Studying Animation for Real-Time Visual Analytics: A Design Study of Social Media Analytics in Emergency Management

Nadya A. Calderon
Interactive Arts and Technology
Simon Fraser University
ncaldero@sfu.ca

Richard Arias-Hernandez
Interactive Arts and Technology
Simon Fraser University
ariaher@sfu.ca

Brian Fisher
Interactive Arts and Technology
Simon Fraser University
bfisher@sfu.ca

Abstract

Domains such as emergency management have a need for real-time change monitoring and pattern analysis, but interface design principles for real-time visual analysis situations are still under development. In this paper, we present early results from a design study in social media visual analytics for emergency management. Our motivation is a main information visualization challenge: the lack of clear design principles informed by research in human cognition for the use of animation in real-time streams. We discuss three domain-specific challenges: (1) Coping with the high volume of social media data that is generated during disaster response, (2) analysts’ need to quickly extract relevant features for real-time sense-making; and (3) the effective analysis of social media streams even when some critical attributes are absent. This paper presents preliminary results on a research-based design principle for the use of animation in real-time visual analytics, targeted to support the real-time analysis of social media data in emergency management.

1. Introduction

Social media has gained increasing attention in the crisis and emergency management community during the past six years, specially after its use by citizens during the 2007 Virginia Tech shooting [37], the 2007 California wildfires [38], the 2010 Haiti earthquake [19], the 2011 Norway attacks [33], the 2011 Fukushima nuclear disaster [30], and the 2012 strike of Hurricane Sandy in the USA [26]. Surveys conducted by the Red Cross in USA in 2010 and in Canada in 2012[9] have also enhanced the interest of practitioners in social media since these surveys have clarified current citizens positions, perceptions, and expectations about the place of social media during crisis response.

However, only recently, information visualization and visual analytics researchers have been working on this application domain [23,32] and there are still many challenges presented by crisis-related social media data that these researchers need to attend to. One of these challenges is the immediacy of the analysis of social media data for emergency management. Computational processing of social media data for crisis management and its subsequent visual representation has mostly focused on supporting retrospective visual analytics rather than the ad-hoc, real-time visual analytics that is required during crisis response. One of the caveats that have prevented these kinds of approaches is the lack of consensus on what constitutes the best way for visually representing continuous streams of data to support analytical processes.

We report on qualitative and quantitative research conducted with emergency management practitioners involved in social media data analysis. The results of this research structure the domain problem, the target users, and the analytical tasks that configure pragmatic design requirements. We also report on the development of a first prototype for the visual encoding of streaming social media data in this domain. We use our research results to justify design decisions for the visual representation of real-time data, such as the use of animation, choice of visual encoding, and choice of colors (See Fig. 1).

The theoretical focus of this paper is on cognitive-informed design principles for real-time visualization and analysis of textual streaming data, such as the one provided by Twitter. In this paper, we talk about cognitive-research under the understanding of perception as visual cognition. Our laboratory conducts more of the higher order reasoning works as presented in [15], however, this study explores more of the perceptual saliency and lower order cognitive aspects. We still refer to it as cognitive research, as other works investigating animation and visualization do [17].

Although results are yet at an early stage, the two main contributions of this paper are: (1) theoretical contribution: a cognitive-informed research on a design
principle to make animation work for real-time visual analytics; and (2) applied and domain-specific contribution: the study of a visualization technique to support the real-time analysis of social media data in emergency management.

2. Related Work
2.1. Social media for emergency management

An in-depth content analysis of all of the papers published on the proceedings of the International Conference on Information Systems for Crisis Response and Management from 2008 to 2012 showed an increasing interest from researchers on current and potential uses of social media data for emergency response and management. The number of papers that included social media for emergency management as a research subject went from 4 papers in 2008 (4.2% of the total) to 13 in 2012 (12.9% of the total). Most of the research reported (60%) focused on Twitter-related uses, given the open access provided by the Twitter Search API and Twitter Stream API to harvest data for design and analysis.

