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REGULAR PAPER

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Exploring OD patterns of interested region based on taxi trajectories

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Abstract Traffics of different regions in a city have different Origin-Destination (OD) patterns, which potentially reveal the surrounding traffic context and social functions. In this work, we present a visual analysis system to explore OD patterns of interested regions based on taxi trajectories. The system integrates interactive trajectory filtering with visual OD patterns exploration. Trajectories related to interested region are selected by a suite of graphical filtering tools, from which OD clusters are detected automatically. OD traffic patterns can be explored at two levels: overview of OD and detailed exploration on dynamic OD patterns, including information of dynamic traffic volume and travel time. By testing on real taxi trajectory data sets, we demonstrate the effectiveness of our system.

Keywords Urban Visualization · OD pattern · Trajectory · Filtering

1 Introduction

Understanding the movement of human beings and vehicles in large cities is crucial in transportation studies. Such movement, known as the Origin-Destination (OD) pattern, reveals the traffic context of a city, including the hot OD regions and regular commuting patterns among regions. Many research efforts have been devoted in studying urban OD patterns. For example, regular commuting patterns are extracted by studying traffic flows between OD regions (Peng et al. 2012). Regions' land-use patterns are inferred by analysing the dynamics of traffic flow related to the regions (Pan et al. 2013).

OD patterns in urban can be indicated from different types of movement data. Travelling around the city in a considerable spatial and temporal scale, taxis are viewed as the representative of urban traffic. Many traffic related researches are conducted based on taxi trajectory data, such as inferring traffic jams by studying taxis' traffic speed (Liu et al. 2011b; Wang et al. 2013), studying traffic condition of single route (Lu et al. 2015c) or multiple routes (Liu et al. 2011a; Lu et al. 2015a) from passing taxis. As a typical urban movement data, we use taxi trajectories to study urban OD patterns in this work.

Different from work to study the global traffic flows around the city (Andrienko and Andrienko 2011), we focus on local OD pattern analysis which may be dimmed in global analysis. Given the regions of interest, our goal is to extract related OD regions and explore the OD patterns. Specifically, we target at exploring OD patterns from two levels:

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- Overview of OD regions: to explore where the traffic flows mainly come/go and understand traffic related statistics of OD regions.
- Detail exploration on OD patterns: to explore how traffic related measurements of traffic flows, i.e. the travel flow volume and travel time cost, change along time.

Targeting to the above two tasks, we extend the OD-Wheel (Lu et al. 2015b) which only explores the OD patterns related to a central region, to a visual analytics system which supports exploration on OD patterns detected from general filtered trajectories. Meanwhile, the designs of the region glyph and OD-Wheel are refined. Specifically, the system integrates: (1) an intuitive visual query interface to define the region of interest and filter taxi trajectories; (2) an automatic clustering algorithm to extract OD, O/D regions from trajectories; (3) a spatial and statistical overview of regions; (4) an adapted OD-Wheel to explore the dynamic OD patterns in details .

2 Related work

Our work is related to trajectory filtering, OD visualization and temporal data visualization. We discuss existing works in those areas below.

2.1 Trajectory filtering

Trajectory filtering techniques aim at extracting a subset of trajectories satisfying specific conditions. By driving a spatial geometric query object (such as a circle), filtering result is dynamic updated. Many interactive query methods have been designed. MagicLens (Fishkin and Stone 1995) is generic lens used in 2D spatial space. Lenses with different functions embed different visualizations of selected area. Kr*ü*ger et al. propose TrajectoryLenses (Krüger et al. 2013) to filter trajectories. Ferreira et al. (2013) also develop a system for taxi OD data, which executes OD queries and visualizes the results in multiple views. In addition to fully visual queries, filtering can also be performed via spatial visual query language. The query command can be interactively composed by predefined icons which represent either the spatial objects or operators (Aufaure-Portier and Bonhomme 1999).

Similar to TrajectoryLenses, we develop graphical fitlering tool to help user select taxi trajectories. Our system supports more complex settings on geometric constraints.

2.2 OD visualization

OD data can either be collected from discrete movement data (Wang et al. 2014) or aggregated from continuous trajectory data (Andrienko and Andrienko 2011). Such OD data can be visualized with a set of techniques, including flow map, OD matrix and OD map. Flow map (Thompson and Lavin 1996) shows the origins and destinations as nodes on a geographic map. The directed links connecting the origin and destination nodes represent the traffic flows between the OD pair. Flow map suffers from serious visual clutter. Possible solutions alleviate such visual clutter including edge-filtering (Rae 2009), edge-bundling (Holten and van Wijk 2009), node hierarchy (Guo 2009) or allow only one origin or one destination (Phan et al. 2005). OD matrix (Andrienko and Andrienko 2008) visualizes the OD data in an abstract space. It represents origins and destinations as rows and columns of a matrix. Each cell encodes an OD, whose flow magnitude is represented as color of the cell. Due to lack of spatial information, OD matrix are usually used in conjunction with a geographic map. OD map (Wood et al. 2010) makes a balance between clutter-free and spatial information preservation. It partitions a geographic region to subregions with a 2D grid and defines ODs between the subregions. More recently, taxi OD visual analytics is conducted for understanding metropolitan human movement patterns (Jiang et al. 2015).

In our work, we visualize OD data from two views respectively. In spatial view, we focus on the spatial overview of ODs. In abstract view, the dynamics of traffic flow volume and travel time of ODs are explored within a hybrid linear-circular design.

