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Visual Analytics of Topological Higher Order Information for Emergency Management based on Tourism Trajectory Datasets

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Abstract

Trajectory datasets have presented new opportunities for spatial computing applications and geo-informatics technologies with regard to emergency management. Existing research of trajectory analysis and data mining mainly employs algorithmic approaches and analyzing geometric information of trajectories. This study presents an efficient analytics tool based on visualization approaches for analyzing large volume of trajectory datasets. This approach is particularly useful for emergency management when critical decisions based on semantic information are needed. Tourism trajectory datasets are used to demonstrate the proposed approach.

Keywords: Higher order information, visual analytics, Voronoi diagram, emergency management

1 Introduction

Trajectory data, trails of moving objects, are valuable sources of information. They include spatial and temporal aspects of moving entities and additional quantitative and qualitative attributes about the movement as well as the environment or context in which the movement takes place. Especially, trajectory data plays an important role in the increasing number of emergency management applications. Emergency/disaster management is the discipline related to avoiding and dealing both natural and man-made disasters. Decision-making can be a crucial difficulty throughout unexpected emergencies. The rise of GPS-empowered mobile devices, advance of Internet technologies, and affordable data storage mechanisms allowed collection and distribution of huge amounts of user-generated trajectory data. It has presented new opportunities for spatial computing applications and geo-informatics technologies with regard to emergency management.

As our society moves into a more data-rich, information-rich, but knowledge-poor environment, people try to access a rich set of data to obtain information for decision-making. Due to uncertainties and complexities of trajectory dataset, High Order Information (HOI) for what-if analysis when the first preferred solution is no longer in use is highly demanded. For instance,

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the second nearest evacuation center information is required when the first nearest evacuation center is full or closed in emergencies. Analyzing trajectory dataset and HOI could provide great benefits for emergency management.

Existing approaches for analyzing trajectory datasets are mainly based on data mining techniques such as DBSCAN [12], k-mean/k-medoid [10], k-nearest neighborhood [5] and regions-of-interest [3, 4, 7]. Recently, a few visual tools are found in existing studies. These tools have used colors, lines, textures, shapes, shadings, and bevels to represent HOI [11, 14, 16].

However, research on visualizing large trajectory datasets and HOI trajectories is limited. This study aims to use topological visualization approach for analyzing large trajectory datasets and HOI trajectories. This approach is particularly efficient to provide topological HOI to help decision-making required for semantic answers such as far/close, yes/no, same/different etc instead of accurate numerical or geometric information. Moreover, this approach is computationally efficient and will not create a huge burden of computation typically suffered by algorithmic trajectory analysis approaches.

This paper is organized as follows. Section 2 reviews background preliminaries and previous works to draw problem statements. Section 3 proposes the data structure and algorithm for computing topology higher order trajectory information and discuss various visual analytical approaches. Section 4 presents applications with tourism trajectory datasets. Section 5 briefly reviews and concludes this study.

2 Preliminaries

HOI is information about more than one object for a given set of objects. That is,"Higher" means more than one target object and "Order" means the number of query (source) objects. There are two popular HOI: k-Nearest Neighbor (kNN) information and k-Order Region (kOR) information. In this research, HOI refers to kNN and kOR information. HOI can also be classified into three categories depending on its geospatial characteristics: geometric, topological and directional. Geometric HOI is information about shape, size, location and the properties of space. Topological HOI analyzes information of such basic properties of relationships as space, dimension, and transformation. Directional HOI is about relative positioning properties with distance information. Existing research of HOI mainly focuses on geometrical information with limited attention on topological and directional information. This study attempts to fill part of this research gap; and hence focuses on topological HOI.

2.1 Problem Definition

The areas data mining and information visualization offer various techniques, which effectively complement one another supporting discovery of pattern in the data. Whereas traditional (algorithmic) techniques are analyzing the data automatically, information visualization techniques can leverage the data mining process from an orthogonal direction by providing a platform for understanding the data and generating hypotheses about the data based on human capabilities such as domain knowledge perception and creativity. To successfully apply data mining algorithms, visualization and interaction capabilities become crucial factors since they enable the user to incorporate domain knowledge, to steer the data mining process and to better understand the results. While existing research on trajectory analysis and HOI trajectory used mainly data mining algorithmic approaches to analyze trajectory datasets, this study attempts to a visual analytics approach to facilitate trajectory analysis and visualize HOI trajectories.

