Expert Systems With Applications 108 (2018) 28–35

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

DNA-chart visual tool for topological higher order information from spatio-temporal trajectory dataset

Ye Wang, Kyungmi Lee, Ickjai Lee*

Information Technology Academy, College of Business, Law and Governance, James Cook University, Cairns QLD 4870, Australia

ARTICLE INFO

Article history:
Received 15 August 2017
Revised 1 February 2018
Accepted 27 April 2018
Available online 30 April 2018

Keywords:
Higher order information
Topological information
Voronoi diagram
Visualisation
Trajectory

ABSTRACT

With increasing amount of trajectory dataset being generated and collected, trajectory data has become a ubiquitous type of data important in many different application domains. Research challenges faced are to analyse and retrieve useful higher order information from trajectory datasets to deal with dynamic and "what-if" complex decision making problems. In this paper, we propose a new visualisation approach and quantitative metrics to model and analyse topological higher order information from trajectory datasets. The proposed higher order DNA chart can help decision makers to compare different topological higher order information from different trajectories. We also define higher order trajectory area that models a geometrical area representing the same higher order information. We introduce a higher order DNA impact factor that defines top-k higher order information, and the relationship between trajectory datasets and points-of-interest. A case study using trajectory data extracted from Flickr illustrates the applicability and usefulness of these proposed visual tools and metrics.

1. Introduction

Due to the prevalence of GPS-enabled devices and wireless internet connectivity, trajectory data is being generated and collected at an unprecedented pace. Trajectory data captures information about events and movements. Trajectory datasets, 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. Trajectory data is a ubiquitous type of data important in many different application domains. Researchers have been investigating different methodologies and analytical tools for analysing trajectory datasets in order to reveal useful information and knowledge from this massive amount of trajectory datasets (Giannotti & Nanni, 2007; Jeung, Shen, & Zhou, 2008; Zheng & Zhou, 2011). As our modern society and environment get more dynamic and complex, Higher order information (HOI) has attracted a great deal of attention in order to respond to "what-if" analysis for moving objects represented by trajectories (Okabe, Boots, & Sugihara, 1992; Okabe, Boots, Sugihara, & Chiu, 2009).

In terms of HOI visualisation, research focuses on developing methods and approaches to leverage human perception and understanding of spatial data in order to provide effective means for presenting, analysing, and understanding of trajectory datasets (Wang, Lee, & Lee, 2014b; Wang, Lu, Yuan, Zhang, & Wetering, 2013). Visual analytics is particularly useful when dealing with complex trajectory datasets (Andrienko, Andrienko, & Gatalsky, 2003; Schreck, Bernard, von Landesberger, & Kohlhammer, 2009), and it has been used for various geometrical and directional HOI visualisation for trajectory datasets (Wang et al., 2014b; Wang et al., 2013).

In this study, we propose an innovate approach to visualise topological HOI of trajectory datasets. HOI includes k-nearest neighbour (kNN) information and k-order region (kOR) information that are of great importance in highly dynamic and complex environments (Lee, 2016). HOI for "what-if" analysis allows users to deal with the dynamic complexity of trajectory analysis especially when the best possible solution is unavailable/malfunctioning/fully booked. For instance, in emergency planning and management phases, HOI provides useful information to situations where more than k response centres are required to participate in the response and recovery phases.