2.3 Temporal data visualization

Visualizing temporal data is very common in visualization field. Animation is one of the most popular visualization techniques. However, it is widely believed that animation does not work well for analysis tasks (Robertson et al. 2008). Therefore, many static methods are developed.

If the data have certain known periodicity, then calender view (van Wijk and van Selow 1999) and spiral view (Weber et al. 2001) can be good options. However, for general temporal data, timeline is the most popular visualization method. To compare different temporal data, timelines can be juxtaposed (McLachlan et al. 2008) or superimposed (Hochheiser and Shneiderman 2004) for visual comparison. For example, Guo et al. (2011) embeds traffic directions into superimposed ThemeRiver (Havre et al. 2000) to compare different type of vehicles over time. Wang et al. (2014) align the trajectories to time and stack them in juxtaposition space for comparison. Temporal data visualization techniques have been used to analyze OD data. In Ferreira et al.'s taxi trip exploration work (Ferreira et al. 2013), once users select multiple ODs and execute the query, the dynamics of trip number on each OD will be shown in a timeline. Boyandin et al.'s Flowstrates (Boyandin et al. 2011) analyze the refugee flow with a specially designed three part interfaces. Two maps are used for origin and destination selection, while a heatmap is embedded between to compare the flow volume between different ODs. Here the heatmap is in fact a juxtaposition of timelines.

In our work, we use a circular design for flow volume comparison, as that in KronoMiner (Zhao et al. 2011). In addition, we also embed a linear timeline component for travel time comparison.

3 Overview

In this section, we first introduce the related terminologies and define the problem to be solved in the work. Then the tasks are clarified further and system's overview is given.

3.1 Terminologies and research problem

To facilitate the discussion, we discuss some common terminologies in this work. Trajectory is a list of positions recording the movement in temporal order. Origin/Destination (O/D) refers to the beginning/ending position of the movement. Origin/Destination Region is the region where lots of trajectories start or end, i.e. the cluster of Origins/Destinations. OD Region is where both an Origin Region and a Destination Region. Region of Interest is generalized as interest region where trajectories travel through in this work. It can either be a specific region, or a compound of several regions combined in certain logic operations.

In this work, we aim to explore the ODs of trajectories related to region of interest. Comparing to previous work (Lu et al. 2015b) (Fig. 1b), to-be studied trajectories are filtered by a suite of spatial filter (Sect. 4), which include, but not be limited to, those starting from/ending in a central region, e.g. the orange trajectories in Fig. 1a. For instance, the OD patterns of trajectories passing a certain crossing is in the scope of this work.

3.2 Task

Starting from the two tasks introduced in Sect. 1, we specify the tasks supported by our system further, as following:

- Extraction of O/D clusters related to region of interest (T1): to customize the region of interest and then extract the O/D, OD regions based on the trajectories travelling through.

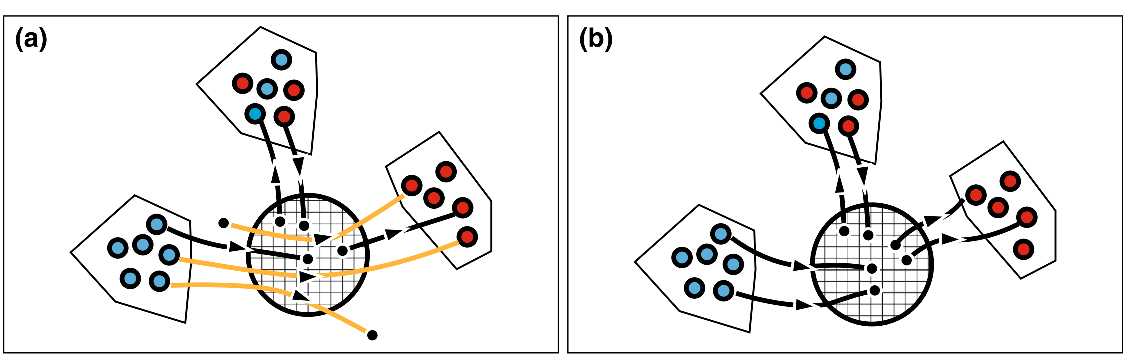

Fig. 1 Illustration of problem: besides trajectories starting from/ending in a central region (**b**), trajectories (*orange*) passing region of interest are in the scope of this work (**a**)

– Spatial overview of O/D, OD regions (T2): to give an overview of how the regions distribute in spatial space.
– Statistical overview of O/D, OD regions (T3): to show the statistical overview of regions.
– Traffic volume comparison among regions (T4): to compare traffic volume among OD clusters.
– Detail exploration of OD pattern dynamic (T5): to explore traffic flow's dynamic measurements in detail, including travel time cost etc.

3.3 System overview

To support exploring OD patterns of interested region, the system composes of four major parts: data preprocessing, trajectory filtering, OD clustering, and visual analysis on OD patterns. System's pipeline is shown in Fig. 2.

Following the preprocessing steps in early studies (Wang et al. 2013, 2015), we cleaned both GPS dataset and road network dataset, and performed map matching to map the trajectories to the road network. To facilitate trajectory filtering, a spatial quad-tree index is built on trajectory data set.

In the beginning of run-time stage, trajectories can be filtered interactively from spatial and temporal aspects. With a suite of circular graphical filters, user is able to configure the region of interest by multiple filters. With region of interest settled done, trajectories satisfying certain spatial constraints are filtered. Additionally, a two-layer time filter can set temporal constraints in date and time scales. After filtering, the selected trajectories are fed as an input to an adaptive DBSCAN clustering algorithm (Pan et al. 2013), by which O regions and D regions are detected from the origins and destinations of trajectories respectively. OD regions are recognized where O regions and D regions are within a distance threshold.

