EventStacks: Integration of Event Visualizations for Physical and Social Sensor Data

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Abstract— This paper presents a framework for spatio-temporal event visualization that integrates multiple visualizations generated from different sensor data using stacked 3D layers. It enables us to complementarily and mutually explore data from physical sensors such as smart cards and social sensors such as Twitter to discover new events, explore reasons for them, and understand their impacts on each other. We implement an example system applying a part of the framework as the first prototype and demonstrate its possibilities by showing a case study related to a date on which two mega-scale events occurred in Tokyo.

Index Terms—Physical sensor; social sensor; spatio-temporal visualization

1 INTRODUCTION

Various sorts of problems such as accidents and disasters occur every day in urban spaces. These incidents vary in area, duration, and impact and can greatly affect daily activities of many people. Conversely, activities of people that sometimes concentrate in huge public gathering events often affect the operation of traffic systems. Understanding such interactions between the incidents, traffic systems, and activities of people is important and useful for urban planning and disaster response by city government, traffic management by transportation operating companies, and activity planning by citizens. Therefore, environments for complementarily exploring data from physical sensors such as smart card and social sensors such as Twitter are needed to discover new events, explore reasons for them, and understand their impact on each other.

Some analysis systems have utilized both mobility data and social media data to understand human behavior and traffic anomalies [6,13]. Pan et al. provided a system for detecting anomalies from taxi trajectory data and describing reasons for traffic anomalies using microblogs [13]. Itoh et al. provided a system for exploring events from changes in passenger flows on the Tokyo Metro network extracted from smart card data and exploring reasons for and effects of them by using Twitter data [6]. However, these systems cannot enable us to mutually explore effects among events on traffic systems or events caused by activities of people through overlaying events extracted from multiple sensor data on the same spatio-temporal spaces. Although Krüger et al. provided a system for visualizing trajectory data and information about destination places extracted from Foursquare at the same time on a map [12], they could not provide a system to explore whether any events occurred or what kinds of events occurred.

This paper proposes a framework for spatio-temporal event visualization that overlays events extracted from different sensor resources on stacked 3D layers in spatio-temporal visualization space. Visualization systems based on 3D stacked layers are defined by combinations of mapping time attribute and visualization targets such as sensor types or event types to axes. This enables us to complementarily and mutually explore events, reasons, and effects among different layers. We utilize two systems (visualization of passenger flows on Metro [7] and geo-located word-cloud visualization [8]) as base systems and integrate them to show application examples of a proposed framework. Both systems utilize the height of 3D spaces: the former shows the changes in the number of passengers by using heights of 3D stacked ribbons,

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Proceedings of the IEEE VIS 2016 Workshop on Temporal & Sequential Event Analysis. Available online at: http://eventevent.github.io and the latter uses height to represent word-clouds for different kinds of events. By using the integrated 3D visualization systems, we then show a case study to demonstrate the effectiveness of our framework on real huge events extracted from physical and social sensors.

2 FRAMEWORK

A visualization result generated by each sensor dataset is displayed on a plane (geo-space) in a 3D space in our framework. Combinations of mapping time attributes and visualization targets (sensor/event/representation types) to axes enable us to generate four types of visualization systems (Figure 1). Axes consist of x-axis (horizontal), y-axis (vertical), and animation. Visualization targets include visualization results generated from different types of sensor data, events, and visual representations. We assign only time to the animation axis in Figure 1, but assigning visualization targets to the animation axis for switching targets is an alternative idea.

Figure 1 (A) stacks different kinds of layers to explore relationships between them and uses animation to explore changes in events over time. Figure 1 (B) is similar to the idea of a space-time cube [11] or GeoTime [10]. However, our framework utilizes the y-axis for stacking geo-spaces. Positions of the y-axis in Figure 1 (B) represent time, and we can animate the geo-spaces by moving their positions, which is the same idea as TimeSlices [5]. Figure 1 (C) provides snapshots of visualizations at different times on the x-axis to easily compare different time stamps. Users can define time intervals between a set of layers or can interactively generate snapshots through playing animations. Figure 1 (D) does not use the y-axis for any purpose. However, a visualization result for one sensor dataset itself can sometimes utilize multiple layers as explained in Section 3.2.

Beck et al. provided a taxonomy of dynamic graph visualization [1]. To represent time sequential changes in graphs, they focus on animated diagrams or static charts based on a timeline. However, they do not consider the visualization of multiple spatial-temporal events extracted from different data resources, which we consider to be a novel problem. Our framework enables users to generate various types of integrated spatio-temporal event visualization systems to track changes in events, explore effects among events, and compare different time stamps or events.

