AN INTERACTIVE VISUALIZATION TOOL FOR MOBILE OBJECTS

by

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ABSTRACT

Recent advancements in mobile devices – such as Global Positioning System (GPS), cellular phones, car navigation system, and radio-frequency identification (RFID) – have greatly influenced the nature and volume of data about individual-based movement in space and time. Due to the prevalence of mobile devices, vast amounts of mobile objects data are being produced and stored in databases, overwhelming the capacity of traditional spatial analytical methods.

There is a growing need for discovering unexpected patterns, trends, and relationships that are hidden in the massive mobile objects data. Geographic visualization (GVis) and knowledge discovery in databases (KDD) are two major research fields that are associated with knowledge discovery and construction. Their major research challenges are the integration of GVis and KDD, enhancing the ability to handle large volume mobile objects data, and high interactivity between the computer and users of GVis and KDD tools.

This dissertation proposes a visualization toolkit to enable highly interactive visual data exploration for mobile objects datasets. Vector algebraic representation and online analytical processing (OLAP) are utilized for managing and querying the mobile object data to accomplish high interactivity of the visualization tool. In addition, reconstructing trajectories at user-defined levels of temporal granularity with time aggregation methods allows exploration of the individual objects at different levels of

movement generality. At a given level of generality, individual paths can be combined into synthetic summary paths based on three similarity measures, namely, locational similarity, directional similarity, and geometric similarity functions. A visualization toolkit based on the space-time cube concept exploits these functionalities to create a user-interactive environment for exploring mobile objects data. Furthermore, the characteristics of visualized trajectories are exported to be utilized for data mining, which leads to the integration of GVis and KDD.

Case studies using three movement datasets (personal travel data survey in Lexington, Kentucky, wild chicken movement data in Thailand, and self-tracking data in Utah) demonstrate the potential of the system to extract meaningful patterns from the otherwise difficult to comprehend collections of space-time trajectories.

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1 INTRODUCTION

1.1 Background

Recent advancements in mobile devices — such as Global Positioning System (GPS), cellular phones, car navigation system, and radio-frequency identification (RFID) — have greatly influenced the nature and volume of data about individual-based movement in space and time (Golledge & Stimson, 1997). These mobile devices are used in various applications: navigation systems that support the best route choice for vehicles; wayfinding to support navigation; real-time tracking of individuals, vehicles, animals, and other mobile objects; emergency management as responses to accidents, interruptions of essential services, and disasters (Brimicombe & Li, 2006). This infrastructure provided by mobile devices, generally called Location-Based Services (LBS), is changing the lifestyles of people in urban areas dramatically (Li & Longley, 2006).

Individual-based information acquired by LBS is often utilized within applications of Geographic Information Science (GISci). LBS are defined as the delivery of data and information services where the content of those services is customized to the current or some projected location and context of the user (Brimicombe & Li, 2006). They attract the attention of the GISci community because of their potential to provide the basis of location-aware information. Location-aware information enables individuals on the move to communicate with others using wireless mobile devices, and user-solicited information — real-time information such as weather forecast, traffic conditions, and maps (Brimicombe & Li, 2006). Although LBS have just started to be developed, much research has been done to cultivate and strengthen their implementability and demand (Laurini, Servigne, & Tanzi, 2001; Leonhardt, Magee, & Dias, 1996; Sage 2001). For example, some research proposes a tourism information system to support the decision making of tourists (Mountain & Raper, 2001; Zipf, 2002) while others focus on the user's needs of location-aware services (Kaasinen, 2003). Moreover, RFID tags can track patients in hospitals to enhance the operational efficiency of a health delivery network (Sangwan, 2005). These applications generate locational information with respect to time for individuals in vehicles or objects with location recording devices. These individual-based spatio-temporal data are often called mobile objects data (MOD).

MOD have a more complicated structure than traditional spatial data. As stated above, what is common to all LBS is time-stamped locational data. In other words, the user of mobile devices can record their locations across time as digital information stored in databases for future use. In GIS, an object is represented as a point that is moving through space according to time. Thus, the movement of an object is represented as a trajectory within three-dimensional space – two spatial dimensions and one time dimension (Pfoser 2002).

Since mobile objects can change their locations continuously through time, dynamic representation of entities is required to handle the time component of MOD. However, most current GISci theories are based on a static place-based standpoint, or static approach, and thus, they are not well-suited in providing tools for incorporating the time dimension of geographic information (Mark 2003). Although many efforts have been made to incorporate a time component in GIS (Peuquet & Duan, 1995; Yuan, 1999), those methods are not adapted to analyze the dynamics of activity and travel behavior of disaggregate data, or MOD (Wang & Cheng, 2001).

Because of their unique characteristics, the change from static-approach to dynamic-approach data representation brings many research challenges for MOD: high data volume, complex data relationships, and nonstandard data query and data analysis requirements (Shaw & Wang, 2000). Individual-based data is very detailed and therefore, the data volume can be large. Due to the prevalence of mobile devices, vast amounts of MOD are being produced and stored in databases (Mountain, 2005). Tools and applications in current GISci are not designed with the needed capacity to handle the large volume data associated with MOD (Wang & Cheng, 2001). Second, individual-based data can have complex relationships among entities. For example, each mobile object has its own trips and anchors but the movement or trip can be interrelated with other mobile objects. This complex relationship among mobile objects must be represented or computed. Third, to represent the complex relationships among the entities in individual-based data, a new database design is required for data query and data analysis of mobile objects (Wolfson, Xu, Chamberlain, & Jiang, 1998).

In addition to the research challenges stated above, there is an urgent need to develop analytical methods for MOD in GISci. Traditional spatial analytical methods were developed when data collection was difficult and computational power was low (Miller, 2009). Traditional statistical methods such as spatial statistics, for example, require high computational loads. Therefore, traditional methods that are based on small volumes of information are not applicable for large volume and diverse geographic information, including MOD. Moreover, traditional spatial analytical methods are confirmatory and the researchers need to have an *a priori* hypotheses. Therefore, traditional spatial analytical methods cannot discover unexpected patterns, trends, or relationships that are embedded in large volume spatio-temporal data such as MOD. A major challenge is to develop appropriate models and techniques to manage, analyze, and visualize such large datasets to extract meaningful patterns, trends, and relationships (Frihida, Marceau, & Theriault, 2004).

Conceptual and technological frameworks have been developed to address useful patterns and relationship within large, multivariate spatio-temporal data including MOD (Frihida et al., 2004). These are referred to as Geovisualization (GVis) and Knowledge Discovery in Databases (KDD): they are two major research fields that are associated with knowledge discovery and construction. Although their approaches to knowledge discovery are different from each other, their primary goal is to find, relate, and interpret interesting, meaningful, and unanticipated features (objects or patterns) in large data sets (MacEachren, Wachowicz, Edsall, & Haug, 1999). The difference is that GVis relies upon human vision whereas KDD is based on computational methods. In addition, methods of GVis and KDD both require interactivity to be effective (MacEachren et al., 1999). Neither a single visual exploration nor a single data mining run is helpful to find the interesting, unexpected knowledge embedded in data – repeated application of the methods are required.

There are several research challenges in GVis and KDD to handle spatio-temporal datasets such as MOD. One of the major research challenges is the integration of GVis and KDD: much KDD research emphasizes the importance of visualization, although GVis is mostly used as a technique to interpret and evaluate the results of analysis in

KDD (MacEachren et al., 1999). Another research challenge is to incorporate large volume spatio-temporal datasets into GVis tools. Although KDD tools are designed for large volume datasets, many GVis tools are not applicable for large datasets. Efficient GVis tools that can handle massive volumes of spatio-temporal data are required. In addition, interaction between human and machine is also a research challenge in GVis and KDD — high interactivity of GVis tools is necessary to accomplish better intuitive knowledge discovery.

