Visual Analytics of Higher Order Information for Trajectory Datasets

Ye Wang, Ickjai Lee

Abstract—Due to the widespread of mobile sensing, there is a strong need to handle trails of moving objects, and trajectories. This paper proposes three visual analytics approaches for higher order information of trajectory datasets based on the higher order Voronoi diagram data structure. Proposed approaches reveal geometrical, topological, and directional information. Experimental results demonstrate the applicability and usefulness of proposed three approaches.

Keywords—Visual Analytics, Higher Order Information, Trajectory Datasets, Spatio-temporal data.

I. INTRODUCTION

SPATIAL data contain thematic and geographic attributes. The thematic attribute could be a type of disaster such as tornado, or a land feature such as city. The geographic attribute is the location of the thematic attribute, such as the location where a tornado occurs, or the location of a city. Time is another interesting dimension as spatio-temporal datasets get their popularity [1]. A trajectory is the trail of a moving object with the time dimension attached to the thematic and geographic attributes. Trajectory data are getting bigger and more complex as various location-aware mobile sensing devices collect trajectories.

As our society moves into a more data-rich, information-rich but knowledge-poor environment, people try to access a rich set of data through information for decision-making. Due to uncertainties and complexities of trajectory datasets, Higher Order Information (HOI) for what-if analysis when the first preferred solution is no longer in use is highly required. For instance, the second nearest hospital information is required when the first nearest hospital is fully booked or closed in emergent situations. HOI includes a higher order information including the k-Nearest Neighbor (kNN) information and k-Order Region (kOR) information [2]. HOI of trajectory data is important, but it is complex and not a trivial task.

As trajectory data get bigger and larger, it becomes more difficult to analyze HOI of trajectory data. Trajectory data representing moving objects contain useful dynamic information that needs to be highlighted and visualized [3]. There are many visual tools that can help people understand data and amplify cognition. Readability is one of the most important aspects of visualization, but when higher mathematical approaches were used, a new problem called poor-readability arises.

Existing kNN visual techniques require numbers, areas and

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points to describe information. Traditionally, color, line, and shape have been used by different visual tools for geometric information [4]-[6]. There is not much research in topological and directional information visualization. In this paper, we introduce a more generic concept called *General Geometrical Bar* then we show that the Geometrical Bar can be used to efficiently build geometric information about size, length, and the properties of space. Consider a set of static data $P = \{p_1, p_2, \cdots, p_n\}$ where q_i represents a point in the Euclidean space and denotes the location of a place or city. Given a trajectory dataset $Q = \{q_1, q_2, \cdots, q_m\}$, kNN returns a subset of P for $q_i \in Q$ with geometrical information. Second, we display a more abstract concept named *General Topology Parallel*. It shows when q_i is changing over time, the information/relations from kNN will change over time based on trajectory data Q. Third, we will identify a new definition in HOI called *General Direction-4*. It displays q_i directional information of kNN from P.

This paper is organized as follows. Section II reviews background preliminaries and previous work to draw problem statements. Section III introduces a proposed interactive visualization framework for higher order information for trajectory datasets, and discusses various proposed visual analytical approaches. Section IV presents application with Moore tornado 2013 in American, and Section V briefly reviews and concludes.

II. PRELIMINARIES

Moving point object data is getting more and more popular as the development of GPS (Global Positioning System) and radio transmitters. Data analysts are interested in the automatic development of patterns from a big amount of recorded movement datasets [7]. For example, farmers could be interested in finding movement patterns of cattle to figure out grazing behaviors and to place water tanks.

HOI has been researched for many years in emergency management. kNN queries and kOR queries are of great importance for GIS (Geographic Information Systems) and "what-if" scenarios [2], [8]. HOI can be used for mitigation, preparedness, response, and recovery phases of emergency management in this dynamic environment [9]. Even though HOI is useful for many applications, most research has focused on either algorithmic aspects, or application areas of HOI. Visual analytical aspects of HOI have received less attention. It has been widely used for visualizing domain-specific datasets [4]-[6]. Recently, there have been some approaches proposed but received relatively less attention due to their complex nature. Interactive visualization combines

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human interaction with computers to focus on visual illustrations of information. It is good to prune away unnecessary information, and to focus on interested areas to highlight. However, datasets of this previous research are static, and do not consider movement or changes over time. It is more complex when HOI of moving objects and trajectories is considered.