Traffic flows of O/D, OD regions are extracted and corresponding dynamics are computed. To help user explore OD patterns, our system provides two level visualizations. As an overview, glyphs on the map are designed to show regions' spatial distribution. Meanwhile, statistical distribution, e.g. travel distance and travel time cost are also given. In detail level, a refined OD-Wheel visualizes the dynamics of traffic volume at finer temporal granularity. Interactions on OD-Wheel support user to compare temporal dynamics among clusters.

4 Filters

In this section, we first introduce our filter model and then present visual design of spatial and temporal filters.

4.1 Filter model

Our filter model selects trajectories from spatial and temporal aspects. The filter model is built on a series of atomic queries, which are formalized in Table 1. With these atomic queries, complex filtering can be composed.

From the spatial aspect, considering the spatial relationships between trajectory and region, the atomic spatial queries can be further divided into two classes: location and direction. Six location options are provided according to six possible relationships between trajectory and region: origin, destination, origin/

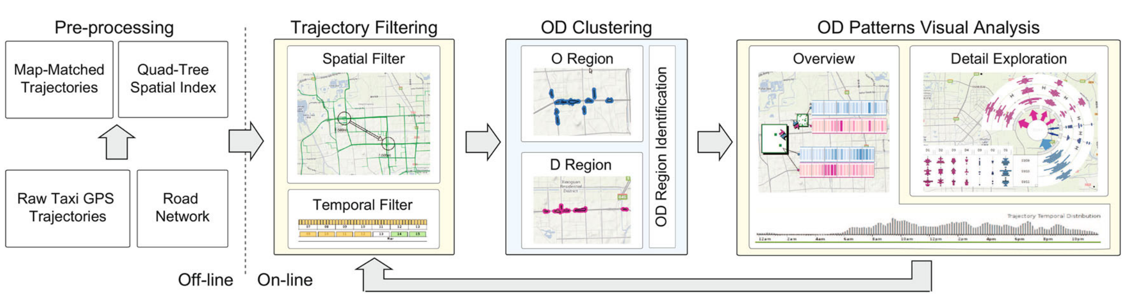

Fig. 2 System's pipeline: off-line trajectory preprocessing, interactive trajectory filter, automatic OD clusters extraction, and OD patterns visual analysis

Table 1 Filter model: spatial and temporal filtering are supported

Category	Attribute	Type	Formalization	Description (filtered out)
Spatial	Location	Origin	Traj.origin $\in$ region_defined	Trajectories originating from defined region
		Destination	Traj.destination $\in$ region_defined	Trajectories destinating for defined region
		Origin/ destination	Traj.origin $\in$ region_defined $\cup$ Traj.destination $\in$ region_defined	Trajectories originating from or destinating for Defined region
		Passing	Traj.loctaion $\in$ region_defined $\cap$ Traj.origin $\notin$ region_defined $\cap$ Traj.destination $\notin$ region_defined	Trajectories passing through defined region
		Inclusion	Traj.location $\in$ region_defined	Trajectories intersecting with defined region
		Exclusion	Traj.location $\notin$ region_defined	Trajectories not intersecting with defined region
	Direction	Direction	Traj.direction = direction_defined	Trajectories following defined direction
Temporal	Date	Date range	Traj.date $\geq$ begindate_defined $\cap$ Traj.date $\leq$ enddate_defined	Trajectories travelling in defined date range
	Time	Time range	Traj.time $\geq$ beigntime_defined $\cap$ Traj.time $\leq$ endtime_defined	Trajectories travelling in defined time range

destination, passing, inclusive, and exclusive. Particularly, exclusive option provides the function of filtering out trajectories passing certain area. On the other hand, with two or more filters, direction can be assigned to filter trajectories following certain flow direction.

From the temporal aspect, a date-time temporal concept model is used. In additional to regular continuous time setting, it also allows users to set time constraints with daily periodicity, for example, setting a date range from March 2 to March 5 and time range from 8:00 to 12:00.

The filter model allows user to set constraints iteratively. Complex query can be made based on querying result from previous queries. For example, user can set several location queries to filter trajectories travelling through all these regions. As mentioned in Sect. 3.1, the region of interest can be defined by either a spatial filter or multiple filters.

4.2 Filter design

Similar to TrajectoryLenses (Krüger et al. 2013), we choose circle as the basic filtering shape, whose points on boundary have equal distance to center point. The circular filter is embedded in spatial view so that it is intuitive to directly manipulate the filter in spatial context. There are two design considerations:

Semantic visibility For the ease of parameter perception, parameters are explicitly encoded in the circular filter. As shown in Figure 3a, text below informs the radius of underlying region. The top part shows spatial filter with current location constraint (e.g. inclusion constraint here). Figure 3b shows filters with different location options. For the assigned direction, a arrow links between filters as Fig. 3c shows.

