Earthquake Emergency Response Visualization

Wentao Mao
20438891
psxwm4@nottingham.ac.uk

Hao Zhang
20469292
alyhz34@nottingham.ac.uk

Sebastian Dohoda
20284024
psysd9@nottingham.ac.uk

INTRODUCTION

An earthquake emergency response visualisation challenge was released, which is VAST 2019. In this project, an interactive visualisation dashboard will be developed to help emergency responders to make better decisions. Visual mapping is designed carefully based on previous knowledge. Furthermore, Composite view and Interactivity are used to improve the process of retrieving information. Moreover, three questions of the VAST 2019 Challenge 1 will be answered using this visualisation dashboard. Finally, our work will be evaluated by setting three related tasks for participants to complete for testing whether our visualization system meets expectations.

RELATED WORK

To analyze large datasets with spatial-temporal characteristics just like our large dataset, it is important to consider multiple views and interactions. Aigner [1] argues that these techniques can help with the analysis of time series data. Additionally, uncertainty should be considered due to the nature of temporal data. Thus, throughout this paper we will discuss not only background knowledge about interactive visualization techniques but will also talk about multiple view design patterns and visual encoding. Furthermore, some previous work will be explored on visualizing spatial-temporal data and uncertainty data to provide a good understanding (of the problem/task?) and to provide a good starting point for our own design.

Visualization Design

This section introduced the interactive visualization techniques, design patterns and visual encoding techniques background knowledge. Because the size of our data set is not trivial, it needs to be carefully designed based on previous knowledge.

Yi [2] proposed a taxonomy of 7 interaction techniques based on the user ' s intention. Explore interaction techniques allow users to switch the view between different subsets of the data. This addresses the problem caused by limited screen size, large datasets, and the limited information processing ability of humans. "Panning" and " Directed-Walk " are two common Explore interaction techniques. Reconfigure interaction technique allows the user to change the order of data to help the user understand information better and address over-plotting. The encoding interaction technique gives the user the ability to change the way the data is encoded into visual language. Abstract/Elaborate interaction technique enables the users to change the level of detail of a visualization. Zooming, tooltip and drill-down in a tree map are such techniques. Filter interaction techniques provide the users with the ability to set up some conditions and change the data being shown in the charts while the perspective on the data stays the same. Moving slider, dynamic query and key pressing are examples of a filter. Connect interaction technique reveals the relationship and association information and displays the hidden information of a chosen item. This can be used on both single views and multiple views. These interaction techniques can be considered when designing our interactive visualization systems so that visualization problems such as plots and limited screens can be resolved.

Javed & Elmqvist [3] introduced different design patterns of composite visualization views. Juxtaposed views (Figure 1a) and integrated views (Figure 1b) display several charts in a single view. The former has no explicit linking, but the latter has. Superimposed views (Figure 1c) plot two or more visualization on the same location of one single chart. Overloaded views (Figure 1d) host client charts into another chart, and nested views (Figure 1e) host client charts into the visual marks of another chart. The advantages, disadvantages and suitable application of each pattern were also explained in the paper. These would be discussed in section 3.

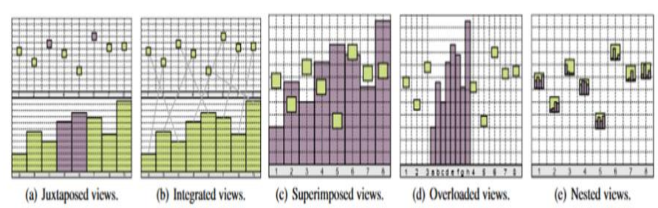


Figure 1. Different Composite Visualization

Mackinlay [4] argued the importance of the expressiveness and effectiveness of a visualization chart and provided several design principles for better visualization.

They suggested that a good visualization should present all the information and only presents this information. To make the graph effective, the correct visual variable should be used for the different data types. Quantitative data should be encoded in size or saturation, ordinal data should use size, saturation, and texture, or a subset of colour, and nominal data should be encoded into texture, colour, orientation, or shape. Additionally, a good visualization graph can be perceived faster by the user than other visualization graphs. To achieve effectiveness, a ranking of perception tasks (Figure 2) can be a reference for choosing visual encoding. Mackinlay suggested that the more important variable should be encoded into a more effective visual variable.