Generally, Ordinary Voronoi Diagram (OVD) and its Oigher Order Voronoi Generalizations (HOVD) can provide a robust framework for both kNN and kOR queries.

2.2 Related Work

Visual Analytics (VA) leveraging analytical capabilities of humans is greatly needed to answer questions for better decision-making. VA is a human-centric interactive visualization based analysis approach. It is based on the fact that the human brain is an excellent pattern recognition machine [2]. With VA, human solves complex problems with the perceptual and cognitive capabilities of the human. VA also uses the computing and processing power of computers, thus it combines the strengths of humans and computers to deal with complex information [1]. The main aim of VA is to enable analysts to use their perceptual and cognitive skills to gain insights, detect the expected, and discover the unexpected from data through progressive deepening analysis and exploration (overview first, zoom in and filter to show details-on-demand) [13], and steerable analysis through interactions [8].

Studies on HOVD visualization emerge recently, but not HOI support for kNNQ and kORQ. Palmer [11] investigates visual aspects of OkVD (highlighting unordered kORQ) through contour lines and textures based on raster OkVD. He introduces order-k plots (overlaying nearest neighbor plots for 1,...,k-1). For instance, order-3 plot is the order-3 Voronoi diagram overlaid with contour lines of order-1 and order-2 (1st nearest plot and second nearest plot). Since order-k plot is based on raster Voronoi diagrams (without data structure model) it does not support interactive visualization. It is neither well suited for visual analytics, nor dynamic what-if analysis. It also becomes too complex when k or n grows. Another approach [14] attempted to visualise OkVD regions using color, shading and bevels. Shading with cushion (different intensity levels of shading) is used to represent the distance to the closest site; brighter as closer to the generators and darker as close to the edges. Bevels are used for visualizing OkVD with colored for influencing sites and scaled to reflect the kth order distance and hierarchy), and to superimpose to implicitly show the k sites. Basically these approaches focus on visually answering which are the k sites that influence a given partition. Although all of these pervious works provide visual tools for trajectory dataset, none of the research could support HOI. Wang et al. [16] used different widths and colors to highlight topological relationships between/among HOVD families, and enhances the readability of ordered order-k diagram. Also, they used interactive visualization to display interested area.

These traditional approaches share some common drawbacks: 1) non-interactivity; 2) based on raster Voronoi diagrams, thus incapable of visualizing rich topological relations; 3) based on without data structure model that is not well suited for dynamic what-if analysis; 4) only for visualizing one OkVD for a given k; 5) unable to visualize various topological relations (for instance the relationship between 4NNQ and 5NNQ) of kNNQ for various k; 6) lack of visual analytics support.

3 Computing Higher Order Topological Trajectory Information

3.1 Unified Data Structure

This paper is based on the unified Delaunay triangle based data structure which consists of a complete set of data structure. It consists of a complete set of Order-k Delaunay triangles (from Order-0 to Order-(k-1)) [9]. A complete set of HOVD families could be drawn from this

Table 1: The relationship between HOVD families and the unified data structure.

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

data structure, and the relationship between the data structure and HOVD families is shown in Table 1. For example, O4VD can be obtained by a combination of Order-2 triangle and Order-3 triangle; OO4VD is an overlay from O1VD to O4VD, while 4NVD is a join of O3VD and O4VD.

The Delaunay triangulation is a dual graph of the OVD with edges connecting neighboring points. It can be constructed by linking two adjacent Voronoi generators if they share a Voronoi edge together. For Order-0 triangles, no generator is on the circumcircle of each Delaunay triangle in the triangulation. However, 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. Therefore, Order-k triangles are those ones whose corresponding circumcircles include k generators in it. Please refer to [9] for more details.