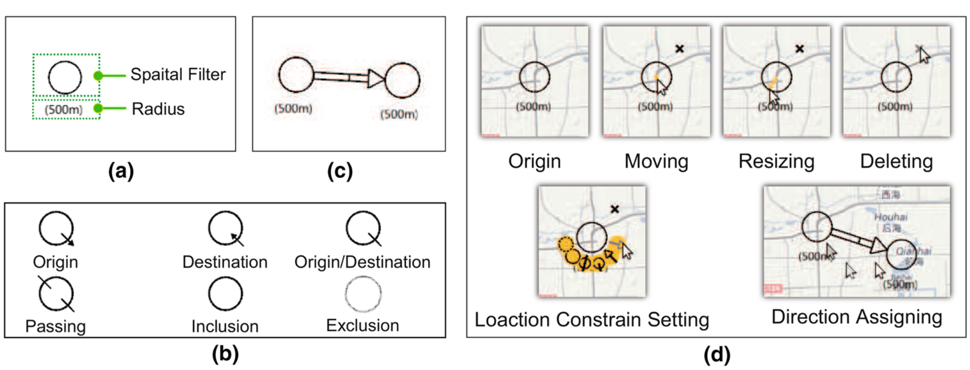

Fig. 3 *Circular filter* design and interactions: **a** *circular filter* glyph: radius and spatial filter with location constraints are explicitly encoded. **b** Six types of spatial filters (*the left-top circle in glyph*) with different location constraints. **c** *Arrow* encoding the direction between *circular filters*. **d** Different function is invoked by hovering on different regions. Direction between filters is assigned by dragging operation

Usage simplicity Parameter tuning is integrated into the circular filter, which is made free from keyboard and menu. As Fig. 3d shows, different functions are invoked when hovering in certain regions and corresponding manipulating handles are visible. For example, when hovering on the center of circular filter, the moving function is invoked and a cross mark is visible in the center. Different from parameter setting on a single filter, direction between filters can be assigned by mouse dragging operation.

A two-level temporal filter is provided: date and time. Users can select any date(s) and time range. Time granularity in this work is set as 10 mins. In date part, weekday is colored in white and weekend is in green. By dragging and moving, user can define a date range and time range respectively, and those selected are colored in orange. User can cancel current selection by double clicking in blank area.

5 Overview of OD clusters

In this section, we first introduce the extraction of regions from filtered trajectories and then present the visual design of OD overview and detail pattern exploration.

5.1 O/D, OD region extraction

After filtering trajectories of interested region, we adopt the iterative DBSCAN algorithm Pan et al. (2013) on origins and destinations respectively to obtain O clusters and D clusters (T1). The convex hull underlying each cluster is detected as O or D region by Graham's scan (Graham 1972). Regions within a certain distance (threshold *D*) are merged into a larger region. Specifically, if the merged region contains both O and D regions, it is an OD region.

5.2 Overview

Overview of regions consists of spatial overview (T2) and statistical overview (T3). As Fig. 4 shows, two types of spatial overview are provided. Figure 4a shows the original clusters' convex hulls, which give precise spatial description of regions. However, constrained by absolute spatial shape, it is not convenient to encode more information upon it. Hence, as Fig. 4b shows, spatial view with glyphs is designed as a trade-off between the abstract and spatial space.

As Fig. 4c illustrates, each region is represented by a square glyph. The information of the region's traffic volume is mapped to the size of square. The square's frame color is used to distinguish whether the it is O or D or OD region. Taking O regions as examples, a sequential blue list is assigned to them from dark to light in descending traffic volume order. So is the red list for D regions and green list for OD regions. To make it more intuitive, an arrow in the right-bottom explicitly encodes the direction of traffic flow, as an going-out direction in O region glyph. For each region, to emphasize the traffic flow related to other detected regions, the volumes of related traffic flows are visualized in color dithering manner inside the glyph. The ratio of certain color inside one glyph is proportional to the traffic volume related to the corresponding region. Additionally, the average traffic volume distribution in a day can be unfolded by clicking the dot handle in the right-top. From left to right, the average traffic volume distribution is displayed in hour

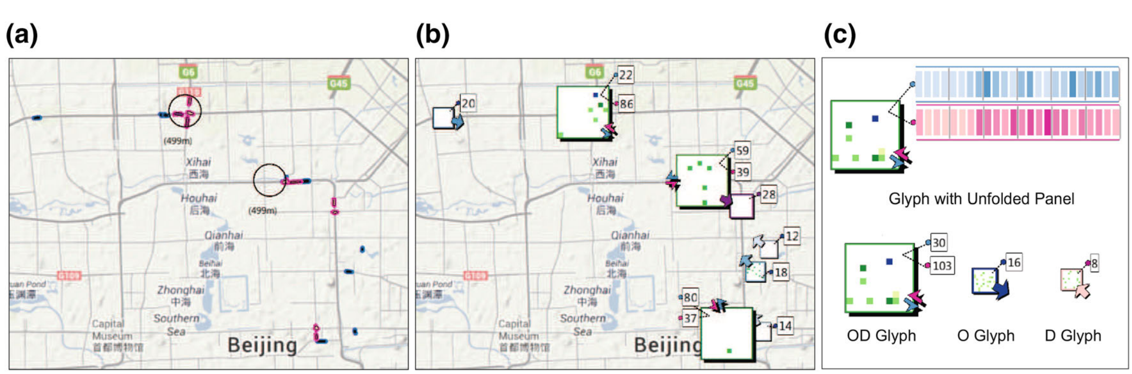

Fig. 4 Spatial overview: **a** regions are visualized with convex hulls. **b** Glyphs are used to represent the detected regions. **c** Glyph design for O/D, OD Regions

Fig. 5 Wrapped statistical distributions

granularity from 00:00 to 24:00, higher magnitudes in lightness encoding smaller values. A gray vertical line is drawn every four hours to help with hour reading. When folded, the number of trajectories is labelled aside to the dot handle. Particularly for OD glyph, there are two dots, one for the coming-in and other for the going-out flow.