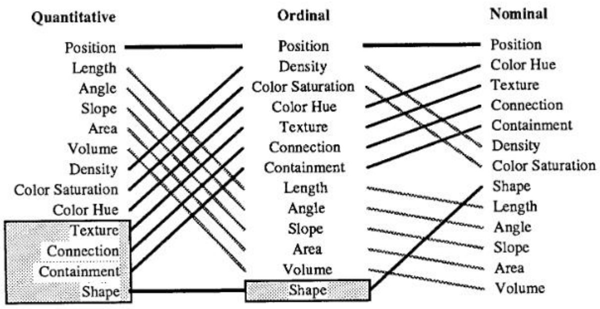


Figure 2. This is a rank of the effectiveness of different visual variables for different data types. The position is the best for all data types

Visualization Uncertainty

In this section, previous work on visualizing uncertainty data would be discussed.

Lucchesi & Wikle [5] compared three ways of visualizing the uncertainty of data, which are bivariate choropleth map (Figure 3.1), pixelation (Figure 3.2), and rotating glyph (Figure 3.3). Additionally, animated pixelation was also included in this paper. They successfully encoded both the value and the uncertainty of the value on a single map. However, they are limited because the bivariate choropleth map can't encode variables with a big number of levels. Pixelation is not accurate enough for the user to find out the quantity of the uncertainty. Another downside is that these visual techniques were not evaluated by user studies, so the performance is unknown. Similarly, in Monmonier's [6] work, fade, fuzziness, or intermittently flashing was considered to be useful for indicating the accuracy of data.

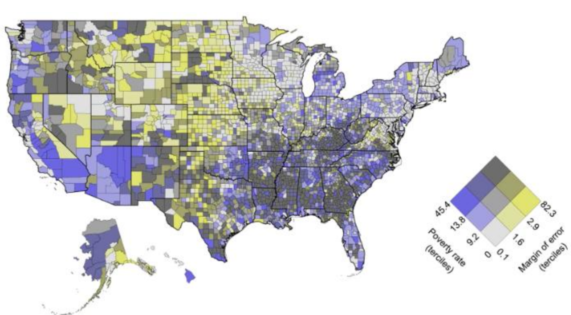


Figure 3.1. This is a bivariate choropleth map. The level of Poverty and the level of uncertainty were both encoded into colours.

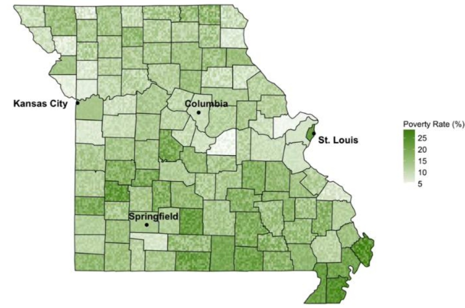


Figure 3.2. In this chart, the level of poverty rate was represented by the colour saturation, and the level of uncertainty was presented by the pixelization. The author also provided an animated version of this map.

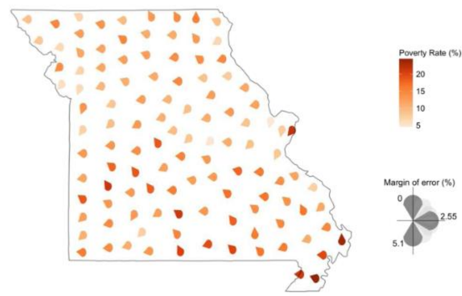


Figure 3.3. In this chart, the uncertainty of the data was represented by the rotation of the glyph.

Visualization For Spatial-temporal Data

This section will discuss previous work related to time series visualization. One work shows many useful visualizations designed for spatial-temporal data. Another paper evaluated several glyph designs for visualizing time-series geographic data on a small multiple set.

Monmonier [6] introduced different strategies for visualizing spatial-temporal data. They provided a framework for spatial-temporal data visualization. They addressed the problem of overplotting too many lines by only showing the average value and the chosen series of data. Error bars were used for demonstrating the uncertainty level. Multiple maps are also used for the data with a small number of time instants and attributes. Additionally, Glyphs including clocks, calendars, and lines were also used for time-series data. Furthermore, they also illustrated an interactive visualization system (Figure 4) with scatter plots brusher, time brusher and brusher on the map.

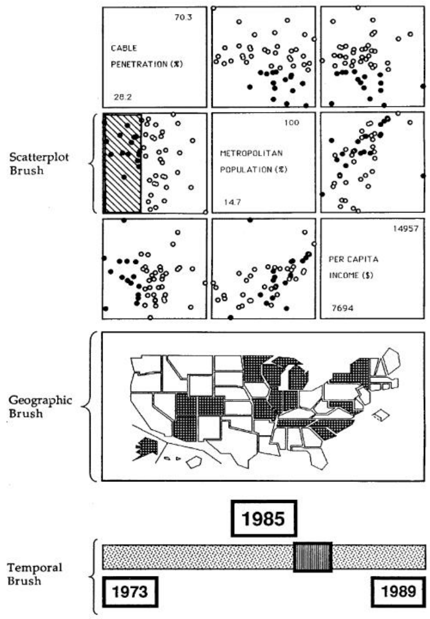


Figure 4. An Interactive visualization system for geospatial time series data [6]. The trend cannot be found easily by this system.

