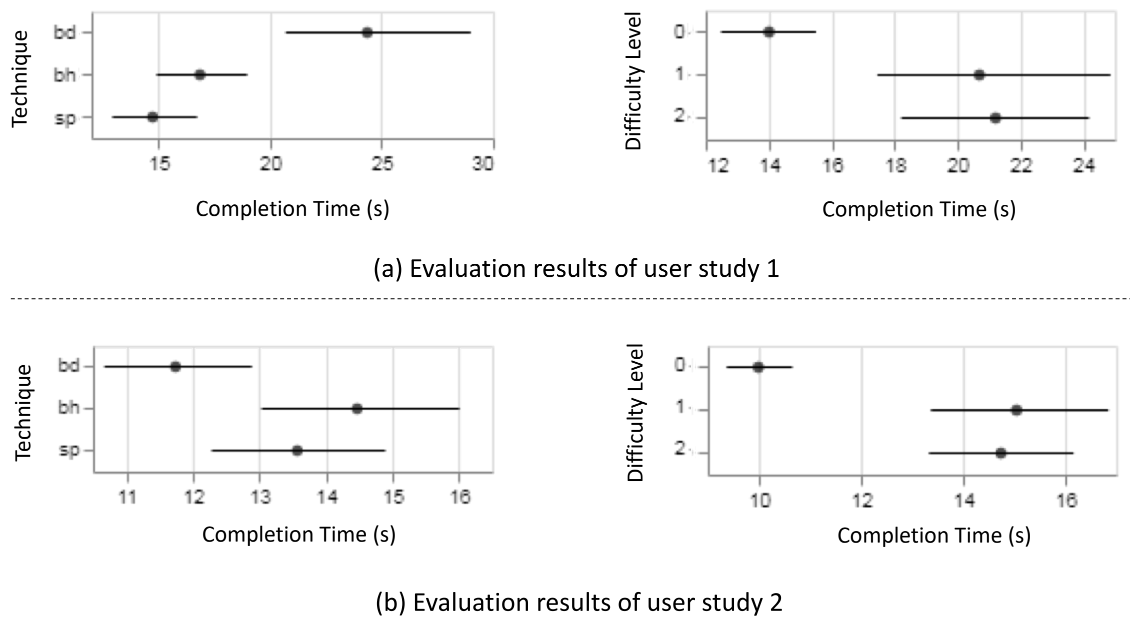


Fig. 5.6. Evaluation results based on the bootstrapping method showing (a) the boundary-based technique was the least efficient design for the semantic dimension and (b) the space-filling-based techniques were less efficient than the boundary-based technique when illustrating the hierarchical information.

5.3.3 Study 1: Results and Observations

The accuracy across the three techniques ranges from 90.6% to 94.1% (92.5% on average) and showed no statistical significance. This is because the visualization provides the necessary information—the keywords to search among aggregates—for the participants to identify the correct answer and there was no time limit for the tasks.

Figure 5.5(left) shows the distribution of completion time of the three techniques using box plots. Visualization technique V had a significant main effect on completion time ($F(2, 26) = 17.14$, $p < .0001$). Pairwise comparison between visualization techniques using a Tukey HSD showed that the pairs (M-bd, M-sp) and (M-bd, M-bh) have statistical significance ($p < .0001$). Difficulty level D also had a significant main effect on completion time as well ($F(2, 26) = 10.59$, $p < .0001$). We also calculated the 95% confidence interval of the mean value based on the bootstrapping method [94] (the number of iterations equals 1000), and examined the result based on the overlap-test [95] and t-test [96]. The bootstrapping method revealed consistent results. As shown in Figure 5.6(a), the participants spent the most time on the boundary-dominant technique (M-bd) (24.36 seconds on average) and showed statistical significance. This was followed by the hybrid technique (M-bh) (16.86 seconds on average) and the space-dominant technique (M-sp) (14.74 seconds on average). The difficulty level also showed statistical significance between the easy level and middle/hard levels. However, there was no statistical significance between the middle level and the hard level.

These results indicate that the boundary-dominant technique (M-bd) was inefficient in conveying the textual information. This can be explained by the fact that placing text on the boundary may potentially distort the letters and hamper readability. In order to read text along the boundary, the participants had to visually cover a larger distance in the screen space, thus requiring a longer time. In contrast, the space-dominant technique (M-sp) and the hybrid technique (M-bh) rendered text in a fixed direction without distortion, enabling an easier visual perception. Moreover, as the space-dominant technique filled text entirely, the amount of information presented within the unit of screen space was maximal. This enabled the users to focus on a smaller region to search or match keywords, thus reducing the overhead to switch visual focus across distant areas on the screen.

The subjective feedback was consistent with the analysis on the completion time. 9 participants (64%) agreed that the space-dominant technique (M-sp) was the most efficient. One participant noted that *filling text compactly helped the finding of keywords in the cluster. The transparency distinguishes the boundary of clusters.* Most participants (86%) disliked the boundary-dominant technique (M-bd). One participant mentioned that *I have to keep "relocating" my eye focus in order to read the text.* Another participant noted that *words are written in different orientation, so I* *had to twist my head to read words.* 3 participants (21%) preferred the hybrid technique (M-bh) over the space-dominant technique (M-sp). They seemed to have been distracted by the transparency effect: *I had to squint a lot to read the fading out effect.*

5.3.4 Study 2: Results and Observations

The accuracy across the three techniques ranges from 90.9% to 95.2% (93.2% on average) and showed no statistical significance. Similarly, the participants were able to successfully understand the hierarchical relationships within the visualization presented and the time spent on each trial was not constrained.