Additionally, the statistical overviews of the traffic volume distribution over time and the distributions of average travel distance and travel time are provided. Aware of extreme values, As Fig. 5 shows, we wrap the extreme values and count them as full height bars in the two ends of bar plot.

6 Adapted OD-Wheel

OD-Wheel (Lu et al. 2015b) is adapted to explore the OD clusters detected from interested trajectories, which is not restricted to OD clusters related to a central region. Given the O/D, OD regions, the adapted OD-Wheel is designed to explore dynamic change of clusters (T4) and compare OD patterns among clusters (T5).

6.1 Visual design

The main idea of OD-Wheel is to warp a part of linear view to circular one. O, D clusters are placed in descending traffic volume order from two ends of circle respectively. Particularly in this work, OD region is decomposed into a pair of O and D clusters, which counts the in and out traffic flows to the region respectively. A link is built between the pair, whose color is consistent with the OD glyph in the spatial overview. Additionally, an arrow towards/outwards the circular center is used to distinguish O and D clusters further. Arrow size is proportional to the cluster's traffic volume. In much more detail, the dynamic traffic volume of each cluster is visualized as a bar plot along radial time axis. Sharing the same axis with

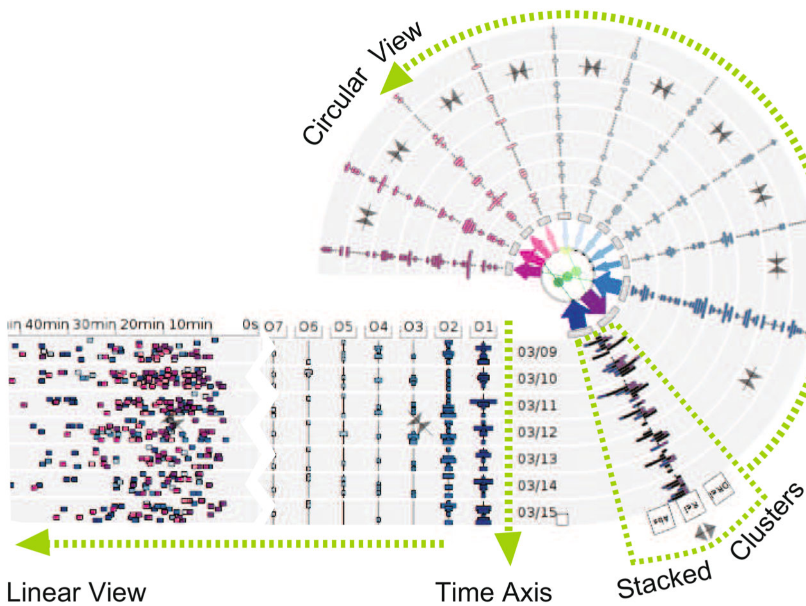

Fig. 6 Visual design of adapted OD-Wheel: *linear and circular view* displays the temporal distribution of travel flow volumes. Two possible dynamic linear visualizations are in the *linear view*

circular view, undistorted linear layout benefits more precise dynamic analysis. For example, as Fig. 6 shows, analysis on travel time cost or dynamic traffic volume can be performed in the linear view. It is also easy to extend to other dynamic variation analysis.

6.2 Interactions on OD-Wheel

Several interactions are developed for easy comparison among clusters. A cluster can be relocated by dragging-and-moving the gray annulus around the circle. Clicking black button (><) between pair of neighbouring clusters stacks the two clusters to a common middle line, as the right bottom part in Fig. 6 shows. To facilitate the comparison, differences between the two clusters along time are explicitly encoded as black bars. By clicking the black button (<>) outside the circle, the stacked bars can be unstacked.

When mouse hovering on bars, its time interval pops out. Circular view and linear view cooperate in brush-and-link manner. Hovering on the arrow glyph in circular view highlights corresponding cluster in the linear view. Similarly, lasso selection on trajectories in linear view highlights corresponding ones in circular view and spatial view.

7 Case studies

We apply the system to real taxi trajectory data to show its effectiveness. Our dataset is a taxi GPS dataset recorded in the city of Beijing in 24 days, from March 2nd to 25th, 2009. Estimated from a government report by Beijing Transportation Research Center (2010), the data include information of 43% of all licensed taxis in Beijing, and account for 7 % of the traffic flow volume within Beijing's 4th Ring. We only use trajectories carrying passengers. After preprocessing, the dataset size is 12.8 GB.

7.1 OD spatial overview of interested region

In this case, we demonstrate an OD spatial overview for an interested road. As Fig. 7 shows, the interested road is defined by two filters on the 2^{nd} ring road. The O/D, OD regions of trajectories travelling through this road are detected and visualized in Fig. 7a and b. (Because regions in Fig. 7b are far away from Fig. 7a on the map, so we cut them out and place aside for the purpose of saving space.) Most of the regions are along the 2^{nd} ring. Two OD regions (Fig. 7b) locate at the two terminals of Beijing Airport. Unfolding the average distributions of regions marked by 1, 2 as Fig. 7c shows, we found out that there is an early morning peak (6:00–9:00) and evening peak (18:00–21:00) at 1 and 2 respectively. Unfolding in-coming and out-going traffic flows at airport, the two terminals have similar OD patterns over days. For the coming-in traffic flow, it becomes active in early morning and keeps active during the daytime. On the contrary, the out-going flow becomes active from the noon until evening.

