Towards Interaction Techniques for Social Media Data Exploration on Large High-Resolution Displays

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Abstract

Exploring large geolocated social media datasets is now an important task in many pursuits e.g. crisis response. Yet there is still a lack of effective methods to view and interact with large amounts spatially-disturbed user-generated content. In this work, we explore interaction techniques for an extended version of ScatterBlogs — an interactive application for exploring massive twitter datasets on large high-resolution displays. We designed an interaction technique that employs multiple tablets to enable multiple users to effectively manipulate geolocated twitter massages on a large screen. In a preliminary user study, we compared our technique with using a desktop computer. Results indicate that the technique offers superior performance and user experience. In future work, we will explore how our technique can enhance the user experience of interacting with analytics applications.

Author Keywords

Social media; interaction patterns; multidisplay environment; large-high resolution displays.

ACM Classification Keywords

H.5.2 [User Interfaces]: Graphical user interfaces (GUI).

Introduction and Related Work

Over the last decade social networking service have developed to a common and widely used communication channel. Today it is not only used to exchange messages between people know each other, but also to share opinions, information about events experience publicly [7]. Hence, twitter users can be seen as "human sensors" (e.g. [21]) providing i.a. social trends, that are complicated to detect with electronic sensors. Furthermore, social network services have become one of the most important information source about emergency cases [10]. Data collected by using this approach is not only relevant for marketing strategies, but also for crisis management. As social networking service twitter is in particular an important data source, because all twitter messages are public and some contain information about the user location while tweeting. This enables to classify events and trends as local or global. Furthermore, if users tweet multiple times, also movement patterns can be created.

Sakaki et al. [17] use Twitter messages (tweets) to generate notification about large events such as earthquakes in realtime. However, some tweets contain incorrect or false information. Hence, analysts need tools to extract or validate important information from tweets [12]. A set of publications discuss approaches to visualize tweets for sense-making. MacEachren et al. [11] conducted an online survey asking practitioners in emergency management about their expectations and requirements for an visualization and analysing tool using tweets as basis. As a result they designed a web-application showing aggregated geo-located information on a map in combination with the possibility to access single tweets. Hao et al. [5] proposed colour coding for positive and negative statements in tweets. Inter alia the authors also present the aggregated data on a map to detect local trends. Besides analysing the content of Twitter messages, Krüger et al. [9] present an analytics tool to derive movement patterns from tweets. These movement data can not only be relevant for emergency management, but can also be used as basic information for urban planning. All these social network analysing tools use at least for some visualizations maps.

Through the spatial characteristic of maps, performing map related task on large high-resolution displays (LHRDs) is natural. A number of research projects used map based task to explore the utility of LHRDs. Ball et al. [1] asked participants to navigate and to compare targets on a map, which was displayed on different sized displays. Results show that participants were faster when using more display space and preferred physical navigation. Yost and North [20] displayed a map overlayed with bar charts and line graphs. Even when a large number of bar charts and line graphs was displayed, users were not overwhelmed and able to draw connections between single visualisations. Reda et al. [16] showed that juxtaposing visual information, including maps, spatially empowers insight acquisition.

Efficient comparison of visual information is in particular for observations and control tasks important. Prouzeau et al. [14] propose displaying traffic information with multiple views on a LHRD. The authors argue that seeing current state of traffic and the prediction of the future helps the operator to make better decisions. However, traffic control is not the only application domain benefit form visualisations on LHRDs. Onorati et al. [13] built a system to analyse behaviour in crisis situation based on twitter messages on an LHRD. Chokshi et al. [4] propose using multidisplay environments, including LHRDs and tablets, for emergency management. Such multidisplay environments allow to combine a large number of different data sets and foster the collaboration between different stakeholders.

To enable collaboration tablets are well suited as input device. Furthermore, they can be used as private interaction space. Chapuis et al. [3] presented a system providing the connection between a LHRD and multiple tablets. The system creates an cursor for every connected tablet. Hence, all users can manipulate content on the LHRD through touch gestures on the private tablet. Krone et al. [8] propose a comparable approach to control scientific visualisations. The authors present an android application which allows to manipulate a visualisation displayed on a LHRD by using a smartphone or a tablet.