There have been many efforts in GVis and KDD research to solve the problems stated above. Some studies enhanced the interactivity of visualization tools by extracting features that characterize the mobile objects such as direction and velocity (Laube, Imfeld, & Weibel, 2005; Mountain, 2005; Smyth, 2001). Other research proposed new methods of representation and visualization of mobile objects (Imfeld, 2000; Laube et al., 2005). Moreover, data mining methods were incorporated in visualization tools for further data exploration (Dykes & Mountain, 2003; Mountain, 2005). This research expanded the capability of GISci to be applicable to handle spatio-temporal data, including MOD.

In addition to the grand challenges in GVis and KDD for spatio-temporal datasets, some research problems describing the movement of mobile objects have been proposed (Laube et al., 2005). They are as follows:

- Uncertain and missing data
- Interpolation issues
- Analysis granularity for time component
- Aggregation of mobile objects
- Factors or characteristics of the motion attributes.

First, there are usually uncertain and missing data in real-world tracking data. However, existing methods are designed for complete data that are without uncertain or missing portions, and methods to deal with those incomplete data should be developed. Second, to solve the problem of uncertain and missing data, interpolation methods for missing tracking points of mobile objects are needed (Wentz, Campbell, & Houston, 2003). Third, the sampling rate in time for the mobile objects should be the same so that the analysis will be performed with the data of the same time granularity. Since MOD collected by different devices may have different time sampling rates, compatibility between data from different data collection process should be discussed and solved to incorporate and analyze the data from various data sources. Fourth, similar to the spatial scale problem known as Modifiable Areal Unit Problem (MAUP), the time scale should also be considered in the analysis of MOD (Hornsby, 2001). If MOD are explored in different time granularity with the interactive visualization tools, different patterns or relationships can be detected from the data exploration. Therefore, aggregation methods for the time component should be developed. Fifth, more factors or characteristics of the mobile objects can be added to interactive data exploration. Previous works show that only a few characteristics – such as direction, speed, or velocity – are available to the user of the visualization tools to explore the data. There can be more characteristics or attributes of the trajectories of mobile objects and those factors should be added to the visualization tools. It is not only that these five challenges still remain unsolved, but also that there is no standard method to deal with the problems. Although the interactive visualization tool must be data-driven or task-driven (Andrienko, Andrienko, & Gatalsky, 2005), these challenges are the tasks that can be applied to any kinds of MOD – a more integrated visualization tool that overcomes these three problems should be developed.

1.2 Research Objectives

This dissertation proposes methods to uncover patterns, trends, and relationships that are hidden in massive volumes of MOD data. Emergence of MOD data enables us to develop geographic theories from a people-based perspective instead of a place-based approach, which is basically a collection of functions of locations and was the mainstream when data were scarce and computational platforms were weak (Miller, 2005a).

A people-based perspective focuses on individual-based (or disaggregate) activity patterns and accessibility in space and time (Miller, 2005b). The mobility of individuals has increased due to the development of advanced transportation systems and settlement systems. In addition, telecommunication systems, The World Wide Web, and related internet technologies, including location-aware technologies and social medias, have been altering the nature of allocating space and time in people's daily lives. As Miller (2005a) states;

> the world is shrinking in an absolute sense: transportation and communication costs have collapsed to an incredible degree over the last two centuries (Janelle, 1969). The world is also shriveling as relative differences in transportation and telecommunications costs are increasing at most geographic scales (Tobler, 1999). The world is also fragmenting: people and activities are becoming disconnected from location (Couclelis & Getis, 2000). (p. 216)

A place-based approach is not well-suited in the era of massive mobility information that contains dynamic spatial, temporal, and attribute information of individuals.

As stated previously in this chapter, there is an urgent need to develop methods that can handle massive volumes of disaggregate level mobility data. Since there is no standard *a priori* knowledge about the nature of individual mobility information established yet, exploratory analysis rather than confirmatory analysis is appropriate to discover underlying patterns. Therefore, exploratory spatial data analysis such as data visualization and data mining plays a key role in this phase.

This dissertation proposes a visualization toolkit as a means of exploratory visual and quantitative analysis for MOD data, which leads to research at a more detailed and deeper level, such as hypothesis creation of geographic theories, and assessment of geographic models that have not been discovered or developed. Insights from exploratory analysis have great potential in transforming MOD data into useful and meaningful geographic thoughts.

The visualization toolkit in this dissertation also provides GVis tool components to overcome research problems for MOD, integration of GVis and KDD, handling large volumes of MOD, enhancement of interactivity of GVis tool, manipulation of time granularity, and aggregation and summarization of mobile objects. The research objectives are as follows:

- To create a highly interactive graphical user interface (GUI) for visual data analysis of mobile objects
- To develop methods to visualize large volume MOD using vector algebra and online analytical processing (OLAP)

- To propose methods for aggregation and summarization of vector algebraic representation of MOD for better visual data exploration and knowledge discovery construction.

A highly interactive visualization toolkit enables users to explore the data from various perspectives. The users manipulate data using spatial, temporal, geometric, and other geographical components of the data, which is explained in detail in Chapter 3. The ability to handle large volume data has been one of the major research challenges in GISci. Moreover, functionalities such as aggregation and summarization of MOD data enhance the interactivity of the data exploration and provide new insights in visual data exploration. Also, the integration of GVis and KDD is accomplished by incorporating the functionality of data mining in the toolkit. The toolkit consists of novel functionalities for pattern detection in MOD data towards knowledge construction of individual human activity in space and time.

1.3 Structure of This Dissertation

This dissertation consists of six chapters. Chapter 1 introduces the current research challenges, proposing goals and objectives of this dissertation. Chapter 2 reviews literature of related research fields that contributed to GISci research for MOD: time geography, GVis, knowledge discovery in databases, and activity-based analysis. Since this research focuses on visualization and knowledge discovery, a large portion of the literature review is dedicated to these two research fields. Chapter 3 describes techniques that are utilized in the visualization tool and management of MOD: vector algebra and OLAP. It also proposes the methods for aggregation and summarization of vector representation of mobile objects; several similarity functions are presented.

Chapter 4 describes the MOD that are used in this dissertation: wild chicken data in Thailand; GPS tracked data of Lexington, Kentucky; and GPS self-tracking data of the investigator. Chapter 5 presents the results of the visual data exploration and data mining, evaluating the versatility of the visualization tool to various MOD. Chapter 6 then summarizes and concludes the dissertation and proposes the future agenda that this research suggests.

2 LITERATURE REVIEW

2.1. Time Geography

Time geography is the study of individual-based human behavior in space and time. It was originally introduced to the English-speaking world by Hägerstrand in 1970. Time geography focuses on constraints on human behavior rather than the prediction of human spatial behavior. The core notion of time geographic framework is that events comprising an individual's existence have both spatial and temporal attributes.

Three constraints limit the ability of individuals to move and participate in activities: capability constraint, coupling constraint, and authority constraint. Capability constraint refers to the person's ability to trade time for space in movement. For example, the need for food or sleep constrains peoples' movement because people need such things for everyday life. Coupling constraint relates to the possibility of two or more persons interacting. Authority constraint limits the movement of people to certain places or domains in space and time. For example, people cannot go inside a shopping mall when it is closed (Hägerstrand, 1970).

There are two main concepts in time geography to visualize and analyze actual or potential movements in space and time – *space-time path* and *space-time prism*. The space-time path draws the locations of travel in space and time (Figure 2.1). The space-time region is represented by three axes, x, y, and t. The space generated by x and y axes represents two-dimensional space, and the t axis represents time. In this region, the space-time path is depicted as a trajectory with a group of points that represent the sequence of locations of individual movement in space and time.

In addition to space-time path, the space-time prism provides the possible movement areas that an individual can access with a limited amount of time. Figure 2.2 illustrates a basic prism without the activity time. The area bounded by the upper cone and lower cone is called the potential path space (PPS); this represents the area an individual can travel in space based on leaving the first location at time t_i and arriving at the second location at time t_j, traveling at the maximum velocity. Also, the area in two-dimensional space projected from the PPS is called the potential path area (PPA). Using these basic time geographic entities, the possibility and limitation of individual movements can be determined. Figure 2.3 shows a more general case of the space-time prism. The first activity is at a fixed location $x_{i,}$ which ends at time $t_{i,}$ while the second activity location is at the fixed location x_j, which starts the activity at time t_j. The minimum time required for the individual to participate in the activity is represented as a_{ij}.

