Multimedia Tools and Applications

VR System for Spatio-Temporal Visualization of Tweet Data and Support of Map Exploration

--Manuscript Draft--

Manuscript Number:	MTAP-D-18-03409R1
Full Title:	VR System for Spatio-Temporal Visualization of Tweet Data and Support of Map Exploration
Article Type:	1126T - Information Visualization (iV 2018) (Invitation only)
Keywords:	Temporal visualization; virtual reality; Social media; tweet data; immersive visualization; route recommendation
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Answer and amendment list

We greatly appreciate the constructive comments made by all two reviewers. We carefully checked their comments and revised the manuscript accordingly. A point-by-point response to all of the comments are given below.

Reviewer #4

Some remarks about the experimental evaluation. Why only female participants? Why only 4 out of 13 with no VR experience? Why all participants have been to the tweeted area? If all these choices are voluntary then the authors should explain them better.

Thank you for the comment. We added some sentences which explain the choice of participants and the tweeted area. Section 6.2 was corrected as follows.

"Participants of our evaluation were 16 female university students aged between 20 and 28 belonging to the department of computer science. All participants were female students because we called for participants of this experiment in a women's university. The department equipped VR devices, and therefore many students already had experiences of VR devices. As a result, six participants had no VR experience, eight participants had one to five hours, and two participants had used VR many times. We selected TDL as the tweeted area in this paper because we expected to receive more detailed comments if we chose a famous area. TDL is especially preferable for young women, and therefore we thought it is one of the best places for this experiment. Actually, fourteen participants have been to the tweeted area more than three times, while the other two participants have been there just once."

Page. 2 row 29: according fig. 2 should be (XZ-plane) instead of (XY-plane)

Thank you for the comment. It is corrected.

Other

Number of participants increased to 16 from 13. We needed to have a review according to the research ethics policy of the university. We are also required to re-conduct the user experiment. Note that the results of the user experiment mainly have not changed from the previous paper.

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(will be inserted by the editor)

VR System for Spatio-Temporal Visualization of Tweet Data and Support of Map Exploration

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Received: date / Accepted: date

Abstract Social media analysis is helpful to understand the behavior of people. Human behavior in social media is related to time and location, which is often difficult to find the characteristics appropriately and quickly. We chose to apply virtual reality (VR) technologies to present the spatio-temporal social media data. This makes us easier to develop interactive and intuitive user interfaces and explore the data as we want. This paper proposes a VR system featuring two visualization techniques. One of the techniques is a three-dimensional temporal visualization of tweets of microblogs with location information. It consists of the two-dimensional map and a time axis. In particular, we aggregate the number of tweets of each coordinate and time step and depict them as piled cubes. We highlight only specific cubes so that users can understand the overall tendency of datasets. The other technique provides a route recommendation based on tweets of microblogs. Our technique supports users to explore attractive events and places by selecting effective tweets and sug-

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gesting routes. We also developed user interfaces for operating these objects in a VR space which indicate details of tweets.

Keywords temporal visualization · virtual reality · social media · tweet data · immersive visualization · route recommendation

1 Introduction

Social media analysis brings us important knowledge. Conversation data on Twitter and Facebook contain characteristics of the corresponding area such as where, when and why events are held, or people gathered. People who have not visited these places and do not have enough knowledge can also find interesting information. Many analysis methods such as text mining or human network analysis have been applied to social media analysis. However, it often happens that these methods are not sufficiently effective to understand the complex data of human behavior involving various factors. Meanwhile, interactive visualization is also useful to understand complex social media data. Thus, we applied immersive analytics techniques using Virtual Reality (VR) technologies for social media exploration. VR is suitable for not only entertainment fields but also for visualization. It makes us easier to observe the spatial data intuitively and in detail.

This paper proposes a 3D spatio-temporal visualization system with an interactive user interface (UI) for tweets of microblogs. The presented system features two visualization components. One of the components visualizes the spatio-temporal statistics of tweets by assigning a geographic map onto a 2D plane (XY-plane) and the time to the y-axis (vertical direction against the map). The proposed technique aggregates the number of tweets in each time and blocks divided into the appropriate sizes. Then, we set colors and highlight only important portions of the 3D space which has many tweets by controlling the transparency. Users can immerse into this map and observe overview of the data while they look at the time change of the number of the tweets in each time periods with a small map which is the duplicated map of the large one. The other component features the routes recommendation system for supporting users to explore the more attractive places and events. This technique recommends interesting directions based on the movement of past Twitter users and the places where many interesting tweets including important words have been posted. Moreover, we implemented intuitive operations supposed to use the VR device "HTC Vive" [1]. Users are supposed to fly around and explore the data by themselves by using VR so that they will experience the environment of this area. It will help users to memorize the map and the data they found.

In this study, we introduce the example applied tweets with location information in Tokyo Disneyland (TDL). The visualization brings knowledge of congestion or remarkable events for users who rarely go to TDL and makes feel them as if they are in there.

2 Related Work

In this section, we mainly introduce 3D-based techniques which can represent both spatial and temporal information. Then, we also introduce route recommendation methods and VR-applied visualization techniques.

2.1 Spatio-Temporal visualization

Space-Time Cube [5] is a typical representation of 3D temporal data visualization. It is often used for visualization of human behavior as the forms of spatio-temporal paths and geo-time. Fukada et al. [11] developed a method to represent walking routes and congestion areas by visualizing mobility of sightseeing behavior with GIS (Geographic Information System). They mainly focused on the walking speed of tourist and assigned it to the height of the space-time path method. Cuboid Matrix [17] arranged dynamic network information in a 3D space consisting of a plane and a time axis. Users can observe overview and detail of spatio-temporal information. However, the technique often caused insufficient readability of crowded regions, and therefore required operations for breakdown into 2D display spaces.

2.2 Routes recommendation using SNS analysis

There have been several studies on the route recommendation based on geographical information and the results of SNS data analysis. Fu et al. [10] proposed a method which extracts trend words based on their tf-idf values calculated from multiple Twitter accounts relating transportation and then recommends the routes while providing the text summary. They have four types of route selecting techniques: the shortest path, the safest path, the path which has a large number of points of interest places and optimal path. Wakayama et al. [18] developed a method to explore the optimal paths based on the useful landmark extracted from SNS and geographical information. They applied the Dijkstra algorithm and the genetic algorithm to calculate their routes. Criteria for selecting the landmarks include popularity, direct visibility (tall and distinctive structure), and indirect visibility (popular structure). Both methods show their routes on a 2D display.

2.3 Visualization of tweet data using VR

Guttentag [13] demonstrated that VR has potentials for tourism and marketing. This paper also claims that VR models allow planners to observe an environment from an unlimited number of perspectives instead of just applying a bird's-eye view. As a result, travelers can make appropriate decisions based on the information displayed graphically and had practical expectations.

Moreover, the experiential nature of VR makes it an optimal tool for providing rich data to tourists. This study concluded that VR has the potential to revolutionize the promotion and selling of tourism.

Immersive Analytics [7] is a recent framework for supporting the analytics of real data. Virtual reality environment such as a large-sized touch panel, Oculus Rift [2], Cave2 [9] and tracking devices like Kinect make users immerse into the data. Specialists and analysts can easily access large complex data using this environment. ImAxes [8] is a typical example of immersive analytics framework. Users can generate visualization displays freely by using Vive controller. A scatterplot is generated when we select and combine any axes in a VR space, and a parallel coordinate plot (PCP) appears after we put together multiple scatterplots. This method makes users immersing experiences into the data while users can freely explore the visualization space and search for information by themselves.

Moran et al. [15] visualized tweet data in a VR space. This study indicates the characteristics of tweets as object attributes. Users can focus on the characteristic individual tweets contrary to our method focuses on characteristic tweets of certain time and location. Also, the method does not show a temporal variation of the number of tweets at the same time. There is a study that places the historical materials on Google Earth in VR space [19]. Watanave reveals the relationship between materials and geographical information by arranging photos of people and buildings on the actual coordinates.

Based on the above, we chose to visualize the temporal change of the tweets and to recommend attractive directions in a VR space so that users themselves can go through and operate the data. This study visualized the tweets around Tokyo Disneyland (TDL) as an example the experiential nature provides the best affection. The operation of an unlimited number of perspectives using VR solves the problem of insufficient data comprehensibility in 3D spaces.

3 Visualization with space-time cubes

This section presents the processing flow of the proposed 3D spatio-temporal visualization technique.

3.1 VR environment

We developed the visualization on Unity3D [3] game engine. Unity Assets have rich supports including the SDK (Software Development Kit) for the VR devices which makes us easier to develop the complicated applications. We used HTC Vive Virtual Reality Headset.

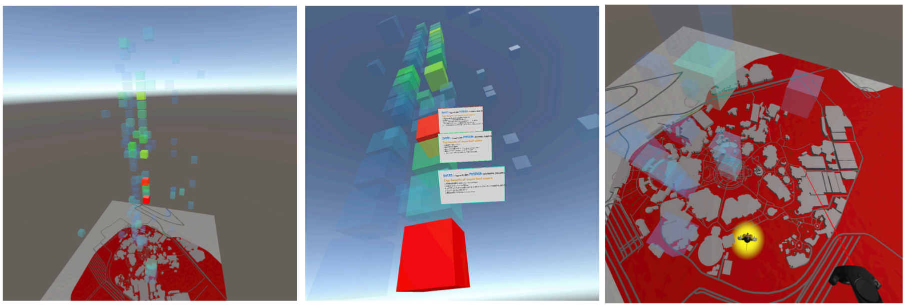

Fig. 1 WorldView. (Left) Temporal change of the number of tweets is shown as the overview in a VR space. (Center) Panels which display actual tweets included in each cube appeared when users select each cube. (Right) The character icon with yellow highlight indicates the position of a user to prevent missing his/her current position.

3.2 Engine

The proposed technique analyzes a set of tweets in advance. The procedure is divided to aggregation and selection of tweets.

3.2.1 Aggregation

For the comprehensive understanding of tweets data and people behavior, the technique divides the map into appropriate sizes of blocks and aggregates the number of tweets in each block and time step. It then normalizes the number of tweets included certain blocks and time step to a range[0,1]. In the following equations, n_{ij} denotes the frequency of tweets at the i-th date in the j-th block, and v_{ij} denotes its score.

$$v_{ij} = \frac{n_{ij} - n_{min}}{n_{max} - n_{min}} \tag{1}$$

3.2.2 Tweets selection

Tweet datasets may contain a lot of noises and meaningless information because of the nature on the limitation of the number of character. Thus, we need to extract important words and texts relating to the location. We developed a text extraction methods after presenting our previous implementation [16]. We applied Latent Dirichlet Allocation (LDA) and tf-idf to remove the texts including trivial words while picking up those including meaningful words. Furthermore, we eliminated overlapping texts because multiple same tweets regarding location information are posted automatically.

3.2.3 Topic classification

The proposed technique classifies the words relating the location to the predefined number of topics. It makes us possible to eliminate the words and texts classified to the topics which are not related to the location. We applied the Latent Dirichlet Allocation (LDA) in this study. The procedure is as follows:

1. Collect the articles relating to the location from Wikipedia (15 pages in this implementation)
2. Extract noun words with MeCab
3. Remove symbol and stopwords
4. Generate the dictionary and corpus which have a higher frequency of appearances of words in each document
5. Build a model, classify the words to topics and rank the words with probability

3.2.4 Words extraction

We apply the tf-idf method to the tweets to extract important texts and remove general-meaning tweets like "I'm at Tokyo Disneyland."