Fuchs et al. [7] evaluated 4 types of small multiple glyphs for 3 tasks (Figure 5). They accomplish this by designing and conducting user studies. As a result, they found that line Glyph is better for peak and trend detection. Star Glyph and Clock Glyph are more effective for finding temporal locations. The performance of these designs works better with a small number of data densities. The benefit of using this glyph is that at the given size of space, a lot of information could be displayed. The problem with using glyphs is that the user may spend a long time perceiving the information according to the result of the user study conducted by Fuchs et al. [7].

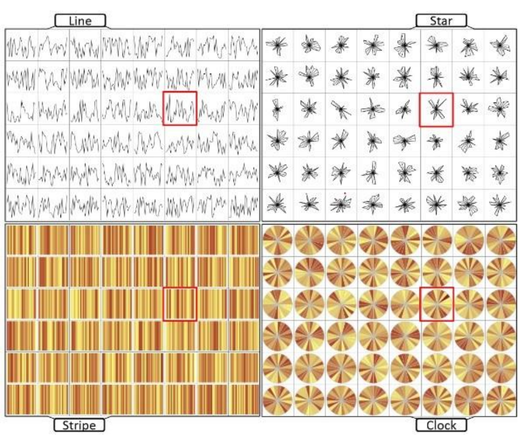


Figure 5. Different types of Glyphs for temporal data. The line is good for peak and trend detection, and the star and clock are better for finding the temporal location. The higher the data density is, the worse the performance is [6].

METHODS/DESIGN

In our app, context and focus, multiple views, and interactivity are used. Do so because according to Aigner et al. [8], when visualizing time-serious data, multiple views, and interactions would better be used. We used linear time rather than cyclic time because our data has no seasonal effects. According to Aigner et al. [8], linear time is a nice way for finding general trends.

We used four charts and some buttons (Figure 6). There are two bar charts, a line chart and a stacked area chart.

Line Chart

In the chart, each line represents a region. The x-coordinate of the line represents time, and the y-coordinate represents the mean damage. Do this because they are the most effective visual variable.

Data is transformed so that the Y value is the meaning of all reported injuries for each facility in the area at that time. For example, site 2 has two reports in the first report, the damage of facilities 1 to 5 is 4, 3, 7, 8, 9. In the second report, the damage to facilities 1 to 5 is 1, 2, 3, 4, 5. So the meaning is (4+3+7+8+9+1+2+3+4+5)/10. This aggregation prevented overplotting.

The interactivity is that the user chooses to display the location, emphasize the location, and display the specified location on the stacked area map. In addition, user mouseover causes tooltips and markers to be displayed. The benefits of these interactive features enable the exploration of information.

Composite Bar Chart

In the composite bar chart, the user can choose what data to encode into the length of bars. The location is encoded into position y. There are very effective visual channels.

The value encoded into length is the aggregated mean damage value, count, or standard deviation. These data are transformed similarly to the line chart. The aggregation can avoid overplotting.

This chart supports the reconfiguration of the order of the bars by either the major axis, minor axis, or the location name. The reconfiguration can potentially make the user find the top value faster. The user can also choose what value to display on the chart. This gives the flexibility to the user to choose what to represent uncertainty.

Bar Chart (Context)

The idea of context and focus is used. The time series bar chart is the context, and the others are the focuses.

In this chart, each bar represents the aggregated value of all the reports in a time interval. The value type can be the mean damage value, the number of reports or the damage deviation. The first is for the damage, the last two are for the uncertainty. Value is encoded into the height of the bars, and the time is encoded into position x. The length of the period is encoded into the width of each bar. The reason to