The visualization of trajectory dataset has been studied for few years. Researchers try to present a method that interactively explores multiple attributes in trajectory data using density maps such images to show an aggregate overview of massive amounts of data [10]. Reference [11] provides a visual-interactive cluster analysis for effectively analyzing trajectory datasets. They applied *Kohonen Feature Map* on different trajectory clustering problems to combine both unsupervised and supervised processing to produce appropriate cluster results. Although all of this research provides visual tools for trajectory dataset, none of the research could support HOI. Visual analysis tools amplifying analytical capabilities of humans are greatly needed to answer questions for better decision-making. This paper addresses important issues and investigates visual tools for highlighting HOI of trajectory data
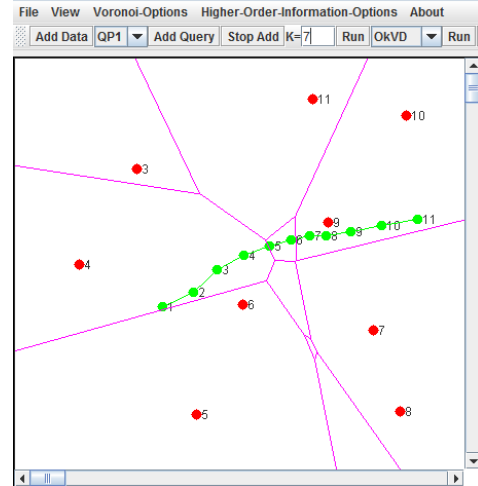
III. COMPUTING TRAJECTORY HOI
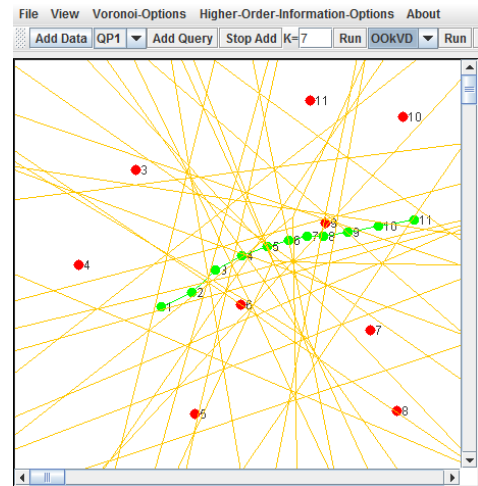
A. Unified Data Structure of HOI

This paper is based on the unified Delaunay triangle based data structure which consists of a complete set of Order-k Delaunay triangles (from Order-0 to Order-(k-1)) [2]. A complete set of HOVD (Higher Order Voronoi Diagrams) families could be drawn from this data structure, and the relationship between the data structure and HOVD families is shown in Table I. For example, O3VD can be obtained by a combination of Order-1 and Order-2 triangles; OO3VD is an overlay from O1VD to O3VD, while 3NVD is a join of O2VD and O3VD.
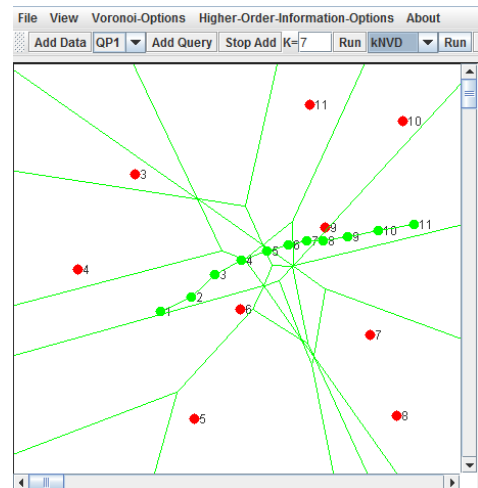
TABLE I
DATA STRUCTURE