The kind of research reported on the subject is also shifting. Early research tended to focus on descriptive approaches, which focused on understanding what citizens actually do when engaging with social media during crisis and disasters [37, 38]. More recently, the tendency is towards prescriptive and design-oriented approaches, which focus on what citizens, agencies, and designers should do to make the most of social media for effective crisis response and emergency management. Examples of this latter kind of approach includes: proposed syntaxes for ease of management of emergency Tweets [32], systems that automate the harvesting and classification of social media data using NLP and machine learning algorithms [34], and applications that provide visual representations and interactions with social media data for emergency management practitioners [23]. This shift towards a prescriptive and design-oriented approach is also the result of the progressive understanding of the value that social media has in this particular application domain and the specific challenges that need to be addressed, such as: large volumes of data, ill-structured and incomplete data, source trustability, multiple/unstable ontologies used by social media analysts in emergency management, and the need for real-time processing and analysis of streaming social media data.

2.2. Visual analytics of social media for emergency management

A more specialized sub-field that relates to the topic of this paper is the one found in the intersection between visual analytics and social media for emergency management. Independently both fields are relatively recent and, so far, there are not too many developments on studies and applications of visual analytics for the analysis of crisis-related social media data. However, the challenges presented by the analysis of this particular data/domain and what visual analytics can offer to leverage on these challenges have a natural correspondence.

In a recent review of visual analysis of social media data conducted by Schreck and Keim [31], the authors highlighted the challenges this kind of data and analytics present. Among them: large volume of data, high frequency data streams, multimodality, ambiguous content, rapidly changing contents and communication patterns, data types complex to process, and analytic tasks highly context- and user-dependent [31]. These challenges, according to the authors, cannot be matched solely by fully automated analysis methods. What is needed is a combination of computer-driven data processing/pattern search with human-driven reasoning mediated by interactions with visual interfaces [31]. Recent studies have supported this argument by demonstrating how visual analytics can be put to work for social media analysis, specifically in emergency management.

Some of the research reported in visual analytics for social media is not explicit in its application to emergency management, but its potentiality can be inferred from uses in other domains. For example, Dörk et al. [11] developed a visual analytics system to get an overview of evolving and changing topics on Twitter to increase the level of meaningful participation during meetings and events. Their strategy was to use “Visual Backchannel,” an interactive interface with four main views: a temporally adjustable ThemeRiver that visualizes topics over time, a linked visualization of the most active participants, a chronologically ordered list of posts, and an image cloud representing the popularity of event photos by size [11].

Kumar et al. [22] and MacEachren et al. [23] provide some of the first explicit attempts to develop visual analytics tools for the analysis of social media data in this domain. In 2011, Kumar et al. [22] introduced “TweetTracker,” a visual analytics tool targeted to help humanitarian aid and disaster relief (HADR) respondents increase their situational awareness and gain insights from microblogging data [22]. TweetTracker monitors and extracts location and keyword specific tweets with near real-time trending, data reduction, historical review, and integrated data mining tools. Interactions include filters to focus on
tweets of interest and playback of streaming data. Linked heat maps and reTweet network graphs allow analysts to drill down into the specifics of the data. The tool was designed to support situational awareness, planning, and coordination tasks and it was used by the HADR organization Humanitarian Road when Hurricane Sandy hit the Northeastern United States in Oct. 2012. Also in 2011, MacEachren et al. introduced SensePlace2 [23]. SensePlace2 is a map and web-based, visual analytics tool designed to support sense-making of crisis-relevant information harvested from Twitter. Developed using a user-centered design approach, SensePlace2’s main goal is to increase emergency management practitioners situational awareness during disasters. In addition to visual analytics features that support analysis, such as the time filter that combines a range slide with a heat-bar to help analysts choose a strategic range of tweets over time, key innovations of SensePlace2 were: the automated extraction of location information from textual content to increase the number of tweets that can be plotted on a map, visual distinctions between tweets generated from the crisis location and about the crisis location, and explicit support for reasoning processes such as recall of past search parameters [23]. The current version of SensePlace2, however, uses pre-harvested social media data sets and does not support real-time analysis of streaming data. For our design study, we follow Kumar et al. approach of visual analytics of streaming social media data, but we also build upon the user-centered design approach followed by MacEachren et al.