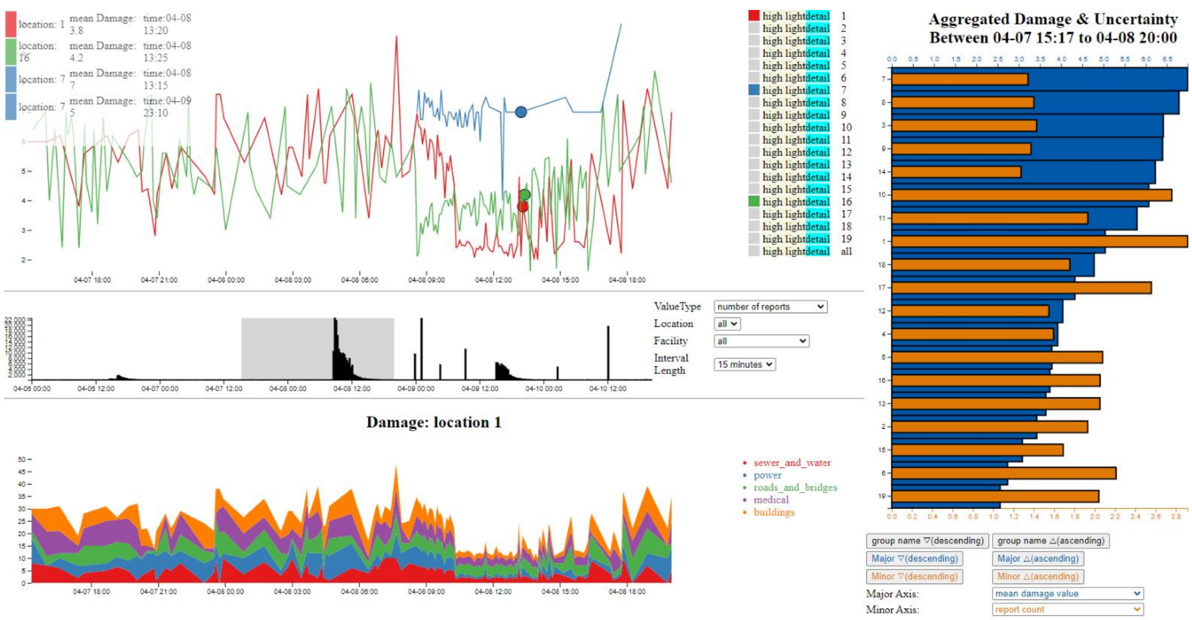


Figure 6. Interactive Visualization

use time intervals rather than time points is that there is no report at some time point.

The interactivity of this chart is that the user can choose the location and facility (include "all"), value type and interval length. This leads to good flexibility for the user.

Stacked Area Chart

This chart shows the mean damage of each facility in each location. The facility is encoded into colour. The time is encoded into the position x and mean damage is encoded into the position y. This chart makes the entire visualization app more expressive, as it shows the facility damage information which is hidden in the line chart. The visual encoding in this chart is also effective.

The data of this chart is controlled by the line chart legend button and the time brusher on the black bar chart. In the area chart, for each time point, the y value is the stacked mean damage of all the reports at that time point.

The interactivity of this chart is that the user can choose the time and the location of this chart.

IMPLEMENTATION

Javascript, d3.js, HTML, CSS and SQLite, and R are used to implement the app. The interface and web page are wroten by javascript, d3.js, css. The data was converted to long by R. The data prepared for each chart was processed by D3.js.

When trying to find out the written code to prepare data, the console in Chrome is widely used. Those long-nested Array. map, and Array. filter methods were first tested in the console and then put into the ".js" file.

To prepare the long data, the "gather" function in R is used. To transform the data for each chart. D3 rollup and group functions are widely used, and the returned map project was converted to suitable data by using javascript map, filter, and flat functions. Data was also sorted so that some operations could be faster.

For the line chart, the data was transformed by the "getLineChartData" function into an array of "{location: …, meanDamageValue: …, time: …}".

For the area chart, data was first transformed by the getAreaChartData function into long data. Then they are transformed into stacked data inside the AreaChart Class.

For the composite bar chart, data was transformed into an object of three arrays. Each array stands for a different value type including mean damage, number of reports and damage deviation. Once the reconfigure button is clicked, the BarChart2.updateVis() method would be called to change the chart.

For the stacked area chart, the original long data is mapped to the time interval data, which is an array of objects with location, value type and value information.

For plotting the chart. This tutorial (Michael Oppermann, 2023) is strongly followed, some online resources are also searched when coding. The code that was inspired by the internet was clarified below or right to the code as a comment in the ".js" files.

RESULTS

Task 1

Emergency responders need quick and efficient methods to determine which parts of the affected area are hit the worst. Shake maps are a good way of determining struck areas, first responders however need access to more reliable data to get to the most affected area, which our visualization app accomplishes. Figure 6 displays what our visualization app looks like. Using a composite bar graph in Figure 7 and 8, emergency responders can get a deeper insight into damage intensity in different locations. We can see that in location 3 we have the highest number of reports and damage intensity throughout the whole period (Figure 7). Emergency responders would be able to use the interactive composite bar graph and allocate more resources to this location as it has been affected more than the rest of the locations.