3.2 Algorithm

Figure 1(a), (b), and (c) display screen captures of visualization tools developed by the authors with O7VD diagrams for a given P and trajectory data Q. Figure 1(a) shows Order-7 Voronoi Diagram (O7VD), Figure 1(b) depicts Ordered Order-7 Voronoi Diagram (OOV7VD) and Figure 1(c) displays 7th Nearest Voronoi Diagram (7NVD). The implementation enables users to change various k values to get different types of HOI from trajectory data. Since different HOVDs are visualized from the same dataset P, users could interact with the program to retrieve dataset points for any user-interested location within the study query point [15].

Figure 1(d), (e), and (f) illustrate topology trajectory dataset Q_1 and Q_2 and generators P. For topology trajectory information, the visualization tools will try to go through every single data point in all the datasets to perform a classification in relation to the HOI. For each single data point, if they have the same HOI, then they are clustered into the same group. The runtime of this approach is $O(n)$. This approach is faster compared to other data mining approaches. Some examples of visualizations of topological trajectory HOI are shown in next section.

4 Applications

Emergency management is composed of four basic phases: mitigation, preparedness, response, and recovery [6]. This section demonstrates how the topological visual analytics of trajectory HOI can be used for each stage of emergency management. We explain this with a study using geo-tagged photos from Flickr in Queensland, Australia, in the years of 2010-2011 and tourism

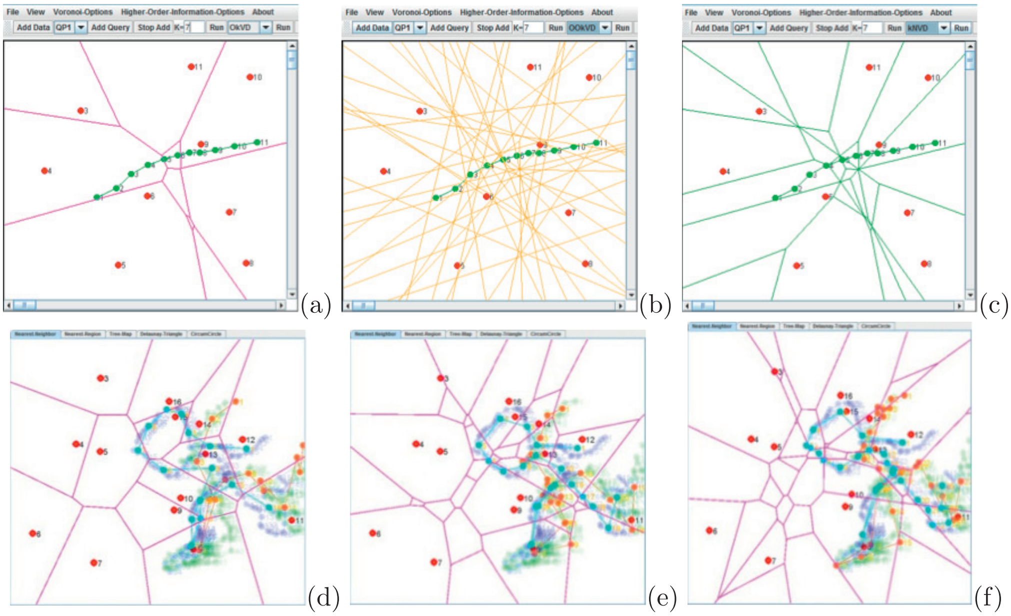

Figure 1: OkVD: (a) O7VD; (b) OO7VD; (c) 7NVD with trajectory dataset Q and generators P; (d) O1VD; (e) O2VD; (f) O3VD with two trajectory datasets Q_1 and Q_2 and generators P.

trajectory datasets. For the Flickr dataset, there are 17,066 records preprocessed to produce the dataset used in this study. Figure 2(a) shows the distribution of the dataset using Google Earth 6.0 (earth.google.com). Most of these records appear along the coastline of the country where the major cities are located. This application will take a subset of the dataset with data points from Cairns, a regional city in Queensland, Australia to demonstrate the usefulness and applicability of our approaches. Figure 2(b) shows a subset Q of clusters within the central business district of Cairns. These locations can be set up as information centers.