Based on the spatio-temporal characteristics of HOI, HOI can be classified into three different types: namely geometrical HOI, directional HOI and topological HOI. Topological HOI analyses information of such basic properties of relationships as space, dimension, and transformation. A topological order of a given point x to $P = \{p_1, p_2, \ldots, p_n\}$ is a linear re-ordering $P' = \{p'_1, p'_2, \ldots, p'_n\}$ of P such that $|p'_j - x| \le |p'_{j+1} - x|$ for $1 \le j \le n$ where $|x, y|$ is a given distance metric between the point x and the point y. The linear

* Corresponding author.
E-mail addresses: ye.wang@my.jcu.edu.au (Y. Wang), joanne.lee@jcu.edu.au (K. Lee), ickjai.lee@jcu.edu.au (I. Lee).

https://doi.org/10.1016/j.eswa.2018.04.036
0957-4174/

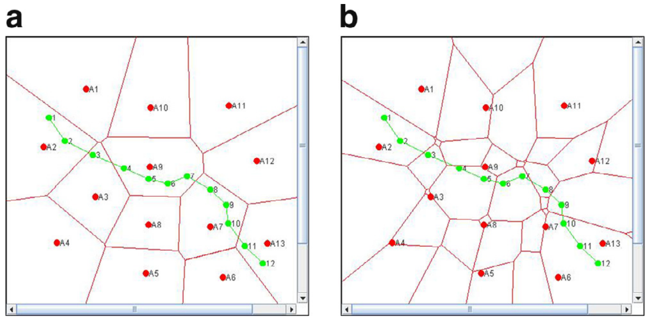

Fig. 1. Voronoi diagrams: (a) Order-1 Voronoi diagram (O1VD); (b) Order-3 Voronoi diagram (O3VD) with 13 generators P_1 (labeled from A1 to A13), and trajectory T_1 (12 timestamps).

re-ordering P' indicates topologicial HOI. Despite the importance of topology in spatio-temporal analysis (Okabe et al., 1992), topological HOI has attracted very little attention even through some studies investigated and applied geometrical HOI (Wang et al., 2013) and directional HOI (Wang, Lee, & Lee, 2011). Qualitative Spatial Reasoning (QSR) is a long-standing spatial discipline that qualitatively reasons about spatial phenomena and objects (Cohn & Hazarika, 2001). Topological information is the heart of QSR and also in many spatial queries and analysis (Renz, 2002). Topological HOI can provide a dimension reduction and robustness to filter the complexity of trajectory data analysis when compared to geometrical HOI and directional HOI.

Consider an example shown in Fig. 1 which shows different Points-of-Interest (POIs) datasets and trajectory datasets with Voronoi diagrams (there are several ways to model topological information but the Voronoi diagram (Okabe et al., 1992) is the most popular approach, and it is utilised in this paper). Fig. 1(a) displays P_1 13 POIs data representing tourist attractions labelled from A1 to A13 (red point), and a trajectory denoting tourist movements with 12 timestamps (green point) with Order-1 Voronoi diagram (O1VD). The geometrical HOI based on nearest neighbours as the trajectory travels along the study region with regard to the generators. Fig. 1(b) shows corresponding Order-3 Voronoi diagram (O3VD) with labels P_1 and T_1. For example, for T_1 in Fig. 1(a), the nodes can be classified into 5 clusters as the Voronoi diagram tessellates. In this case, the node of T_1 timestamps (2-3-4) change their topological information (A2-A3-A9), whilst timestamps (8-9-10) keep the same topological information (A7) all the time in O1VD. However, in Fig. 1(b), timestamps (2-3-4) keep changing their order-3 topological information (A1A2A3-A2A3A9-A3A8A9) in O3VD, and timestamps (8-9-10) change their topological information as well. This type of HOI conveys important higher order relationships, however it has received little attention. There are several important questions to consider for decision making. For example, which trajectory is more topologically efficient when moving around the region or required path? What is the best k-order information for the trajectory? How to justify the impact and relationship for a trajectory on each level of HOI and the impact and relationship between each trajectory nodes. This study aims to introduce new topological visualisation approaches, and new geometrical trajectory area visualisation approaches based on topological HOI and HOI topological impact factor methods for analysing the relationship between POIs and trajectory datasets. These approaches are particularly useful for enabling new ways to represent topological HOI to provide and justify semantic answers to problems such as how trajectory HOI has stable topological information with respect to POIs and what is the best kth nearest neighbors with the smallest topological HOI change. For example, during crisis like flooding or fire, information like the kth nearest emergency response centre is very useful. The proposed visual analytical tool provides an implementation to topological HOI, as well as a new calculation method to simplify, analyse, justify, and visualise relationships between POIs and trajectory datasets.