1. Extract noun and verb words with MeCab
2. Remove stopwords
3. Calculate tf-idf value of each block

3.3 User interfaces

The system provides the following two display components.

WorldView: 3D spatio-temporal view for the overview of a certain period of time (one-month data in this study)
MiniMap: a small map for operation and viewing the time change of each time zone (one-day data in this study)

Both of these maps display objects to indicate details of tweets according to interactive operations.

3.3.1 WorldView

Fig. 1 shows the large map which users immerse into. Users can fly around the objects of visualization and observe outline of the data by operating TrackPad of HTC Vive. WorldView makes us recognize the remarkable time and area especially. Thus, users can seek the data with a focus on this part. At this moment, an icon is set on the map just under the users to avoid losing the positions of themselves. The icon informs the positions of cubes and the users themselves. We used utymap [4] to reproduce the map and obtained the map data from Open Street Map (OSM). Zoom level is 16 in our implementation. Peculiar interactions of VR make us easier to understand the data. We explain technical components in WorldView and provided operations below.

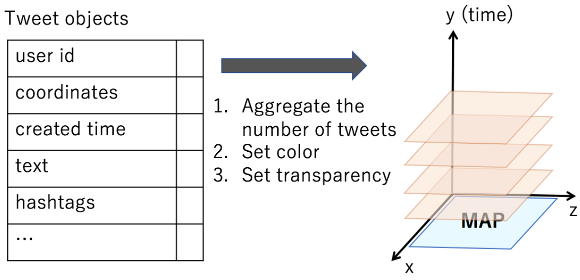

Fig. 2 Processing flow of cubes generation in WorldView.

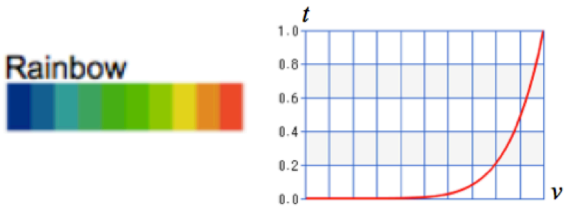

Fig. 3 Colormap and the transfer function for setting transparency.

3.3.2 Cubes

This technique regards the frequency of tweets as temporal data and represents as a set of cubes. Our visualization consumes tweets data written in a JSON file as tweet objects. The processing flow of cubes generation is shown in Fig. 2.

3.3.3 Setting of Colormaps

Next, the technique prepares colormaps automatically to represent values of cubes. Borland et al. [6] describe the correspondence between data types and colormaps. We applied a common rainbow colormap based on the hue. Hue h of the HSV color space is generated as follows.

$$h_{ij} = \frac{160}{240}(1.0 - v_{ij}) \tag{2}$$

3.3.4 Setting of Transparency

Then, we define the transfer function for setting transparency. Cluttering is a common problem of 3D visualization techniques depending on viewpoint setting. The technique represents important portions which have projecting values opaquely, and other portions transparent, to prevent the cluttering and improve the comprehensibility. Thus, the important parts are only highlighted.

Fig. 4 The panel displays the detailed information of each cube. It contains the date, coordinate and text of representative tweets and gives us the knowledge about the reason why people made many tweets in a certain area and time.

We define the transfer function as an exponential function of the values of cubes. The equation is as follows and the graph is shown in Fig. 3.

$$t_{ij} = v_{ij}^a \tag{3}$$

3.3.5 Panels

Fig. 4 shows the panels, which appear when users select a cube they want to see the details with the pointer. Panels show details about the tweets corresponding to the selected cubes, including date, coordinates (latitude/longitude), and texts of representative tweets. This technique selects the tweets as 3.2.2. These panels make easier for users to find when, where and why people were gathered or events have occurred. Also, panels and the operation of them make the switchover between overview and detail more intuitive.

3.3.6 Operation procedure in WorldView

Following is the list of controller operations in WorldView.

TrackPad of the left controller
Moving and flying around the map and cubes.

Trigger button of the right controller
Pointing for the selection of cubes and panels. Cubes will be highlighted when users select them.

Grip button of the right controller
Grabbing the panels.

Snapping the right controller
Destroying the panels. Snap upward rapidly.

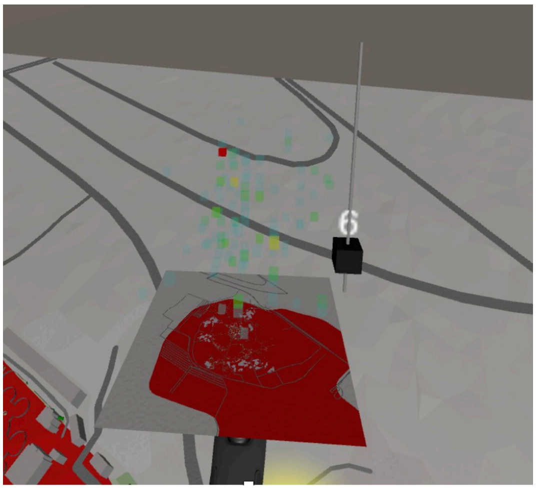

Fig. 5 MiniMap displays the time change of the number of tweets in a day. Cubes in MiniMap indicate the aggregation of one-hour data different from those in WorldView. Users can observe the time change more specifically.

3.3.7 MiniMap

Fig. 5 shows MiniMap, a small duplication of "WorldView" attached to the left controller. It appears by turning over the controller. This map also provides the overview, but this provides a time change of the data in a shorter time range differently from WorldView. Our current implementation of MiniMap represents a particular day, where cubes of MiniMap depict the aggregation per hour. Users can select the date to observe details with the slider attached to MiniMap. Users are required to press the trigger and the grip button at the same time while using the slider. They can also warp to the positions of the corresponding cubes of WorldView after the users point the cubes of MiniMap by pressing the trigger button on the right controller and releasing. This operation saves time to move to the distant cubes and explore the tweets included in these cubes.

4 Route recommendation

Another mode implemented on the proposed system also applies the same data and VR environment as Sec. 3 space-time cube visualization. This mode suggests the paths and areas where large numbers of attractive and characteristic tweets appear.

Fig. 6 WorldView as the routes recommendation system. (Left) The scenery from the users' viewpoint. Panels including detailed tweets in each area and photos attached to the tweets are displayed. (Right) The panel is zoomed when users select the arranged panel.

4.1 Engine

The route recommendation technique also requires to process tweets in advance. The procedure is divided into tweet aggregation, tweet selection and identification of recommended routes. We applied the tweet selection methods explained in Sec. 3.2.2 again. Procedures for aggregation and route calculation are introduced in the following sections.

4.1.1 Aggregation

The technique divides the map into appropriate sizes of blocks and aggregates the number of tweets in each block to quantify the spatial distribution of moving people. At first, we calculate the angle between tweets 1 and 2 as follows in each block.

1. a tweet posted at area a_{ij}
2. a tweet posted after a user tweeted at area a_{ij} and then move to the direction k

Then tweets are classified to the nine directions (eight directions divided at 45 degrees and no moving) according to the calculated angle value. At this time, we count only the number of Twitter users who tweet multiple time in a day. The tweets posted by the same users on the different date is treated as the tweets posted by the different user. The technique then normalizes the number of tweets of certain blocks and directions to a range[0,1]. In the following equations, n_{ik} denotes the frequency of tweets in the i-th block to the k-th direction, and v_{ik} denotes its score.

$$v_{ik} = \frac{n_{ik} - n_{min}}{n_{max} - n_{min}} \tag{4}$$

4.1.2 Route calculation

Our proposed technique suggests interesting routes from the current positions of users to the destinations selected by them. For users exploring the shortest and interesting paths, we developed a routing algorithm based on the Dijkstra algorithm. Here, we determine the weighting of edge costs based on the two factors, the number of Twitter users who passed the area, and the number of selected tweets posted in the area.

$$\min_{\substack{E \\ S \to D}} \{ \sum_{e \in E} \{ \alpha \cdot (1 - naggregation(e)) + (1.0 - \alpha) \cdot (1 - nselectedtweets(e)) \} \} \quad (5)$$

where, naggregation(e) is the normalized number of people who passed the area, and nselectedtweets(e) is the normalized number of selected tweets posted in the area. These factor is weighted by $\alpha \in [0, 1]$.

$$\begin{aligned} naggregation(e) &= aggregation(e) / \max_{e' \in E} \{aggregation(e')\} \\ nselectedtweets(e) &= selectedtweets(e) / \max_{e' \in E} \{selectedtweets(e')\} \end{aligned} \quad (6)$$

4.2 User interfaces

The system displays two maps, WorldView, and MiniMap, similarly as the space-time cube visualization. Here, the maps for the route recommendation have the following different roles:

WorldView: Display the detail texts of selected tweets, photos and navigations
MiniMap: Suggest the optimal routes

4.2.1 WorldView

WorldView (see Fig. 6) suggests the places where a large number of attractive tweets have posted. The system navigates users to the places while arranging panels which display the detailed information of tweets. We adopted the same tweet selection method with that described in Sec. 3.2.2. Panels indicate the recent tweets if the number of selected tweets is too large. Against the tweet selecting method presented in our previous paper [16] leaves the problem that less-interesting information increased while the number of tweets is increased, we improved the method as described in this paper. As a result, the panels such as that in Fig. 6 displays the information related to the target venues (TDL, especially about a cafe and attractions, in this paper).

Characters on the panels are sometimes difficult to read in WorldView if the panels are distant. We developed a zoom operation to solve this problem. The duplicated panel shows close to the users when the original panels are selected. Only one duplicated panel appear at the same time, so the panel disappears when a next original panel is selected.

Photos are also displayed in WorldView so that users can feel the experiences of the actual environment. These photos are downloaded from the URLs

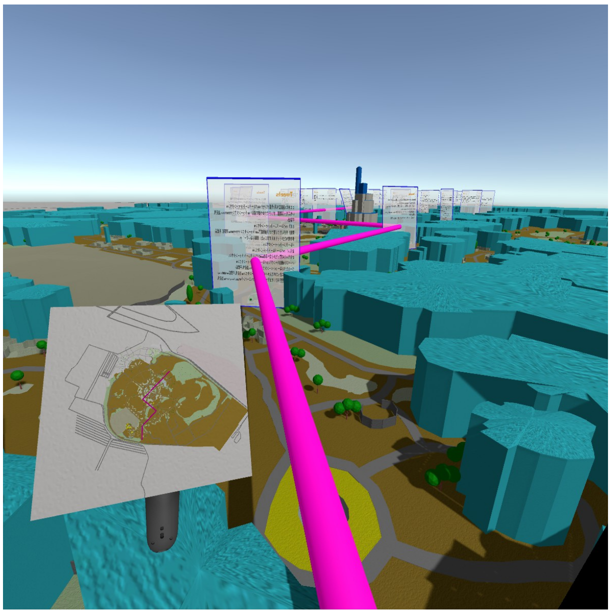

Fig. 7 MiniMap as the routes recommendation system. MiniMap shows the navigation from the current position to the destination panel. Navigation also appears in the WorldView to guide users.

inserted in the tweet texts in advance. They are loaded when the system starts and placed on the corresponding position where the original tweets are posted in the VR space. According to the combining of these elements, users can walk and look around the VR space without complicated operations.

4.2.2 MiniMap

MiniMap displays the specified routes from the user's current position to the destination. The destination is determined by the position of the panel which users selected at last. Routes are updated when users turn their left controller and the navigation also appear in WorldView as shown in Fig. 7. Panels on the recommended routes notify us the information of attractions where we pass by. Therefore, the panels help our decision making where to move next. Users can walk in WorldView while they watch their MiniMap as if they walk in the actual world while watching digital maps (e.g., Google map running on a smartphone).