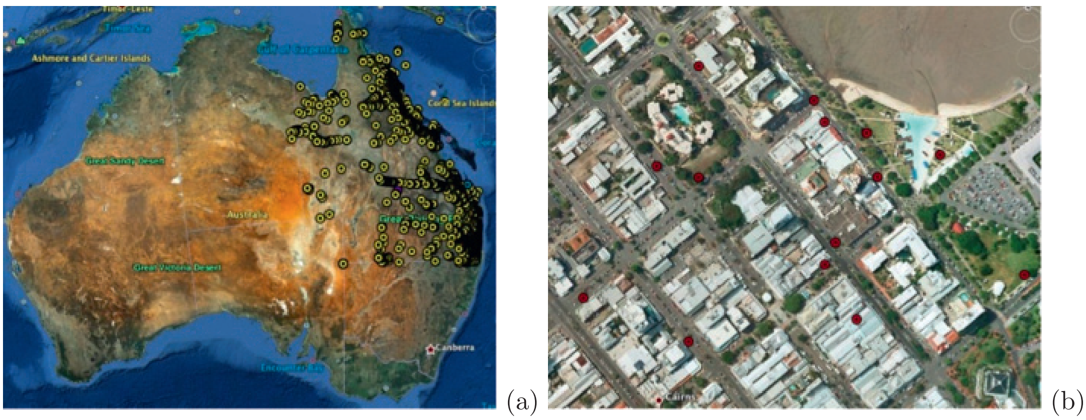

Figure 2: Dataset: (a) Geo-tagged photos from Flickr; (b) Distribution of clusters in CBD of Cairns ($|Q|$=14).

4.1 Mitigation

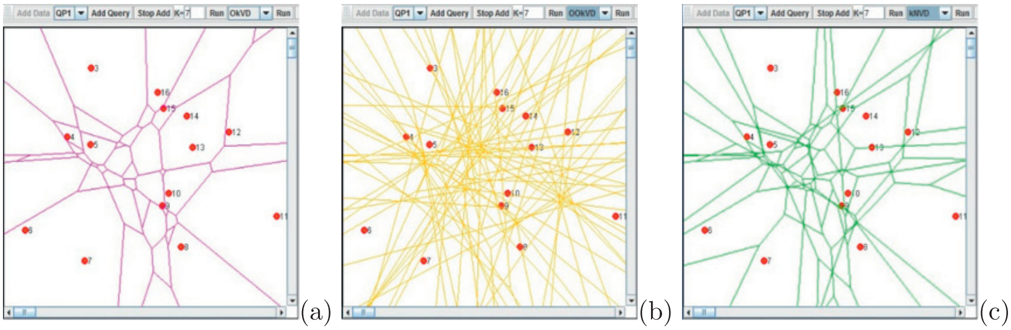

Figure 3: Various HOVDs with differnt visual analytical approaches: (a)O7VD; (b) OO7VD; (c) 7NVD.

Mitigation is a realization that eliminates or decreases the causes of risk/disaster, and is a factor that provides prevention of (removing, eliminating, reducing) the effects of inescapable disaster. Figure 3 demonstrates higher order families of locations of 14 clusters. Figure 3(a) shows O7VD, Figure 3(b) displays OO7VD, and Figure 3(c) depicts 7NVD. These clusters can be used to represent Points of Interest (POIs) related to emergency management.

4.2 Preparedness

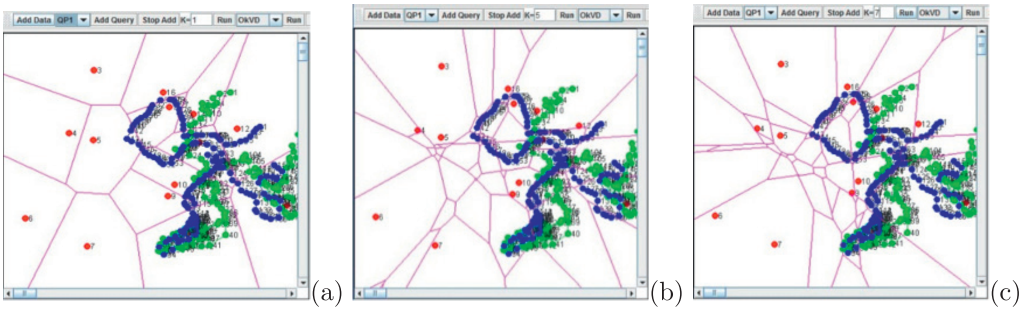

Figure 4: Preparedness: (a)O1VD; (b) O5VD; (c) O7VD with two trajectory datasets Q_1 and Q_2.