Visual analytics have proven to be quite efficient at identifying which locations should be prioritized for a response. Given Figure 7 and Figure 8 we can clearly see that during the time intervals (Day 1-4) the composite bar graph shows us location 3 needs the most attention while locations 12 and 16 might have the same mean damage intensity. But given that location 16 has more damage reports coming in that location would be given priority. Another factor that plays into which locations require the most resources would be shown by Figure 1. This figure displays location 2 which shows that even though there is a low mean damage intensity in the area. There are still a lot of damage reports which would give this location a higher priority than those such as location 7 shown in Figure 7 which has a high mean damage intensity but a very low report count.

Furthermore, emergency responders can also use the number of reports being placed at a specific time to determine which locations may need more assistance. We can see that in Figure 9 where only a specific time interval is selected for analysis.

Emergency responders can also use the times at which the people are reporting to get a better understanding of how many people have been affected at certain time intervals which could also further the help they are providing. For example, in Figure 10 we are shown the number of reports in location 7. Most of the calls happened on 04.08 towards 12pm, this would tell first responders that a lot of assistance is needed at that location during the times. In Figure 11 we have the report times for location 3. As shown in this figure, a lot of call have been made on 3 different occasions which would again show the need of assistance in that location during certain hours.

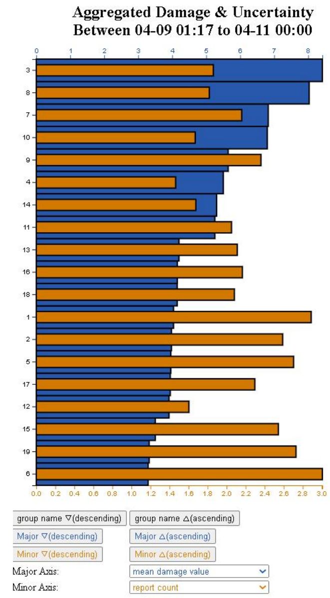


Figure 7

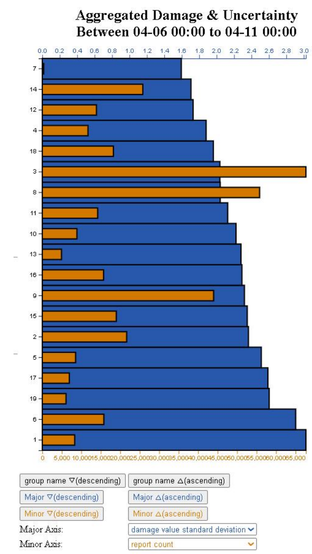


Figure 8

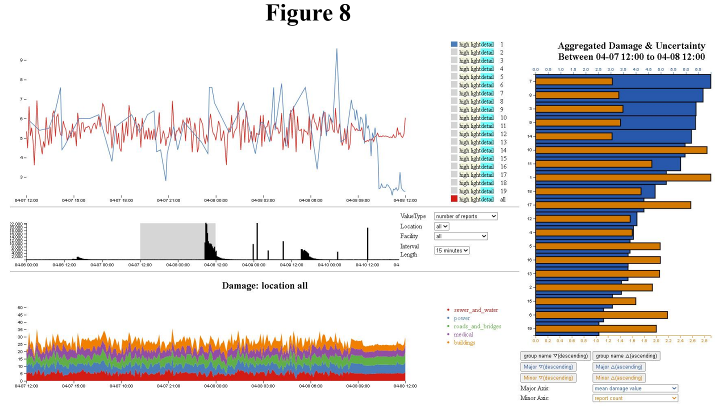


Figure 9

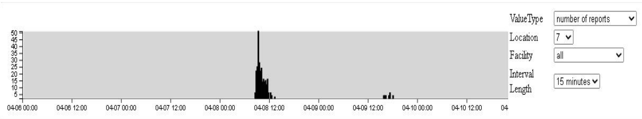


Figure 10

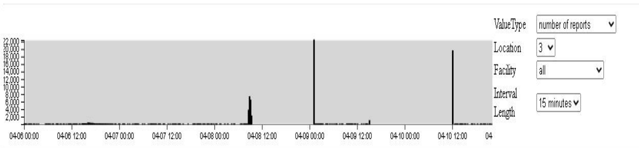


Figure 11

Task 2

In the assessment of neighborhood reports, it is essential to examine factors such as report count, mean deviation, and standard deviation. By analyzing these factors, we can identify which locations provide more reliable data when evaluating the data. We must consider that higher report counts typically result in more accurate estimates, whereas lower standard deviation indicates less variability and more consistent reporting. Based on the data, some areas provide us with more reliable data than others, this can be seen in Figure 8: The height of the bar inside the orange bar chart, represents report count or deviation. And the location, facility and value type and time interval can be chosen. It shows that location 3 had the highest report count with moderate standard deviation. Moreover, locations 8 and 9 also have a high report count with moderate standard deviation. this indicates that the data for these locations have high reliability.