5 Example

This section introduces an example with a tweet dataset described in Sec. 5.1. We applied visualization with space-time cubes (Sec. 3) in this example. Our implementation adopted a picture of Mickey Mouse as the icon of WorldView.

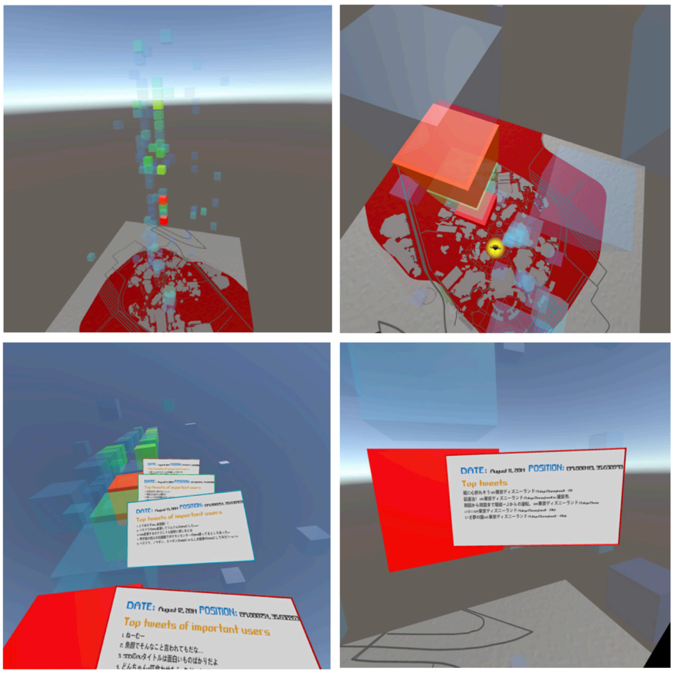

Fig. 8 Example. The top-left figure shows people tweet a lot during Japanese summer vacation. The top-right figure is the map looked down from the position of cubes. It indicates that user is in front of Cinderella castle. Panels in both figures below pick up actual tweets.

We also developed some visual effects including a firework effect mimicking fireworks in Tokyo Disneyland (TDL) displayed while destroying the panels in WorldView.

5.1 Tweet data

We applied approximately 16,000 tweets with location information posted in August 2014. Those latitude and longitude were inside the rectangular area surrounding TDL. Tweet objects have various attributes such as coordinates (latitude/longitude), created time, user id, and text. We gathered these data via Twitter API and saved in JSON format.

5.2 Use case

At first, we found that opaque cubes concentrated around the middle of this month, from the overview shown in Fig. 8 (upper-left). TDL was crowded with people in this period because it was during the summer vacation week in Japan, and therefore tweets also increased in this period. Then, we moved the viewpoint to the position of cubes, as shown in Fig. 8 (upper-right). We found that many people tweeted in front of Cinderella castle located at the center of TDL.

The rest figures in Fig. 8 show the real tweets in front of the Cinderella castle. Tweets related to Disneyland are displayed in the lower-right figure. It is predictable that many tourism had appeal tweets including "Tokyo Disneyland" that they were at TDL in this position.

6 Experimental evaluation

This section introduces our experimental evaluations conducted to measure the effectiveness of our route recommendation technique presented in Sec. 4. We conducted two experiments. The former was the comparative experiments providing two implementations of the exploration system where one was with navigation, and the other was without navigation. The latter experiment was conducted to identify the optimal weight in Equation 5. We referenced several studies to determine the questionnaire items and experiment procedure. Lam [14] classified the experimental evaluation by seven scenarios. Our technique corresponds to User Experience (UE) in this paper. [12] evaluates VR rehabilitation system and [20] compares two VR systems.

6.1 Dataset

We applied approximately 146,000 tweets with location information posted from 2014 to 2016. Those coordinates and object structure are as described in Sec. 5.1.

6.2 Participants

Participants of our evaluation were 13 female university students aged between 20 and 28. Four participants had no VR experience, six participants had less than one hour, two participants had two to five hours, and one participant had used VR on a daily basis. Eleven participants have been to the tweeted area (TDL in this paper) more than three times, while the other two participants have been there just once.

6.3 Procedure

At first, we gave a brief introduction of this experiment to the participants. They practiced our system for three or four minutes while hearing our instruction of operation. Then, we started our comparative experiments. We provided participants either with or without navigation system randomly. After they experienced the provided system during 10 to 20 minutes, the other system they had not experienced yet were provided. Next, we asked them to select the starting point and the destination and showed routes. Each participant observed three routes which have the same starting point and the same destination. These three routes had different weight α in Equation 5: $\alpha = 0.2$, 0.5 and 0.8. We showed these routes in the random order. Just one participant took a break because of getting sick during the experiments. The total average time spent on the experiments by each of the participants was approximately 60 minutes.

6.4 Questionnaires

The questionnaire survey was conducted after they experienced the system. Questions for the comparative experiment were as follows:

1.1 How much did you feel immersed into the environment? (quantity)
1.2 How much did you feel satisfied with the system? (quantity)
1.3 How much did you get motivated to explore the map? (quantity)
1.4 How easy to compare each tweet? (quantity)
1.5 Did you find the places, attractions, restaurants or events you want to go? (quantity) Where is that? (quality)
1.6 Did you find the places, attractions, restaurants or events you do not want to go? (quantity) Where is that? (quality)
1.7 Do you think this system helps to make a tourism planning? (quantity)

Each question was evaluated in five points Likert scale, where "1" was the most negative while "5" was the most positive. Participants were required to answer the same questions regarding each system with and without navigation. In addition, we ask them these questions:

2.1 Which one is the best among 3 routes? Why did you think so? (quality)
2.2 Which one is the better system, with navigation or with no navigation? Why did you think so? (quality)
2.3 What functions were helpful? Why did you think so? (quality)
2.4 Do you have any idea of other function you want or to improve this implementation? (quality)
2.5 Comments for the whole system (quality)
2.6 Did you feel sick? (quantity)

6.5 Result

6.5.1 Comparison

Table 1 shows the evaluation result of the system with navigation and Table 2 shows that of the system without navigation. Evaluation values are totally higher in Table 1 than in Table 2. Especially, the questions 1.4 (motivation), 1.5 (places participants want to go) and 1.7 (help tourism planning) have remarkable differences. Several participants mentioned that they got to want to go the recommended attractions just because they were on the routes. Moreover, they realized the attractions and restaurants they did not know, such as Camera center and Picnic area, or have not visited on the way to the destination. In question 2.2, 12 participants chose the system with navigation. The reasons for this choice were:

- Participants got able to make up their mind soon.
- They got easier to imagine the order of visiting attractions in TDL.
- Navigation was convenient while they did not explore out of the route.

We suppose the above factors affected the results of questions 1.4, 1.5 and 1.7. Besides, participants tended to favor beautiful photo spots such as restaurants or in front of Cinderella castle. On the other hand, they answered they wanted to avoid crowded places or dormant attractions.

Table 1 System with navigation

Question	Average	Variance
1.1 sense of immersion	4.384615385	0.756410256
1.2 satisfaction	4.076923077	0.576923077
1.3 motivation	4.230769231	0.358974359
1.4 ease of tweet comparison	3.461538462	0.602564103
1.5 places participants want to go	4	0.5
1.6 places participants do not want to go	1.692307692	1.064102564
1.7 help tourism planning	4	1

Table 2 System with no navigation

Question	Average	Variance
1.1 sense of immersion	4.230769231	0.858974359
1.2 satisfaction	3.692307692	0.564102564
1.3 motivation	3.461538462	0.935897436
1.4 ease of tweet comparison	2.923076923	0.41025641
1.5 places participants want to go	3.307692308	1.230769231
1.6 places participants do not want to go	2.076923077	0.91025641
1.7 help tourism planning	3.307692308	0.564102564

6.5.2 Identifying the optimal weight of routes calculation

Participants compared three routes in question [2.1]. Options were as follows:

- **Route 1:** $\alpha = 0.2$
  Distribution ratio of nselectedtweets(e) is larger than naggregation(e). Thus the number of selected meaningful tweets in each area is the important factor.
- **Route 2:** $\alpha = 0.5$

- **Route 3:** $\alpha = 0.8$
  Distribution ratio of naggregation(e) is larger than nselectedtweets(e). Thus the number of past Twitter users passed each area is the important factor.

As a result, four participants selected Route 1 as the best route, another four participants selected Route 2, one participant selected Route 3 and the other four participants mentioned they felt no different among the three routes. Comments of participants selected Route 3 included "The routes included more attractions than other routes" and "I could imagine the routes easily." Moreover, comments of participants selected Route 2 included "The area looked fun was included" and "I found the panel I could not find while using the system without navigation." From this result, we expect that many Twitter user passed by and tweeted at several attractions. Also, we realized that many participants chose the routes based on the attraction they knew. This result might cause due to the fact that all participants had been to TDL. We suppose the result might be different if we apply different venues.

6.5.3 Other results

In question 2.3, seven participants selected viewing panels with detail tweets, nine participants selected navigation in WorldView, ten participants selected viewing photos and five participants selected navigation in MiniMap. Navigation in WorldView helped participants to understand which directions they should go. Photos also notified them their positions and enhanced their feeling of immersion.

Participants gave us several ideas to improve this system in question 2.4. At first, multiple participants requested a function to highlight panels they had already checked. They could not distinguish distant panels, so they sometimes chose the same panels repeatedly. Because of the same reason, participants felt that a function for panel recommendation would be necessary. Participants were interested in the panels on the routes; however, they did not check the distant panels out of the routes. Suggestions of the panels which have contents similar to the panels users already looked may help the explorations of users. Besides these ideas, they suggested the following ideas: viewing area or attraction name, notifying time information and current their positions on MiniMap and the optimization of the order of tweets viewing.

Overall, most participants felt fun with this experiment. Several participants felt as if they were in TDL and used it as an alternative of experience in TDL. We expect participants would get other funs by applying other sightseeing venue datasets and more recent tweet datasets in addition to the dataset applied in this experiment.

7 Conclusion

This paper proposed spatio-temporal visualization and route recommendation techniques applying a VR space consisting of “WorldView” and “MiniMap.”

For the procedure of realizing spatio-temporal visualization, we aggregated the number of tweets in each block of coordinates and time step and represented the scores as cubes applied color and transparency. At the same time, by displaying the detail of tweets included in cubes, users can grasp the characteristics of human behavior in a constant duration and observe the critical times and regions. Moreover, they can get the detailed information in the particular times and regions corresponding to the remarkable cubes. We also developed the navigation method based on two factors. One of the factors is the number of people passed the area past, and the other one is the number of selected tweets in each area. This helps decision making of users. VR realizes simple operation and motivates users to explore the environment. Users will be familiar with the environment while exploring and experiencing the data by themselves. We also introduced a brief example and reported the result of the experimental evaluation in this paper.

We have several future issues. At first, we would like to reflect the result of the experimental evaluations. We found several issues as described in Sec. 6.5.3. Especially, highlighting of checked panels and recommendation of panels will affect to usability directly. As further steps, we would like to apply the most recent Twitter data and the other social media data. We found that attractions which had already replaced were mentioned in some tweets in the dataset. We will be able to find actual information more efficiently by applying the newest tweet datasets. Meanwhile, datasets of other social networking services such as Facebook, Instagram, and Flickr have attributes of text, images, and hashtags as well as Twitter. We often use different services depending on our own situation, because each of these services has different features and limitation. Also, user segmentation is different among the services. Therefore, we can highly expect to get new knowledge from such various services.