Figure 5.5(right) shows the distribution of completion time of the three techniques using box plots. In terms of the completion time, visualization technique V had a significant main effect on completion time ($F(2, 30) = 5.37$, $p < .005$). Pairwise comparison between visualization techniques using a Tukey HSD showed that the pairs (M-bd, M-sp) and (M-bd, M-bh) have statistical significance ($p < .05$). Difficulty level D had a significant main effect on completion time as well ($F(2, 30) = 22.97$, $p < .0001$). Similarly, we calculated the 95% confidence interval of the mean value based on the bootstrapping method [94] (the number of iterations equals 1000), and examined the result based on the overlap-test [95] and t-test [96]. As shown in Figure 5.6(b), the participants spent the most time on the hybrid technique (M-bh) (14.47 seconds), followed by the space-dominant technique (M-sp) (13.57 seconds), followed by the boundary-dominant technique (M-bd) (11.74 seconds). The difficulty level also showed statistical significance between the easy level and middle/hard levels. However, there was no statistical significance between the middle level and the hard level.

The results indicate that the boundary-dominant technique (M-bd) was the most effective design for visualizing the hierarchical structure of the multi-scale aggregates. In the perspective of visual perception, this technique utilized the minimum space resource that was required to convey the aggregate hierarchy, thus reducing the cognitive overload to the readers. The space-filling-based approaches (M-bh and M-sp) were less effective, especially when a parent had too many children and the children were located near the boundary of the parent. In these cases, the visual space between the adjacent boundaries was filled with text labels and made it challenging for the readers to understand the shape of the aggregates. In the experiment, the participants spent less time on average on the space-dominant technique (M-sp) than on the hybrid technique (M-bh). One explanation may be the fact that the visual perception of the boundary was enhanced by the higher-order transparency gradient. In contrast, the hybrid technique had labels of varying sizes near the aggregate's boundary, adding potential visual confusion to the readers. However, we note that we did not find statistical significance between the two techniques.

In the post-experiment survey, all of the participants agreed that the boundary-dominant technique (M-bd) was the most effective in terms of conveying the hierarchical relationships among aggregates. One participant noted that *the boundaries of the clusters were clear and distinct and helped me identify the children easily. I had to put more efforts in the other designs.* Another participant noted that *it's clear even for a deeply nested structure.* A majority of the participants (75%) disliked the hybrid technique (M-bh). The major limitation commented by them was its inefficiency at distinguishing between the parent and children visually. One participant who disliked the hybrid design said that *the words along the boundary had different lengths and looked messy.* One participant mentioned that *the transparency change helped to better recognize the boundary shape compared to the one without it.*

Takeaways: The two user studies show that visualizing the text on the boundary (M-bd) more effectively depicts the aggregates' hierarchy while filling text inside the space (M-sp, M-bh) more effectively convey the textual information. These results essentially reflect the fact that when the visualization budget is limited, a trade-off exists between retaining an effective overview of the multi-scale hierarchy and providing detailed information related to individual aggregates. In the typical multi-scale exploration process, the boundary-dominant approach might be suitable for the initial or pilot stage that requires the analysts to obtain a coarse-grained understanding of the analysis space and identify potential exploration directions. With the analysis narrowed down to small-scale subspaces, the space-dominant approach can present more detailed information and support a fine-grained investigation. However, designing an optimal solution is challenging, and requires taking into account different perspectives such as the problem, task, and user requirement.

5.4 Case Studies

We present two use cases to demonstrate the capability of TopoText for visualizing the textual information and maintaining the semantic context in the multi-scale aggregate space.

5.4.1 Keene Pumpkin Festival Riot

We analyzed the location-based social media (Twitter, 1507 tweets) generated during the 2014 riots in the city of Keene in the state of New Hampshire during its annual pumpkin festival. We started the exploration by extracting the trending topics during the event using LDA topic modeling. The top five topics related to jobs (”hiring”, ”job”, ”career”, ”retail”), festival (”#pumpfest”, ”pumpkin”, ”#pfest”), entertainment (”drinking”, ”beer”, ”music”), riot (”riot”, ”crazy”, ”injured”) and police (”cop”, ”helicopter”, ”police”). We filtered out the job-related topic since most of the relevant posts were online advertisements, and visualized the textual information related to the other three topics in TopoText as shown in Figure 5.7(b). The festival-related topics were prominent at the abstract level in this region, as the majority of the keywords associated with the outward aggregate were rendered in yellow. Some keywords related to the riot and law enforcement (e.g., swat, riot, crazy) also appeared in the outward aggregate, indicating that quite a few social media users discussed about the riot. We also noticed that at the lower levels, a large aggregate was generated around the Keene State College that mainly contained riot-related (e.g., crazy, insane) and police-related (e.g., helicopter) keywords (aggregate A). This reflects the fact that the riot mainly originated from the college. In contrast, the northern (aggregate B) and eastern (aggregate C) regions had more tweets related to the festival and entertainment. Since the aggregate B occupied a relatively small screen space, instead of the text-based visualization, the yellow dashed lines [11] were rendered on the boundary of the aggregate to indicate the major topics were festival-related.