Since this time geographic concept has been proposed, many efforts have been conducted to improve the analytical framework of time geography (Miller, 1991, 1999; Kwan & Hong, 1998). Recently, an analytical definition of time geography has been proposed to expand the availability of the time geographic concept in geographic information science (Miller, 2005c). In addition, detailed descriptions of time geographic concepts, such as error analysis and uncertainty analysis, have been discussed as well (Hall, 1983; Neutens, Witlox, Van De Weghe, & De Maeyer, 2007). Hornsby and Egenhofer (2002) developed a framework that enables space-time queries in multiple time granularity for space-time paths, space-time prisms, and when paths and prisms are combined.

A primary concern of time geography is individual accessibility. This includes issues such as pattern detection of accessibility in urban areas (Kwan, 1999; Lenntorp, 1976, 1978), coupling possibility (Neutens, Schwanen, & Miller, 2009), and detection of gender differences in space-time movements (Kwan, 2003). In addition, a desktop software application of GIS to measure and visualize the PPA was developed to support the decision making of journeys using a public transportation system (O'Sullivan Morrison, & Shearer, 2000). Furthermore, the prediction of the travel behavior rising from cognitive maps was also attempted (Mondschein, Blumenberg, & Taylor, 2005). These efforts facilitate the development of applications using a time geographic framework and extend the scope of time geographic research.

This dissertation applies the time geographic framework for the visualization of space-time paths in a three-dimensional view. Space-time queries with multitemporal granularity that are similar to Hornsby and Egenhofer (2002) are utilized as time aggregation methods. Querying and visualizing space-time paths at different time granularities extends the ability of exploratory pattern detection and knowledge discovery. This is an important aspect of Knowledge Discovery in Databases (KDD) and Geovisualization (GVis).

2.2. Knowledge Discovery in Databases and Geovisualization

The volume, scale, and scope of digital geographic datasets are expanding at a tremendous rate from the advances in technologies and techniques. Due to the inadequacy of traditional spatial analysis methods for these massive geographic datasets, it is time to create a new paradigm to handle large volume, highly multivariate datasets that require high levels of computation power. Exploratory Data Analysis (EDA), KDD, and GVis are the research fields that attempt to provide methods of exploration, analysis, and representation of a massive amount of data to extract deeply hidden patterns, trends, and relationships, and perform knowledge discovery. Although those three research fields have similar objectives, their foci are different from each other.

2.2.1. Exploratory Data Analysis

EDA seeks patterns and relationships in observational data, as well as explanations for such patterns and relationships. The basis of EDA is the idea that data analysis is essentially regarded as an interactive circular process where knowledge is constructed through the association of theory — such as spatial statistics — and observational data, or raw data (Tukey, 1977). In this sense, EDA sheds new light on scientific methods that have never been considered. In addition, scientists no longer have to rely on *a priori* assumptions about the data: they can generate new hypotheses rather than testing existing hypotheses with statistics (Wachowicz, 2005). It is an approach that searches for patterns and relationships in data and generates hypotheses simultaneously (Yuan, Buttenfield, Gahegan, & Miller, 2004).

The need for EDA is growing as large volume datasets have been generated with a variety of applications such as marketing, transportation, finance, and medicine (Gahegan, 2005). In addition, continuous growth of spatio-temporal datasets in their size and complexity also facilitates the need for improvements in EDA techniques. One of the trends in scientific research is the development of interactive visualization tools. Some EDA methods utilize not only statistical analyses but also cartographic maps for data exploration (Guo, Liao, & Morgan, 2007; Wachowicz, 2005). Gahegan (2005) identified two reasons why visualization is useful in exploring such large datasets. First, a virtual environment, such as three-dimensional immersive virtual reality, enables observers' greater access to a large amount of data than figures and tables. Second, the process of visualization requires many data transformations, such as 3D-scatterplot and parallel coordinate plot (Gahegan, Takatsuka, Wheeler, & Hardisty, 2002) — these kinds of transformations fulfill roles such as querying and focusing operators, and facilitating the process of uncovering hidden patterns and structures in data. Furthermore, leveraging human vision in addition to computational methods may lead to deeper insight. This is why GVis is taking a leading role in the data exploration of massive datasets, including datasets with complex structure such as spatio-temporal data. It is difficult to distinguish EDA from GVis and KDD, but EDA is more suitable for very rich datasets, where the dimensionality of attributes is large, but the size of datasets is smaller. On the other hand, GVis and KDD are developed for large volume datasets (Wachowicz, 2005).

2.2.2. Geovisualization

A knowledge discovery concept that integrates cartography and scientific visualization is GVis. It focuses on visual explorations and analysis of geographic information in the knowledge construction process (Kraak & MacEachren, 1999). GVis relates to researches in many disciplines such as cartography, scientific visualization, image analysis, information visualization, exploratory data analysis (EDA), and GIScience (Dykes, MacEachren, & Kraak, 2005). In addition, GVis tools allow the user to interact with spatial datasets to seek interesting patterns and structures that are embedded in the datasets to support the construction process of refined knowledge. It is also useful as a communication tool in a group for discussions and decision-making processes.

The Commission on Visualization and Virtual Environments of the International Cartographic Association (ICA) has proposed challenges in GVis and announced recommendations for actions. According to Dykes et al. (2005), there are four major research challenges in GVis, namely, representation, visualization-computation integration, interface design, and cognition-usability.

Representation is a core theme in GVis. The challenge is to develop new forms of geographic representation based on the new technological advances in both hardware and data formats. Many geographic representation methods for GVis have been proposed, including interpolation methods such as triangular irregular network (TIN) and geostatistical interpolation methods, including kriging (DiBiase, 1990), cartographic animation (Lobben, 2003), spatialization (Skupin & Fabrikant, 2003), interactive color arrangements (Brewer, 1997), self-organizing maps for geographic information (Skupin & Hagelman, 2005; Yan & Thill, 2007), and virtual environments (Dykes, Moore, & Wood, 1999). Spatio-temporal data collected by emerging devices such as GPS and other remote sensors can be visualized to analyze spatiotemporal human movements (Laube, Imfeld, & Weibel, 2005; Mountain, 2005).

Interactions among many variables in large datasets are so complex that purely visual data exploration by human vision cannot be successful. The aim of visualization-computation integration is to develop knowledge construction tools through visual data exploration that enhance the user’s ability to discovering hidden patterns, trends, and relationships in complex geographic data, and explaining the results of data exploration. Integration of KDD and GVis to support visual data exploration by processing and analyzing datasets before visualization is one of the challenges in this integration research agenda. This effort is often accomplished and implemented through the interface design for GVis.

Development and improvement of GVis interface design is requisite to facilitate the use of hands-on GVis tools by the public, providing better opportunities for interactions with large volume geographic data for knowledge discovery. Interface design ranges from simple color arrangement tools (Brewer, 1997) to complex analysis such as the combination of visualization and multivariate statistics by GeoVista Studio toolkit (http://www.geovistastudio.psu.edu/jsp/index.jsp), exploratory data analysis toolkits for activity/travel data (Buliung & Kanaroglou, 2004) and remotely-sensed data analysis of individual motions (Laube et al., 2005). Although there are some efforts to create the interactive properties of GVis with the purpose of creating more understandable tools, there are few tools that validated the efficiency of visualization methods. Therefore, the cognition and usability of GVis must be addressed.

The cognitive aspects of GVis focus on human-computer interaction (HCI) such as perception and reaction of people to the visual representation in GVis tools. Research with experiments or surveys attempt to explain the human perception of fundamental geographic notions such as distance, proximity, and scale – these notions are evaluated for testing cognitive aspects of visualization (Fabrikant, 2001; Fabrikant, Montello, Ruocco, & Middleton, 2004; Montello & Fabrikant, 2003). In addition, experiments and surveys are often conducted to evaluate the usability of GVis tools (Dêmsar, 2007; Fuhrman et al., 2005; Lobben, 2008).