In the preparedness phase, governments, organizations, and emergency centers involve making plans to save lives and minimizes disaster damage such as having emergency personnel on standby or determining the nearest evacuation places with dynamic (moving/changing over time) data. In other words, preparedness also explores ways to improve damage response operations. Figure 4 shows the O1VD, O5VD and O7VD of the two trajectory datasets collected every 10 seconds for half an hour from two different tourist groups walked in the CBD of Cairns. The data collected from tourist Q_1 (Group 1) is represented in green and Q_2 (Group 2) is shown in blue in Figure 4. If we assume that P represents information centers then people moving around regions will have different nearest information center as time progresses. Thus, people staying in different regions will have a clear understanding of which area has the same higher order information when they move.

4.3 Response

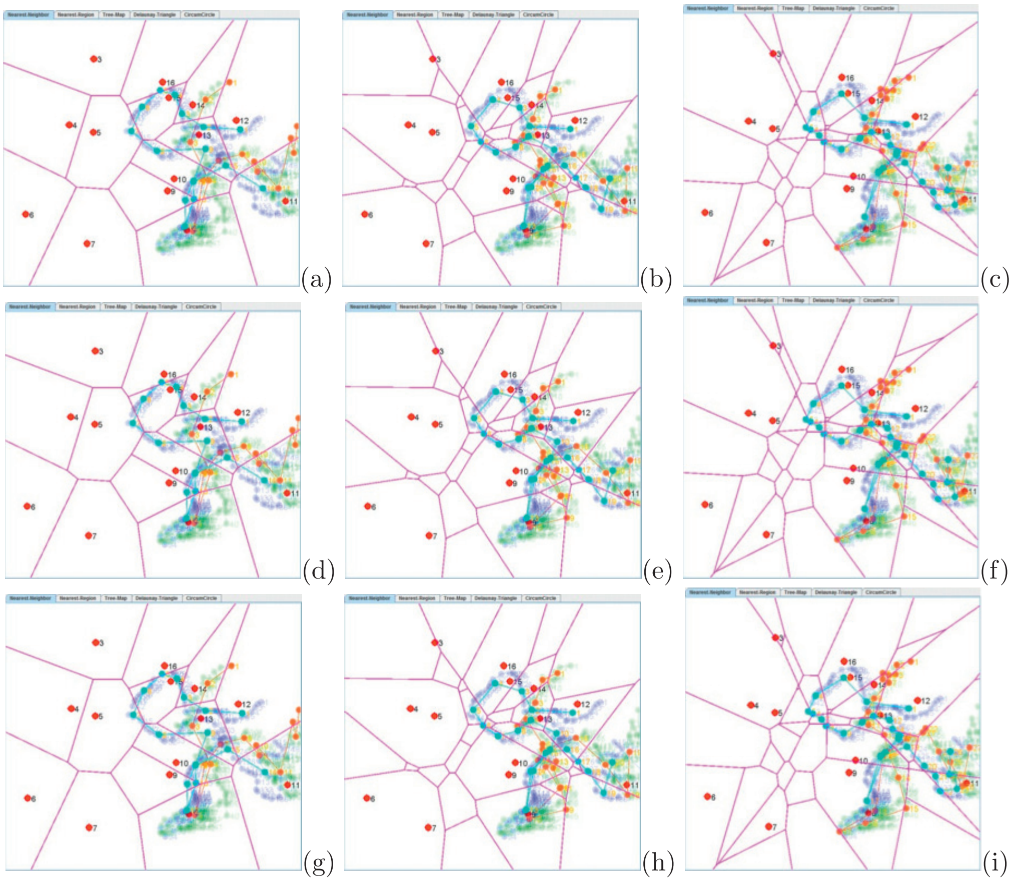

Figure 5: Response: (a)O1VD; (b) O2VD; (c) O3VD; (d) O5VD; (e) O9VD; (f) O13VD with two new trajectories; (g) O1VD; (g) O2VD; (i) O3VD highlighting area with two new trajectories.