Moreover, we have been discussing to apply tweet datasets at other types of venues, such as other entertainment parks and sightseeing spots like Kyoto. We and experiment participants used famous attractions as a mark because we were familiar with TDL. On the other hand, we do not know any landmarks if we apply unknown venues. In such a situation, it is helpful to take advantage of navigation, and finally, we should be able to get more new unknown information.

Acknowledgements This work has been partially supported by Japan Society of the Promotion of Science under Grant-in-Aid for Scientific Research.

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Noname manuscript No.
(will be inserted by the editor)

VR System for Spatio-Temporal Visualization of Tweet Data and Support of Map Exploration

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Received: date / Accepted: date

Abstract Social media analysis is helpful to understand the behavior of people. Human behavior in social media is related to time and location, which is often difficult to find the characteristics appropriately and quickly. We chose to apply virtual reality (VR) technologies to present the spatio-temporal social media data. This makes us easier to develop interactive and intuitive user interfaces and explore the data as we want. This paper proposes a VR system featuring two visualization techniques. One of the techniques is a three-dimensional temporal visualization of tweets of microblogs with location information. It consists of the two-dimensional map and a time axis. In particular, we aggregate the number of tweets of each coordinate and time step and depict them as piled cubes. We highlight only specific cubes so that users can understand the overall tendency of datasets. The other technique provides a route recommendation based on tweets of microblogs. Our technique supports users to explore attractive events and places by selecting effective tweets and sug-

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gesting routes. We also developed user interfaces for operating these objects in a VR space which indicate details of tweets.

Keywords temporal visualization · virtual reality · social media · tweet data · immersive visualization · route recommendation

1 Introduction

Social media analysis brings us important knowledge. Conversation data on Twitter and Facebook contain characteristics of the corresponding area such as where, when and why events are held, or people gathered. People who have not visited these places and do not have enough knowledge can also find interesting information. Many analysis methods such as text mining or human network analysis have been applied to social media analysis. However, it often happens that these methods are not sufficiently effective to understand the complex data of human behavior involving various factors. Meanwhile, interactive visualization is also useful to understand complex social media data. Thus, we applied immersive analytics techniques using Virtual Reality (VR) technologies for social media exploration. VR is suitable for not only entertainment fields but also for visualization. It makes us easier to observe the spatial data intuitively and in detail.

This paper proposes a 3D spatio-temporal visualization system with an interactive user interface (UI) for tweets of microblogs. The presented system features two visualization components. One of the components visualizes the spatio-temporal statistics of tweets by assigning a geographic map onto a 2D plane (XZ-plane) and the time to the y-axis (vertical direction against the map). The proposed technique aggregates the number of tweets in each time and blocks divided into the appropriate sizes. Then, we set colors and highlight only important portions of the 3D space which has many tweets by controlling the transparency. Users can immerse into this map and observe overview of the data while they look at the time change of the number of the tweets in each time periods with a small map which is the duplicated map of the large one. The other component features the routes recommendation system for supporting users to explore the more attractive places and events. This technique recommends interesting directions based on the movement of past Twitter users and the places where many interesting tweets including important words have been posted. Moreover, we implemented intuitive operations supposed to use the VR device "HTC Vive" [1]. Users are supposed to fly around and explore the data by themselves by using VR so that they will experience the environment of this area. It will help users to memorize the map and the data they found.

In this study, we introduce the example applied tweets with location information in Tokyo Disneyland (TDL). The visualization brings knowledge of congestion or remarkable events for users who rarely go to TDL and makes feel them as if they are in there.

2 Related Work

In this section, we mainly introduce 3D-based techniques which can represent both spatial and temporal information. Then, we also introduce route recommendation methods and VR-applied visualization techniques.

2.1 Spatio-Temporal visualization

Space-Time Cube [5] is a typical representation of 3D temporal data visualization. It is often used for visualization of human behavior as the forms of spatio-temporal paths and geo-time. Fukada et al. [11] developed a method to represent walking routes and congestion areas by visualizing mobility of sightseeing behavior with GIS (Geographic Information System). They mainly focused on the walking speed of tourist and assigned it to the height of the space-time path method. Cuboid Matrix [17] arranged dynamic network information in a 3D space consisting of a plane and a time axis. Users can observe overview and detail of spatio-temporal information. However, the technique often caused insufficient readability of crowded regions, and therefore required operations for breakdown into 2D display spaces.

2.2 Routes recommendation using SNS analysis

There have been several studies on the route recommendation based on geographical information and the results of SNS data analysis. Fu et al. [10] proposed a method which extracts trend words based on their tf-idf values calculated from multiple Twitter accounts relating transportation and then recommends the routes while providing the text summary. They have four types of route selecting techniques: the shortest path, the safest path, the path which has a large number of points of interest places and optimal path. Wakayama et al. [18] developed a method to explore the optimal paths based on the useful landmark extracted from SNS and geographical information. They applied the Dijkstra algorithm and the genetic algorithm to calculate their routes. Criteria for selecting the landmarks include popularity, direct visibility (tall and distinctive structure), and indirect visibility (popular structure). Both methods show their routes on a 2D display.

2.3 Visualization of tweet data using VR

Guttentag [13] demonstrated that VR has potentials for tourism and marketing. This paper also claims that VR models allow planners to observe an environment from an unlimited number of perspectives instead of just applying a bird's-eye view. As a result, travelers can make appropriate decisions based on the information displayed graphically and had practical expectations.

Moreover, the experiential nature of VR makes it an optimal tool for providing rich data to tourists. This study concluded that VR has the potential to revolutionize the promotion and selling of tourism.

Immersive Analytics [7] is a recent framework for supporting the analytics of real data. Virtual reality environment such as a large-sized touch panel, Oculus Rift [2], Cave2 [9] and tracking devices like Kinect make users immerse into the data. Specialists and analysts can easily access large complex data using this environment. ImAxes [8] is a typical example of immersive analytics framework. Users can generate visualization displays freely by using Vive controller. A scatterplot is generated when we select and combine any axes in a VR space, and a parallel coordinate plot (PCP) appears after we put together multiple scatterplots. This method makes users immersing experiences into the data while users can freely explore the visualization space and search for information by themselves.

Moran et al. [15] visualized tweet data in a VR space. This study indicates the characteristics of tweets as object attributes. Users can focus on the characteristic individual tweets contrary to our method focuses on characteristic tweets of certain time and location. Also, the method does not show a temporal variation of the number of tweets at the same time. There is a study that places the historical materials on Google Earth in VR space [19]. Watanave reveals the relationship between materials and geographical information by arranging photos of people and buildings on the actual coordinates.

Based on the above, we chose to visualize the temporal change of the tweets and to recommend attractive directions in a VR space so that users themselves can go through and operate the data. This study visualized the tweets around Tokyo Disneyland (TDL) as an example the experiential nature provides the best affection. The operation of an unlimited number of perspectives using VR solves the problem of insufficient data comprehensibility in 3D spaces.

3 Visualization with space-time cubes

This section presents the processing flow of the proposed 3D spatio-temporal visualization technique.

3.1 VR environment

We developed the visualization on Unity3D [3] game engine version 2017.2.0f3. Unity Assets have rich supports including the SDK (Software Development Kit) for the VR devices which makes us easier to develop the complicated applications. We used HTC Vive Virtual Reality Headset.

Fig. 1 WorldView. (Left) Temporal change of the number of tweets is shown as the overview in a VR space. (Center) Panels which display actual tweets included in each cube appeared when users select each cube. (Right) The character icon with yellow highlight indicates the position of a user to prevent missing his/her current position.

3.2 Engine

The proposed technique analyzes a set of tweets in advance. The procedure is divided to aggregation and selection of tweets.

3.2.1 Aggregation

For the comprehensive understanding of tweets data and people behavior, the technique divides the map into appropriate sizes of blocks and aggregates the number of tweets in each block and time step. It then normalizes the number of tweets included certain blocks and time step to a range[0,1]. In the following equations, n_{ij} denotes the frequency of tweets at the i-th date in the j-th block, and v_{ij} denotes its score.

$$v_{ij} = \frac{n_{ij} - n_{min}}{n_{max} - n_{min}} \tag{1}$$

3.2.2 Tweets selection

Tweet datasets may contain a lot of noises and meaningless information because of the nature on the limitation of the number of character. Thus, we need to extract important words and texts relating to the location. We developed a text extraction methods after presenting our previous implementation [16]. We applied Latent Dirichlet Allocation (LDA) and tf-idf to remove the texts including trivial words while picking up those including meaningful words. Furthermore, we eliminated overlapping texts because multiple same tweets regarding location information are posted automatically.

3.2.3 Topic classification

The proposed technique classifies the words relating the location to the predefined number of topics. It makes us possible to eliminate the words and texts classified to the topics which are not related to the location. We applied the Latent Dirichlet Allocation (LDA) in this study. The procedure is as follows:

1. Collect the articles relating to the location from Wikipedia (15 pages in this implementation)
2. Extract noun words with MeCab
3. Remove symbol and stopwords
4. Generate the dictionary and corpus which have a higher frequency of appearances of words in each document
5. Build a model, classify the words to topics and rank the words with probability

3.2.4 Words extraction

We apply the tf-idf method to the tweets to extract important texts and remove general-meaning tweets like "I'm at Tokyo Disneyland."

1. Extract noun and verb words with MeCab
2. Remove stopwords
3. Calculate tf-idf value of each block

3.3 User interfaces

The system provides the following two display components.

WorldView: 3D spatio-temporal view for the overview of a certain period of time (one-month data in this study)

MiniMap: a small map for operation and viewing the time change of each time zone (one-day data in this study)

Both of these maps display objects to indicate details of tweets according to interactive operations.

3.3.1 WorldView

Fig. 1 shows the large map which users immerse into. Users can fly around the objects of visualization and observe outline of the data by operating TrackPad of HTC Vive. WorldView makes us recognize the remarkable time and area especially. Thus, users can seek the data with a focus on this part. At this moment, an icon is set on the map just under the users to avoid losing the positions of themselves. The icon informs the positions of cubes and the users themselves. We used utymap [4] to reproduce the map and obtained the map data from Open Street Map (OSM). Zoom level is 16 in our implementation. Peculiar interactions of VR make us easier to understand the data. We explain technical components in WorldView and provided operations below.

Fig. 2 Processing flow of cubes generation in WorldView.

Fig. 3 Colormap and the transfer function for setting transparency.

3.3.2 Cubes

This technique regards the frequency of tweets as temporal data and represents as a set of cubes. Our visualization consumes tweets data written in a JSON file as tweet objects. The processing flow of cubes generation is shown in Fig. 2.