More recently Chae et al. [8] have explicitly extended work on social media event detection and topic extraction in visual analytics to applications in emergency management. Their focus was on increasing situational awareness by detecting and exploring abnormal topics and events in social media data that are relevant to crisis management. Rather than ranking events by volume [11] or topics by immediate novelty, topics are ranked by their lack of correspondence with global and seasonal trends, in other words, by their anomalous character [8]. The analyst interacts with the parameters of the topic extraction and seasonal trending algorithms to determine levels of granularity in topic extraction, thresholds for seasonal trends, and selection of specific topic for cross reference with other social media datasets. The author’s workbench ScatterBlogs extracts and pre-process streaming Twitter data. A key innovation of ScatterBlogs is the combination of computer-driven semi-automated processes and human-driven setting of parameters to refine the selection of data. Similar to MacEachren et al.’s, Chae et al.’s design study emphasizes novel applications of algorithms and interactions for the visual analysis of social media data in emergency management, however neither of them conducted experimental studies to test the effectiveness of their visualizations or interactions on leveraging human cognition during their design process. We explicitly address this aspect in our research. We also focus on one kind of analysis that has recently emerged as central in studies of visual analysis of social media data for emergency management, namely that of real-time affective content or sentiment analysis [34, 21, 12].

2.3. Real-time visual analytics

2.3.1. Visualizations. One of the main challenges of exploring real-time series is to track changing data streams without a-priori search targets to identify general structure and patterns. For this reason, using a visual representation constitutes an advantage for monitoring what is happening and allowing fast access to the information [13].

Visualizing temporal datasets starts with the basic principle of a time series chart. Depending on the analysis requirements, time can be better represented on spiral visualizations [40] or pixel-like visualizations [20]. Weber argues that besides the representation, including the ability to parameterize scales, intervals and cycle lengths, as in the case of the spiral, leads to better outcomes during the exploration of data [40]. However, most of these techniques require computation over the whole dataset, which represents a restriction when information is dynamic as is the case with real-time streams. Additionally, Aigner et al. [1] highlight that when dealing with time-oriented data, the notion of time varies between problems, and more consistency is required in order to aid designers and developers in their endeavors. From different taxonomies of time, Aigner et al. selected Frank’s [14] taxonomy to categorize time along the following dimensions: 1) linear vs. cyclic time; 2) time points vs. time intervals; and 3) ordered time, branching time, and time with multiple perspectives. Understanding these differences is important for both, the designer and the analyst, since an effective visualization is the result of appropriate combinations of visualization and interaction techniques, consistent with the characteristics of the time domain represented by data.

In streams of social media data generated during emergency situations, time is linear and ordered. However, especially during the response and recovery stages, the analysis of aggregated intervals could be as relevant as the analysis of specific time points. Accordingly, Krstajic et al. [21] described two basic requirements for processing real-time streaming data: 1) a time interval in which data is considered relevant has to be defined, and 2) the size of the memory pool that contains streamed data objects has to be
determined [21]. Considering this, they designed a visualization for the analysis of news streams that represents data as soon as it arrives without aggregation or clustering. In a second view, they represented visually the aggregation of feeds into topic-threads according to pre-established categories, time of creation, and relevance. They also supported the adaptive change of the time interval in which the analysis is performed, just as SensePlace2 does it [23]. The value in computing and presenting aggregation is the possibility to detect relationships between data items, distinguish relevance, and optimize performance for the visualization.

Aigner et al. [1] referred to ThemeRiver to illustrate the representation of an ordered-time problem, and they considered that most of time-related problems would fall into this class. Originally, the system was introduced as a technique to analyze the evolution of dynamic themes within the exploration of documents [18]. Later work by Byron and Wattenberg [7] built up on the ThemeRiver concept, explored the same representational goal (multiple time series or categories) and discussed the importance of legibility of labels and aesthetic characteristics. The resultant technique is known as a streamgraph [7]. We built upon ThemeRiver for our visual encoding of streaming social data since ThemeRiver allows for the simultaneous exploration of multiple dimensions of data at the same time while depicting the temporal behavior of each one. However, different than ThemeRiver we switch from a solely categorical perspective to a combined categorical-ordinal perspective, supported by an ordered set of affective content polarities. This allows us to take advantage of the representation of volume of data and the ordered position of representations of data among categories.

2.3.2. Motion and Animation. Considering the dynamic nature of streams of data, linear time visualizations have relied on the use of animation (whether interactive or not) to represent the time update, especially when the information space is too large. This has been usually done by animating time from right to left on the X-axis of a 2D representation, where the rightmost limit represents the present and old data gets discarded from the view at the leftmost side [1, 18].