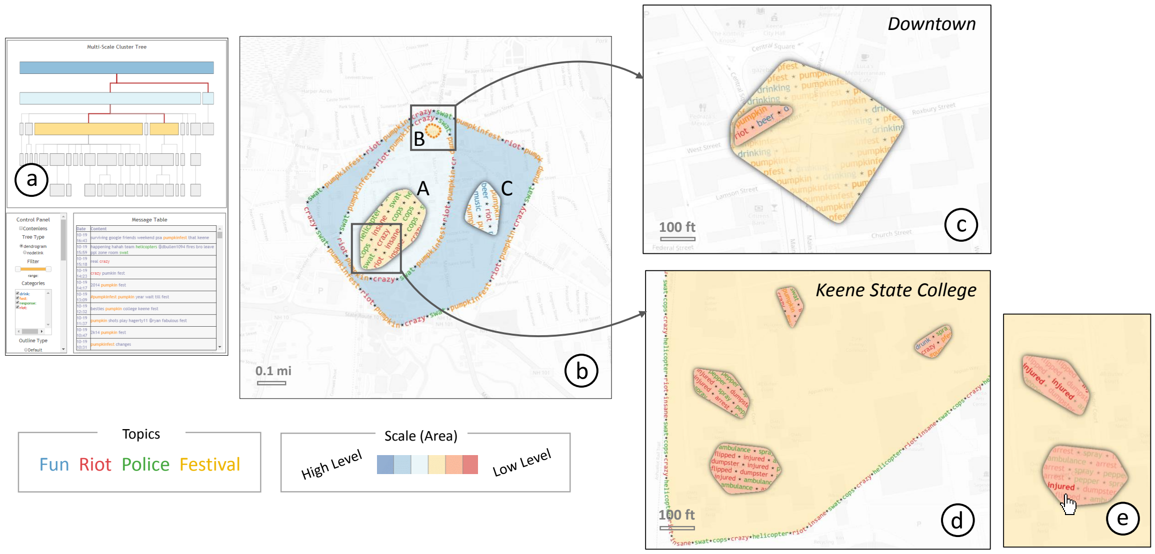


Fig. 5.7. The interface of TopoText consists of a geographic map view (b) for visualizing the multi-scale aggregates and their textual information and a tree view that provides an overview of the multi-scale hierarchy (a). TopoText utilizes a blue-red color scheme to render the inner space of the aggregates based on their aggregation levels. TopoText also allows for text-oriented interactions: e.g., hovering on a specific keyword highlights similar keywords in other aggregates (e).

We zoomed further into the college region to explore the event in details (Figure 5.7(d)). Two large aggregates (bottom left) on the campus were identified that contained keywords including "#injured", "#flipped", "#dumpster", "pepper", and "spray", which indicated that the celebration spun out of control and the law enforcement had to use pepper spray to subdue the rioters. We hovered on a keyword (e.g, "#injured"), with the interface automatically highlighting similar keywords in other aggregates (Figure 5.7(e)). We then navigated and zoomed into the northern region in the city (Figure 5.7(c)) and identified that this region was the downtown of the city (Central Square) where there were a lot of bars and clubs. Since the riot did not spread to this region, the riot-related keywords rarely appeared.

The topic summaries provided by TopoText allow the users to not only capture what has happened (e.g., the chaos), but also understand to what spatial extent the event has spread (e.g., the campus area) and identify locally concentrated actionable information (e.g., "flipped", "dumpsters") that were overshadowed by more general discussions (e.g., "crazy", "insane"). By utilizing the visual outcome from TopoText, an emergency manager is able to further evaluate the scale and impact of the event and perform effective resource allocation (e.g., city police or college police); A journalist who hear a series of reports from the witnesses at the incident is able to corroborate the first-hand accounts to determine whether each story fits with the overall trends of what was happening at the time.

5.4.2 Republican National Convention

We investigated the social media posts (8839 tweets) collected during the 2016 Republican National Convention (RNC) in the region around the city of Cleveland, OH. Similarly, we filtered out job-related posts and identified four major topics: RNC-related ("gop", "#rnc", "convention"), traffic-related ("vehicle", "blocked", "accident"), protest related ("#protest", "police", "#rally") and drinking-related ("drinking", "wine").

As Figure 5.8 shows, the region was dominated by the RNC-related topic since the outward aggregate mainly contained keywords such as "#rncincle", "trump" and "convention". As we continued to examine the lower levels, the multi-scale text-based visualization clearly revealed different topical patterns at the city level. A large aggregate around the city of Cleveland (highlighted in the figure) showed a high frequency of RNC-related and protest-related topics, potentially enhancing situational awareness for public safety personnel. In contrast, the nearby cities surrounding Cleveland contained more posts relevant to drinking and traffic. By further investigating the details associated with the individual aggregates, we found that the delegates and attendees were accommodated in the hotels in the nearby cities and suburbs and there were traffic restrictions near the convention center, causing some congestion and acci-

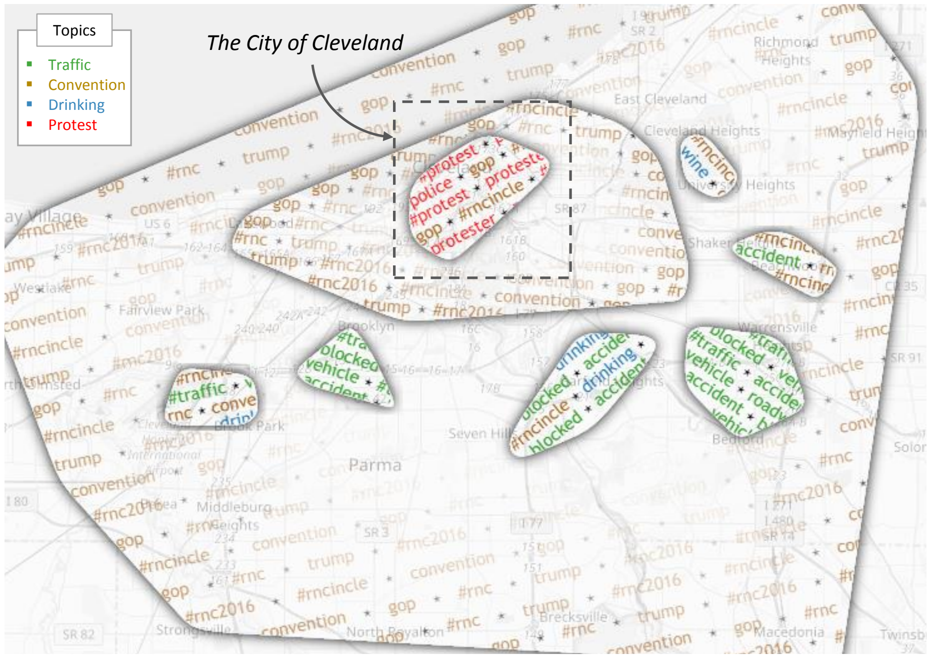


Fig. 5.8. Applying the TopoText technique to visualizing the social media data around the city of Cleveland, OH, during the 2016 Republican National Convention (RNC). The halo effect is enabled to highlight the aggregates' hierarchy. While the region shows a high frequency of RNC-related topics, the area of Cleveland also contains topics related protest. In contrast, suburban areas have more posts relevant to traffic and drinking.

dents. Therefore, the visual outcome generated by TopoText effectively preserves the semantic context and highlights the variance of spatial patterns at multiple scales.