Some systems utilize 2.5D representation for visualizing multi-layers in 3D space. 2.5D representations are mainly used for visualizing multiple situations in 3D environments such as visualizing different content, visualizing time sequential changes, and visualizing different visual representations and/or models [2, 3, 9, 14]. Although VisLink [3] can link two different layers such as word-cloud layers and map layers, it does not consider geo-locations in word-clouds or their temporal changes to explore influential events among layers.

Overlaying multiple visualization in one 2D map is an alternative idea. However, many visualization systems for sensor data have utilized 3D representations to show multiple attributes' values. Our framework

	А	В	С	D
X-axis	-	Sensors/Events	Time	Sensors/Events
Y-axis	Sensors/Events	Time	Sensors/Events	-
Animation	Time	-	-	Time
				inne

Fig. 1. Taxonomy of multiple types of spatial-temporal event visualizations based on 3D stacked layers using combinations of mapping time attribute and visualization targets such as sensor types or event types to axes in our framework.

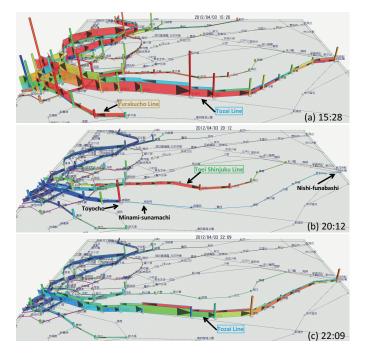


Fig. 2. Animated changes in passenger flows and propagation of crowdedness on AnimatedRibbon view related to the spring storm in April 2012 [7].

enables us to use 3D visualizations in each stacked 2D planes in 3D space.

3 BASE SYSTEMS FOR VISUALIZING DATA FROM MULTIPLE SENSORS

In this section, we briefly introduce two previously developed systems as base systems for integration.

3.1 Visualization of Passenger Flows on Metro

Itoh et al. provided a system for visualizing changes in passenger flows on complicated metro networks [7]. To understand changes in passenger flows and spatial propagation of unusual phenomena in a complex metro network, they introduced AnimatedRibbon view, which provides the functions for displaying animated temporal changes in the number of passengers and crowdedness or emptiness of each section on the metro network (Figure 2).

It dynamically shows changes in two attribute values (absolute number of passengers going in both directions on each section every 10 minutes by using height of 3D stacked ribbons and deviation from average by using color-coding) simultaneously while maintaining ge-

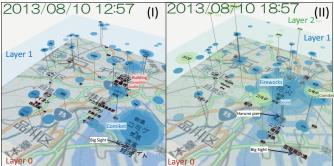


Fig. 3. Multi-layer spatio-temporal word-clouds on August 10, 2013 on which two mega-scale events (comic market (Comiket) and fireworks display) were held in the Tokyo Bay area [8].

ographical context in the metro network. The 3D bar on each station presents the number of passengers who exited the station every 10 minutes. Colors represent relative crowdedness or emptiness compared with the average at that time: red indicates crowdedness, blue indicates emptiness, and green indicates mostly normal.

They demonstrated the system by using a large scale dataset of travel records from March 2011 on the Tokyo Metro extracted from its smart card system. Since transfer information was not included, they estimated the probable route for each trip. Figure 2 shows a case study of 3 April 2012, when a spring storm as intense as a typhoon hit the Japanese mainland and many companies in Tokyo urged employees to go home early. Figure 2 (a) show the Tozai, Toei Shinjuku, and Yurakucho Lines became very crowded before the normal rush hours. Figure 2 (b) shows that after the Tozai Line was suspended, many passengers exited Toyocho Station and more passengers than usual used the Toei Shinjuku Line to go eastwards. Figure 2 (c) shows passengers who had been stuck in central Tokyo started to move out eastwards again on the Tozai Line after it had resumed.

3.2 Word-Clouds in the Sky

Itoh et al. provided a system for visualizing spatio-temporal events with a multi-layered geo-locational word-cloud representation from a geo-parsed microblog stream called Word-Clouds in the Sky [8].

It first associates posts in the stream with geo-locations by using not only geo-tags but also mentioned places and facilities as clues. Temporal local events are then identified and represented by a set of words specifically observed in a certain location and time grid and then displayed above a map as word-clouds. It detects the locality of events to split them into multiple independent layers to avoid occlusions between local (e.g., music concerts) and global (e.g., earthquakes and marathon races) events. Users can thereby distinguish local from global events and see their interactions over the layered maps.