Order k	OkVD	OOkVD	kNVD
1	Order-0 triangle	O1VD	O1VD
	Order-0 triangle	O1VD	O1VD
2	&	~	~
	Order-1 triangle	O2VD	O2VD
	Order-1 triangle	O1VD	O2VD
3	&	~	~
	Order-2 triangle	O3VD	O3VD
	Order-2 triangle	O1VD	O3VD
4	&	~	~
	Order-3 triangle	O4VD	O4VD
…	…	…	…
	Order-(k-2) triangle	O1VD	O(k-1)VD
k	&	~	~
	Order-(k-1) triangle	OkVD	OkVD

(a)

(b)

(c)

Fig. 1 Trajectory dataset Q and generators P with HOVDs: (a) O7VD; (b) OO7VD; (c) 7NVD

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The Delaunay triangulation is a dual graph of the OVD (Ordinary Voronoi Diagram). It can be included by connecting two adjacent Voronoi generators when they share a Voronoi edge together. The circumcircle of each Delaunay triangle in the triangulation does not contain any other generators in it. Delaunay triangles for the OVD are called Order-0 triangles. But, there could be triangles whose circumcircles include a number of generators within them. Order-1 triangles are those triangles whose corresponding circumcircles include only one generator in it. So, Order-k triangles are those ones whose corresponding circumcircles include k generators in it. Please refer to [2] for more details.

B. Algorithm

Fig. 1 displays a screen capture of higher order-7 Voronoi diagram for a given P and trajectory data Q. Order-7 Voronoi Diagram (O7VD) (shown Fig. 1(a)), Ordered Order-7 Voronoi Diagram (OO7VD) (shown Fig. 1(b)), 7th Nearest Voronoi Diagram (7NVD) (shown Fig. 1(c)). The framework is implemented in such a way that it enables users to change various k values as they want to get different types of HOI from trajectory data Q. Since different HOVDs are drawn from the same dataset P, user could interact with the program to retrieve dataset points for any user-interested location within the study query point. The program can support what user is interested in.

General Geometrical Bar. Bar chart or bar graph is a popular visualization approach for lengths proportional to the values. This approach is to show how much percentage of the distance for k^{th} generators from a user selected point. When user highlights the generator point, it will display how the generator moves from trajectory data q_i to q_j.
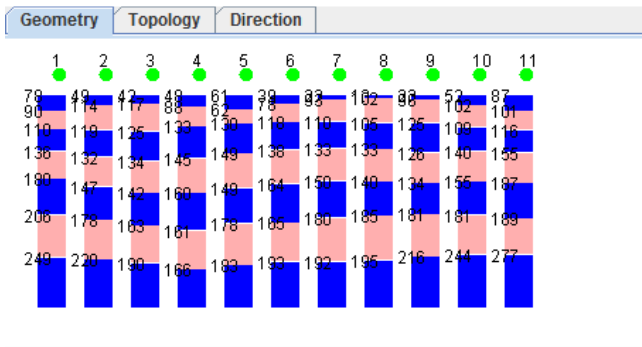

Fig. 2 Geometrical bar chart for trajectory dataset with Higher Order-7 information
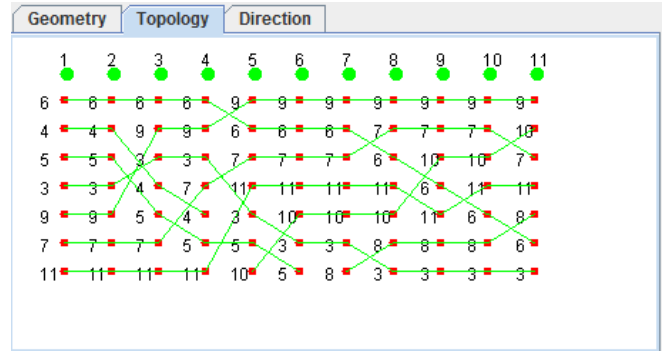

