Visual exploration of multivariate movement events in space-time cube

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Abstract

Analyzing large amounts of complex movement data requires appropriate visual and analytical methods. This paper proposes a 2-D star-icon based visualization technique for the visual exploration of multivariate movement events in a space-time cube. To test the proposed method, we derive multivariate events from massive real-world floating car data and visually explore spatio-temporal patterns. The experimental results show that our proposed methods are helpful in identifying interesting locations or functional areas, and assist the understanding of dynamic patterns.

Keywords: multivariate visualization, movement events, star-icon, space-time cube

1 Introduction

Location positioning and communication technologies (e.g. GPS devices, mobile phones) cause an increase of movement data (e.g. floating car data, mobile phone data). Those massive movement data contain rich information and bring new opportunities to investigate and understand urban dynamics, which are crucial for decision making in environmental or transportation planning. Movement data analysis is currently a hot research topic with numerous studies including modeling human mobility patterns [1, 2], visualizing object dynamic behaviors [3], uncovering taxi driving behaviors [4], mining interesting locations or places [5], and inferring urban land uses and city structures [6].

Due to the inherent spatiotemporal complexity and uncertainty, analysis of movement data is still challenging and demands joint research efforts from multiple disciplines such as cartography, geovisualization, scientific visualization, information visualization, and the recently coined discipline visual analytics.

Icon-based visualization techniques from the subfields of scientific visualization have been investigated to show compact patterns of multiple variates and their interrelationships simultaneously [7]. In cartography, the technique of space-time cube [8] is widely applied to reveal objects' behavior and interactions across space and time. There are several studies on general multivariate space-time cube visualization methods [9], but very little has been reported by synthesizing the icon-based multivariate visualization method with a space-time cube.

In this paper, we visually explore the spatiotemporal patterns of multivariate events by displaying them via multivariate icons in a space-time cube. To achieve this, we propose a star-icon to represent multiple point-based events extracted from floating car data. The experiment results show that our proposed methods are helpful in identifying interesting locations or functional areas, and understanding the traffic dynamic patterns.

2 Movement events and preliminaries

2.1 Movement events

Basically, movement data consist of position records generated by moving objects. Each record can be represented by a point, e.g. of $\mathrm{p} = (\mathrm{x}, \mathrm{y}, \mathrm{t})$. A series of chronologically ordered points form a spatial trajectory $(p_1;\ p_2; \ldots\ p_n)$. There are different views of movement data. For instance, Andrienko, Andrienko, and Heurich [10] stated that movement can be viewed as continuous paths in space and time, referred as trajectories, or as a composition of various spatial events. Hence, movement data can be analyzed both as trajectories and as spatial events [11].

In this paper, we consider each discrete point (e.g. a GPS entry) as a point-based spatial event. According to different attributes associated with the point, we derive different types of events. For instance, if a GPS point acquired from floating taxi data, has an attribute "occupied with passengers", then we can derive an "occupancy" event from the point. Likewise, if a GPS point has an attribute "velocity" with a value of "0 km/h", we can then derive a "stop" event from the point.

2.2 Test data

Our raw dataset are temporally ordered position records collected from about 2000 GPS-enabled taxis within 47 days from 10th May to 30th June 2010, in Shanghai. The temporal resolution of the dataset is 10 seconds. Each position record has seven attributes, i.e. car identification number, company name, current timestamp, longitude, latitude, instantaneous velocity, and the GPS effectiveness.

Firstly, we differentiate and derive four types of events from the raw data GPS points according to their respective definitions in Table 3.1. Occupancy and non-occupancy GPS points can be directly discerned based on the value of "car status", i.e. occupancy with a "car status" value of 1, and non-occupancy of 0. The pick-up and drop-off events are defined as the transit occurrences connecting two different "car status". If a point with a status of "occupied" and its previous time stamped point of "non-occupied", then the point is regarded as a "pick-up" point; vice versa, it is defined as a "drop-off" point.

Table 3.1: Four types of point-based events: $(\mathrm{O}, \mathrm{N}, \mathrm{P}, \mathrm{D})$.

Event type	Description
Occupancy (O)	A taxi is occupied by a passenger
Non-occupancy (N)	A taxi is without a passenger
Pick-up (P)	A taxi is picking up a passenger
Drop-off (D)	A taxi is dropping off a passenger

In addition, we select the Shanghai Hongqiao international airport as the study area. The floor plan of the Hongqiao international airport and its location in Shanghai are shown in Figure 1.