On the other hand, we can check location 7, The data for this location is quite unreliable because it had the lowest report count seen in Figure 8. Location 1 was also unreliable as it has the highest standard deviation as seen in Figure 9. It may lead to less reliable estimates in these areas. When comparing the charts, we can see the difference in report counts compared to mean damage or standard deviation. These charts provide a visual representation of how accurate the data is and may help first responders better understand which areas need more assistance. Mean damage and standard deviation can be affected by factors such as population density, age and quality of infrastructure and socioeconomic status. Locations with a higher population density may generate more reports due to a larger number of affected individuals. Areas with higher economic status on the other hand may have better-maintained infrastructure which would result in lower mean damages.

The accuracy of the data may also be affected by the way the damage analysis was done from location to location. Moreover, a location perception of the local authorities may also affect how and if these locations report on damage to the local authorities.

In conclusion, by analyzing report counts, mean damages and standard deviation on Figures 8 and 9 we can identify which nighborhoods provide more reliable reports which can be seen in location 3, 8 and 9. However, it is essential to recognize that additional factors such as population. density, infrastructure quality and the perception of authorities could influence the reliability of these reports. A comprehensive understanding of these factors can help inform decision-making and resource allocation for addressing damages and improving overall living conditions in St. Himark.

Task 3

With the use of our visualization app, it is very easy to play around with the visualizations to sort and filter the data and time you want to display. We can clearly see in Figure 12 and Figure 13 how conditions in certain locations change.

As seen in the figures above day 1-2 and day 3-4 show similar results to damage intensity and report count. One key change that can easily be seen is how location 10 on day 1-2 had a lot more report count than that on day 3-4 yet the mean damage intensity has increased. This states that this location may be of higher priority due to the high population and change in damage intensity. Most of the locations damage intensity on the two paired dates stay similar although some locations for example location 1 has a high population density but the mean damage severity has decreased on day 3-4.

We also have the brush tool to select specific time intervals, and a specific location which further shows us how uncertainty has increased/decreased over time given the value we are assessing. In Figure 9, we have selected a specific time interval and all the locations and as seen there is a wider bar that indicates greater uncertainty, while a narrower bar indicates greater precision. Along with the width of the bar, we also see that the bar chart allows us to sort the chart to display what we want. When looking at how uncertainty changes, we can see in Figures 14, 15 that for std and mean damage intensity the spacing between the bars is narrow which indicated that the values for these measurements are relatively similar which specifies that there would be low uncertainty. Whereas when looking at the report count as seen in Figure 16, we can see that the spacing is wider which indicates that there is more uncertainty in the data.