2.2.2.1. Research Challenges in GVis

Although GVis has great potential to contribute to knowledge discovery and construction, GVis research has just begun and there are still many research challenges. The ICA research agenda provides four "GVis research challenges" (MacEachren & Kraak, 2001). The next four sections explain those research challenges.

2.2.2.1.1. Experimental and multimodal "maps." Emerging technologies such as Virtual Reality reflect the demands of experiential and multisensory interaction (Dykes et al., 2005). Development of GVis technologies for these modes of information access is one of the research challenges. There is a general assumption in current GVis research that the abstraction, summarization, or aggregation of information is essential to discover meaningful knowledge, while virtual reality explores a more experiential representation of information for knowledge discovery. Developing technologies that can utilize the potential of virtual realism and multisensory representation is important for GVis research in order to incorporate the power to visualize and analyze geographic information in a more realistic view (Wood, Kirschenbauer, Döllner, Lopes, & Bodum, 2005). Practical applications for immersive environments are navigation systems with mobile devices (Coors, Elting, Kray, & Laakso, 2005), and training of fieldworkers (Dykes et al., 1999). Data representation of geographic data and spatio-temporal data requires powerful rendering techniques due to the size and complexity of those datasets. Therefore, the capability of handling large datasets is another research challenge.

2.2.2.1.2. Large datasets. Large volume, complex geographic data demands new techniques, tools, and approaches for better knowledge discovery with GVis. Although the concept of GVis is to draw upon human visual ability to discover patterns, trends, and relationships from complex data, existing GVis tools are not applicable to large volume datasets. A key issue here is the development and integration of GVis methods with geocomputational techniques (discussed later in this chapter) (Gahegan, Wachowicz, Harrower, & Rhyne, 2001). Since data exploration of complex datasets, such as spatio-temporal datasets or mobile object data (MOD), requires exploratory functionality from many perspectives, visualization methods combined with geocomputational methods, including self-organizing maps and neural networks, have been proposed (Guo, Gahegan, MacEachren, & Zhou, 2005).

2.2.2.1.3. Group work. Multiuser systems have become more available due to the advances of telecommunication technologies, providing more opportunities for group work. However, GVis research has been driven mostly by individual experts, resulting in tools and methods for individual use (Dykes et al., 2005). There is a growing demand for developing techniques to support collaborative GVis for better decision-making in applications such as the decision making process in a time of emergency or crisis (MacEachren & Cai, 2006). There are several research challenges in this field (MacEachren & Brewer, 2004):

- Developing a theoretical understanding of the cognitive and social aspects of both local and remote collaboration mediated through display objects in a geospatial context (Fuhrman & Pike, 2005; MacEachren & Cai, 2006)
- Development of approaches to multiuser system interfaces that support, rather than impede, group work (Gahegan et al., 2001; MacEachren, 2005)
- Understanding ways in which the characteristics of methods and tools provided to support collaboration influence the outcome of group work (Hopfer & MacEachren,

2007)

- Initiation of a concerted effort focused on integrating, implementing, and investigating the role of the visual, geospatial display in collaborative science, education, design, and group decision support (Brodlie, 2005).

As stated above, works with multidisciplinary efforts are important aspects to achieve these goals. In addition, it is important to develop and evaluate human-centered tools and methods for collaborative works that enhance effective human-computer interaction for better decision making.

2.2.2.1.4. Human-centered approach. Another significant challenge is the incorporation of human-centered approaches to GVis methods and tools, which leads to the integration of technological advances of GVis and efforts in human spatial cognition and the potential of visual representations to enable thinking, learning, problem solving and decision making (Fabrikant & Skupin, 2005). This is a field that is closely related to information visualization, whose goals is to provide compact graphical presentations and user interfaces for interactively manipulating large numbers of items, possibly extracted from far larger datasets. Plaisant (2005) proposed research challenges towards universal usability of information visualization tools:

- Development of tools that can handle large volume datasets
- Development of tools that are accessible to a wider group of diverse users

From a GVis perspective, Slocum et al. (2001) proposed research challenges in the context of cognitive usability:

- Development of geospatial virtual environments
- Dynamic representation methods

- Metaphors and schemata in interface design
- Difference in individual work and group work
- Collaborative GVis
- Evaluating the effectiveness of GVis methods

GVis research topics are interrelated to each other since some of the challenges overlap with other research challenges that MacEachren and Kraak (2001) proposed. For example, research on spatialization has been utilizing the basic notions of geography — such as distance and scale — to understand the cognitive aspect in visualization (Fabrikant et al., 2004; Montello & Fabrikant, 2003) as well as the browsing ability of spatialized large datasets (Fabrikant, 2000). Classification of interactivity types in GVis and discussion on the benefits of those interactivity types provide insights for better user-centered tools (Crampton, 2002). To understand the cognitive aspect of GVis tool users, evaluation of interactivity and visualization methods is important as well (Brewer, 1997; Dykes, 2005; Fabrikant, 2001; Fuhrman et al., 2005; Lobben, 2008; Tobón, 2005). In addition, there are needs for the development of both theories and applications for universal access and usability for geographic data, requiring new approaches and methods to support personalization of GVis tools for particular users and groups of users for GVis tasks (Brodlie, 2005; MacEachren & Kraak, 2001).

Although GVis seeks tools and methods to find patterns and trends in data with visual exploration, computational methods are also useful to evaluate the results or findings from visual exploration. In the next section, Knowledge Discovery in Databases (KDD) focuses on computational methods in data exploration, which can complement GVis methods.

2.2.2. Knowledge Discovery in Databases

KDD is a strategy for analyzing large volume datasets that are stored in databases. It is defined as '*the non-trivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data*' (Fayyed, 1996). A need of techniques for the emerging large volume datasets – along with the improvement in information technology and subsequent development of monitoring techniques — accelerated the development of KDD (Miller & Han, 2009; Wachowicz, 2005). The purpose of KDD is to seek hidden information, trends, characteristics, or structure in the data and create knowledge based on the findings from the search process. KDD was originally developed by several disciplines such as statistics, machine learning, pattern recognition, numeric search, and scientific visualization as an approach for exploring massive datasets that are too complex and difficult for human abilities to handle (Miller & Han, 2009). Although data mining is the more popular word for knowledge discovery, KDD is a broader process than data mining.

There are different descriptions of KDD process, including the nine-step process proposed by Fayyed (1996) as follows:

- Developing an understanding of the application domain, the relevant prior knowledge, and the goal of the end-user
- Creating a target data set: selecting a data set, or focusing on a subset of variables or data samples, on which discovery is to be performed
- Data cleaning and preprocessing: operations such as noise or outlier removal, strategies for handling missing data fields, and so on
- Data reduction and projection: finding useful features to represent the data depending

on the goal of the task

- Choosing the data mining task: determination of the goal of KDD such as classification, regression, clustering, and so on
- Choosing the data mining algorithm(s): choice of method(s) to be used to seek for patterns and trends in datasets
- Data mining
- Interpreting mined patterns, possible return to any of the steps above
- Consolidating discovered knowledge: incorporating this knowledge into the performance system, or simply documenting it and reporting it to users.

Although the process above suggests a linear process for KDD, KDD is an interactive process that often requires iterative tasks; therefore, KDD does not often follow a linear progression (Fayyad, 1996; MacEachren et al., 1999). The KDD tasks — such as segmentation, dependency analysis, deviation and outlier analysis, trend detection, generalization, and so on— are tied to specific methods — classification, clustering, querying, and so on: see Miller and Han (2009) and MacEachren et al. (1999) for more detailed descriptions of KDD tasks and methods.