3.3.3 Setting of Colormaps

Next, the technique prepares colormaps automatically to represent values of cubes. Borland et al. [6] describe the correspondence between data types and colormaps. We applied a common rainbow colormap based on the hue. Hue h of the HSV color space is generated as follows.

$$h_{ij} = \frac{160}{240}(1.0 - v_{ij}) \tag{2}$$

3.3.4 Setting of Transparency

Then, we define the transfer function for setting transparency. Cluttering is a common problem of 3D visualization techniques depending on viewpoint setting. The technique represents important portions which have projecting values opaquely, and other portions transparent, to prevent the cluttering and improve the comprehensibility. Thus, the important parts are only highlighted. We define the transfer function as an exponential function of the values of

Fig. 4 The panel displays the detailed information of each cube. It contains the date, coordinate and text of representative tweets and gives us the knowledge about the reason why people made many tweets in a certain area and time.

cubes. Transparency t is calculated with score v to the power of a. The equation is as follows and the graph is shown in Fig. 3.

$$t_{ij} = v_{ij}^{a} \tag{3}$$

3.3.5 Panels

Fig. 4 shows the panels, which appear when users select a cube they want to see the details with the pointer. Panels show details about the tweets corresponding to the selected cubes, including date, coordinates (latitude/longitude), and texts of representative tweets. This technique selects the tweets as 3.2.2. These panels make easier for users to find when, where and why people were gathered or events have occurred. Also, panels and the operation of them make the switchover between overview and detail more intuitive.

3.3.6 Operation procedure in WorldView

Following is the list of controller operations in WorldView.

TrackPad of the left controller
: Moving and flying around the map and cubes.

Trigger button of the right controller
: Pointing for the selection of cubes and panels. Cubes will be highlighted when users select them.

Grip button of the right controller
: Grabbing the panels.

Snapping the right controller
: Destroying the panels. Snap upward rapidly.

Fig. 5 MiniMap displays the time change of the number of tweets in a day. Cubes in MiniMap indicate the aggregation of one-hour data different from those in WorldView. Users can observe the time change more specifically.

3.3.7 MiniMap

Fig. 5 shows MiniMap, a small duplication of “WorldView” attached to the left controller. It appears by turning over the controller. This map also provides the overview, but this provides a time change of the data in a shorter time range differently from WorldView. Our current implementation of MiniMap represents a particular day, where cubes of MiniMap depict the aggregation per hour. Users can select the date to observe details with the slider attached to MiniMap. Users are required to press the trigger and the grip button at the same time while using the slider. They can also warp to the positions of the corresponding cubes of WorldView after the users point the cubes of MiniMap by pressing the trigger button on the right controller and releasing. This operation saves time to move to the distant cubes and explore the tweets included in these cubes.

4 Route recommendation

Another mode implemented on the proposed system also applies the same data and VR environment as Sec. 3 space-time cube visualization. This mode suggests the paths and areas where large numbers of attractive and characteristic tweets appear.

Fig. 6 WorldView as the routes recommendation system. (Left) The scenery from the users' viewpoint. Panels including detailed tweets in each area and photos attached to the tweets are displayed. (Right) The panel is zoomed when users select the arranged panel.

4.1 Engine

The route recommendation technique also requires to process tweets in advance. The procedure is divided into tweet aggregation, tweet selection and identification of recommended routes. We applied the tweet selection methods explained in Sec. 3.2.2 again. Procedures for aggregation and route calculation are introduced in the following sections.

4.1.1 Aggregation

The technique divides the map into appropriate sizes of blocks and aggregates the number of tweets in each block to quantify the spatial distribution of moving people. At first, we calculate the angle between tweets 1 and 2 as follows in each block.

1. a tweet posted at area a_i
2. a tweet posted after a user tweeted at area a_i and then move to the direction k

Then tweets are classified to the nine directions (eight directions divided at 45 degrees and no moving) according to the calculated angle value. At this time, we count only the number of Twitter users who tweet multiple time in a day. The tweets posted by the same users on the different date is treated as the tweets posted by the different user. The technique then normalizes the number of tweets of certain blocks and directions to a range[0,1]. In the following equations, n_{ik} denotes the frequency of tweets in the i-th block to the k-th direction, and v_{ik} denotes its score.

$$v_{ik} = \frac{n_{ik} - n_{min}}{n_{max} - n_{min}} \tag{4}$$

4.1.2 Route calculation

Our proposed technique suggests interesting routes from the current positions of users to the destinations selected by them. For users exploring the shortest and interesting paths from the starting point S to the destination D, we developed a routing algorithm based on the Dijkstra algorithm. Here, we determine the weighting of edge costs based on the two factors, the number of Twitter users who passed the area, and the number of selected tweets posted in the area.

$$\min_{\substack{E \\ S \to D}} \{ \sum_{e \in E} \{ \alpha \cdot (1 - N\_Aggregation(e)) + (1.0 - \alpha) \cdot (1 - N\_SelectedTweets(e)) \} \} \tag{5}$$

where, N_Aggregation(e) is the normalized number of people who passed the area, and N_SelectedTweets(e) is the normalized number of selected tweets posted in the area. These factor is weighted by $\alpha \in [0, 1]$.

$$\begin{gathered} N\_Aggregation(e) = Aggregation(e) / \max_{e' \in E} \{ Aggregation(e') \} \\ N\_SelectedTweets(e) = SelectedTweets(e) / \max_{e' \in E} \{ SelectedTweets(e') \} \end{gathered} \tag{6}$$

4.2 User interfaces

The system displays two maps, WorldView, and MiniMap, similarly as the space-time cube visualization. Here, the maps for the route recommendation have the following different roles:

WorldView: Display the detail texts of selected tweets, photos and navigations
MiniMap: Suggest the optimal routes

4.2.1 WorldView

WorldView (see Fig. 6) suggests the places where a large number of attractive tweets have posted. The system navigates users to the places while arranging panels which display the detailed information of tweets. It helps users to get knowledge about the interesting stores and places efficiency and make plans to travel. We adopted the same tweet selection method with that described in Sec. 3.2.2. Panels indicate the recent tweets if the number of selected tweets is too large. Against the tweet selecting method presented in our previous paper [16] leaves the problem that less-interesting information increased while the number of tweets is increased, we improved the method as described in this paper. As a result, the panels such as that in Fig. 6 displays the information related to the target venues (TDL, especially about a cafe and attractions, in this paper).

Characters on the panels are sometimes difficult to read in WorldView if the panels are distant. We developed a zoom operation to solve this problem. The duplicated panel shows close to the users when the original panels are

Fig. 7 MiniMap as the routes recommendation system. MiniMap shows the navigation from the current position to the destination panel. Navigation also appears in the WorldView to guide users.

selected. Only one duplicated panel appear at the same time, so the panel disappears when a next original panel is selected.

Photos are also displayed in WorldView so that users can feel the experiences of the actual environment. These photos are downloaded from the URLs inserted in the tweet texts in advance. They are loaded when the system starts and placed on the corresponding position where the original tweets are posted in the VR space. According to the combining of these elements, users can walk and look around the VR space without complicated operations.

4.2.2 MiniMap

MiniMap displays the specified routes from the user's current position to the destination. The destination is determined by the position of the panel which users selected at last. Routes are updated when users turn their left controller and the navigation also appear in WorldView as shown in Fig. 7. Panels on the recommended routes notify us the information of attractions where we pass by. Therefore, the panels help our decision making where to move next. Users can walk in WorldView while they watch their MiniMap as if they walk in the actual world while watching digital maps (e.g., Google map running on a smartphone).

Fig. 8 Example. The top-left figure shows people tweet a lot during Japanese summer vacation. The top-right figure is the map looked down from the position of cubes. It indicates that user is in front of Cinderella castle. Panels in both figures below pick up actual tweets.

5 Example

This section introduces an example with a tweet dataset described in Sec. 5.1. We applied visualization with space-time cubes (Sec. 3) in this example. Our implementation adopted a picture of Mickey Mouse as the icon of WorldView. We also developed some visual effects including a firework effect mimicking fireworks in Tokyo Disneyland (TDL) displayed while destroying the panels in WorldView.

5.1 Tweet data

We applied approximately 16,000 tweets with location information posted in August 2014. Those latitude and longitude were inside the rectangular area surrounding TDL. Tweet objects have various attributes such as coordinates (latitude/longitude), created time, user id, and text. We gathered these data via Twitter API and saved in JSON format.

5.2 Use case

At first, we found that opaque cubes concentrated around the middle of this month, from the overview shown in Fig. 8 (upper-left). TDL was crowded with people in this period because it was during the summer vacation week in Japan, and therefore tweets also increased in this period. Then, we moved the viewpoint to the position of cubes, as shown in Fig. 8 (upper-right). We found that many people tweeted in front of Cinderella castle located at the center of TDL.

The rest figures in Fig. 8 show the real tweets in front of the Cinderella castle. Tweets related to Disneyland are displayed in the lower-right figure. It is predictable that many tourism had appeal tweets including "Tokyo Disneyland" that they were at TDL in this position.

6 Experimental evaluation

This section introduces our experimental evaluations conducted to measure the effectiveness of our route recommendation technique presented in Sec. 4. We conducted two experiments. The former was the comparative experiments providing two implementations of the exploration system where one was with navigation, and the other was without navigation. The latter experiment was conducted to identify the optimal weight in Equation 5. We referenced several studies to determine the questionnaire items and experiment procedure. Lam [14] classified the experimental evaluation by seven scenarios. Our technique corresponds to User Experience (UE) in this paper. [12] evaluates VR rehabilitation system and [20] compares two VR systems.

6.1 Dataset

We applied approximately 146,000 tweets with location information posted from 2014 to 2016. Those coordinates and object structure are as described in Sec. 5.1.

6.2 Participants

Participants of our evaluation were 16 female university students aged between 20 and 28 belonging to the department of computer science. All participants were female students because we called for participants of this experiment in a women's university. The department equipped VR devices, and therefore many students already had experiences of VR devices. As a result, six participants had no VR experience, eight participants had one to five hours, and two participants had used VR many times. We selected TDL as the tweeted area in this paper because we expected to receive more detailed comments if we chose a famous area. TDL is especially preferable for young women, and therefore we thought it is one of the best places for this experiment. Actually, fourteen participants have been to the tweeted area more than three times, while the other two participants have been there just once.

6.3 Procedure

At first, we gave a brief introduction of this experiment to the participants. They practiced our system for three or four minutes while hearing our instruction of operation. Then, we started our comparative experiments. We provided participants either with or without navigation system randomly. After they experienced the provided system during 10 to 20 minutes, the other system they had not experienced yet were provided. Next, we asked them to select the starting point and the destination and showed routes. Each participant observed three routes which have the same starting point and the same destination. These three routes had different weight α in Equation 5: $\alpha = 0.2$, 0.5 and 0.8. We showed these routes in the random order. Just one participant took a break because of getting sick during the experiments. The total average time spent on the experiments by each of the participants was approximately 60 minutes.

6.4 Questionnaires

The questionnaire survey was conducted after they experienced the system. Questions for the comparative experiment were as follows:

1.1 How much did you feel immersed into the environment? (quantity)
1.2 How much did you feel satisfied with the system? (quantity)
1.3 How much did you get motivated to explore the map? (quantity)
1.4 How easy to compare each tweet? (quantity)
1.5 Did you find the places, attractions, restaurants or events you want to go? (quantity) Where is that? (quality)
1.6 Did you find the places, attractions, restaurants or events you do not want to go? (quantity) Where is that? (quality)
1.7 Do you think this system helps to make a tourism planning? (quantity)

Each question was evaluated in five points Likert scale, where "1" was the most negative while "5" was the most positive. Participants were required to answer the same questions regarding each system with and without navigation. In addition, we ask them these questions:

2.1 Which one is the best among 3 routes? Why did you think so? (quality)
2.2 Which one is the better system, with navigation or with no navigation? Why did you think so? (quality)
2.3 What functions were helpful? Why did you think so? (quality)
2.4 Do you have any idea of other function you want or to improve this implementation? (quality)

2.5 Comments for the whole system (quality)
2.6 Did you feel sick? (quantity)

6.5 Result

6.5.1 Comparison

Table 1 shows the evaluation result of the system with navigation and Table 2 shows that of the system without navigation. Evaluation values are totally higher in Table 1 than in Table 2. Especially, the questions 1.3 (motivation), 1.5 (places participants want to go) and 1.7 (help tourism planning) have remarkable differences. Several participants mentioned that they got to want to go the recommended attractions just because they were on the routes. Moreover, they realized the attractions and restaurants they did not know, such as Camera center and Picnic area, or have not visited on the way to the destination. In question 2.2, 14 participants chose the system with navigation. The reasons for this choice were:

- Participants got able to make up their mind soon.
- They got easier to imagine the order of visiting attractions in TDL.
- Navigation was convenient while they did not explore out of the route.