In this work, we combine visual analytics approaches of social media analysis with the advantages of LHRDs and tablets as input devices. The presented system allows to explore events based on geo-tagged twitter messages in a collaborative way. The LHRD displays a map with filtered and aggregated twitter messages. On connected tablets users see an additional map view and can manipulate the content on the LHRD.

System

Social media analysis becomes more important for emergency management as well as for marketing. In particular geolocated social media data is an important data source. Displaying a map with geolocated data as an overlay on a large high-resolution display (LHRD) allows fast and efficient visual exploration. In this work we focus on the exploration of geolocated twitter messages.

Our application is based on ScatterBlogs[1]. We adopted the ScatterBlogs' map view. ScatterBlogs analyses twitter messages and displays important terms, as text, on the geoposition of the twitter message on a map. Therefore, most

Figure 1: Tablet application in front of the map view on the LHRD.

common words in English, so called stop words, are filtered. As a result events are easier to detect. Thom et al.[19] describe in detail how the text is visualized.

The map view based on ScatterBlogs is a Java application displayed on a LHRD. For our study we use three 50$''$ 4K Panasonic TX-50AXW804 screens in portrait mode. This resulted in a display with an size of approx. $2.01 \times 1.13\,\mathrm{m}$ (see Figure 1). All three displays were driven by one Microsoft Windows 8.1 workstation.

LHRDs have the advantage to enable physical navigation and enhanced collaboration between multiple users. However, the used input device has to support physical navigation as well as multiuser input. Hence, the input device has to be easy to carry around and easy to operate. Furthermore, the user might use the device while standing, walking or sitting. When multiple users explore social media data collaboratively, they need private as well as shared visualisations. Tablets are comfortable to use while standing or sitting. Additionally, they provide sufficient display space for content manipulation and pre-filtering [15]. Hence, we

[1] https://www.scatterblogs.com/

Figure 2: Tablet application in front of the map view on the LHRD.

designed and implemented an Android application as control for the map view on the LHRD. The Android application provides an additional map view. This map view shows currently detailed geo-information (see Figure 2). However, it would also be possible to display another social media data set as overlay on the map view.

The Android application allows users to define word-filters for filtering the twitter tags and highlight the appearance of the filtered term. The appearance of a term will be indicated through a textual overlay as well as through a heatmap. To identify correlations between the appearance of different terms, users can assign colours for each filter. When multiple filters are activated, all heat maps will displayed as overlays. Besides, filtering for particular terms, the application allows to filter the twitter tags by time. This allows to discover spatial and temporal spreading and trends. Furthermore, the Android application allows users to pan and zoom the map view on the LHRD.

Communication between the map view on the LHRD and all user input tablets is managed by a central server. The map view application running on the LHRD and all tablet devices connect to this communication server. This server distributes required information over a network protocol to all requiring devices. This communication server allows to connect an optional number of user controls. Furthermore, it would be possible to connect also multiple map views displayed on LHRDs for remote collaboration.

Evaluation

For a first preliminary evaluation of our interaction technique, we recruited 12 participants (2 female) aged between 20 and 30 ($M = 22.5$, $SD = 3.37$) through our university mailing list. We then conducted a within-groups controlled experiment.

We asked pairs of participants to explore two large events based on twitter messages collaboratively. We used recorded and pre-filtered twitter messages. One data set contained a large fair in 2012 and the other data set contained twitter messages about a flood 2013 in Germany. This size of both data sets was limited so that the task did not require specialist data analysis knowledge. We were aware that building two data sets of equal complexity was impossible unless they were artificial. We opted for two real data sets with same size to maintain the real-life context of the task and focus on the user experiences of browsing and analysing twitter data. The task consisted of answering nine factual questions about the geographical area and time frame presented in the data set. The task was complied when the two participants answered all questions correctly.