Figure 1: The location and floor plan of Hongqiao airport

2.3 Spatiotemporal data partition

For computational efficiency, we decompose the study area into regular cells with a spatial resolution of $20\mathrm{m} * 20\mathrm{m}$, resulting in a matrix of $\mathrm{M(i,j)}, 1 < \mathrm{i} < \mathrm{m}, 1 < \mathrm{j} < \mathrm{n}$. Furthermore, along the temporal dimension, we use an hourly interval H_t, $0 \leq t < 24$.

For each voxel $(\mathrm{i,j,t})$ in the spatial and temporal data cube, we can calculate the total number of event occurrences $\left(\mathrm{O_{ijt}}, \mathrm{N_{ijt}}, \mathrm{P_{ijt}}, \mathrm{D_{ijt}}\right)$ for four events $(\mathrm{O}, \mathrm{N}, \mathrm{P}, \mathrm{D})$. Figure 2 shows the respective spatio-temporal distributions of the four variates for each hour. Each dot represents a presence of event inside the corresponding spatiotemporal division. To

Figure 2: The spatial and temporal distributions of occupancy, non-occupancy, pick-up and drop-off events.

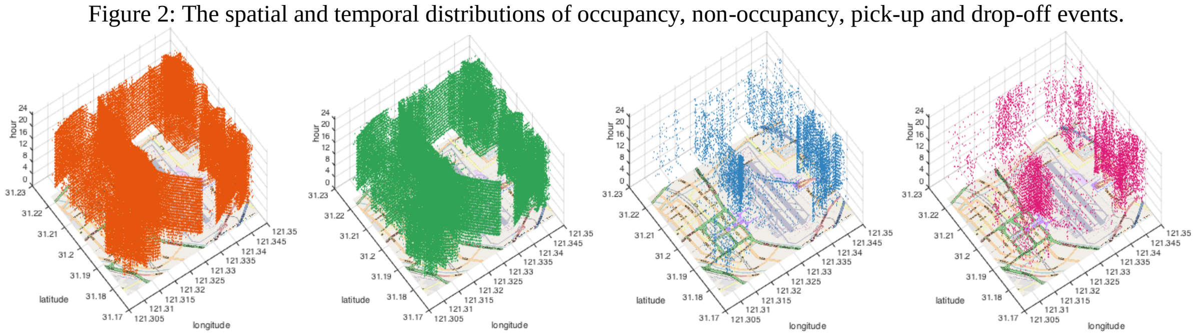
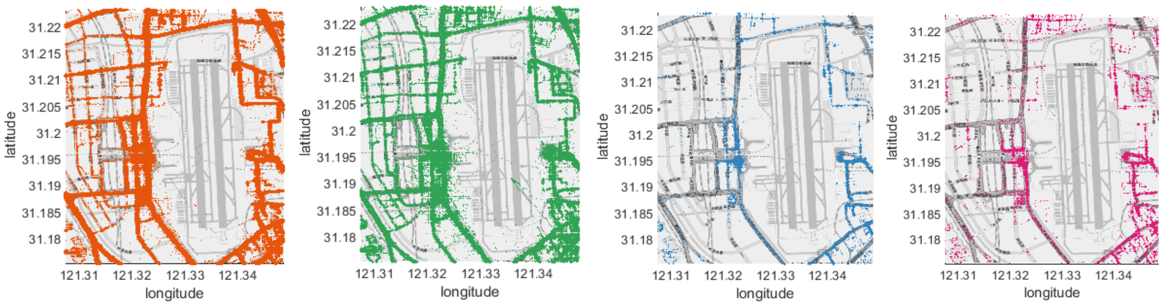


Figure 3: The projection views of occupancy, non-occupancy, pick-up and drop-off events.



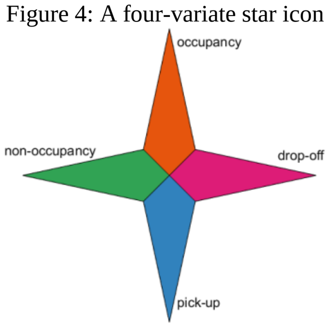
get an overview of the spatial distribution, we project each 3-D view to the 2-D XY plane shown in Figure 3.