We suppose the above factors affected the results of questions 1.3, 1.5 and 1.7. Besides, participants tended to favor beautiful photo spots such as restaurants or in front of Cinderella castle. On the other hand, they answered they wanted to avoid crowded places or dormant attractions.

Table 1 System with navigation

Question	Average	Variance
1.1 sense of immersion	4.25	1.0
1.2 satisfaction	4.125	0.517
1.3 motivation	4.188	0.296
1.4 ease of tweet comparison	3.25	0.733
1.5 places participants want to go	3.875	0.517
1.6 places participants do not want to go	1.563	0.929
1.7 help tourism planning	3.813	1.363

6.5.2 Identifying the optimal weight of routes calculation

Participants compared three routes in question [2.1]. Options were as follows:

- **Route 1:** $\alpha = 0.8$
  Distribution ratio of N_Aggregation(e) is larger than N_SelectedTweets(e). Thus the number of past Twitter users passed each area is the important factor.

Table 2 System with no navigation

Question	Average	Variance
1.1 sense of immersion	4.063	1.129
1.2 satisfaction	3.75	0.6
1.3 motivation	3.563	0.796
1.4 ease of tweet comparison	2.75	0.467
1.5 places participants want to go	3.313	1.029
1.6 places participants do not want to go	1.875	0.917
1.7 help tourism planning	3.25	0.867

- **Route 2:** $\alpha = 0.5$
- **Route 3:** $\alpha = 0.2$
  Distribution ratio of N_SelectedTweets(e) is larger than N_Aggregation(e). Thus the number of selected meaningful tweets in each area is the important factor.

As a result, two participants selected Route 1 as the best route, another six participants selected Route 2, four participants selected Route 3 and the other four participants mentioned they felt no different among the three routes. Comments of participants selected Route 3 included "The routes included more attractions than other routes" and "I could imagine the routes easily." Moreover, comments of participants selected Route 2 included "The area looked fun was included", "The route had more meaningful tweets than other routes" and "I found the panel I could not find while using the system without navigation."

The routes based on the number of selected tweets passed by the several popular attractions because the many attraction names were extracted with the words extracted method. We realized that many participants chose the routes based on the attraction they knew. This result might cause due to the fact that all participants had been to TDL. We suppose the result might be different if we apply different venues.

6.5.3 Other results

In question 2.3, eight participants selected viewing panels with detail tweets, ten participants selected navigation in WorldView, thirteen participants selected viewing photos and six participants selected navigation in MiniMap. Navigation in WorldView helped participants to understand which directions they should go. Photos also notified them their positions and enhanced their feeling of immersion.

Participants gave us several ideas to improve this system in question 2.4. At first, multiple participants requested a function to highlight panels they had already checked. They could not distinguish distant panels, so they sometimes chose the same panels repeatedly. Because of the same reason, participants felt that a function for panel recommendation would be necessary. Participants were interested in the panels on the routes; however, they did not check the distant panels out of the routes. Suggestions of the panels which have contents similar to the panels users already looked may help the explorations of users. Besides these ideas, they suggested the following ideas: viewing area or attraction name, notifying time information and current their positions on MiniMap and the optimization of the order of tweets viewing.

Overall, most participants felt fun with this experiment. Several participants felt as if they were in TDL and used it as an alternative of experience in TDL. We expect participants would get other funs by applying other sightseeing venue datasets and more recent tweet datasets in addition to the dataset applied in this experiment.

7 Conclusion

This paper proposed spatio-temporal visualization and route recommendation techniques applying a VR space consisting of "WorldView" and "MiniMap." For the procedure of realizing spatio-temporal visualization, we aggregated the number of tweets in each block of coordinates and time step and represented the scores as cubes applied color and transparency. At the same time, by displaying the detail of tweets included in cubes, users can grasp the characteristics of human behavior in a constant duration and observe the critical times and regions. Moreover, they can get the detailed information in the particular times and regions corresponding to the remarkable cubes. We also developed the navigation method based on two factors. One of the factors is the number of people passed the area past, and the other one is the number of selected tweets in each area. This helps decision making of users. VR realizes simple operation and motivates users to explore the environment. Users will be familiar with the environment while exploring and experiencing the data by themselves. We also introduced a brief example and reported the result of the experimental evaluation in this paper.

We have several future issues. At first, we would like to reflect the result of the experimental evaluations. We found several issues as described in Sec. 6.5.3. Especially, highlighting of checked panels and recommendation of panels will affect to usability directly. As further steps, we would like to apply the most recent Twitter data and the other social media data. We found that attractions which had already replaced were mentioned in some tweets in the dataset. We will be able to find actual information more efficiently by applying the newest tweet datasets. Meanwhile, datasets of other social networking services such as Facebook, Instagram, and Flickr have attributes of text, images, and hashtags as well as Twitter. We often use different services depending on our own situation, because each of these services has different features and limitation. Also, user segmentation is different among the services. Therefore, we can highly expect to get new knowledge from such various services.

Moreover, we have been discussing to apply tweet datasets at other types of venues, such as other entertainment parks and sightseeing spots like Kyoto. We and experiment participants used famous attractions as a mark because we were familiar with TDL. On the other hand, we do not know any landmarks if we apply unknown venues. In such a situation, it is helpful to take advantage of navigation, and finally, we should be able to get more new unknown information.

Acknowledgements This work has been partially supported by Japan Society of the Promotion of Science under Grant-in-Aid for Scientific Research.

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Noname manuscript No.
(will be inserted by the editor)

VR System for Spatio-Temporal Visualization of Tweet Data and Support of Map Exploration

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Received: date / Accepted: date

Abstract Social media analysis is helpful to understand the behavior of people. Human behavior in social media is related to time and location, which is often difficult to find the characteristics appropriately and quickly. We chose to apply virtual reality (VR) technologies to present the spatio-temporal social media data. This makes us easier to develop interactive and intuitive user interfaces and explore the data as we want. This paper proposes a VR system featuring two visualization techniques. One of the techniques is a three-dimensional temporal visualization of tweets of microblogs with location information. It consists of the two-dimensional map and a time axis. In particular, we aggregate the number of tweets of each coordinate and time step and depict them as piled cubes. We highlight only specific cubes so that users can understand the overall tendency of datasets. The other technique provides a route recommendation based on tweets of microblogs. Our technique supports users to explore attractive events and places by selecting effective tweets and sug-

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gesting routes. We also developed user interfaces for operating these objects in a VR space which indicate details of tweets.

Keywords temporal visualization · virtual reality · social media · tweet data · immersive visualization · route recommendation

1 Introduction

Social media analysis brings us important knowledge. Conversation data on Twitter and Facebook contain characteristics of the corresponding area such as where, when and why events are held, or people gathered. People who have not visited these places and do not have enough knowledge can also find interesting information. Many analysis methods such as text mining or human network analysis have been applied to social media analysis. However, it often happens that these methods are not sufficiently effective to understand the complex data of human behavior involving various factors. Meanwhile, interactive visualization is also useful to understand complex social media data. Thus, we applied immersive analytics techniques using Virtual Reality (VR) technologies for social media exploration. VR is suitable for not only entertainment fields but also for visualization. It makes us easier to observe the spatial data intuitively and in detail.

This paper proposes a 3D spatio-temporal visualization system with an interactive user interface (UI) for tweets of microblogs. The presented system features two visualization components. One of the components visualizes the spatio-temporal statistics of tweets by assigning a geographic map onto a 2D plane (XZ-plane) and the time to the y-axis (vertical direction against the map). The proposed technique aggregates the number of tweets in each time and blocks divided into the appropriate sizes. Then, we set colors and highlight only important portions of the 3D space which has many tweets by controlling the transparency. Users can immerse into this map and observe overview of the data while they look at the time change of the number of the tweets in each time periods with a small map which is the duplicated map of the large one. The other component features the routes recommendation system for supporting users to explore the more attractive places and events. This technique recommends interesting directions based on the movement of past Twitter users and the places where many interesting tweets including important words have been posted. Moreover, we implemented intuitive operations supposed to use the VR device "HTC Vive" [**?**]. Users are supposed to fly around and explore the data by themselves by using VR so that they will experience the environment of this area. It will help users to memorize the map and the data they found.

In this study, we introduce the example applied tweets with location information in Tokyo Disneyland (TDL). The visualization brings knowledge of congestion or remarkable events for users who rarely go to TDL and makes feel them as if they are in there.

2 Related Work

In this section, we mainly introduce 3D-based techniques which can represent both spatial and temporal information. Then, we also introduce route recommendation methods and VR-applied visualization techniques.

2.1 Spatio-Temporal visualization

Space-Time Cube [?] is a typical representation of 3D temporal data visualization. It is often used for visualization of human behavior as the forms of spatio-temporal paths and geo-time. Fukada et al. [?] developed a method to represent walking routes and congestion areas by visualizing mobility of sightseeing behavior with GIS (Geographic Information System). They mainly focused on the walking speed of tourist and assigned it to the height of the space-time path method. Cuboid Matrix [?] arranged dynamic network information in a 3D space consisting of a plane and a time axis. Users can observe overview and detail of spatio-temporal information. However, the technique often caused insufficient readability of crowded regions, and therefore required operations for breakdown into 2D display spaces.

2.2 Routes recommendation using SNS analysis

There have been several studies on the route recommendation based on geographical information and the results of SNS data analysis. Fu et al. [?] proposed a method which extracts trend words based on their tf-idf values calculated from multiple Twitter accounts relating transportation and then recommends the routes while providing the text summary. They have four types of route selecting techniques: the shortest path, the safest path, the path which has a large number of points of interest places and optimal path. Wakayama et al. [?] developed a method to explore the optimal paths based on the useful landmark extracted from SNS and geographical information. They applied the Dijkstra algorithm and the genetic algorithm to calculate their routes. Criteria for selecting the landmarks include popularity, direct visibility (tall and distinctive structure), and indirect visibility (popular structure). Both methods show their routes on a 2D display.

2.3 Visualization of tweet data using VR

Guttentag [?] demonstrated that VR has potentials for tourism and marketing. This paper also claims that VR models allow planners to observe an environment from an unlimited number of perspectives instead of just applying a bird's-eye view. As a result, travelers can make appropriate decisions based on the information displayed graphically and had practical expectations. Moreover, the experiential nature of VR makes it an optimal tool for providing rich data to tourists. This study concluded that VR has the potential to revolutionize the promotion and selling of tourism.

Immersive Analytics [?] is a recent framework for supporting the analytics of real data. Virtual reality environment such as a large-sized touch panel, Oculus Rift [?], Cave2 [?] and tracking devices like Kinect make users immerse into the data. Specialists and analysts can easily access large complex data using this environment. ImAxes [?] is a typical example of immersive analytics framework. Users can generate visualization displays freely by using Vive controller. A scatterplot is generated when we select and combine any axes in a VR space, and a parallel coordinate plot (PCP) appears after we put together multiple scatterplots. This method makes users immersing experiences into the data while users can freely explore the visualization space and search for information by themselves.