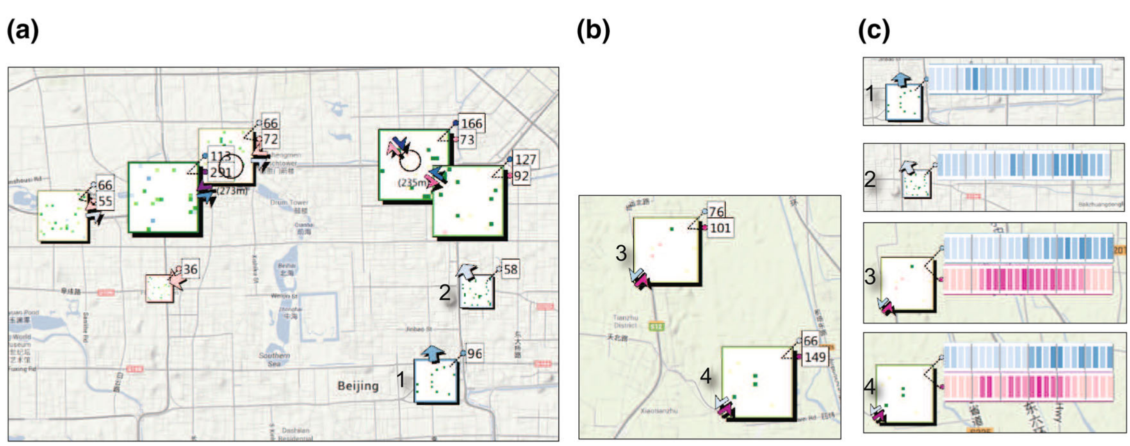

Fig. 7 OD spatial distribution of a road: **a** the detected O/D, OD regions in down-town. **b** The two detected OD regions at Beijing Airport. **c** Unfolded distribution panel of region *1* and *2* in (**a**) and region *3*, *4* in (**b**)

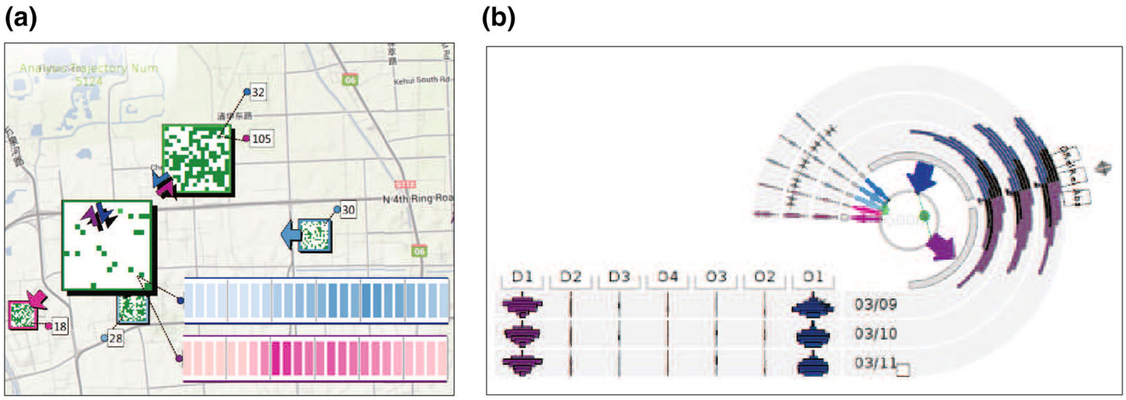

Fig. 8 Explore traffic volume with OD-Wheel: **a** O/D, OD regions detected at the interested region, with unfolded in and out traffic flow distributions of the largest OD region. **b** In and out traffic volume comparison in the OD-Wheel

7.2 Detail exploration on volume dynamic change

Besides the OD overview, our system supports to explore the dynamic OD patterns in details by the adapted OD-Wheel. In this case, the interested region is set at the west-north corner on the 4^{th} ring road. 5124 trajectories passing this region are selected from March 9th to 11th. The spatial distribution of O/D, OD regions are as Fig. 8a shows. The dark green OD region has the largest traffic volume. For all the other regions, there are dense dark green inside their cluster glyphs. That is, there are high ratio of traffic flows between those regions and the largest OD region. It is particularly obvious for the second largest OD region, which is east-north to the largest one in a short distance. Unfolding the in and out traffic volume distribution of the largest OD region (Fig. 8a), the average distributions over the day can be observed respectively. Examining them in OD-Wheel for detail (Fig. 8b), the pair of in and out traffic volume has definitely different distribution shapes in the linear view. To compare them day by day clearly, the two are stacked. The black difference bars clearly show that there is larger out traffic rather than in traffic flow at beginning of a day and then larger in traffic flow in the afternoon and evening.