3 Star icon for multivariate visualization

In Figure 2 and Figure 3, the spatial and temporal distribution of each variate can be clearly recognized. However, the limitation is that the correlation of those variates cannot be easily investigated. One possible solution is to use icons to represent multiple variates simultaneously by encoding each data item to the icon, which may result in compact textures that allow users to gain insight into the overall relations among the multivariate.

We propose a four-variate star icon to explore the spatiotemporal patterns of movement events and their relationships. The star icon (shown in Figure 4) has four branches and each branch represents a variate. The color of each branch represents an individual variate and the length of the branch is proportional to the value of variate.

Figure 4: A four-variate star icon



The four variates are projected to the four star branches with the top, left, bottom and right branches corresponding to the order of $(\mathrm{O}, \mathrm{N}, \mathrm{P}, \mathrm{D})$. Their colors are respectively in orange, green, blue, and magenta. Regarding the data item values, we normalize the data items using the range scaling method based on the maximum value of each variate.

More specifically, for each spatiotemporal composition $(\mathrm{i}, \mathrm{j}, \mathrm{t})$ with a total number of events E_{ijt} $(E\ in\ (O, N, P, D))$, we use a normalized value of $E_{ijt}/\max(E_{ijt})$ and proportionally scaled to the length of the braches.

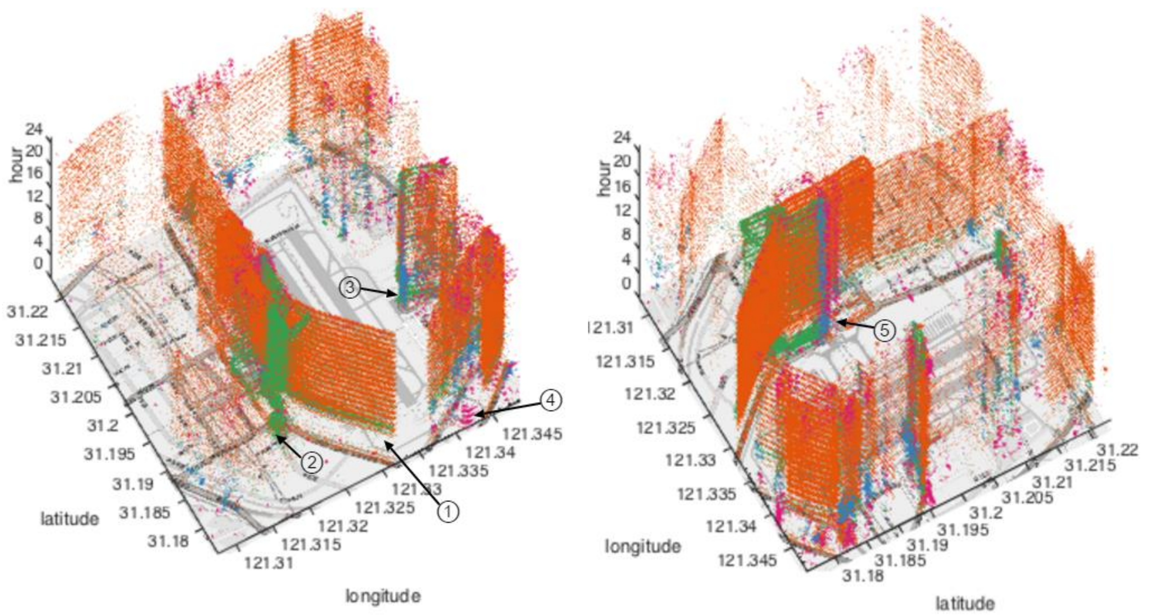
4 Experiments and Analysis

We apply the proposed star icon to the derived movement events in the test area. Figure 5 shows two snapshots of the multivariate visualization results from two different viewpoints. To get an overview of their spatial distribution, we also project the results to the 2-D XY plane shown in Figure 6. From these visualization results, we can inspect the following spatiotemporal patterns.

It is easy to differentiate distinct spatial patterns of the multiple events in both Figure 5 and Figure 6. Obviously, the most significant event is “occupancy” (in orange) which is continuously distributed forming several connected lines. There are several relatively large areas with “non-occupancy” events (in green) distributed in Figure 6 on the left bottom, the right middle and the top-middle parts. A few places in the test areas in blue and magenta show intense taxis “pick-up” and “drop-off” events.