The design challenge when using animation for representing change in streaming data is to leverage on humans pre-attentive visual processing in order to reduce cognitive workload that could be placed by attentive visual processing. All examples mentioned in 2.3.1 use animation, as the illusion of movement in screen, to visualize updates in time streams. We are interested in investigating if animation can be used more actively to depict patterns rather than being used only as the necessary illusion of time updating.

Visualization researchers have often used motion as a visual variable, which means using the perceptual properties of movement to map data attributes as much as we would do with other visual attributes, such as color. One of the theoretical foundations to argue such an approach is the Gestalt principle of Common Fate for perceptual grouping. As Ware [39] presents it, Common Fate is a principle that states that elements moving together are perceived pre-attentively as a group. Such idea has been used as a design guideline when the purpose is to draw our attention towards a specific group of objects from a larger set. An example of a visual interface recurring to this principle is the Trendalyzer software for animation of statistics [28]. The system uses color, size, 2D space and time animation as visual variables to present comparisons of multidimensional data in the form of an animated bubble chart. The movement of groups of bubbles, representing for example countries, depicts the evolution in time of variables plotted in XY axes.

A comparative study of Trendalyzer versus small multiples for the analysis of trends over time revealed that, for analytical purposes, the use of static images in the form of small multiples is more effective for the discovery of patterns [27]. However, when information is dynamic, as is the case with real-time updates and social media data, using small multiples is impractical given that the time interval is not fixed. In such case, animation of objects is still a promising solution.

Animation and its cognitive limitations and advantages have been subject of study for researchers in diverse areas. Geographic information systems, interactive map design and research on the value of animation for learning are some few other examples [36, 17]. Tversky et al. conducted a thorough survey on the role of animations teaching complex systems (like mechanical, or biological). They critically argue against many experiments conducted to evaluate the effectiveness of animation when learning abstract concepts and systems. Their conclusions, similarly to Robertson et al.’s work [27], suggest that such studies are overstated rationalizations of the benefits of animation and do not consider the comparison to static images. However, such conclusions are restricted to those situations. They briefly note that other uses of animation, especially in computer interfaces “have perhaps passed the test” and foresee that “the most promising uses of animation seem to be to convey real-time changes” [36], which is the very issue of the work presented in this paper.

Along with this idea, Albrecht-Buehler [2] proposed as design guideline that if motion is to be used in visualizations of data, it should be used to
represent change in data, and objects that are semantically related should move similarly. Bartram [5] also advocated for the use of animation as it can provide insights when the patterns can only be seen as visual change. She argued for the use of animation as a strategy to cope with visual fragmentation and perceptual inference, common challenges found when visualizing large datasets of multivariate data in a single screen [5]. Moreover, Sirisack & Grimvall [29] insisted in the use of animated bubble charts (as Trendalizer) by arguing that groups of objects moving together draw attention when they move in the same direction and highlight outliers moving in completely different directions. However, neither Sirisack & Grimvall’s nor any other reported study have evaluated directly the use of the Common Fate principle in visualizations of streaming data or the use of animation on real-time series plotted as 2D charts moving along the X-axis.

3. Study Design

In this section, we present the results of the first phase of our design study. We start describing the target problem and the design requirements that resulted from a six-day fieldwork with emergency management practitioners from the cities of Richmond and Vancouver in British Columbia. We then proceed to present the visual encoding that we designed to fulfill the requirements and the experimental results.

3.1. Social media data analysis in emergency operations centers in Richmond and Vancouver

A series of non-participant observations, surveys, and interviews were conducted with emergency management staff of the cities of Richmond and Vancouver between May and December 2011. The observations included: a total of five full days of regular administrative operations in Richmond, a 1-day session with Richmond staff operating an emergency notification system, a 1-day tabletop interagency exercise that included the activation of the Richmond EOC, a 2-day multi-jurisdictional table-top exercise that activated Emergency Operation Centres (EOCs) in Richmond and Vancouver, and a 2 days of a real-life activation at the Vancouver EOC. The main goal of this fieldwork was to understand and model the workflow and current information flows in order to find leverage points for visual analytics support [3]. One of the identified leverage points was the analysis of social media data for emergency response [3].