Moran et al. [?] visualized tweet data in a VR space. This study indicates the characteristics of tweets as object attributes. Users can focus on the characteristic individual tweets contrary to our method focuses on characteristic tweets of certain time and location. Also, the method does not show a temporal variation of the number of tweets at the same time. There is a study that places the historical materials on Google Earth in VR space [?]. Watanave reveals the relationship between materials and geographical information by arranging photos of people and buildings on the actual coordinates.

Based on the above, we chose to visualize the temporal change of the tweets and to recommend attractive directions in a VR space so that users themselves can go through and operate the data. This study visualized the tweets around Tokyo Disneyland (TDL) as an example the experiential nature provides the best affection. The operation of an unlimited number of perspectives using VR solves the problem of insufficient data comprehensibility in 3D spaces.

3 Visualization with space-time cubes

This section presents the processing flow of the proposed 3D spatio-temporal visualization technique.

3.1 VR environment

We developed the visualization on Unity3D [?] game engine version 2017.2.0f3. Unity Assets have rich supports including the SDK (Software Development Kit) for the VR devices which makes us easier to develop the complicated applications. We used HTC Vive Virtual Reality Headset.

3.2 Engine

The proposed technique analyzes a set of tweets in advance. The procedure is divided to aggregation and selection of tweets.

Fig. 1 WorldView. (Left) Temporal change of the number of tweets is shown as the overview in a VR space. (Center) Panels which display actual tweets included in each cube appeared when users select each cube. (Right) The character icon with yellow highlight indicates the position of a user to prevent missing his/her current position.

3.2.1 Aggregation

For the comprehensive understanding of tweets data and people behavior, the technique divides the map into appropriate sizes of blocks and aggregates the number of tweets in each block and time step. It then normalizes the number of tweets included certain blocks and time step to a range[0,1]. In the following equations, n_{ij} denotes the frequency of tweets at the i-th date in the j-th block, and v_{ij} denotes its score.

$$v_{ij} = \frac{n_{ij} - n_{min}}{n_{max} - n_{min}} \tag{1}$$

3.2.2 Tweets selection

Tweet datasets may contain a lot of noises and meaningless information because of the nature on the limitation of the number of character. Thus, we need to extract important words and texts relating to the location. We developed a text extraction methods after presenting our previous implementation [?]. We applied Latent Dirichlet Allocation (LDA) and tf-idf to remove the texts including trivial words while picking up those including meaningful words. Furthermore, we eliminated overlapping texts because multiple same tweets regarding location information are posted automatically.

3.2.3 Topic classification

The proposed technique classifies the words relating the location to the predefined number of topics. It makes us possible to eliminate the words and texts classified to the topics which are not related to the location. We applied the Latent Dirichlet Allocation (LDA) in this study. The procedure is as follows:

1. Collect the articles relating to the location from Wikipedia (15 pages in this implementation)
2. Extract noun words with MeCab
3. Remove symbol and stopwords
4. Generate the dictionary and corpus which have a higher frequency of appearances of words in each document
5. Build a model, classify the words to topics and rank the words with probability

3.2.4 Words extraction

We apply the tf-idf method to the tweets to extract important texts and remove general-meaning tweets like "I'm at Tokyo Disneyland."

1. Extract noun and verb words with MeCab
2. Remove stopwords
3. Calculate tf-idf value of each block

3.3 User interfaces

The system provides the following two display components.

WorldView: 3D spatio-temporal view for the overview of a certain period of time (one-month data in this study)
MiniMap: a small map for operation and viewing the time change of each time zone (one-day data in this study)

Both of these maps display objects to indicate details of tweets according to interactive operations.

Fig. 2 Processing flow of cubes generation in WorldView.

Fig. 3 Colormap and the transfer function for setting transparency.

3.3.1 WorldView

Fig. 1 shows the large map which users immerse into. Users can fly around the objects of visualization and observe outline of the data by operating TrackPad of HTC Vive. WorldView makes us recognize the remarkable time and area especially. Thus, users can seek the data with a focus on this part. At this moment, an icon is set on the map just under the users to avoid losing the positions of themselves. The icon informs the positions of cubes and the users themselves. We used utymap [**?**] to reproduce the map and obtained the map data from Open Street Map (OSM). Zoom level is 16 in our implementation. Peculiar interactions of VR make us easier to understand the data. We explain technical components in WorldView and provided operations below.

3.3.2 Cubes

This technique regards the frequency of tweets as temporal data and represents as a set of cubes. Our visualization consumes tweets data written in a JSON file as tweet objects. The processing flow of cubes generation is shown in Fig. 2.

3.3.3 Setting of Colormaps

Next, the technique prepares colormaps automatically to represent values of cubes. Borland et al. [**?**] describe the correspondence between data types and colormaps. We applied a common rainbow colormap based on the hue. Hue h of the HSV color space is generated as follows.

$$h_{ij} = \frac{160}{240}(1.0 - v_{ij}) \tag{2}$$

3.3.4 Setting of Transparency

Then, we define the transfer function for setting transparency. Cluttering is a common problem of 3D visualization techniques depending on viewpoint setting. The technique represents important portions which have projecting values opaquely, and other portions transparent, to prevent the cluttering and improve the comprehensibility. Thus, the important parts are only highlighted. We define the transfer function as an exponential function of the values of cubes. Transparency t is calculated with score v to the power of a. The equation is as follows and the graph is shown in Fig. 3.

$$t_{ij} = v_{ij}^{a} \tag{3}$$

3.3.5 Panels

Fig. 4 shows the panels, which appear when users select a cube they want to see the details with the pointer. Panels show details about the tweets corresponding to the selected cubes, including date, coordinates (latitude/longitude), and texts of representative tweets. This technique selects the tweets as 3.2.2. These panels make easier for users to find when, where and why people were gathered or events have occurred. Also, panels and the operation of them make the switchover between overview and detail more intuitive.

3.3.6 Operation procedure in WorldView

Following is the list of controller operations in WorldView.

TrackPad of the left controller
: Moving and flying around the map and cubes.

Trigger button of the right controller
: Pointing for the selection of cubes and panels. Cubes will be highlighted when users select them.

Grip button of the right controller
: Grabbing the panels.

Snapping the right controller
: Destroying the panels. Snap upward rapidly.

Fig. 4 The panel displays the detailed information of each cube. It contains the date, coordinate and text of representative tweets and gives us the knowledge about the reason why people made many tweets in a certain area and time.

Fig. 5 MiniMap displays the time change of the number of tweets in a day. Cubes in MiniMap indicate the aggregation of one-hour data different from those in WorldView. Users can observe the time change more specifically.

3.3.7 MiniMap

Fig. 5 shows MiniMap, a small duplication of “WorldView” attached to the left controller. It appears by turning over the controller. This map also provides the overview, but this provides a time change of the data in a shorter time range differently from WorldView. Our current implementation of MiniMap represents a particular day, where cubes of MiniMap depict the aggregation per hour. Users can select the date to observe details with the slider attached to MiniMap. Users are required to press the trigger and the grip button at

Fig. 6 WorldView as the routes recommendation system. (Left) The scenery from the users' viewpoint. Panels including detailed tweets in each area and photos attached to the tweets are displayed. (Right) The panel is zoomed when users select the arranged panel.

the same time while using the slider. They can also warp to the positions of the corresponding cubes of WorldView after the users point the cubes of MiniMap by pressing the trigger button on the right controller and releasing. This operation saves time to move to the distant cubes and explore the tweets included in these cubes.

4 Route recommendation

Another mode implemented on the proposed system also applies the same data and VR environment as Sec. 3 space-time cube visualization. This mode suggests the paths and areas where large numbers of attractive and characteristic tweets appear.

4.1 Engine

The route recommendation technique also requires to process tweets in advance. The procedure is divided into tweet aggregation, tweet selection and identification of recommended routes. We applied the tweet selection methods explained in Sec. 3.2.2 again. Procedures for aggregation and route calculation are introduced in the following sections.

4.1.1 Aggregation

The technique divides the map into appropriate sizes of blocks and aggregates the number of tweets in each block to quantify the spatial distribution of moving people. At first, we calculate the angle between tweets 1 and 2 as follows in each block.

1. a tweet posted at area a_i
2. a tweet posted after a user tweeted at area a_i and then move to the direction k

Then tweets are classified to the nine directions (eight directions divided at 45 degrees and no moving) according to the calculated angle value. At this time, we count only the number of Twitter users who tweet multiple time in a day. The tweets posted by the same users on the different date is treated as the tweets posted by the different user. The technique then normalizes the number of tweets of certain blocks and directions to a range[0,1]. In the following equations, n_{ik} denotes the frequency of tweets in the i-th block to the k-th direction, and v_{ik} denotes its score.

$$v_{ik} = \frac{n_{ik} - n_{min}}{n_{max} - n_{min}} \tag{4}$$

4.1.2 Route calculation

Our proposed technique suggests interesting routes from the current positions of users to the destinations selected by them. For users exploring the shortest and interesting paths from the starting point S to the destination D, we developed a routing algorithm based on the Dijkstra algorithm. Here, we determine the weighting of edge costs based on the two factors, the number of Twitter users who passed the area, and the number of selected tweets posted in the area.

$$\min_{\substack{E \\ S \to D}} \{ \sum_{e \in E} \{ \alpha \cdot (1 - N\_Aggregation(e)) + (1.0 - \alpha) \cdot (1 - N\_SelectedTweets(e)) \} \} \tag{5}$$

where, N_Aggregation(e) is the normalized number of people who passed the area, and N_SelectedTweets(e) is the normalized number of selected tweets posted in the area. These factor is weighted by $\alpha \in [0, 1]$.

$$\begin{gathered} N\_Aggregation(e) = Aggregation(e) / \max_{e' \in E} \{Aggregation(e')\} \\ N\_SelectedTweets(e) = SelectedTweets(e) / \max_{e' \in E} \{SelectedTweets(e')\} \end{gathered} \tag{6}$$

4.2 User interfaces

The system displays two maps, WorldView, and MiniMap, similarly as the space-time cube visualization. Here, the maps for the route recommendation have the following different roles:

WorldView: Display the detail texts of selected tweets, photos and navigations
MiniMap: Suggest the optimal routes

4.2.1 WorldView

WorldView (see Fig. 6) suggests the places where a large number of attractive tweets have posted. The system navigates users to the places while arranging panels which display the detailed information of tweets. It helps users to get knowledge about the interesting stores and places efficiency and make plans to travel. We adopted the same tweet selection method with that described in Sec. 3.2.2. Panels indicate the recent tweets if the number of selected tweets is too large. Against the tweet selecting method presented in our previous paper [?] leaves the problem that less-interesting information increased while the number of tweets is increased, we improved the method as described in this paper. As a result, the panels such as that in Fig. 6 displays the information related to the target venues (TDL, especially about a cafe and attractions, in this paper).

Characters on the panels are sometimes difficult to read in WorldView if the panels are distant. We developed a zoom operation to solve this problem. The duplicated panel shows close to the users when the original panels are selected. Only one duplicated panel appear at the same time, so the panel disappears when a next original panel is selected.

Photos are also displayed in WorldView so that users can feel the experiences of the actual environment. These photos are downloaded from the URLs inserted in the tweet texts in advance. They are loaded when the system starts and placed on the corresponding position where the original tweets are posted in the VR space. According to the combining of these elements, users can walk and look around the VR space without complicated operations.