Data warehousing is a system that integrates data from several sources. It contains large volume datasets that were collected from many different sources and is often maintained separately from the operational databases (Shekhar, Lu, Tan, Chawla, & Vatsavai, 2009). The advantage of utilizing a data warehouse is to provide an integrated system of dispersed heterogeneous databases so that decision makers receive benefits from decision support tools that can provide aggregated and summarized data (Bédard &

Han, 2009). In short, the goal of data warehousing is to extract useful knowledge from massive and detailed data dispersed in heterogeneous datasets.

Data warehousing technologies provide functionalities to manipulate datasets for data exploration. One of the common tools for summarization and integration of datasets is online analytical processing (OLAP). OLAP provides interactive functionality for multidimensional summarization of data with simple functions such as drill-down, drill-up, and drill-across that are built into the data warehousing tools so that the user can explore multidimensional data at arbitrary granularity levels.

The *data cube* is an effective OLAP method for summarization of highly multivariate data. The data cube is an operator that allows the user to aggregate the data with all the dimensions that user needs. Its extension to geographic data is known as the *map cube*. A map cube can handle all the geographic components of spatial data such as raster format, vector format, network component, reference systems, and so on (Shekhar et al., 2009).

Although most KDD research focus on nonspatial data, advancement of technology enabled us to collect a large amount of complex and highly multidimensional geographic data, including spatio-temporal data, which has led to the development of geographic KDD methods (Andrienko, Andrienko, Fischer, Mues, & Schuck, 2006; Frihida et al., 2004; Mennis & Peuquet, 2003). In geographic information science (GISci), data mining and knowledge discovery techniques applied to explore spatial data are often called Geographic Knowledge Discovery (GKD).

KDD methods for nonspatial data are not directly applicable to geographic information because of the data's nature of high dimensionality, inherent spatial dependency and heterogeneity, the complexity of spatio-temporal objects and rules, and its diverse data types (Miller & Han, 2009). Geographic information usually has high dimensionality because it has its locational information, which needs at least two dimensions, as well as high levels of attribute information. Second, spatial dependency represents the notion that attributes at proximal locations are more closely related to each other. On the other hand, however, spatial heterogeneity derives from the uniqueness of geographic locations. These characteristics are usually treated as something cumbersome in statistical analysis but they are useful information for exploring geographic phenomena. Third, it is more complex and difficult to handle spatio-temporal objects and relationships than handling nongeographic objects and relationships. In addition, handling time in spatial entities is also a complex task (Hornsby & Egenhofer, 2002). Fourth, since digital geographic datasets are stored in several different formats, such as vector and raster format, there is the need to create methods to handle different data formats at the same time for knowledge construction (Golledge, 2002).

Spatial data mining is also a powerful technique to extract trends or characteristics from large volumes of geographic information. It encompasses the application of computational tools to seek for hidden characteristics in spatial and temporal databases (Miller & Han, 2009). In contrast to traditional data mining, spatial data mining focuses on the spatial aspects of the data such as locational information of individuals and sometimes the temporal aspects as well. Common spatial data mining techniques include spatial segmentation, spatial clustering, spatial trend detection, geographic characterization and generalization, spatial outlier detection, and so on (see Miller & Han, 2009 for a more detailed description). Studies have also been conducted with activity diary datasets, such as text mining, that contain location, time, the type of activity, and the duration of activity (Kwan, 2000), and also with GPS-based datasets used to explore patterns in spatio-temporal human movements (Smyth, 2009). There is also an effort to discover outliers in the data using distance as the geographic criteria for detecting outliers in individual trajectory datasets (Ng, 2001).

The *space-time cube* is an extended approach of the map cube, especially for disaggregated spatio-temporal data. It defines a graphic environment that allows the exploration of data from three axes; x and y axis as the representation of geographic space, and z axis as the time component (Kraak, 2003). Space-time trajectories can be visualized after necessary data are queried from the databases and processed by the cube methods (Figure 2.4).

2.2.3. Integration of GVis and KDD

It is clear that both GVis and KDD aim to find, relate, and interpret interesting, meaningful, and unknown patterns and relationships in complex and large datasets such as spatio-temporal datasets (Wachowicz, 2005). KDD research often claims the importance of visualization in the process. On the other hand, computational methods expand the capability of visual data exploration not only for map making, including automation, optimization of the workflow, and ability to easily vary design (Buckley & Hardy, 2007), but also deeper and better knowledge construction.

Gahegan et al. (2001) proposed some research challenges for the integration of GVis and KDD in terms of data, system, visual techniques, modes of inference, and collaboration. In those research challenges, The International Cartographic Association (ICA) focuses on three issues, namely, the geographic properties of data, the construction of knowledge, and visualization. First, designing useful visualization techniques for large volume and highly multivariate spatial and spatio-temporal data is an ongoing challenge. Representation of spatial and time components of data should be investigated. Second, since there is no universal language for geographic representation, better conceptual structures are required for computationally based geographical models. It is urgent to specify geographically oriented concepts to identify, and develop, a means of representing them in current GIS or database schema. A definition of computational and visualization methods to detect, observe, and communicate follows below. Third, it is important to create visualization environments that allow the user to interact with tools that construct meaning. The challenge here is to construct an environment that can seamlessly address all mining and knowledge construction activities (Gahegan et al., 2001).

Wachowicz (2005) proposed the GeoInsight approach for the integration of GVis and KDD — this is based on the framework of MachEachren and Kraak (2001). The GeoInsight concept defines integration in three levels: conceptual, operational, and implementational. The goals are as follows:

- the conceptual level for defining the goals of a knowledge construction process;
- the operational level for integrating the methods developed independently in each of the fields;
- the implementation level for combining a variety of tools within a singular system environment.

The conceptual level is used to define the goals of a knowledge discovery process. This is because unclear goals can lead to a choice of inappropriate methods in a knowledge construction process. The goals based on a knowledge discovery process are related to the answers of the following questions:

- What kind of spatio-temporal data is meant to be explored?
- What particular kinds of outcomes are required from the process?
- Who are the users interested in the knowledge construction process?

The answers determine the kind of knowledge to be constructed and how the knowledge is constructed as well. In this conceptual level, no decision is made about the selection of data mining tasks or algorithms, nor about the choice of visual representation or visualization tools to be used. The main focus is to understand the prior experience and the goals of a user, and only after this can we define how the knowledge discovery process will be constructed.

The operational level specifies appropriate methods, and combinations of methods, for achieving conceptual goals. In the GeoInsight approach, task analysis (Kirwan & Ainsworth, 1992) is utilized to support the task-method-operation concept. Tasks are the main stages of a KDD process. Methods define ‘how’ the tasks can be performed to achieve the conceptual goal. An operation is a statement of ‘what’ is to be accomplished by structuring a hierarchical or sequential organization of actions. The main goal of the task-method-operation concept is to facilitate the human-centered approach and enhance the interactive and intuitive properties in the knowledge discovery process.

The implementation level deals with selecting the execution of algorithms to perform the data mining tasks, and also the operations to build effective visual representations and interactive forms. The main concern is to create an integrated computer environment with the necessary components for data exploration for each user — the goal here is to integrate different functionalities into a single computer environment.

The GeoInsight concept aims to develop a more complete integration between GVis and KDD, facilitating the development of a more flexible, interactive, and human-centered knowledge construction process for spatio-temporal data. Spatio-temporal data and MOD are complex in structure and increasing in size, requiring robust methods and tools for data exploration, which is discussed in the next section.

2.2.4. GVis and KDD with MOD

As stated in the introduction chapter of this dissertation, MOD are increasingly available due to the development of mobile devices. Many scientists have been proposing tools and methods for visualizing and analyzing MOD for better knowledge discovery. However, there are many issues that relate to the nature of MOD, such as data acquisition and storage methods, representation methods, computational methods to analyze MOD, and interface design for GVis tools.

First, data acquisition methods and storage methods of mobile objects need careful attention in terms of data accuracy and efficient query functionality for further use of the data. Locational errors and locational uncertainty problem can affect the outcome of analysis, such as visualization, data mining, and statistics (Kuijpers & Othman, 2009). Since locational error always exists in the MOD collected by tracking devices, some researchers have proposed methods to mitigate the effects of errors from data acquisition methods (Laube, Duckham, & Wolle, 2008; Lee, 2004; Nittel, Duckham, & Kulik, 2004).