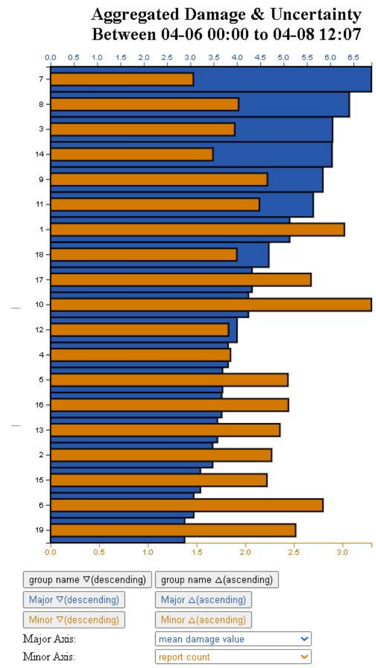


Figure 12

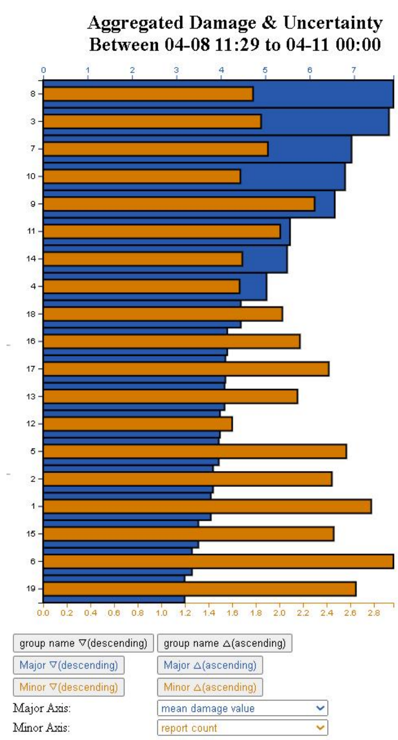


Figure 13

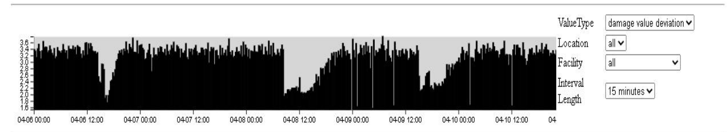


Figure 14

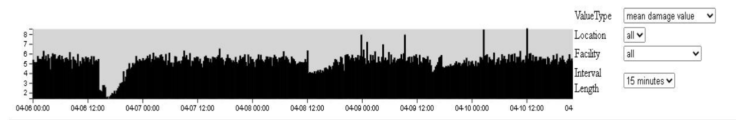


Figure 15

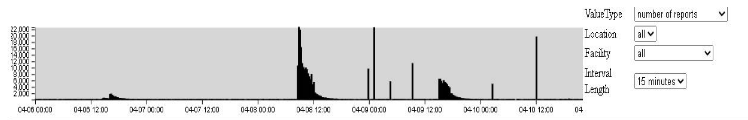


Figure 16

EVALUATION

The purpose of evaluating this designed visualization system is to ensure that it meets our design objectives and to verify its usability. Usability refers to the effectiveness of the information presented in a design, the efficiency of the information conveyed, the usefulness and the ease of understanding [11]. Before deciding on the evaluation approach, we reviewed some relevant literature to explore how other researchers have measured the concept of usability: To evaluate the usability of their visualization system, some researchers have conducted tests where participants were asked to recall details immediately after completing tasks and also at intervals afterwards, measuring both short-term and long-term memory [12, 13]; And some researchers have asked participants to rate each chart in the system after completing the task [14, 15]; Other researchers are measuring the total duration of time required for participants to complete the task and the amount of interaction with the visualization system [16, 17]. Therefore, we intend to design our evaluation experiment by learning from the data collection methods of previous researchers.

Experiment Design

This experiment is a qualitative method. The purpose of this experiment is to verify whether the visualization system we designed can perform the basic three visualization tasks. For this purpose, we designed three experimental tasks for the participants to perform:

Task 1: Find the neighborhood most damaged by the earthquake. (Neighborhood 3)

Task 2: Find the most and least reliable neighbourhoods for providing earthquake damage data. (Based on report count: Neighborhood 3 and 7; Based on standard deviation: Neighborhood 7 and 1)

Task 3: Find a point in time where total facility damage is minimal. (04-06 16:10 or 04-06 16:40)

The answers to the above tasks are established based on the system, which helps us to determine whether the results of the participants are accurate or not. There are three main data obtained in this experiment: First, the time required by the participants to complete each task; Second, the accuracy of the results of each task completed by the participants; Finally, the participants' ratings of the graphs presented in the visualization system after completing all tasks (1-5). Three participants were recruited to participate in this experiment. The three types of data obtained will be defined as the efficiency, accuracy, and understandability of the visualization system respectively. We will compare the efficiency and accuracy of the visualization system in presenting information about the three tasks by creating bar charts. And compare the average ratings obtained for each chart to see their comprehensibility.

Experiment Procedure

We will ask participants to fill in a consent form first. The experiment will not begin until the participant is aware of all his or her rights. It takes place in a room in a flat, and participants are required to experiment on a computer.

To prepare the participants for the experiment, we will provide a brief background of the visualization system and give instructions on how to interact with its various features. After this, we will allow participants approximately 1 minute to explore and familiarize themselves with the system on their own before beginning the actual experiment.

After the practice session, we will conduct the formal experiment by providing the first task in written form to the participants and asking them to contact the experimenter and give the results once they have found the target specified in the task. Once we confirm that the participants are ready, we will start timing. Once the participant completed the first task, the experimenter stopped timing and recorded the relevant data. We will then repeat this process for the second and third tasks.

After all, tasks are completed, the experimenter asks the participants to rate each graph in the visualization system.

Experiment Result

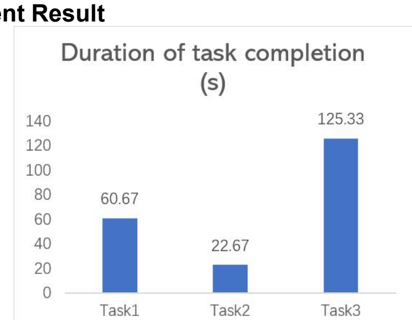


Figure 14

From the Figure 14, we can see that participants spent the longest average time on task 3. This result reflects the low efficiency of our system in completing this task. The reason for this problem could be the difficulty of the task. Therefore, to address this shortcoming, our system could be improved by presenting more clearly the key information in the time series charts. The highest and lowest points in the line graph could be marked with additional colours to help participants locate the target more quickly. On the other hand, the average time taken by participants to complete both tasks 1 and 2 was significantly lower than that of task 3, so we can assume that our system is efficient in transferring information on these two tasks.