5.5 Discussion

TopoText implements a hierarchical aggregation and visualization model [9] by effectively allocating screen space to the multi-scale aggregates and visualizing the semantic summary accordingly. Unlike the original model [9] that "treats" the aggregates at different levels equally, TopoText visually highlights the ones at the lowest level in the current viewport. This is achieved by showing the lowest-level aggregates (focus) on top of other levels (context) and increasing their opacity value [105]. The rationale behind this design is that in various analytical tasks within a hierarchical space, the users are required to navigate from the top level (abstract) to the bottom level (detail). Since the visual representation typically consists of a sub-space of the hierarchy, highlighting the lowest-level aggregates in the current sub-space can visually indicate the entry to the deeper levels and effectively guide the users to navigate within the multi-scale hierarchy.

The text labels rendered within the aggregate or on its boundary may potentially be truncated to visually indicate the shape of the aggregate. We note that this truncation issue is an inherent visual output in TopoText. Essentially, this is an NP-hard packing problem [106] that aims to arrange bins of different sizes into a container in order to minimize the empty space within the container. While applying advanced layout algorithms may reduce the truncation issue, it is beyond the scope of this work. TopoText summarizes the semantic content of multi-scale aggregates by rendering the top K (i.e. less than 10) representative words for each one (G2 and G3). Although the number of words associated with an aggregate could potentially be large, visualizing too many distinct words within the multi-scale context can easily overwhelm the user. When the user is interested in a specific aggregate and narrows down (i.e., perform the zooming operation) to that region, the visual space for that aggregate is enlarged accordingly to accommodate more distinct keywords.

TopoText generates high-quality and resolution-independent SVG imaging that supports efficient interaction handling as the SVG elements are organized as nodes in the browser DOM. However, the rendering performance may degrade when a large number of graphical elements are added in the DOM. While the current interface supports nearly interactive response (the latency is usually less than 2 seconds), the rendering performance can further be improved by precomputing the visual results at different spatial scales and organizing them as hierarchical map tiles in order to improve the interactivity and alleviate the rendering overload in the browser side.

The multi-scale hierarchy established in TopoText represents the spatial proximity of data points at different scales. The application of TopoText is not limited to geographic datasets and includes various types of spatial datasets. It can also be applied to non-spatial datasets that can be spatialized into the 2D space such that the pair-wise distance of the 2D points represents the proximity of certain data dimensions. Typical examples include low-dimensional representations generated from high-dimensional data based on dimension reduction (e.g., SOM, MDS, t-SNE) [107, 108]. As the projection often preserves the pairwise distance of data points, summarizing the multi-scale aggregation hierarchy at the low dimension can potentially provide the insight into the characteristics of the data patterns in the original high-dimensional space.

5.6 Conclusion

In this chapter, we have presented a text-based visualization technique called TopoText for maintaining the semantic context in the multi-scale aggregation space. Our primary contribution includes a set of visual encoding and layout strategies that spatialize visual text labels on the boundary or in the inner space of the aggregates. We have explored and evaluated several design choices that utilize different visual attributes of text labels including color, opacity, density and orientation for multi-scale text exploration tasks.

6. NAVIGATION ACROSS MULTIPLE SCALES BASED ON THE ANIMATED TRANSITION

In this chapter, we describe a novel navigation technique that maintains a smooth visual transition when the users navigate across multiple spatial scales. Compared to the TopoGroups and TopoText techniques that have described in chapter 4 and chapter 5, this animated transition technique is mainly applied to a typical map system where the users interactively perform zooming operations on the map. In this technique, the context 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.

We also apply this technique to the application of real-time social media analytics and exploration for situational awareness. Specifically, we propose a 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 6.3, utilizes a recently developed approach that provides microblog classification resources for information-specific categories related to the crisis social media data [109]. Our system visualizes these categories and spatiotemporal crisis-related microblogs through interactive glyphs in a spatiotemporal context. The 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.

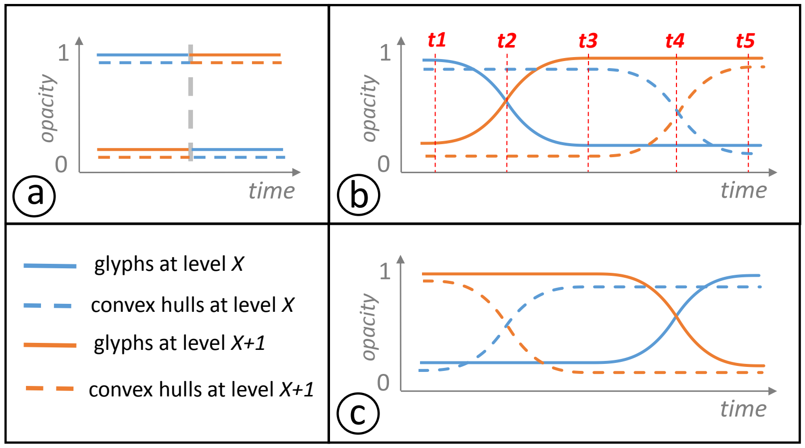


Fig. 6.1. Conventional transition: Zooming in (a). The animated transition: Zooming in (b), Zooming out (c).