In addition, MOD often have missing observations due to limitations in tracking techniques, resulting in the requirement of assessment or interpolation of locations at the missing time periods (Moreira, Ribeiro, & Saglio, 1999; Wentz et al., 2003), as well as noise reduction methods by mathematical approaches (Neutens et al., 2007; Okabe et al., 2006) or by explicit database representation (Jonsen, Myers, & Flemming, 2003; Pfoser, Jensen, & Theodoridis, 1999). Of equal importance are database design and data storage techniques for MOD; this is because of its nature to change position and shape according to time (Pfoser, 2002; Song & Roussopoulos, 2001; Wolfson, Xu, Chamberlain, & Jiang, 1998).

Database design for mobile objects is also important. One of the major actions for databases — querying — plays an important role for aggregation and summarization of MOD (Wolfson et al., 1998). Efforts on the development of mobile object databases (Güting, 2005), and indexing methods for mobile objects (Pfoser, 2002), have led to the fast and efficient extraction of useful information from the database for further usage on MOD, such as representation modeling and computational analysis.

A second research trend in MOD is data representation methods. Representation of MOD is tightly connected to database design since the visualization of data is tied to the structure of data. One of the major approaches for MOD representation is time geography, which was introduced previously in this chapter. Miller (2005c) extended the theoretical framework of Hägerstrand (1970) so that it can be utilized analytically. Similar approaches with the concept of time granularity have been developed in order to query and visualize mobile objects with arbitrary time resolution, which expands the possibility of exploratory data analysis (Erwig, Guting, Schneider, & Vazirgiannis, 1999; Hornsby & Egenhofer, 2002). Hendricks et al. (2003) applied the data representation method by Hornsby and Egenhofer (2002) to model wayfinding behavior. Other efforts of modeling mobile object are application-specific simulations (Bian, 2004; Westervelt & Hopkins, 1999).

Third, geocomputational techniques are essential to find patterns, trends, and relationships in large volume and complex datasets of mobile objects. Geocomputational techniques focus on specific tasks, such as cluster detection and outlier detection, while interactive visualization tools rely on the user's ability to detect patterns (Dykes & Mountain, 2003; Huang, Chen, & Dong, 2008; Imfeld, 2000; Laube, Dennis, Forer, & Walker, 2007). Geocomputational methods often utilize characteristics of mobile objects that can be calculated from data – such as direction, speed, sinuosity, and so on (Hendricks, Egenhofer, & Hornsby, 2003). In addition, algorithms to detect similarity and dissimiliary between mobile objects also detect nominal patterns or outliers in the movements (Cheng & Li, 2006; Ng, 2009; Shirabe, 2006). Computational methods such as Self-Organizing Maps (SOM) are utilized to visually uncover patterns of interaction in movements (Skupin, 2008; Yan & Thill, 2005). SOM is also a useful approach to summarize MOD with many variables, such as demographic data visualized in a two-dimensional view (Skupin & Hagelman, 2005). Moreover, topological relationships between mobile objects have been proposed to store spatial partition information for these data (Tøssebro & Mads, 2004), leading to better organization of MOD. Other methods include fractal analysis and random walk analysis for pattern detection of animal and insect movement (Bascompte & Vila, 1997; Kareiva & Shigesada, 1983; Nams, 2005; Whittington, Clair, & Mercer, 2004), pattern detection by applying methods to abstract the movement data (Hornsby & Cole, 2007), development of queries for pattern detection (Mousa & Rigaux, 2005; Sistla, Wolfson, Chamberlain, & Dao, 1997) and human interaction possibility analysis (Yu, 2006). Computational and visual techniques are often incorporated into GVis tools that enable interaction with the user of those tools by providing more functionality for data exploration.

Fourth, GVis tools for mobile objects provide opportunities to visualize and analyze MOD in order to find patterns, trends, and relationships. Tools also provide flexibility of analysis (interaction) so that the user of tools can manipulate the functionality of tools, such as visualization methods, parameter settings for computational methods, and so on. Many tools incorporate interactivity and capability to incorporate large volume individual-based spatiotemporal datasets (Buliung & Kanaroglow, 2004; Kapler & Wright, 2004; Shaw, Yu, & Bombom, 2008). For example, decomposition of data with specific characteristics of mobile objects such as direction, speed, and so on is utilized to detect similarity or dissimilarity between mobile objects (Andrienko & Andrienko, 2008; Dykes & Mountain, 2003; Laube et al., 2005).

Most tools consist of both visualization components and KDD components in order to enhance the interactive properties for better data exploration (Andrienko & Andrienko, 2008; Wood et al., 2005). Concurrent development of a number of methods and techniques to analyze MOD, as explained above, leads to a deeper understanding of individual-based mobile objects movement in space and time (Andrienko & Andrienko, 2007; Mountain, 2005; Yu, 2006). Although these tools suggest the importance of interactive properties and analytical functionalities of GVis tools, there is no standard agreement about effective methods for visual exploration and pattern detection process. Moreover, these tools are not yet applicable to group work in GVis, which is one of the major challenges for GVis.

In this dissertation, one of the main objectives is to develop an interactive GVis toolkit that will provide high levels of user interaction to explore MOD. The toolkit focuses on detecting similarities between individual mobile objects, and the user can change the settings of several parameters, facilitating deeper explorations of datasets. The toolkit in this dissertation also links the summarized and visualized trajectories to data mining techniques. The toolkit in this research can have applications such as transportation, epidemiology, and evacuation planning. As an example, the next section describes a major application area, namely, activity-based analysis in transportation.

2.3. Activity-based Analysis

Recent decades witnessed a new wave in travel demand analysis in transportation research. Through the so-called 'activity-based' approach, which focuses on individual activities, scheduling and spatial choices started receiving attention as a method to overcome the shortcomings of conventional transportation analysis – the *Urban Transportation Modeling System* (UTMS), or four-step models. In the late 1950s, four-step models were the dominant mode of travel demand modeling at the level of the traffic zones, especially traffic analysis zones (TAZ), indicating that four-step models treat traffic zones as aggregate collections of individuals. Four sequential steps generate the estimated travel demand: trip generation, trip distribution, modal split, and trip assignment. Although this four-step model has been widely accepted and used, the major drawback of these models is the lack of behavioral content (Wang & Cheng, 2001).

Activity-based analysis exploits characteristics of disaggregate-level information. It receives attention as an approach to overcome shortcomings in the four-step approach towards better travel demand prediction. First, the activity-based approach focuses on the decisions of individuals and households for specific activities. The information required is where, when, how, for how long, and with whom such activities will occur (Frihida, Marceau, & Theriault, 2004). Second, dynamic representation of individual-based travel demand modeling is essential in order to incorporate the activities that occur at different locations and different times: four-step models are static. Each vehicle simultaneously appears on the road network, ignoring the realistic space-time conditions (McNeally, 1998). Thus, there is much research on the integration of the activity-based approach and Geographic Information Systems (GIS), since GIS can incorporate a time component in activity modeling, for which the efforts have just begun. Third, it is important to incorporate interdependencies among these decisions as well as interdependencies between household members. Linkage between activities and individual people often occur in daily lives. For example, people may add another unplanned activity between two planned activities — a person may stop by a coffee shop for a few minutes. Another example is that people suddenly change their schedules due to unanticipated incidents. The activity-based approach attempts to incorporate these factors in the sequence of activities, and the interaction among individuals, while a conventional four-step model does not. The characteristics of both an activity-based approach and a conventional modeling approach, proposed by McNeally (1998), are listed in Table 2.1. The activity-based approach is more applicable to the recent social and urban trends, such as nucleus and single-parent families, urban sprawl, the rising number of personal vehicles, the information-based economy, globalization, telecommuting, and environmental concerns (Frihida et al., 2004).