7.3 OD pattern dynamics exploration

Alternative to traffic volume, there can be other traffic measurement in the linear view. In this case, we take the travel time cost as an example of OD dynamic pattern, while our method can be easily extended to additional measurements, such as travel distance. We set the interested region at the north-west corner on the 2nd ring road, which is one of the biggest transportation hub in Beijing. 5762 trajectories are selected from March 9th to 10th. As Fig. 9a shows, the largest OD region is around the transportation hub, which conveys over 1000 taxis in and out every day. Other regions are significantly smaller than the largest one. Comparing the traffic volume of the largest OD region in the OD-Wheel, we found out that the traffic flow of in-direction is larger than that of the out-direction in the morning and the pattern is inversed in the afternoon. The travel time cost along the two directions are visualizes as dot plots in the linear view. Averagely, most of the travel time cost from or to this region is within 30 mins. However, in longer travel time range, the in-direction spans wider than that of out-direction. The link-and-brush function between linear view and map view supports users to check trajectories in details. As Fig. 9b shows, trajectories with small time cost and with large time cost are selected in the linear viw and plotted on the map. Those with small time cost (within 10 min) travel in very short distance and those with large time cost (more than 40 min) reach the 5^{th} ring of Beijing.

8 Discussion

Based on our earlier work (Lu et al. 2015b), we refine the OD region glyph (Sect. 5.2) after collecting feedbacks from several users in visualization field. One of the users commented on the convex hull glyph in work (Lu et al. 2015b) "the number label circle interferes the perception of detected OD region". After we changed it into text square, the user considered it is less confusing. Another is the visual encoding of

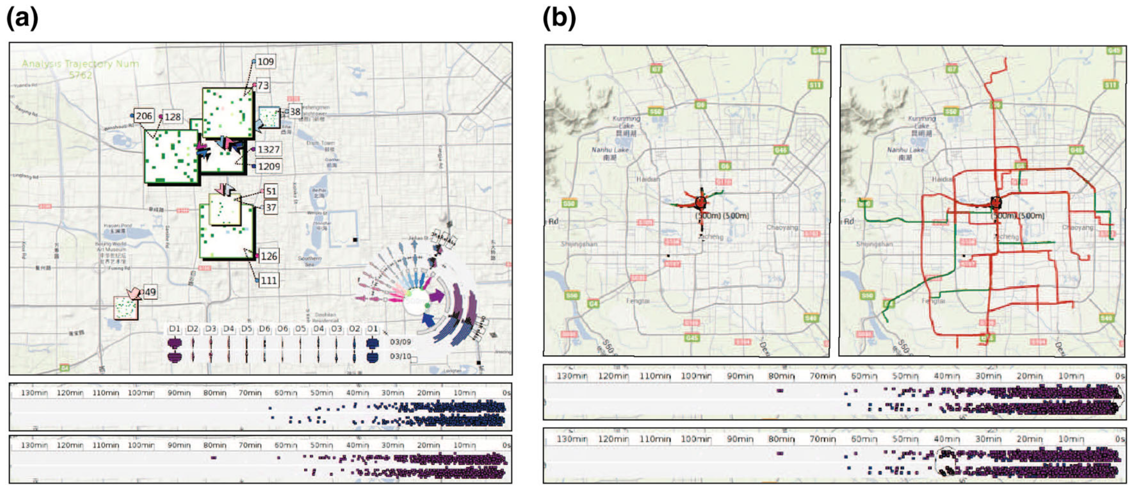

Fig. 9 Exploration on travel time cost: **a** OD regions extracted from trajectories of a transportation hub in the north-west corner on the 2nd ring and travel time cost distributions of the in/out traffic flows to/from the largest OD region. **b** Trajectories with small and large time cost

direction of a region's traffic flow. Previously in work (Lu et al. 2015b), warm and cold color series are used to encode the O and D region respectively. However, users complained that it is not intuitive. It is more intuitive using arrow whose orientation represents the direction. Additionally, besides to the spatial information, users gave positive feedbacks on the average temporal distribution, which helps them quickly target at interesting temporal patterns.

9 Conclusion

In this paper, we present a visual analytics system to explore the OD patterns of interested region. Instead of global OD pattern analysis, we tackle this problem starting from trajectory filtering. With graphical filters, the system supports to set spatial constraints and filter related trajectories. Based on these trajectories, OD clusters are extracted and corresponding regions are detected. To analyse the OD patterns, we adapt a novel visual design, OD-Wheel, to support the comparison among regions, which are not limited to a central region as before. With effective interactions and intuitive visual hints in comparison, the adapted OD-Wheel is capable of comparing dynamic patterns in detail. Finally, applying the method to real taxi GPS trajectories, the system's effectiveness is demonstrated by several cases.

There are some possible research directions in future. OD-Wheel can be generalized as a visual tool to explore large scale time series data. More interactions need to be added on OD-Wheel. For example, a magnifying function could be added for time series with small value. The other is to consider the traffic interchange flows among multiple regions. OD flow or matrix may be integrated into OD-Wheel so that it is possible to explore the traffic flows between pair of two certain regions.

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References

Andrienko G, Andrienko N (2008) Spatio-temporal aggregation for visual analysis of movements. In: IEEE symposium on visual analytics science and technology, pp 51–58

Andrienko N, Andrienko G (2011) Spatial generalization and aggregation of massive movement data. IEEE Trans Vis Comput Graph 17(2):205–219

Aufaure-Portier MA., Bonhomme C (1999) A high level visual language for spatial data management. In: Proceedings of the third International Conference on Visual Information Systems, Amsterdam, The Netherlands, 2-4 June. pp 325–332

Beijing Transportation Research Center (2010) Annual report of beijing transportation development