6.1 Animated Transition Design for Multi-Scale Navigation

Animated transition techniques are commonly applied to provide a smooth change between different visualization states. Current work typically applies animated transition between different representations of the dataset [110], perspectives of the user [111], and positions and layout of the visual elements [112, 113]. 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 [10]. 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 6.1b 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 [110], as shown in the timeline in Figure 6.1. 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 6.1b and Figure 6.2, when the analyst zooms in on the map (Figure 6.2(t1)), the glyphs in Level X fade out while the glyphs in Level $X+1$ fade in (Figure 6.2(t2)). The convex hulls in Level X then fade out, while those in Level $X+1$ fade in (Figures 6.2(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 6.2(t3)).

Zooming out: As Figure 6.1c 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

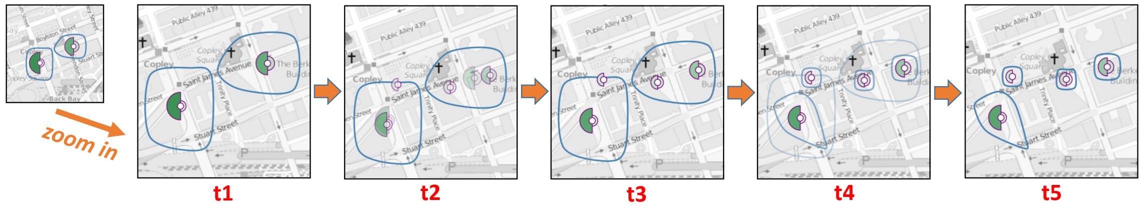


Fig. 6.2. An example of the animated transition in a zooming-in scenario. The transition states correspond to the timestamps in Figure 6.1b.

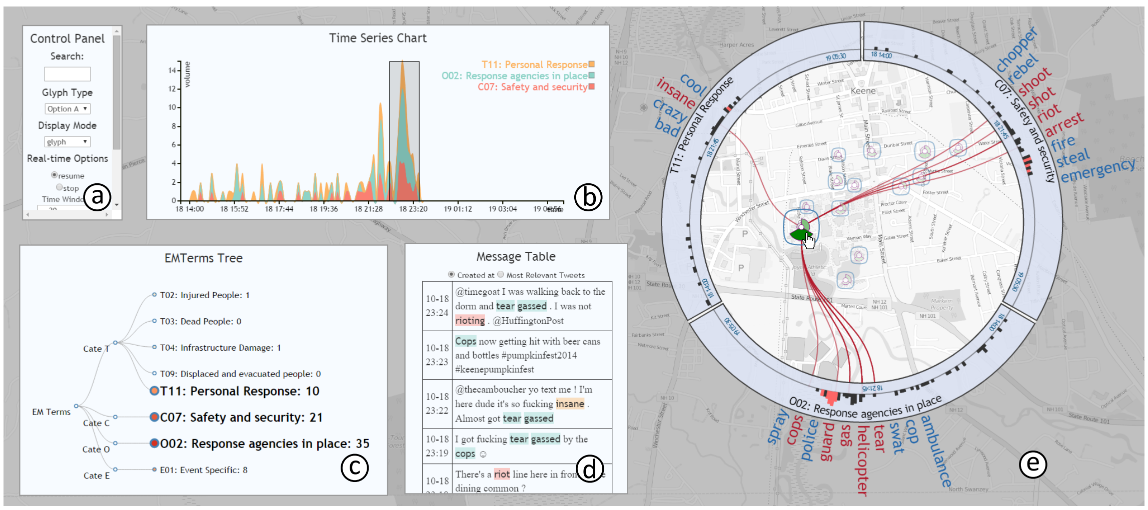


Fig. 6.3. A snapshot of our visual analytics system. (a) Control Panel; (b) Time-Series View; (c) Category Tree; (d) Message Table; (e) Map View. Hovering over a petal glyph (e) highlights the related keywords and connects to the corresponding keywords using threads.

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.

6.2 A Social Media Visual Analytics Framework for Situational Awareness

In this section, we present our visual analytics framework that supports both the real-time and retrospective analysis of social media data for situational awareness.

6.2.1 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 [114, 115]. 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.

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 [116] and topic modeling [117], have been typically focusing 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

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.

Fig. 6.4. Problem and task characterization [114,115] for visual microblog data exploration.

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 [21]. 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.

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 [118] 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 Figure 6.4. 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 [119].

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.

6.2.2 Visual Analytics Framework

Our system, described in Section 6.2.2, is comprised of several linked views that enable exploration and analysis of microblog data at multiple geospatial scales. We utilize a microblog classification scheme [109] that reduces the complexity of the analysis space by automatically classifying the data into appropriate disaster and emergency categories (Section 6.2.2). 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.

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 preprocessing. We utilize a newly developed terminological resource that is especially designed for crisis-related microblogs [109]. 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 6.3c. 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 [120]. 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 [121] 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.

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.

Category Tree Visualization: Our system utilizes a tree structure to depict the organization of the different categories (Figure 6.3c). 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 [122] (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.

Time-Series View: The time-series view (Figure 6.3b) 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).

Message Table: The message table (Figure 6.3d) 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 [123] that identifies the representative microblogs in order to allow the analysts to quickly access the most critical information in a timely manner (G5).

Map View: The main view of the system consists of an interactive geographic map (Figure 6.3e) 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 6.2.2. 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 6.2.2.