Although the activity-based approach has shown the potential toward better travel demand modeling, there are diverse issues to be addressed. According to Pas (1995), they are:

- demand for activity participation;
- activity scheduling in time and space;
- spatial-temporal, interpersonal, and other constraints;
- interactions in travel decisions over time;
- interactions among individuals; and
- household structure and roles.

Wang and Cheng (2001) classified the existing activity-based studies. One trend is to examine observed activity and travel behavior empirically. The purpose is to formulate hypotheses about activity and travel behavior. Indices, such as Representative Activity Pattern (RAP), reveal the overall patterns of activity decisions in order to acquire more detailed and accurate travel trips (McNeally, 1998). Other studies examine one of the aspects of activity-based analysis such as interaction and scheduling (Bowman & Ben-Akiva, 2001). KDD and GVis are also key strategies to find patterns in travel demand survey data (Frihida et al., 2004). A single approach cannot lead to the understanding of individual activity and travel behavior, requiring more focus on the examination of characteristics in the activity-based approach to the development of efficient activity-based models.

Another trend is the development of activity-based models. These models aim to incorporate individual-based activities and travel behavior into a framework that can predict human activity and travel patterns in a more flexible way, reflecting schedule changes in the travel environment (Wang & Cheng, 2001). This stream of studies relates to the approaches in time geography where time geographers attempt to create methods representing space-time behavior of individuals for further analyses (Miller, 2005c; Yu, 2006). Incorporation of time in an activity-based approach with the integration of GIS framework is critical even though current GIS is still inadequate in handling data analysis of flows, complex movements, and temporal changes (Goodchild, 2000; Shaw & Wang, 2000). The relational database approach to develop queries for activity-based analysis succeeds in handling spatio-temporal data of travel behavior to some degree; however, its complexity and high computational burden are still under consideration (Frihida et al., 2004). Some studies proposed an object-oriented paradigm to tackle this issue, adding more flexibility in the modeling process in that the models consist of several entities such as people, activity, trip, activity plan, and activity scheduling (Frihida et al., 2004). In addition to the issue of incorporating time into activity-based analysis, the volume of the activity-data is also a great challenge because the amount of information in activity-based analysis is often large. Development of tools and methods to handle large volume datasets is another issue in the modeling process (Buliung & Kanaroglou, 2004).

Findings in this dissertation can contribute to studies of the activity-based approach by providing useful information and knowledge about individual-based spatio-temporal movements. Collaboration of GVis, KDD and activity-based modeling can lead to the development of more efficient and robust models and tools for activity-based approaches.

2.4. Summary

Research fields introduced in this chapter have significant roles in understanding the movements, activities, and relationships of mobile objects. Time geography can provide a useful framework for conceptualizing and analyzing mobile objects. KDD and GVis provide tools to uncover patterns and trends in the datasets in an exploratory manner. The next chapter introduces the interactive visualization tool in this research. Many interactive properties with visualization methods enhance the flexibility of visual exploration for effective knowledge construction.

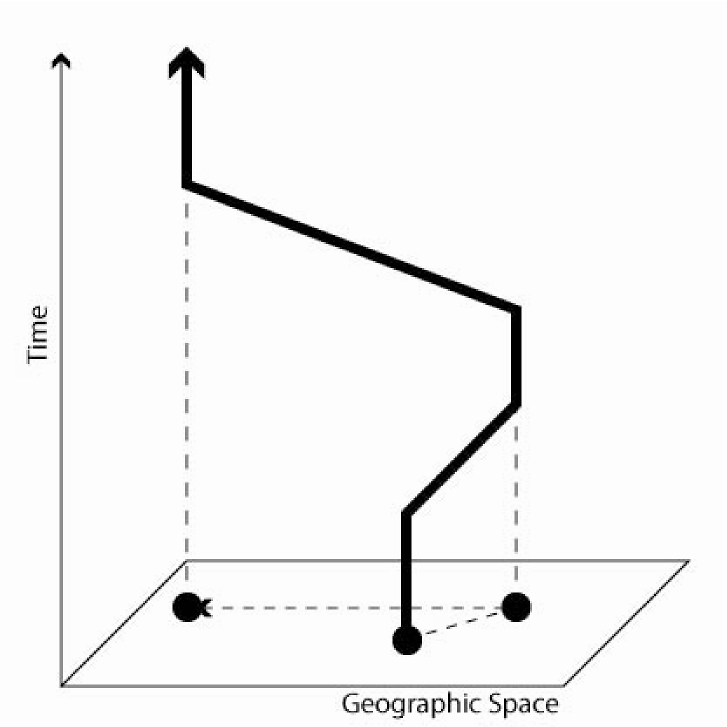


Figure 2.1. Space-time path.

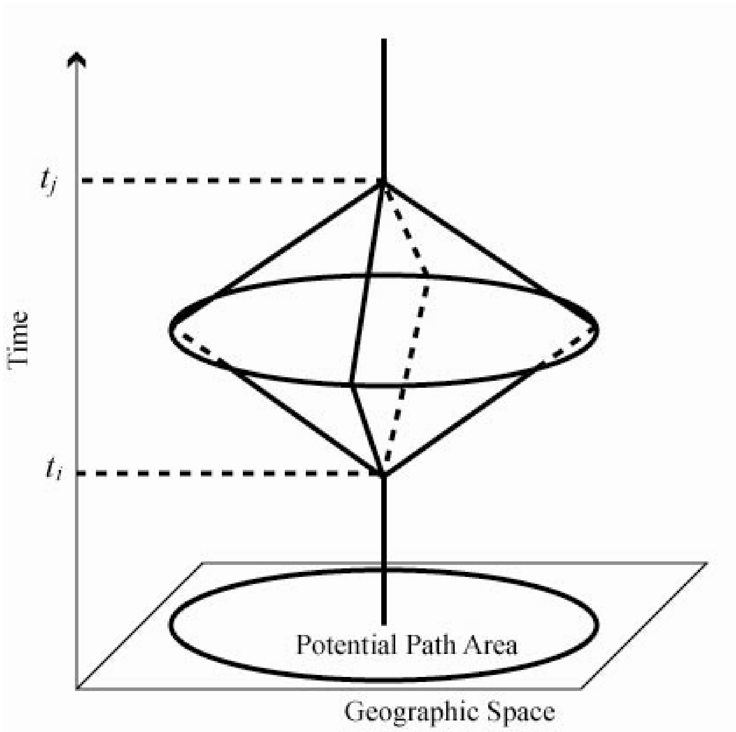


Figure 2.2. Space-time prism.

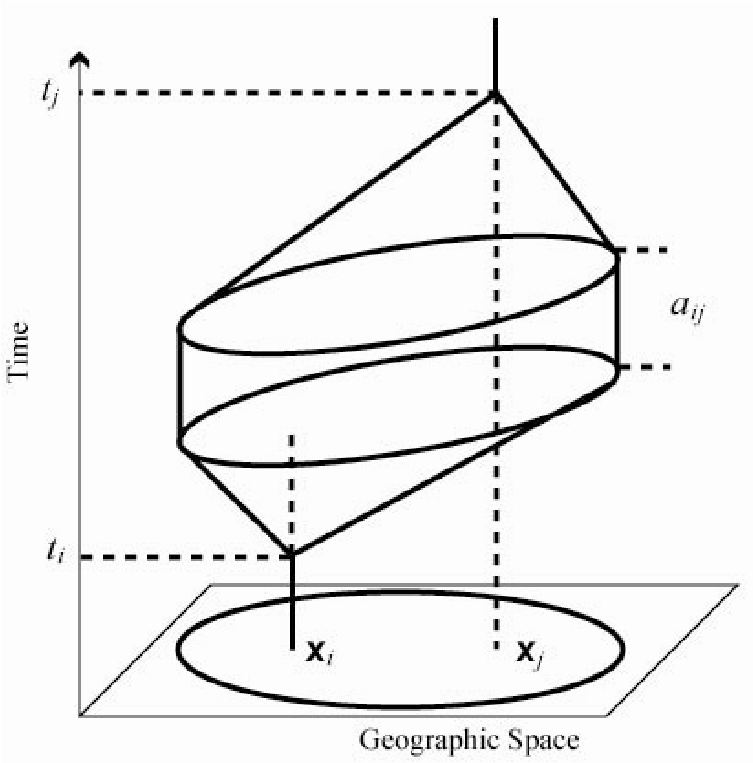


Figure 2.3. A general space-time prism.