It uses word-clouds like representations to track ambulant events. As multiple events can appear in almost the same place and overlap, it is difficult for us to identify the kinds and sizes of events. It therefore visualizes events using term clusters calculated by DBSCAN [4]. Each term cluster is represented as a circle, and the term is plotted at its center.

They demonstrated the system using a five-year archive of 25-billion Twitter posts. Figure 3 shows an example of a day that had two global events. One event is Comiket (Comic Market), which is the worlds largest amateur comic fair held at Tokyo Big Sight¹. Over half a million participants come from all over Japan (and the world), and they wander around Tokyo, talking about Comiket. It is identified as a global event for the entire day, and is displayed on Layer 1 in Figure 3 (I). A fireworks display held on Harumi Pier in the evening is identified as the other global event. Both events are displayed on two layers in Figure 3 (II).We can also see local events of building and demolition on base layer 0 in Figure 3 (I) and (II).

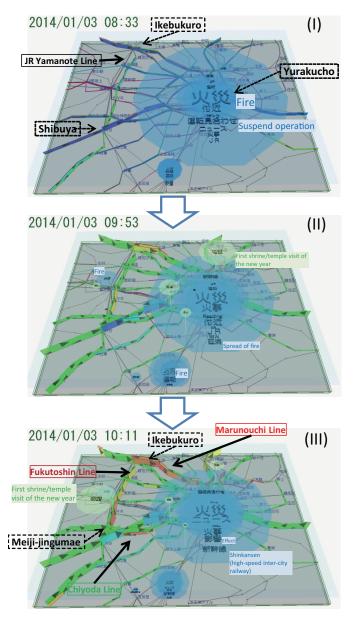


Fig. 4. Example for integration of multiple spatio-temporal events visualizations on January 3, 2014, when fire broke out near Yurakucho station.

¹Comiket, https://en.wikipedia.org/wiki/Comiket

4 CASE STUDY USING AN INTEGRATED VISUALIZATION SYS-TEM

We implement an example system applying the combination in Figure 1 (A) as first prototype. On the prototype system, we show a case study related to a date on which two mega-scale events occurred in Tokyo to demonstrate the possibilities of the system.

Figure 4 visualizes the evolution of events extracted from two different sensor datasets after a fire broke out near JR Yurakucho Station on January 3, 2014, during the New Year holidays when many people in Japan visit shrines and temples to make wishes for the coming year. The fire started at around 6:30 am. It caused services to be suspended on the Shinkansen (high-speed inter-city railway) and the JR Yamanote Line (loop line that circles central Tokyo and connects most major stations in Tokyo), and hence affected many peoples movements.

Figure 4 (I) shows tag-clouds related to fire and suspending operation of JR on the second layer. It also shows the numbers of passengers on most metro lines are lower than average because the color of each section turns blue in the AnimatedRibbon view on the first layer.

In Figure 4 (II), the "fire" event spread over a wider area on the second layer because transportation problems occurred in various places, and the "the first shrine/temple visit of the new year" event appears at the locations of well-known shrines and temples on the third layer. It also shows that almost all lines were operating normally because they are mostly green on the first layer.

Figure 4 (III) shows many people changed their routes to their destinations mainly by using the Fukutoshin, Marunouchi, and Chiyoda Lines instead of the JR Yamanote Line. The number of passengers increased mainly between Ikebukuro and Meiji-Jingumae. Many passengers switched from the JR Yamanote Line to the Chiyoda Line (to go to Meiji-Jingumae). Passengers changed to the Tokyo Metro Marunouchi Line to go to Tokyo Station. It also shows that the "First shrine/temple visit of the new year" became a big event at Meiji-Jingumae Station on the third layer because one of Tokyos most famous shrines (Meiji-Jingu) is near Meiji-Jingumae Station.

5 CONCLUSION

This paper presented a framework for spatio-temporal event visualization that integrates visualizations generated from different sensor data using stacked 3D layers. Our framework enables users to generate various types of integrated spatio-temporal event visualization systems to track changes in events, explore effects among events, and compare different time stamps or events. We implemented the example system applying the combination in Figure 1 (A) as the first prototype and showed a case study related to a date on which two mega-scale events occurred in Tokyo to demonstrate the possibilities of the framework.

Tokyo will host the 2020 Summer Olympics, which will involve large-scale movements of people over a wide area. Powerful inland earthquakes are also estimated to possibly occur in the Tokyo metropolitan area in the coming decades. We therefore consider that spatiotemporal event visualization systems using multiple data resources will increasingly become important and should be included in the ongoing discussions to prepare responses for these events.

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