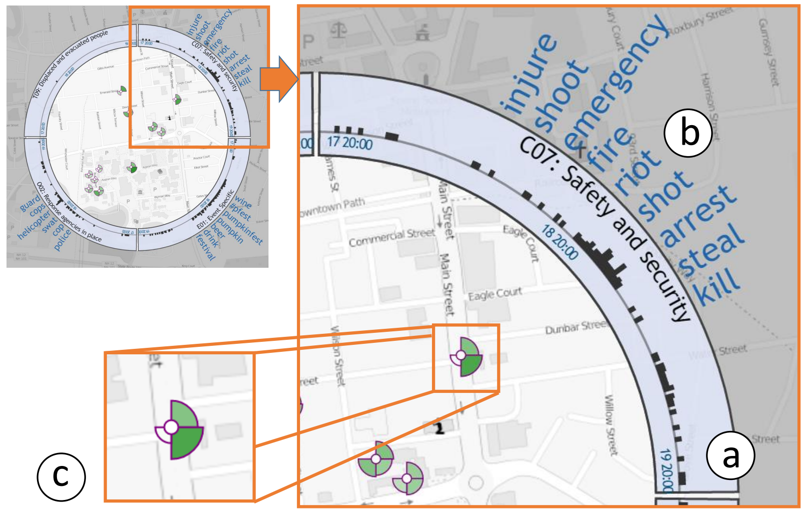


Fig. 6.5. Coupling spatial lens with petal glyphs.

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 [124, 125] (as shown in Figure 6.5).

Seeing the Big Picture — The Spatial Lens. The spatial lens is drawn on the geographical map, as shown in Figure 6.5. This lens is segmented into evenly spaced sectors that correspond to the categories selected by the analysts (Figure 6.3c). The inner ring of the spatial lens embeds a time series view [126] for the corresponding category (Figure 6.5a), along with keywords extracted from the microblogs for the category (Figure 6.5b) (G2) [127]. 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 are fixed in order to maintain the context of the exploration.

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 6.5c). The layout of the outer petals corresponds to the layout of categories in the perimeter of the spatial lens. The size and color of each petal doubly encode 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 [87] 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

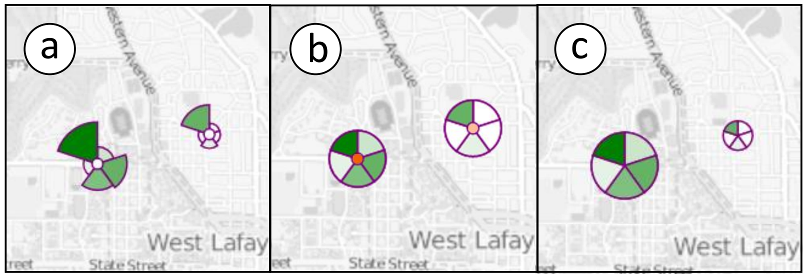


Fig. 6.6. (a): The design of the petal glyph. Two design alternatives are presented in (b) and (c).

on the map view to indicate the geospatial range of the clusters during the transition between the different geospatial scales (Section 6.1).

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 connect the petals to the relevant keywords in the perimeter of the lens (Figure 6.3e). 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 6.3d) 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 6.6). The design shown in Figure 6.6b uses only color to encode the volume of each category. The size of the petals is the same across all the glyphs. The color of the inner circle encodes the overall volume of this cluster. Figure 6.6c is similar to that of Figure 6.6b; 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 6.4.1). 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.

6.3 Case Studies

We present case studies to demonstrate our work in this section. For both case studies, we utilize location-based social media data to demonstrate the capability of our system in terms of real-time monitoring and analytics of the emergency events.

6.3.1 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 6.7). 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 6.7) 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 6.7(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, 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 6.7(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 6.7(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.

6.3.2 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

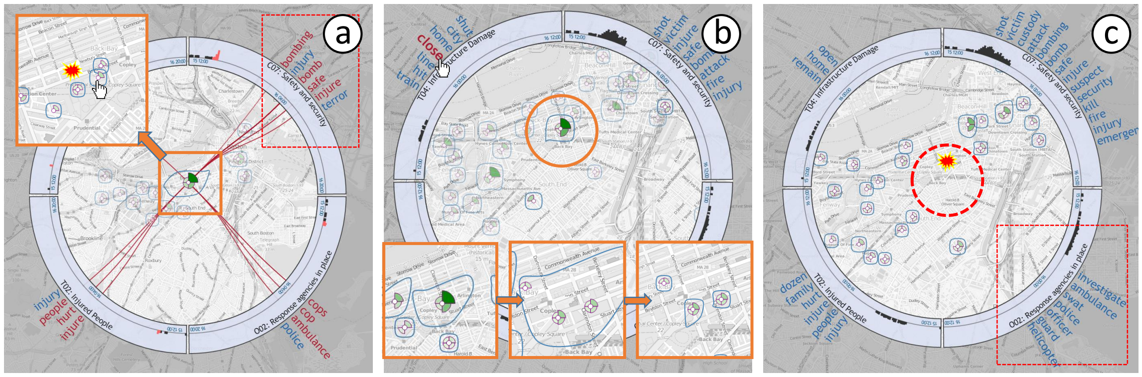


Fig. 6.7. Demonstration of our system using the Boston Marathon bombings incident. Screenshots of our system after 30 minutes (A), 1 hour (B), and 2 hours (C) of the bombings are shown.

for the following categories during the event: *personal response*, *response agencies in place*, and *safety and security* (Figure 6.3). 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 6.3(b)). The category tree also highlights the prominence of these specified categories (Figure 6.3(c)). The analyst further examines the map view and identifies a large spatial cluster near Keene State College (Figure 6.3(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 6.3(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 6.3(e)). Thus, the system provides an increased situational awareness for safety and security relevant incidents during the event.

6.4 Evaluation

We conducted two independent user studies to evaluate our petal-based visual design and the animated transition technique, which are described in Section 6.4.1 and Section 6.4.2. We also interviewed domain experts and presented their feedback in Section 6.4.3.

6.4.1 User Study 1: 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 (Figure 6.6). 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)?

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).