The observations conducted at the Richmond and Vancouver EOC located social media analysis during crisis response as a side-activity performed by the communications officer in order to monitor and identify the emotional state of the general population with respect to ongoing crisis situations and with respect to responses to official press releases. Monitoring of social media content was restricted to Twitter and it was manually conducted by reading individual tweets aggregated by HootSuite. During the observations, practitioners did not incorporate insights from social media analysis into the workflow of other EOC areas, such as planning, which manages situational boards and representations. Interviews conducted with the Richmond staff noted their interest to streamline the monitoring of social media data rather than manually having to go through the time-consuming task of reading individual tweets. They expressed their desire for a heat-map that could quickly visualize the distribution of the emotional states of citizens during crises. A greater operational impact of social media analysis on increasing situational awareness and integration of social media analysis in operational activities was considered impractical by practitioners, according to a survey conducted [10], mainly due to the intense workload associated to social media analysis, their lack of human resources to dedicate to this task, and the lack of mechanisms to verify the validity of social media content [10].

At the Vancouver EOC, social media data analysis was observed differently during one tabletop exercise that tested Ushahidi [24], an application that provides a visual representation of semi-structured social media data. This pilot study tested how an automated tool and a visual representation could aid practitioners overcome some of the obstacles identified in social media analysis by emergency management practitioners. During the exercise, which simulated an earthquake in Metro Vancouver, student-volunteers on the street used the Ushahidi app from their smartphones to report on disaster impacts at different points of the city. The Ushahidi format used required users to specify the kind of event being reported using a pre-established ontology. The interface provided a basic geo-visualization of the posts, a detailed listing of the posts, and basic filtering according to the pre-established ontology.

Operationally, the City of Vancouver moved the analysis from the communications officer to the emergency line unit (311). There, dispatchers monitored the Ushahidi website (while attending the emergency line), read and analyzed individual posts, wrote summaries of the situation on their internal system and sent these messages to the EOC Director.
The main result of this pilot study was that automated tools and visualizations of social media data proved useful in moving social media analysis from public communication management towards operational tasks at the EOC. It was also demonstrated that social media data could increase the situational awareness of emergency managers by adding a citizen-created channel of situation reports. However, the specific implementation of the interactive visualization for the pilot increased the cognitive workload of dispatchers, who split their attention between responding to emergency lines and manually reading posts on the Ushahidi interface. The visualization did not speed up the analysis of the data either, since dispatchers resorted to manually reading individual feeds and manually writing summaries of the posts on the internal emergency management information system. Considering the amount of data created during the exercise, the manual tasks of reading posts/writing summaries were doable, however during a real emergency, when thousands of posts can be created, performing these tasks without automated support becomes unfeasible and impractical.

In order to address the gaps identified during the fieldwork and in collaboration with the practitioners, we defined the following domain-specific requirements: 1) Automated support for affective content analysis of social media data during disasters to detect general patterns of sentiment and detailed and extreme levels of distress to inform operational activities; 2) Visualizations designed for quick detection of extreme values, outliers, and patterns from large volumes of streaming social media data during disasters; 3) Given the incompleteness of geolocated information in social media, provide for alternative dimensions of analysis for such data.

3.2. Design and evaluation

The first phase of the design solution consisted in exploring the representation of sentiment trends using a streamgraph-like visual encoding. We investigated the use of animation, informed by the Gestalt principle of Common Fate, to enhance the perception of patterns within ordinal categories of sentiment values.

By doing this we explicitly addressed the domain-specific requirements for visualizing the stream of social media data and the need to empirically test how the animation of such stream could better be integrated in the visualization to support cognitive processes. Our interest was to investigate if movement of perceptually grouped objects could augment the perception of patterns when visualizing series over time using streamgraphs.

We designed and evaluated three versions of an animated visualization of the sentiment values of the tweet stream. The first version used the traditional animation of ThemeRiver (Fig.1.a). The second version used a group of colored circles (blobs) moving along the Y-axis at the rightmost border of the stream (Fig.1.b). The third version combined the first and the second version (Fig.1.c). Each blob was placed at the right border of each of the contours corresponding to each of the values being represented at the present time. Although inspired in the categories of themes originally used by ThemeRiver, our visual encoding represents the flow of the stream tweets categorized by an ordinal value of sentiment content rather than by categorical values or themes.