Boyandin I, Bertini E, Bak P, Lalanne D (2011) Flowstrates: an approach for visual exploration of temporal origin-destination data. Comput Graph Forum 30(3):971–980
Ferreira N, Poco J, Vo H, Freire J, Silva C (2013) Visual exploration of big spatio-temporal urban data: a study of new york city cab trips. IEEE Trans Vis Comput Graph 19(12):2149–2158
Fishkin K, Stone MC (1995) Enhanced dynamic queries via movable filters. In: Proceedings of the SIGCHI conference on human factors in computing systems, pp 415–420
Graham RL (1972) An efficient algorithm for determining the convex hull of a finite planar set. Inf Process Lett 1:132–133
Guo D (2009) Flow mapping and multivariate visualization of large spatial interaction data. IEEE Trans Vis Comput Graph 15(6):1041–1048
Guo H, Wang Z, Yu B, Zhao H, Yuan X (2011) Tripvista: triple perspective visual trajectory analytics and its application on microscopic traffic data at a road intersection. In: Proceedings of IEEE pacific visualization symposium, Hong Kong, pp 163–170
Havre S, Hetzler B, Nowell L (2000) Themeriver: visualizing theme changes over time, In: Proceedings of IEEE Symposium on Information Visualization 2000. pp 115–123
Hochheiser H, Shneiderman B (2004) Dynamic query tools for time series data sets: timebox widgets for interactive exploration. Information Visualization 3(1):1–18
Holten D, van Wijk J (2009) Force-directed edge bundling for graph visualization. Comput Graph Forum 28(3):983–990
Jiang X, Zheng C, Tian Y, Liang R (2015) Large-scale taxi o/d visual analytics for understanding metropolitan human movement patterns. J Vis 18(2):185–200
Krüger R, Thom D, Wörner M, Bosch H, Ertl T (2013) Trajectorylenses—a set-based filtering and exploration technique for long-term trajectory data. Comput Graph Forum 32(3):451–460
Liu H, Gao Y, Lu L, Liu S, Qu H, Ni L (2011a) Visual analysis of route diversity. In: IEEE conference on visual analytics science and technology (VAST), pp 171–180
Liu W, Zheng Y, Chawla S, Yuan J, Xing X (2011b) Discovering spatio-temporal causal interactions in traffic data streams. In: Proceedings of the 17th ACM SIGKDD international conference on knowledge discovery and data mining, pp 1010–1018
Lu M, Lai C, Ye T, Liang J, Yuan X (2015a) Visual analysis of route choice behaviour based on gps trajectories. In: The 4th international workshop on urban computing (Held in conjunction with the 21th ACM SIGKDD 2015), August 10, Sydney
Lu M, Wang Z, Liang J, Yuan X (2015b) OD-Wheel: visual design to explore od patterns of a central region. In: Proceedings of IEEE pacific visualization symposium (PacificVis 2015 Notes), April 14–17, Hangzhou, pp 14–17
Lu M, Wang Z, Yuan X (2015c) Trajrank: exploring travel behaviour on a route by trajectory ranking. In: Proceedings of IEEE pacific visualization symposium, April 14–17, Hangzhou, pp 311–318
McLachlan P, Munzner T, Koutsofios E, North S (2008) Liverac: interactive visual exploration of system management time-series data. In: Proceedings of the SIGCHI conference on human factors in computing systems. ACM, pp 1483–1492
Pan G, Qi G, Wu Z, Zhang D, Li S (2013) Land-use classification using taxi gps traces. IEEE Trans Intell Transp Syst 14(1):113–123
Peng C, Jin X, Wong K-C, Shi M, Li P (2012) Collective human mobility pattern from taxi trips in urban area. PLoS One 7(4):e34487
Phan D, Xiao L, Yeh R, Hanrahan P (2005) Flow map layout. In: IEEE symposium on information visualization, pp 219–224
Rae A (2009) From spatial interaction data to spatial interaction information? Geovisualisation and spatial structures of migration from the 2001 UK census. Comput Environ Urban Syst 33(3):161–178
Robertson G, Fernandez R, Fisher D, Lee B, Stasko J (2008) Effectiveness of animation in trend visualization. IEEE Trans Vis Comput Graph 14(6):1325–1332
Thompson W, Lavin S (1996) Automatic generation of animated migration maps. Cartogr Int J Geogr Inf Geovisualization 33:17–28
van Wijk J,van Selow E (1999) Cluster and calendar based visualization of time series data. In: IEEE symposium on information visualization, pp 4 –9
Wang Z, Lu M, Yuan X, Zhang J, van de Wetering H (2013) Visual traffic jam analysis based on trajectory data. IEEE Trans Vis Comput Graph 19(12):2159–2168
Wang Z, Ye T, Lu M, Yuan X, Qu H, Yuan J, Wu Q (2014) Visual exploration of sparse traffic trajectory data. IEEE Trans Vis Comput Graph 20(12):1813–1822
Wang Z, Yuan X (2014) Urban trajectory timeline visualization. In: Proceedings of 2014 international conference on big data and smart computing (BIGCOMP), Bangkok, pp 15–17
Wang Z, Yuan X, Ye T, Hao Y, Chen S, Liang J, Li Q, Wang H, Wu Y (2015) Visual data quality analysis for taxi gps data. In: IEEE VIS (Poster), Chicago
Weber M, Alexa M, Muller W (2001) Visualizing time-series on spirals. In: IEEE symposium on information visualization, pp 7 –13
Wood J, Dykes J, Slingsby A (2010) Visualization of origins, destinations and flows with OD maps. Cartogr J 47:117–129
Zhao J, Chevalier F, Balakrishnan R (2011) Kronominer: using multi-foci navigation for the visual exploration of time-series data. In: Proceedings of the SIGCHI conference on human factors in computing systems. ACM, pp 1737–1746