Results

Figure 6.8 shows the distribution of the accuracy and completion time of the three visual designs using box plots. We calculated the 95% confidence interval of the mean value based on the bootstrapping method [94] (the number of iterations equals 1000), and examined the result based on the overlap-test [95] and t-test [96]. The result is shown in Figure 6.9. Based on the accuracy results (Figure 6.9(left)), we found that the accuracy of Design A (Figure 6.6a) was the highest among the three designs (78% on average) and showed statistical significance. The accuracy of Design C (Figure 6.6c) was 54% on average, followed by Design B (Figure 6.6b), which had the lowest accuracy (49% on average). In terms of the task completion time, most of time spans were between 6 and 12 seconds. Design B had the highest completion time (11.47% on average), followed by Design C (9.82% on average) and Design A (9.37% on average).

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 6.6c) 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).

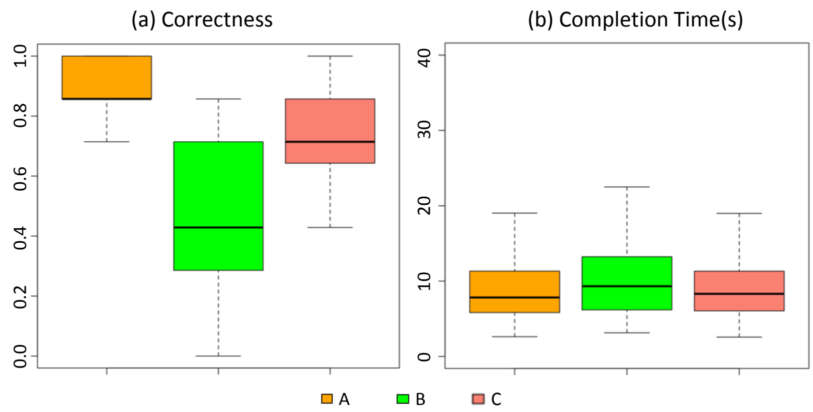


Fig. 6.8. The evaluation results of different petal designs. The box plots display the distribution of results based on the five number summary: minimum, first quartile, median, third quartile, and maximum.

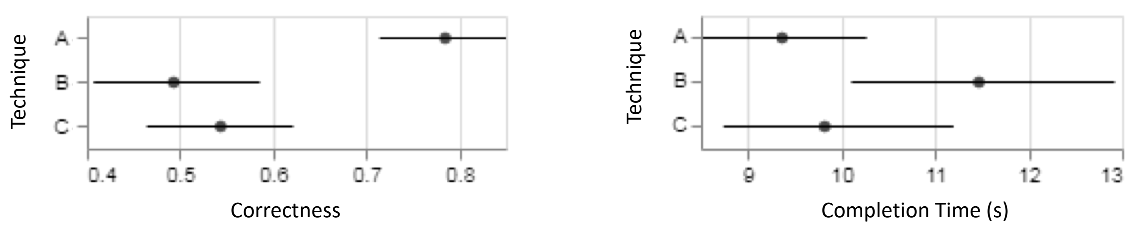


Fig. 6.9. The evaluation results of different petal designs that show the 95% confidence interval of the mean value calculated based on the bootstrapping method.

6.4.2 User Study 2: 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, 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.

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 6.4.1. 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.

Results

Figure 6.10 shows the distribution of the accuracy, completion time, and the number of zooming operations of the two interaction techniques using box plots. Figure 6.11 shows the bootstrapping results of conventional zooming and the animated transition technique. Based on the accuracy results (Figure 6.11(left)), we found that the animated transition technique had higher accuracy (87% on average) than conventional zooming (79% on average) ($p < .05$). As Figure 6.11(right) shows, we also found that participants performed significantly fewer zooming interactions when they used the animated transition technique (1.89 on average) versus conventional zooming (3.52 on average) ($p < .0001$). For task completion time, they spent an average time of 19.4 seconds with conventional zooming versus an average of 24.7 seconds with animated transition ($p < .05$) (Figure 6.11(middle)). 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 is relatively high. We believe this is

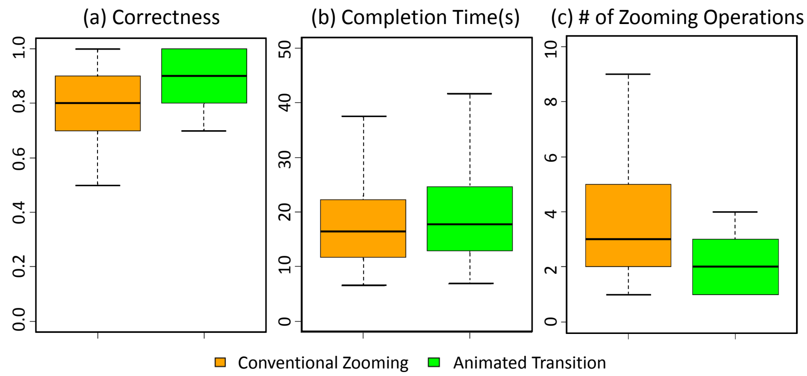


Fig. 6.10. Evaluation results: conventional zooming vs. animated transition. The box plots display the distribution of results based on the five number summary: minimum, first quartile, median, third quartile, and maximum.

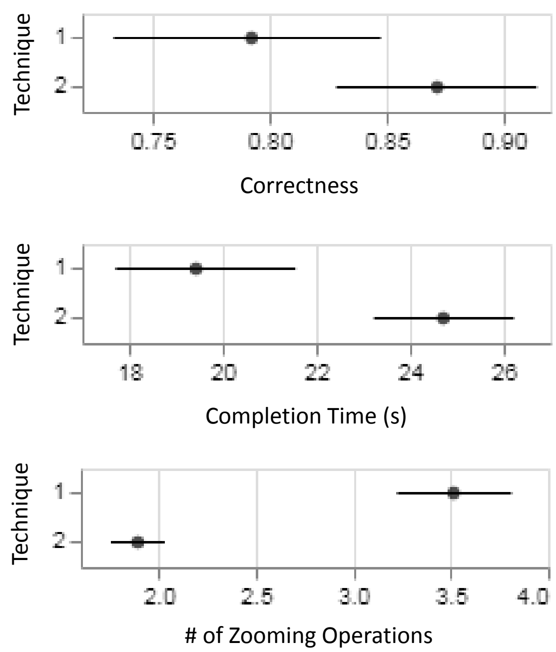


Fig. 6.11. Evaluation results based on the bootstrapping method: conventional zooming vs. animated transition.