Within sentiment analysis, the purpose is to extract affective polarities (positive or negative) from unstructured text. There are multiple algorithms for the mining process but there are not many tools to explore the sentiment values extracted as result [16]. The ordinal values of sentiment content map how positive or negative is the content of tweets. We selected SentiStrength as algorithm to calculate such values. It assigns a positive and negative valence with a corresponding magnitude to every tweet [35]. Magnitude ranges from 1 to 5 with 1 being lowly charged and 5 being very charged. Thus, the sentiment analysis of a tweet results in both, a positive valence magnitude (1-to-5) and a negative valence magnitude (1-to-5). For example, for a person worried about her family, who tweets the following text: “I’m worried about my friends family on the east coast. Hopefully Sandy will take it easy on them”, the sentiment values assigned by the algorithm are (-4, 2), meaning that the affective content is ranked with a magnitude of 4 in the negative valence, and with a magnitude of 2 in the positive valence. Instead of representing both values in the screen, we calculated a single sentiment value as the arithmetic addition of the negative and positive magnitudes. Hence, we visualize 9 possible ordinal values.
sentiment values between -4 and +4. For example, for the tweet presented before, the sentiment value would be a total of -2 (-4+2).

Each category was color-coded using a value of warm orange for positive and a value of cold blue to represent negative. Even though the use of red in emergencies situations is associated with danger, for the case of exploring streaming social media data, practitioners described their interest on visualizing heat maps of sentiment distress relating the metaphor to temperature. Therefore we decided to use orange to represent warm, positive values and blue to represent cold, negative values. Difference in degree was represented using a variation of hue. The scale of colors was created with ColorBrewer [6]. Fig. 1.a depicts a snippet of the stream of data, encoded as sentiment categories and their color-coding.

3.2.1. Evaluation. We conducted an experimental evaluation to determine the effect of the three versions of the animated visualization of the stream on the accuracy of perception of a specific set of patterns. Each animation version (Fig.1.a, 1.b, 1.c) corresponded to an experimental condition and presented the same dataset of sentiment-annotated tweets collected during the Hurricane Sandy strike in New York City in October 2012. The data sample covered 30 minutes of tweets with an approximate volume rate of 450 tweets per minute collected on October 29th 2012. In total, 12,000 annotated tweets were represented for the experimental trials. The X-axis of the graphs represented time and each discrete data point aggregated 5 seconds of data.

Considering the type of information and the target analysts, we were interested in discovering 4 specific patterns. Fig. 2 depicts each of them as: a) the stream of information is turning positive, which should depict a decrease of the blue areas and an increase of the orange ones. Similarly, b) the information turning negative was reproduced as a decrease of oranges and an increase of blue areas. The last two patterns corresponded with the polarities moving in the same direction either c) turning neutral: both converging towards zero, or d) polarizing: both sentiment valences diverge towards opposite values.

21 participants from a convenient sampling selection took part in the experiment. The group consisted of 9 males and 12 females, undergraduate and graduate students, from an art and technology school. The experiment followed a 3X3 between-subjects repeated measures design having animation and trial as factors. Participants were randomly assigned to one of the three conditions and each of them completed 3 trials. Each trial consisted of 10 minutes of data (2 real minutes of interaction as we speeded up the animation since the purpose was distinguishing patterns as soon as they would appear). Each individual was asked to mark, using a specific key from the keyboard, as soon as she would notice one of the patterns, as quick as possible. The measurement under analysis was “accuracy score” contrasting the participants’ answers with a target vector (a truth dataset).

We hypothesized than the group using the combined representation of stream areas and animated blobs, would achieve higher scores on finding patterns. We also expected that for all the groups, there would be a learning effect, described as higher scores over time.

3.2.2. Results. We conducted a 3X3 repeated measures MANOVA analysis on the accuracy scores of recognizing the 4 patterns within the target dataset. Mean accuracy scores were low (accuracy < 18% of correct answers). The between-subjects or group effect was not significant p>0.05. Wilk’s Lambda Test did not show significance for the time by group (animation) interaction p>0.05. Finally, the time effect was found significant F(2,17)=4.94, p=0.02. Further post-hoc test for contrasts revealed a significance difference between trial 2 (T2) and trial 3 (T3), F(1,18)=9.05, p=0.007, as well as borderline significance for (T1) being significantly different to (T3) F(1,18)=3.40, p=0.08, which represented our assumption of learning over time. Figure 3 summarizes the mean scores of the groups for each trial.