Fig. 3 Topology Parallel for trajectory dataset with Higher Order-7 information

General Topology Parallel. Parallel coordinates approach is a common ways of visualizing high-dimensional geometry and analyzing multivariate data. This approach is to display how the topological relationship of trajectory data changes over time. Since the user moves to an interested generator, changing the relationship from different trajectory data will highlight cross-relations.
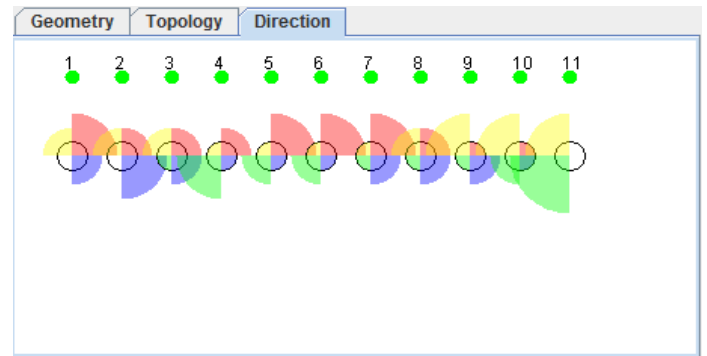

Fig. 4 Direction-4 for trajectory dataset with Higher Order-7 information

General Direction-4. Direction-4 approach focuses on 4 directions which are North-East, North-West, South-East, and South-West. It reveals which direction gets most generators from k, when a trajectory dataset is moving by the time from q_i to q_j, how the directional relationship changes over time. Also this approach highlights the direction where users should focus on where higher information and strong relations with the next trajectory data highlighted.

IV. APPLICATIONS

2013 Moore tornado was an EF5 tornado that made incursions into Moore, Oklahoma on the afternoon of May 20, 2013, with peak winds estimated at 210 miles per hour. That was part of a bigger weather system that had produced several other tornadoes over the previous two days. This application investigates trajectory data from Moore tornado 2013 against city locations.
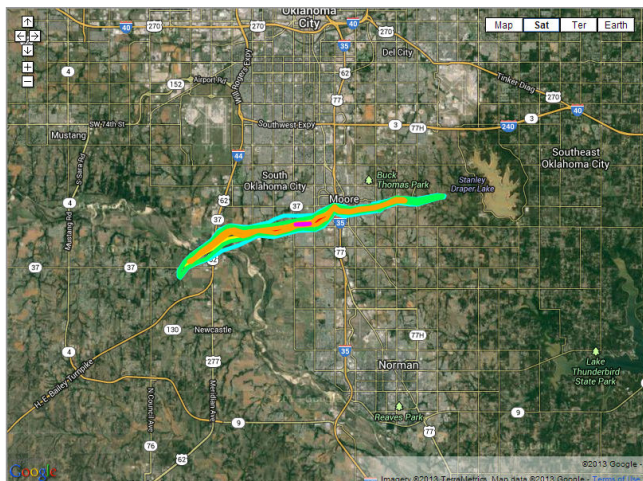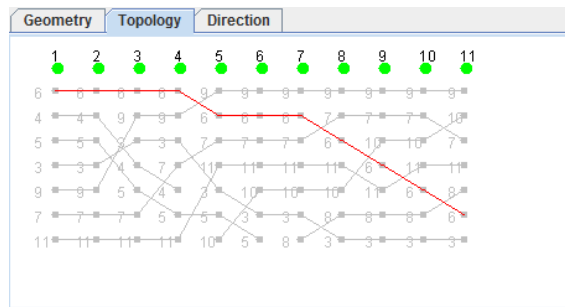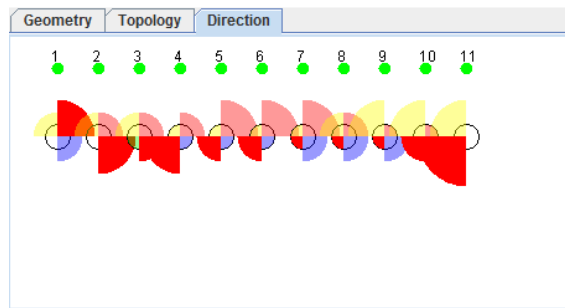
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Fig. 5 Moore tornado dataset from National Weather Service Weather
Forecast Office [12]