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, *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.

6.4.3 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 6.5a). 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 6.3e) 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 6.6), they preferred the petal glyph visualization (Figure 6.6a). 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 6.2), 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 6.2) 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).

6.5 Conclusion

In this chapter, 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 that maintains a cohesive thematic context of the transition between the different geospatial granularity levels and streaming data states. Our experiment result indicates that the proposed technique significantly reduces zooming operations and improves accuracy compared to the conventional navigation paradigm.

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 multiple information dimensions including space, time and semantics. Feedback from domain experts further demonstrates the effectiveness of our approach in terms of preserving context of navigation across geospatial scales and multiple information dimensions.

7. CONCLUSIONS

In summary, this thesis presented a series of visual analytics techniques for context preservation across multiple spatial scales. Our techniques are built upon the condition that spatial clusters at multiple spatial scales form a hierarchical structure, making is possible to overlap multi-scale results into the same visual display. Our techniques include novel visual and interaction designs that take into consideration the trade-offs between information accuracy and visual simplicity. Furthermore, Our techniques can be applied to either a static authoring environment or an interactive and exploratory setting. We reiterate the major contributions of this thesis in the following two perspectives:

- **A context-preserving visualization technique that combines multi-scale aggregates into the same visual display [11, 12]:** We created a cluster hierarchy of spatial data points and distorted the cluster boundary to enable the combination of multi-scale aggregates with minimal visual clutter. We proposed a set of visual encoding and layout methods to visualize heterogeneous data types associated with the spatial data including numerical, categorical, and textual data. These design choices attempted to identify a small and optimal set of orthogonal visual channels such as color, transparency, shading, and shapes, and established a reasonable mapping between them and the data dimensions that need to be conveyed. Our user studies indicated that there is not a one-size-fits-all solution to different use scenarios and the optimal design to choose depends on the problem, task, and user requirements. We also demonstrated practical applications for the proposed approach through location-based social media analysis and crime report analysis.

- **A context-preserving interaction technique that maintains a smooth transition between different spatial scales [7]:** This preservation is achieved through a semi-translucent animated transition of visualizations at adjacent spatial scales so that users are able to maintain a smooth and continuous visual transition and avoid abrupt changes caused by different zoom levels. To demonstrate the proposed technique within a practical context, we have implemented a visual analytics framework for improving situational awareness across multiple geospatial scales by utilizing social media data. 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 and scales.

We also discuss future directions of this work in the following perspectives. These directions are derived based on the limitations of the proposed approaches and new challenges arisen from more complicated data and use scenarios.

- **Addressing the inconsistency issue between the data dimension and the geographical dimension:** Our context-preserving technique utilizes the visual budget associated with the spatial aggregates (i.e., the aggregate boundary or the inner space) to visualize the relevant information. Hence, the amount of visual budget is proportional to the area occupied by the aggregate in the geographic space. Considering that the complexity of the information being presented for an aggregate is usually proportional to the volume of the data within it, instead of the occupied area, our approaches may introduce a potential inefficiency of the visual space utilization. For example, in the context of social media analysis, the tweets posted around the college stadium during a major football game may be more complex than those posted on a common day across the campus, although the aggregate around the stadium occupies a much smaller area than the entire campus. Overcoming this inconsistency between the data dimension and the geographic dimension requires additional distortion or transformation to the visual representation. A future solution to address this issue is to design a cartogram [128] that distorts the shape of the aggregates such that the area is proportional to the data complexity. However, since the aggregates are associated with a geographic context, this distortion can cause fidelity issues and add visual confusion to the users. Therefore, we should take into consideration the trade-off between the visual expressiveness and the geographic accuracy.

- **Adapting the context-preserving approaches to partition-based data aggregation:** In our current techniques, the boundary of a specific aggregate is defined by the outmost or boundary points in the group. Hence, the boundary accurately depicts the spatial scope of the points contained in the aggregate. In contrast, the partition-based aggregation attempts to generate a spatial partition in the 2D space, such that any two aggregates are disjoint, and the union of all the aggregates form the entire space. The partition can either be calculated based on the data points, such as the Voronoi diagram [129], or be defined by data-independent metrics such as geographical or administrative division (i.e., the scales ranging from country and state to county and census block). Future work includes adapting the boundary distortion method to the partition-based aggregation in order to minimize the overlap. The adaptation may include polygon deflation rather than the inflation in the original method, as the adjacent aggregates generated by spatial partition share partial boundaries. Considering that the deflation operation can reduce the size of the polygon and hamper the readability of small polygons, a potential strategy to handle the issue would be deflating large polygons and inflating small ones.

- **Context preservation of streaming data:** The context preservation in our approaches is mainly applied to static data where the aggregate hierarchy is stable. Future work includes extending the approaches to maintaining the context of streaming data in real-time scenarios. To do this, we can manage a moving time window and visualize the aggregate hierarchy within the window.

Since the aggregate hierarchy becomes dynamic and can pose additional cognitive overload, this requires further research that explores effective methods to reduce the overload and ensure visual simplicity to the users.

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Jiawei Zhang is a Ph.D. student in the School of Electrical and Computer Engineering at Purdue University. His research interests include visual analytics and information visualization. Zhang has a Bachelor's degree in Computer Science from Zhejiang University.