Participants explored the two data sets using our interaction technique (with one 8.4-inch Android tablet per participant) and a single laptop computer to control the screens as a baseline. We counterbalanced the data sets and interaction modalities to reduce order effects. After a greeting and

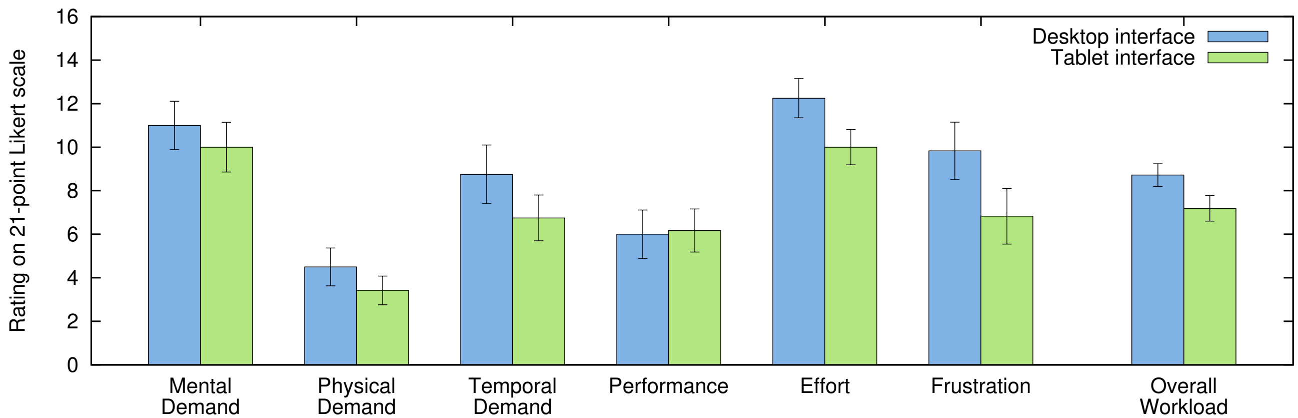

Figure 3: Raw NASA TLX scores comparing the two interaction pattern conditions.

a general introduction to the system, the pair of users was presented with the task and asked to provide the most accurate answers possible. The users were then given full freedom in choosing an analysis strategy and help from the experimenter was available at all times.

We measured cognitive load with the raw NASA TLX [6] and coherence in collaboration using the Networked Minds [2] questionnaire. After the study, we conducted semi-structured interviews with the participants to capture the experience of using our system. We asked about the qualitative differences between the two systems and the suitability for collaboration.

Results

NASA TLX scores indicated that the tablet technique requires significantly less cognitive effort than using the laptop computer as revealed by a Wilcoxon signed-rank test ($p < 0.05$). Figure 3 presents the results. Further, the systems scored comparably in the Networked Minds Questionnaire. Multiple Wilcoxon tests revealed no significant differences.

Reflecting on the qualitative feedback from the participants, we noticed that the large screens had a large novelty effect. All the participants described the experiences as *fun* and *intuitive*. They were impressed by the viewing capabilities of the screen. The participants found the tablet interfaces appealing and easy to use. The ability to work independently of the parter for periods of time was found to be useful.

Discussion and Future Work

We have gained preliminary insights into how multiple mobile devices can support collaboration in data analysis on LHRDs. Our results show that participants found our interaction technique to be less cognitively demanding. We believe this may be not only due to the fact that tablets provide a more intuitive interface, but also because using a personal device reduced the burden of having to negotiate control of the laptop computer with the analysis partner. Further, as tablets allowed users to move more freely around the room, our results may indicate that navigating the large screen space physically reduces cognitive workload.

We found no difference in how users perceived the collaborative aspects of both systems. We hypothesise that the possible existence of such differences may only be revealed in longer tasks or ones that require more sense making. As the networked mind questionnaire is specifically designed to measure contagion, our results may be affected by the fact that the users assessed mainly how well they perceived their partner's qualities. We will address this issue by using different measures in a future between-subjects study.

Yet, the overall positive response of the participant indicates that using mobile devices for collaborative data analysis on LHRDs should be explored further. We plan to conduct a series of studies with low- and high-fidelity prototypes that will enable us to develop interaction patterns for data interactions on LHRDs. Thereby an important aspect will be the collaboration between single users. In the current prototype all users had the same rights to manipulate content on the LHRD. When users focusing on different aspects, they might change the view on the LHRD and hide thereby information an other user is working with. Hence, future systems should manage the need for different views. We believe that readdressing the well-known principles of interactive information visualisation in an LHRD context will produce new interaction opportunities. For example, we will investigate how we can build effective interactions for Shneiderman's "details on demand" [18] interaction pattern.

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