4.2.2 MiniMap

MiniMap displays the specified routes from the user's current position to the destination. The destination is determined by the position of the panel which users selected at last. Routes are updated when users turn their left controller and the navigation also appear in WorldView as shown in Fig. 7. Panels on the recommended routes notify us the information of attractions where we pass by. Therefore, the panels help our decision making where to move next. Users can walk in WorldView while they watch their MiniMap as if they walk in the actual world while watching digital maps (e.g., Google map running on a smartphone).

5 Example

This section introduces an example with a tweet dataset described in Sec. 5.1. We applied visualization with space-time cubes (Sec. 3) in this example. Our implementation adopted a picture of Mickey Mouse as the icon of WorldView. We also developed some visual effects including a firework effect mimicking

Fig. 7 MiniMap as the routes recommendation system. MiniMap shows the navigation from the current position to the destination panel. Navigation also appears in the WorldView to guide users.

fireworks in Tokyo Disneyland (TDL) displayed while destroying the panels in WorldView.

5.1 Tweet data

We applied approximately 16,000 tweets with location information posted in August 2014. Those latitude and longitude were inside the rectangular area surrounding TDL. Tweet objects have various attributes such as coordinates (latitude/longitude), created time, user id, and text. We gathered these data via Twitter API and saved in JSON format.

5.2 Use case

At first, we found that opaque cubes concentrated around the middle of this month, from the overview shown in Fig. 8 (upper-left). TDL was crowded with people in this period because it was during the summer vacation week in Japan, and therefore tweets also increased in this period. Then, we moved the viewpoint to the position of cubes, as shown in Fig. 8 (upper-right). We found that many people tweeted in front of Cinderella castle located at the center of TDL.

Fig. 8 Example. The top-left figure shows people tweet a lot during Japanese summer vacation. The top-right figure is the map looked down from the position of cubes. It indicates that user is in front of Cinderella castle. Panels in both figures below pick up actual tweets.

The rest figures in Fig. 8 show the real tweets in front of the Cinderella castle. Tweets related to Disneyland are displayed in the lower-right figure. It is predictable that many tourism had appeal tweets including “Tokyo Disneyland” that they were at TDL in this position.

6 Experimental evaluation

This section introduces our experimental evaluations conducted to measure the effectiveness of our route recommendation technique presented in Sec. 4. We conducted two experiments. The former was the comparative experiments providing two implementations of the exploration system where one was with navigation, and the other was without navigation. The latter experiment was conducted to identify the optimal weight in Equation 5. We referenced several studies to determine the questionnaire items and experiment procedure. Lam [?] classified the experimental evaluation by seven scenarios. Our technique corresponds to User Experience (UE) in this paper. [?] evaluates VR rehabilitation system and [?] compares two VR systems.

6.1 Dataset

We applied approximately 146,000 tweets with location information posted from 2014 to 2016. Those coordinates and object structure are as described in Sec. 5.1.

6.2 Participants

Participants of our evaluation were 16 female university students aged between 20 and 28 belonging to the department of computer science. All participants were female students because we called for participants of this experiment in a women's university. The department equipped VR devices, and therefore many students already had experiences of VR devices. As a result, six participants had no VR experience, eight participants had one to five hours, and two participants had used VR many times. We selected TDL as the tweeted area in this paper because we expected to receive more detailed comments if we chose a famous area. TDL is especially preferable for young women, and therefore we thought it is one of the best places for this experiment. Actually, fourteen participants have been to the tweeted area more than three times, while the other two participants have been there just once.

6.3 Procedure

At first, we gave a brief introduction of this experiment to the participants. They practiced our system for three or four minutes while hearing our instruction of operation. Then, we started our comparative experiments. We provided participants either with or without navigation system randomly. After they experienced the provided system during 10 to 20 minutes, the other system they had not experienced yet were provided. Next, we asked them to select the starting point and the destination and showed routes. Each participant observed three routes which have the same starting point and the same destination. These three routes had different weight α in Equation 5: $\alpha = 0.2$, 0.5 and 0.8. We showed these routes in the random order. Just one participant took a break because of getting sick during the experiments. The total average time spent on the experiments by each of the participants was approximately 60 minutes.

6.4 Questionnaires

The questionnaire survey was conducted after they experienced the system. Questions for the comparative experiment were as follows:

1.1 How much did you feel immersed into the environment? (quantity)
1.2 How much did you feel satisfied with the system? (quantity)

1.3 How much did you get motivated to explore the map? (quantity)
1.4 How easy to compare each tweet? (quantity)
1.5 Did you find the places, attractions, restaurants or events you want to go? (quantity) Where is that? (quality)
1.6 Did you find the places, attractions, restaurants or events you do not want to go? (quantity) Where is that? (quality)
1.7 Do you think this system helps to make a tourism planning? (quantity)

Each question was evaluated in five points Likert scale, where "1" was the most negative while "5" was the most positive. Participants were required to answer the same questions regarding each system with and without navigation. In addition, we ask them these questions:

2.1 Which one is the best among 3 routes? Why did you think so? (quality)
2.2 Which one is the better system, with navigation or with no navigation? Why did you think so? (quality)
2.3 What functions were helpful? Why did you think so? (quality)
2.4 Do you have any idea of other function you want or to improve this implementation? (quality)
2.5 Comments for the whole system (quality)
2.6 Did you feel sick? (quantity)

6.5 Result

6.5.1 Comparison

Table 1 shows the evaluation result of the system with navigation and Table 2 shows that of the system without navigation. Evaluation values are totally higher in Table 1 than in Table 2. Especially, the questions 1.3 (motivation), 1.5 (places participants want to go) and 1.7 (help tourism planning) have remarkable differences. Several participants mentioned that they got to want to go the recommended attractions just because they were on the routes. Moreover, they realized the attractions and restaurants they did not know, such as Camera center and Picnic area, or have not visited on the way to the destination. In question 2.2, 14 participants chose the system with navigation. The reasons for this choice were:

- Participants got able to make up their mind soon.
- They got easier to imagine the order of visiting attractions in TDL.
- Navigation was convenient while they did not explore out of the route.

We suppose the above factors affected the results of questions 1.3, 1.5 and 1.7. Besides, participants tended to favor beautiful photo spots such as restaurants or in front of Cinderella castle. On the other hand, they answered they wanted to avoid crowded places or dormant attractions.

Table 1 System with navigation

Question	Average	Variance
1.1 sense of immersion	4.25	1.0
1.2 satisfaction	4.125	0.517
1.3 motivation	4.188	0.296
1.4 ease of tweet comparison	3.25	0.733
1.5 places participants want to go	3.875	0.517
1.6 places participants do not want to go	1.563	0.929
1.7 help tourism planning	3.813	1.363

Table 2 System with no navigation

Question	Average	Variance
1.1 sense of immersion	4.063	1.129
1.2 satisfaction	3.75	0.6
1.3 motivation	3.563	0.796
1.4 ease of tweet comparison	2.75	0.467
1.5 places participants want to go	3.313	1.029
1.6 places participants do not want to go	1.875	0.917
1.7 help tourism planning	3.25	0.867

6.5.2 Identifying the optimal weight of routes calculation

Participants compared three routes in question [2.1]. Options were as follows:

– **Route 1:** $\alpha = 0.8$
  Distribution ratio of N_Aggregation(e) is larger than N_SelectedTweets(e). Thus the number of past Twitter users passed each area is the important factor.
– **Route 2:** $\alpha = 0.5$
– **Route 3:** $\alpha = 0.2$
  Distribution ratio of N_SelectedTweets(e) is larger than N_Aggregation(e). Thus the number of selected meaningful tweets in each area is the important factor.

As a result, two participants selected Route 1 as the best route, another six participants selected Route 2, four participants selected Route 3 and the other four participants mentioned they felt no different among the three routes. Comments of participants selected Route 3 included "The routes included more attractions than other routes" and "I could imagine the routes easily." Moreover, comments of participants selected Route 2 included "The area looked fun was included", "The route had more meaningful tweets than other routes" and "I found the panel I could not find while using the system without navigation."

The routes based on the number of selected tweets passed by the several popular attractions because the many attraction names were extracted with the words extracted method. We realized that many participants chose the routes based on the attraction they knew. This result might cause due to the fact that all participants had been to TDL. We suppose the result might be different if we apply different venues.

6.5.3 Other results

In question 2.3, eight participants selected viewing panels with detail tweets, ten participants selected navigation in WorldView, thirteen participants selected viewing photos and six participants selected navigation in MiniMap. Navigation in WorldView helped participants to understand which directions they should go. Photos also notified them their positions and enhanced their feeling of immersion.

Participants gave us several ideas to improve this system in question 2.4. At first, multiple participants requested a function to highlight panels they had already checked. They could not distinguish distant panels, so they sometimes chose the same panels repeatedly. Because of the same reason, participants felt that a function for panel recommendation would be necessary. Participants were interested in the panels on the routes; however, they did not check the distant panels out of the routes. Suggestions of the panels which have contents similar to the panels users already looked may help the explorations of users. Besides these ideas, they suggested the following ideas: viewing area or attraction name, notifying time information and current their positions on MiniMap and the optimization of the order of tweets viewing.

Overall, most participants felt fun with this experiment. Several participants felt as if they were in TDL and used it as an alternative of experience in TDL. We expect participants would get other funs by applying other sightseeing venue datasets and more recent tweet datasets in addition to the dataset applied in this experiment.

7 Conclusion

This paper proposed spatio-temporal visualization and route recommendation techniques applying a VR space consisting of "WorldView" and "MiniMap." For the procedure of realizing spatio-temporal visualization, we aggregated the number of tweets in each block of coordinates and time step and represented the scores as cubes applied color and transparency. At the same time, by displaying the detail of tweets included in cubes, users can grasp the characteristics of human behavior in a constant duration and observe the critical times and regions. Moreover, they can get the detailed information in the particular times and regions corresponding to the remarkable cubes. We also developed the navigation method based on two factors. One of the factors is the number of people passed the area past, and the other one is the number of selected tweets in each area. This helps decision making of users. VR realizes simple operation and motivates users to explore the environment. Users will be familiar with the environment while exploring and experiencing the data by themselves. We also introduced a brief example and reported the result of the experimental evaluation in this paper.

We have several future issues. At first, we would like to reflect the result of the experimental evaluations. We found several issues as described in Sec. 6.5.3.

Especially, highlighting of checked panels and recommendation of panels will affect to usability directly. As further steps, we would like to apply the most recent Twitter data and the other social media data. We found that attractions which had already replaced were mentioned in some tweets in the dataset. We will be able to find actual information more efficiently by applying the newest tweet datasets. Meanwhile, datasets of other social networking services such as Facebook, Instagram, and Flickr have attributes of text, images, and hashtags as well as Twitter. We often use different services depending on our own situation, because each of these services has different features and limitation. Also, user segmentation is different among the services. Therefore, we can highly expect to get new knowledge from such various services.

Moreover, we have been discussing to apply tweet datasets at other types of venues, such as other entertainment parks and sightseeing spots like Kyoto. We and experiment participants used famous attractions as a mark because we were familiar with TDL. On the other hand, we do not know any landmarks if we apply unknown venues. In such a situation, it is helpful to take advantage of navigation, and finally, we should be able to get more new unknown information.

Acknowledgements This work has been partially supported by Japan Society of the Promotion of Science under Grant-in-Aid for Scientific Research.

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