Fig. 5 shows a subset Q of Moore tornado trajectory data with Moore area cities (P). Table II displays details of 2013 Moore tornado data.
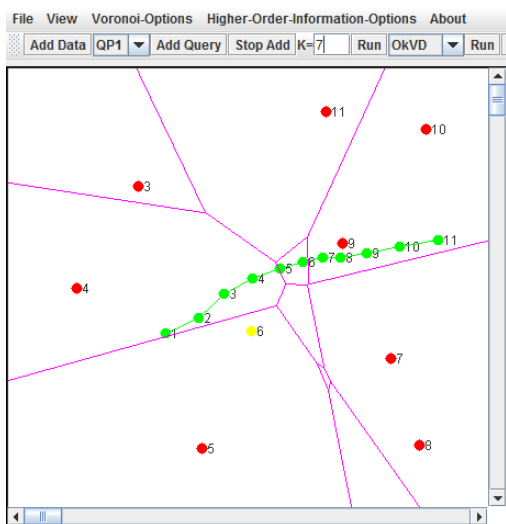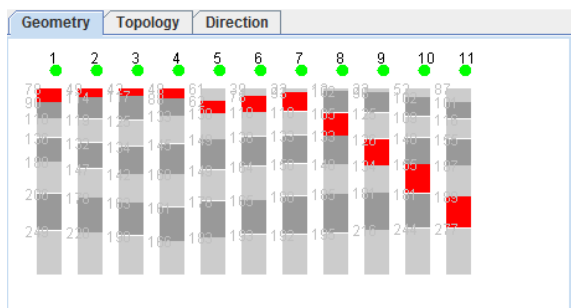

(a)

(b)

(c)

(d)

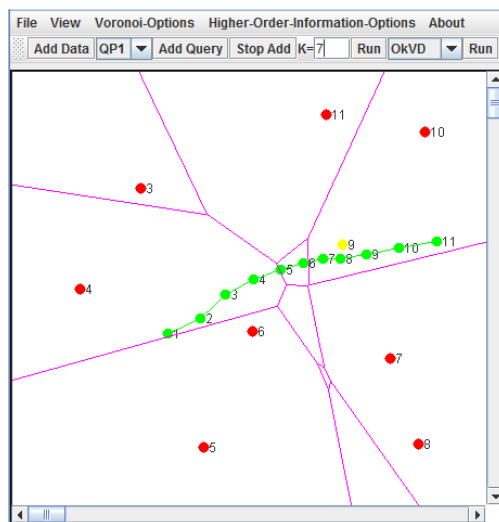Fig. 6 Trajectory HOI of p_6 Newcastle city

Fig. 6 depicts Newcastle city (p_6) to trajectory HOI in different types of visual approaches. Users could interactively explore Higher Order-7 information through trajectory data. As can be seen from the figure, when tornado starts moving from q_1 to q_4, Newcastle(p_6) has always been the first closest city all the time (see Fig. 6(c)). And the distance has not greatly changed during this time (see Fig. 6(b)). Then a higher danger direction is pointing to Newcastle city (see Fig. 6(d)).
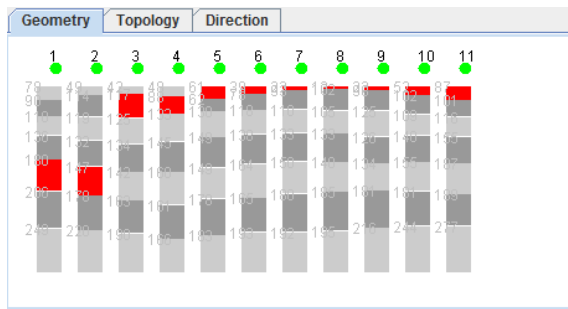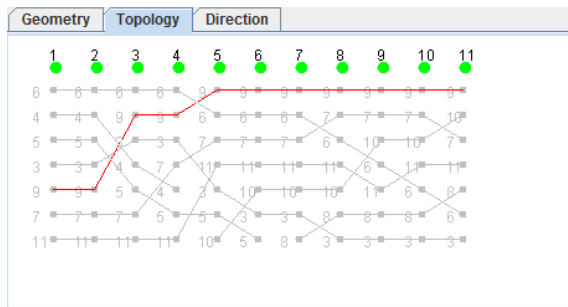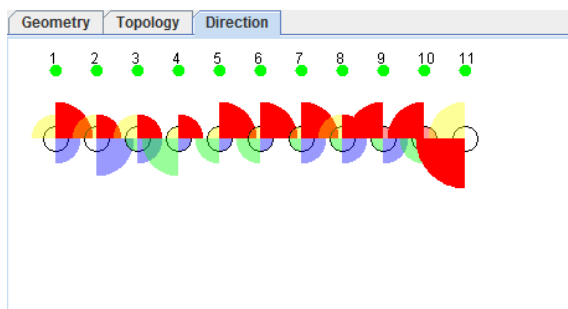