Response consists of activities following emergency assistance for victims. It also explores how to stabilize the situation and to prevent the probability of secondary disaster and to give suggestions for recovery. Typically, the nearest neighbor emergency unit is required to respond to emergencies quickly. Here we use order-k Voronoi diagrams as an example. Figure 5 shows a series of HOVD of the topological HOI of the two trajectories resulting from the visual analytic tool. The data collected points from tourist Q_1 is represented in green and Q_2 is represented in blue in Figure 5(a)-(f). The data collected regions from tourist Q_1 is represented in red and Q_2 is represented in green in Figure 5(g)-(i). When emergencies occur, the nearest neighbor emergency units are required to cooperate and collaborate in order to decrease the disaster. Q_1 and Q_2 can find the closest information center to ask more information. Figure 5(a)$-$(f) show different values of k with Order-k Voronoi diagrams. The information center also can make decisions about the best location for setting up emergency tables for tourist. For the regions, the nearest neighbor emergency units give suggestions about areas which have more activities. When red and green colors are mixed, it means two different trajectories are in the same higher order region. The government can give orders to focus on these top priority regions (orange regions) for emergency center. When topology visual analytic trajectory and regions cooperate and collaborate, it will make more informed decision for the government to reduce the disaster.

4.4 Recovery

K=	Trajectory-1 class number	Trajectory-2 class number
1	14	16
2	19	20
3	27	26
4	35	28
5	31	33
6	35	28
7	20	25
8	26	20
9	24	19
10	23	12
11	28	16
12	23	11
13	3	5

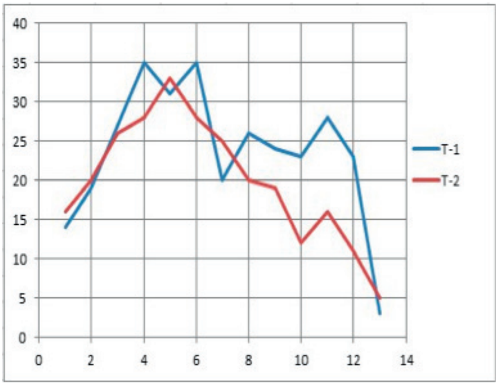

Figure 6: Class numbers of Trajectory-1 and Trajectory-2 from topological visual tool analysis.

Recovery happened when the disaster is over. It is a set of activities that returns all systems back to normal and also prevents secondary damage. These include two phases, short term and long term. From Figure 6, we can see although Trajectory-1 (Q_1) and Trajectory-2 (Q_2) are different, for the higher order information, they are very similar. Both trajectories have an increasing number of classes when k is less than 6, and then a number of classes which generally decreases with $k > 6$. In emergency recovery situation of short term, we can choose recovery plans as soon as possible when the value of k is greater than 6. It also quickly prevents secondary disaster. For long term, recovery plans can be introduced based on $k < 6$ of high order information.

5 Conclusion

Disasters and emergencies can lead to various forms of financial, structural, and environmental damage. Even though it is almost impossible to avoid occurrences of disasters, effective prediction and preparedness along with a post-emergency management program can mitigate the risk and damage. Trajectory analysis has emerged in the last decade as very active research domain with many potential applications for emergency management. While pervious research mainly focused on processing the raw data received from GPS devices and sensors, this research focuses more on enriching the trajectory analysis with trajectory HOI.

This paper proposes a visual analytical approach for topological HOI of trajectory datasets. This approach enables a user to analyze large volume of trajectories, related the trajectories with POIs and trajectory HOI. The visual analytics tools implemented for this study used the unified data structure and relevant algorithms to support the visualization of HOI and topology trajectory information. We show how this approach can be applied to emergency management.

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