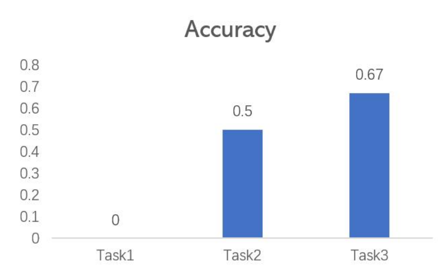
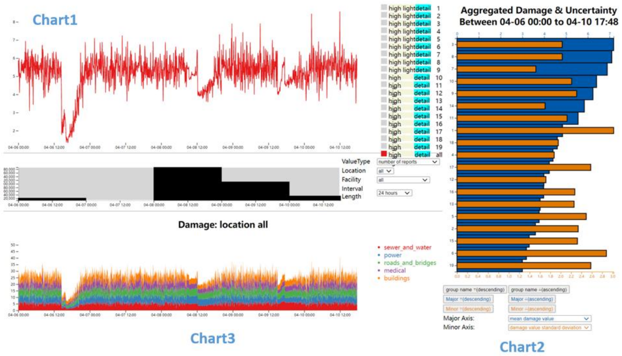


Figure 15

From Figure 15, we can see that the average accuracy of the participants in task 1 is 0. This is a serious problem, which means that our system is passing completely wrong information for this task. During a later check, we found that the problem was caused by the fact that our source code presented the two types of information in opposite ways so that even if the participant located the correct target, the task result was still wrong. Moreover, the accuracy rate for Task 2 was only half. The reason for this is that when participants were instructed to use the system before the experiment, some participants selected data for a period but did not cancel it. Therefore, their responses to Task 2 were only correct for that period and not for the whole period. In response to this shortcoming, we would have made improvements by adding an initialization button to our system to avoid the recurrence of this problem. Finally, our system has a high accuracy rate on task 3, and it can be considered to have a good information transfer accuracy on task 3.



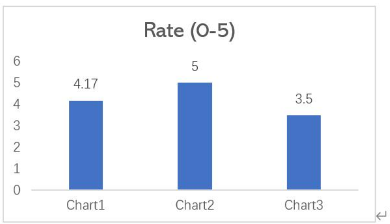


Figure 16

Figure 16 indicates that participants give the lowest rate for Chart 3, which means the understandability of this chart doesn't meet the standard. From the responses participants provided, the reason is that this chart transfers too much information at once, which leads our participants wouldn't spend time reading it. In response to this problem, our idea is to include Chart 3 in Chart 1. Specifically, when the user puts the mouse on a certain time point, Chart 3 will be presented. The presented Chart 3 will appear in the form of a scatter diagram according to the data of each facility. Finally, the other two charts are more understandable because they received good ratings.

DISCUSSION

The visualization system we created helps the audience learn the general status of the reports available in this region. Specifically, our system can give viewers the right to view any data they are interested in. For example, the audience can see how report data for a specific region changes over time or they can also check the average earthquake intensity or the total number of reports for a certain period in various neighbourhoods. Although the system still found some deficiencies during the evaluation process: The histogram caused information errors due to the settings of the users; The information provided by the time series graph was difficult to understand; the time series graph did not mark out the key information to remind users. These issues can all be resolved with a few simple changes. Compared to Nguyen's system [19], the new sights our system provides are: We extracted the data of each region and made a histogram, which can help users compare the situation in each region; Different from Nguyen's system, which can only view data in units of 10 hours at a time, we provide users with the right to view any length of time according to their needs. During the evaluation process, we also found that our participants did not only focus on the task goals, but they were also interested in and interacted with other information provided by the system.

CONCLUSION

In this project, we read and understood the relevant visualization systems made by other researchers to absorb their advantages and made a visualization system with the technology of d3.js. This visualization system mainly consists of two time series graphs: One that can be interacted with to see how the earthquake intensity reports in multiple neighbourhoods change over time; The other shows how the facility damage reports change over time. We have also made an interactive time graph. Users can choose to read the data of a certain period. At the same time, there is also a histogram that can present the earthquake intensity report data of each area, which is easy for users to compare data. To evaluate whether this system can really complete the three data analysis tasks required, we set up three more detailed target tasks based on these three tasks for our participants to finish. The results of this evaluation are not ideal, but fortunately, the system only requires a little improvement to perform these tasks perfectly. For future work, we plan to add an initialization button to our visualization system, which can avoid information confusion caused by random settings by our users. We also would add the information presented in the second time series graph to the first one, to avoid the problem of providing too much information at once and causing users overplotting.

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