(a)

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(b)

(c)

(d)

Fig. 7 Trajectory HOI of p_9

Although tornado moves to q_3 that percentage is similar with other directions, and geometrical information does not change greatly. Emergency officer should keep high attention in this city carefully. However, the next city we should be considering and paying attention too. The second direction of q_4 is northeast where Moore city is. Fig. 7 shows when the user moves into Moore city (p_9) to trajectory higher order information. The program changes highlighting colour in these three different approaches. The tornado moves to Moore city extremely fast after q_2, then keeping the second dangerous city when tornado moves to q_3. The emergency officer of Moore city should be in high alert.

When tornado goes to q_5, p_9 becomes the closest city where emergency officer should focus on (see Fig. 7(c)). It has a high percentage warning direction (see Fig. 7(d)). And also the distance to Moore city is getting closer (see Fig. 7(b)). As tornado changes over time, it does not move that far away from Moore city and topological information is stable with all other cities. But, Newcastle city is out of tornado area (see

Fig. 6). When this disaster finishes, it was going through the northeast way of Moore city.

TABLE II
2013 MOORE TORNADO DATA

Data Point	Meaning	Attribute
Red-3	Mustang	City
Red-4	Tuttle	City
Red-5	Blanchard	City
Red-6	Newcastle	City
Red-7	Norman	City
Red-8	Noble	City
Red-9	Moore	City
Red-10	Midwest City	City
Red-11	Oklahoma City	City
Green-1	Tornado develops west northwest of Newcastle	2:46PM
Green-2	Track NE as it continues to rapidly intensify	2:51 PM
Green-3	Moves parallel to 1-44	2:59 PM
Green-4	Then crosses 1-44 ~4 mi N of Newcastle	3:03 PM
Green-5	Starts to turn more to the east	3:08 PM
Green-6	Crosses SW 19th	3:12 PM
Green-7	Reaches Briarwood Elementary	3:16 PM
Green-8	Reaches Warren Theatres	3:21 PM
Green-9	Crosses 1-33 ~ 3:23PM	3:25 PM
Green-10	Exits the east side of Moore	3:29 PM
Green-11	Rapidly weakens before lake Stanley Draper	3:33 PM

V. CONCLUSION

As we move from data-poor environments to data-rich environments, visual analytics becomes more important to help people amplify cognition. This paper proposes various visual analytical approaches for HOI of trajectory datasets. These general approaches enable a user to prune irrelevant unnecessary information, but to focus on interested information. The proposed approaches are based on the unified Delaunay triangle data structure, thus they effectively and efficiently support what-if analysis and comparative analysis. These data structure based approaches not only provide a rich set of geometrical, topological and directional information, but support cross-relational HOI of trajectory datasets. Future study includes visualization of quantitativeand qualitative HOI. Tight integration to visual data mining is another area of exploration in order to enhance the efficiency aspect of trajectory HOI.

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