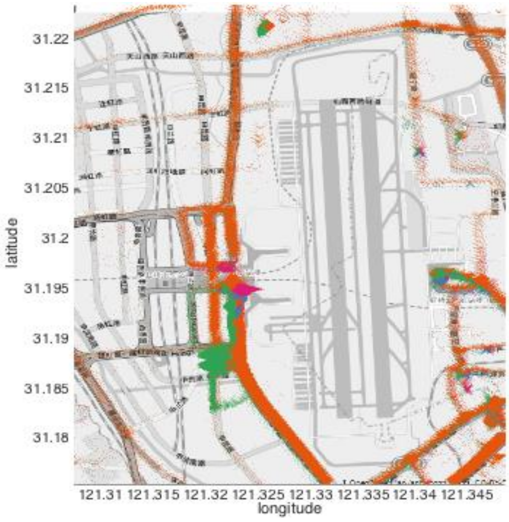
Distinctive spatial patterns of the events may reveal the spatial structure of the test area. For instance, elongated “occupancy” events may correspond to the street network, while the small spots of the non-occupancy, pick-up, and

Figure 5: Two snapshots of the star-icon visualizations.
① a road segment, ② a taxi waiting pool; ③ a taxi stand in Terminal 1; ④ a hotel; ⑤ a taxi stand in Terminal 2.



(a) (b)

Figure 6. The projection of the star-icon visualization.



drop-off events may reflect certain types of functional areas. By comparing the spatial distribution with a base map and the floor plan of the airport, we can infer that the continuously distributed "occupancy" events are located along the road network, the places with dense "non-occupancy" events off the roads are taxi waiting pools, and the spots of significant "pick-up" and "drop-of" events are taxi stands respectively for picking up and dropping off passengers.

Temporal patterns of each variate can be clearly identified from the 3-D event walls in Figure 5. For "occupancy" events (in orange), there are clearly less events from around 2h to 5h reflected by the gaps on the orange wall at location ① in Figure 5(a) and more intense in other time slots.

For "non-occupancy" events, depending on the spatial locations, there are different temporal patterns. In Figure 5(a), along the road there are relatively more "non-occupancy" events around 6h and 7h at location ①, and at the active area off the road there are constantly a lot of "non-occupancy" events located at ②.

For "pick-up" and "drop-off" events, there are different temporal patterns at different spatial locations. For instance, in Figure 5(a) at location ③ there are more "pick-up" events from 0h to 4h and then increased "drop-off" activities from 5h to 9h. From 10h to 22h there are relatively comparable "pick-up" and "drop-off" events. While from 22h to 24h there are more "pick-up" activities.

In Figure 5(b) at location ⑤ we can observe similar temporal variances. On the contrary, the temporal patterns at location ④ in Figure 5(a) shows opposite temporal variance, i.e. the most significant events during 0-4h, 5-9h, 22-24h are respectively corresponding to "drop-off", "pick-up" and "drop-off" events. One plausible explanation based on the analysis of the base map is that locations ③ and ⑤ are taxi stands in Terminal 1 and Terminal 2 while location ④ is a hotel near the airport. Because of the different functionalities of the locations, they have different temporal patterns.

5 Conclusion and Outlook

In this paper, we proposed using star icons to represent multivariate movement events and placed them in a space-time cube for visual exploration of their spatiotemporal patterns. Floating car data acquired from taxies are used to test our proposed methods. The compact visualization results of the experiment reveal interesting spatiotemporal patterns, for instance, the spatial distribution variance among the multivariate, and the temporal traffic dynamics on and off the roads. The visual results at a detailed level can also help infer high-level information, for instance, the functional spatial structure of the study area.

Due to the inherent characteristics of the 3-D view, the method suffers from some limitations. Firstly, the rendering of star-icon inevitably leads to over-plotting problems with some symbols hidden. Secondly, the view perspectives in the 3-D space-time cube may cause occlusions. Interactively rotating and zooming the view can alleviate the occlusion and help to identify more detailed patterns.

Future work will be focused on the assessment of the method using larger test area, and the empowering of the method with interactive functionalities that allow users to design and adjust the star icons.

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