We also conducted qualitative analysis of the perceived difficulty of the task and the animation reported by participants. Emerging topics from a thematic analysis resulted in three categories of themes
related to either our hypotheses or to the experimental design as: 1) issues with learning the keyboard controls 2) self-perception of improved accuracy and 3) attention strategies to cope with the task.

4. Limitations and Next Design Iterations

We have presented the first phase of our design solution, as an approach to investigate the effect of animation on the representation of social media streams of data for emergency response.

From the visualization principles, the literature review and the practitioners requirements we identified two additional requirements for a real-time visualization design: 1) the inclusion of interactive capabilities to explore the streaming information space, and 2) the ability to show more context of the information space while depicting the stream as one of the perspectives.

Interactivity is well known to support cognitive performance. This work is well documented on Tversky and Morrison survey review [36]. We have determined that the next design phase includes the development of details-on-demand interactions; moreover, we are also aware of the importance of the representation of geo-localized data when available (critical to emergency managers), and the compiled overview of events from the beginning of the exploration in order to represent potential periodic patterns. Even though our initial intention was to compensate for the lack of explicit attributes such as geo-localization, common in Twitter data, with the representation of other attributes, such as affective content, recent developments in visual analytics and social media analysis are making the extraction of geo-location from Twitter content more precise and easy to integrate into real-time visual analytics [23, 24].

One of the limitations of this study consists of subject matter experts’ evaluation. The design cycle started with a fieldwork collection of requirements and current practices of emergency management practitioners hence, next phase evaluations should include a qualitative and quantitative evaluation of the interactive visualization with subject matter experts using our Pair Analysis method [4].

5. Conclusions

We began this study by investigating how to make better use of motion in screen (animation) considering it as a common strategy to represent information over time. For the specific case of streaming data, animation is frequently used to keep the flow of information updated, event though there are no specific cognitive-supported design guidelines to use animation of time along the X-axis for the discovery of patterns in the data. We designed a streamgraph of ordinal categories that represent sentiment values of Twitter posts. In order to evaluate the benefit of animation for the
discovery of patterns within such affective categories, we conducted a controlled experiment investigating the effect of implementing the Gestalt principle of Common Fate on a group of blobs moving along the contours of the streamgraphs.

This study is the first towards our investigations, even though it presents preliminary results, we find important to continue investigating if animation, implemented as the group of objects moving along the contour of the curves, act as a pre-attentive processing target that could be easily perceived and that could increase accuracy on identifying patterns formed by the comparison of the different sentiment categories presented in the stream.

We highlight how a cognition-research approach can be adopted for design research in visual analytics of social media, something that we found lacking in current developments. For example, Krstajic et al. [21] have presented a promising set of requirements to visualize real-time streams but the transitions over time or the decay functions to update information have not been evaluated on their effectiveness to perceptually observe changes in their stream of categories of news.

Our design study addressed three domain-specific requirements to support the analysis of social media streams during emergency situations. First, our information visualization, inspired by ThemeRiver, addressed the information deluge challenge during disaster response that prevents emergency practitioners to manually analyze social media streams. It targeted an analytical need considered critical by the emergency management practitioners, namely that of identifying levels of distress and emotional state of citizens during crises or disasters, by providing a more effective way to skim and filter large amounts of tweets. Second, our experimental approach tested three versions of animated time series of streaming data to address another domain-specific requirement: the practitioners need to quickly extract relevant features for sense-making. Third, our design used the affective content dimension in order to make sense of large amounts of data that lack completeness of its geo-location attributes, a common occurrence in Twitter data. This satisfies the requirement of supporting an effective analysis of social media streams even when some critical attributes are absent. Although the literature revealed other approaches to cope with similar situations of incompleteness [2], such work has been developed using multiple validations and queries to the information source after analyzing the raw data. This is a constraint when dealing with real-time streams.

Future work aims to improve on the current version of the visualization by introducing interactions, by providing overview of items for which location can be extracted or approximated, and by supporting every improvement with cognitive-supported evaluations that leverages on human cognitive and reasoning strengths.

10. References