Table 1 lists a glossary of acronyms used in this paper. This paper is organised as follow: Section 2 presents preliminaries and literature review of this study. Then in Section 3, the details of proposed algorithms used to generate the Higher order DNA chart (HODNAC), Higher order trajectory area (HOTA) and the Higher order DNA impact factor (HODNAIF) are discussed. Section 4 presents a case study with real datasets from a photo sharing website, Flickr, to illustrate the applicability of the proposed visualisation approaches and the impact factor method. Section 5 concludes this study and provides possible future work.

2. Preliminaries and literature review

Given a point set P, a query point q and a positive integer k, the kNN Query (kNNQ(q, P)) returns $P_i^{(k)} \subset P$ where $|P_i^{(k)}| == k$, and $\forall\, r \in P_i^{(k)}$ and $\forall\, s \in P - P_i^{(k)}$, $|r-q| \leq |s-q|$ where $|x, y|$ is the Euclidean distance between the point x and the point y. kNN is of particular interest in Geographic Information Systems (GIS), emergency management and "what-if" analysis (Carey & Schneider, 1995; Keim et al., 2008). kNNQ is supplemented by the kth Order Region Query (kORQ) which returns a region R for a certain subset $P_i^{(k)}$ in P where the set of kNN for any location l in R is the same as $P_i^{(k)}$. Both kNNQ and kORQ are two most common HOI types and they need a data structure to efficiently and effectively handle them. Order-k Voronoi Diagram (OkVD) families which are generalisations of the Ordinary Voronoi Diagram (OVD) are a solid candidate data structure for kNNQ and kORQ (Okabe et al., 2009). OkVD tessellates the space into k-order regions based on order-k (k nearest neighbors), thus it is able to answer both kNNQ and kORQ. OkVD families could be constructed based on the unified Delaunay triangle based data structure (Lee & Lee, 2009) which is composed of a complete set of Order-k Delaunay triangles (from Order-0 to Order-(k-1)). An Order-k triangle includes k generators within its circumcircle. That is, Order-0 triangles contain no generator within their circumcircles whilst Order-1 triangles include 1 generator within their circumcircles. OkVD can be obtained from a combination of Order-($k-2$) triangles and Order-($k-1$) triangles for $k \geq 2$. O1VD is obtained from Order-0 triangles by connecting neighboring Order-0 triangles. Refer to Lee and Lee (2009) for more details.

Voronoi diagrams have been widely used for visualising domain-specific datasets (Abellanas & Palop, 2008; Balzer, Deussen, & Lewerentz, 2005; Dupuis, Sadoc, Jullien, Angelov, & Mornon, 2004; Horn, Tobiasz, & Shen, 2009), but little research has been conducted to visualise Voronoi diagrams themselves (Palmer, 2006; Telea & van Wijk, 2001). The OVD has been typically visualised through Voronoi lines, vertices and regions (Okabe et al., 2009). Interactive visualisation could be used to visualise the OVD. Interactive visualisation is a visualisation approach that takes user input to focus on, and displays detailed information on a focused area in real time (Ware, 2012). It is good to highlight areas of focus, but not good for producing an overall view simultaneously. Due to its filtering nature, interactive visualisation is particularly important in complex datasets or data-rich environments where scalability is an issue (Shneiderman, 2010). Voronoi growth models (similar to contour models) could be used to visualise how each generator starts generating Voronoi regions (Okabe et al., 2009). When two growing regions meet each other, they stop growing and formulate a Voronoi edge. This growth model based visualisation dynamically shows how the OVD is formed, but it is not straightforward to use this approach to visualise higher order voronoi