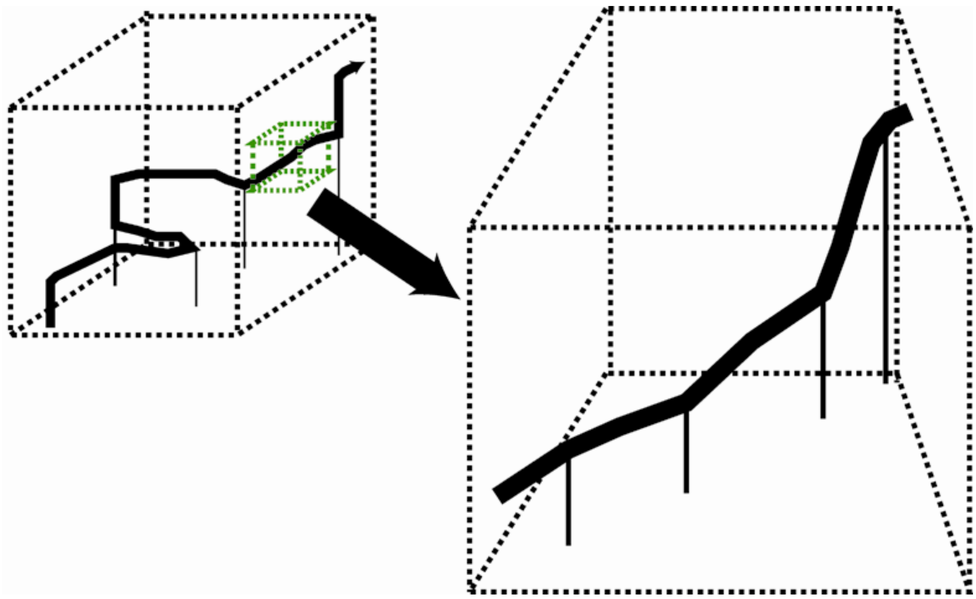


Figure 2.4. Space-time cube.

Table 2.1. Characteristics of activity-based analysis and conventional model process.

Characteristics of Activity-based Approach	Characteristics of Conventional Model Process
Travel is based on activity participation of individuals and households.	Trip-based versus activity-based.
Activity participation involves generation, spatial choice, and scheduling.	Unlinked daily household trip generation rates applied with zonal demographics to expand to zonal trip-ends.
Activity and travel behavior is delimited (or even defined) by constraints.	Distribution of unlinked trip ends accomplished via aggregate interaction models with general network impedances.
Linkages exist between activities, locations, times, and individuals.	Conventional 4-step process models network-level traffic effects via static assignment.
Alternate decision paradigms are probable	All disaggregate spatial and temporal information (chaining and time-of-day) is lost.

3 METHODOLOGY

3.1. Overview

This chapter describes the methodology of this dissertation. The discussion consists of five sections that explain the functionalities of the visualization toolkit developed in this dissertation: 1) vector algebra; 2) time aggregation methods; 3) similarity functions; 4) data summarization; and 5) data mining. This dissertation develops a highly interactive graphical user interface (GUI) for exploratory spatial data analysis (ESDA) of mobile objects, which aims to propose methods to analyze individual and collective mobility patterns of mobile object data that have been produced at a tremendous rate on a daily basis.

First, vector algebra is a simple and less computationally expensive method to draw and visualize trajectories of mobility data. Fast rendering of trajectory visualization facilitates a smooth and more interactive environment of exploratory data exploration with the GUI software. In addition, due to its simplicity, vector algebra is efficient at visualizing a massive number of mobility data at once, which also enhances the fast and smooth interaction between the visualization toolkit and the users.

Second, time aggregation methods allow exploration at different levels of movement generality: the user of the tool can explore mobility data with the temporal scale of their interest. Temporal granularity is a critical parameter for visual data exploration as well as data mining and statistical analysis, since it can cause substantial differences in the results of visualization and analysis (Hornsby, 2001). In addition, since spatial as well as temporal information are essential components of mobile object data, data exploration with arbitrary spatial and temporal scales have a potential to provide new insights and findings that lead to the development of geographic theories and models.

Third, by using time aggregation methods at a given level of generality, individual trajectories can be combined into synthetic summary trajectories or classified into groups based on locational, directional, and geometric similarity. The degree of similarity required to detect similar mobility patterns is left to the user of the toolkit, which is another interactive property in data exploration. In addition, summarizing massive mobility data is efficient because mere visualization of large volume mobility data becomes so cluttered that it is hard to identify any obvious patterns and trends in space and time among the individuals. Therefore, the summarized space-time trajectories can help overcome the problem and facilitate the search for patterns and trends hidden in large mobility datasets (Shaw, Yu, & Bombom, 2008).

Fourth, data summarization methods provide summary information for visualized trajectories that are queried and analyzed by the data aggregation methods. This component is related to confirmatory statistical analysis in geography. In particular, directional statistics are utilized to summarize the visualized mobility data that complements the visual exploration. A GUI screen provides directional statistical information such as the number of trajectories, average velocity of trajectories, and average direction of trajectories. In addition, axis conversion – another interactive property in the visualization toolkit – allows the user to explore the data from different viewpoints. The main screen in the toolkit displays trajectories using *x* and *y* coordinates, which represents the two-dimensional space, and the third axis – time, which is denoted as *t*. The user can choose two of three axes, namely, *x*, *y*, and *t*, to visualize trajectories in a three-dimensional view.

Fifth, the functionality to export mobility properties to data mining analysis is also added to the toolkit, which is an attempt to integrate the geovisualization approach and knowledge discovery in databases approach. Geometric similarity information that is produced by one of the similarity functions explained above is examined to explore the spatial and attribute information of mobility data. This dissertation focuses on decision tree analysis as a means of discovering significant properties of trajectories to explain the detected patterns.

Several techniques enhance the interactive properties of the visualization toolkit. C# programming language is the main language to develop the toolkit. In addition, Microsoft SQL Server 2005 provides the functionality for data storage and query, which manages the transactions between the interface and the database. The sections below explain each component of the visualization toolkit in detail.

3.2. Vector Algebra

Data exploration of large volume datasets requires simple and fast visualization techniques so that users of the toolkits can explore the data smoothly and easily. This is because the visualized trajectories must be updated and redrawn frequently whenever the user changes parameters in the toolkit. Therefore, a simple and straightforward method to represent the space-time path is essential. In addition, the toolkit should be able to easily calculate several values that characterize MOD, such as direction, distance, magnitude, and so forth to provide information including directional statistical information and the outputs for data mining. This functionality gives us more options for exploratory data analysis because those values have the potential to explain and represent the overall trend in movement of the mobile objects (Shirabe, 2006).

Vector algebra is a very simple line geometry that contains essential components for mobile objects, such as length, direction, start point, and end point. It is a collection of two-dimensional vectors that contain an *x* coordinate and *y* coordinate of each observed location. The toolkit delineates trajectories as either a straight line or a polyline of connected vectors (Figure 3.1) based on temporal, spatial, and shape aggregation methods that are explained in the next two sections.

3.3. Aggregation Methods

This dissertation develops time aggregation and similarity measures to enhance the discovery of multiscale patterns in MOD. The time aggregation methods allow the user to state a time interval of interest and a time granularity within that interval to reconstruct individual trajectories at different levels of movement generality. Given these reconstructed trajectories, the user can apply similarity measures to aggregate individual trajectories based on location and geometry to generate synthetic trajectories that reflect collective movement patterns at the selected scale. The following sections explain the details of each component.

3.3.1. Time Aggregation Methods

Since the resolution of time in spatial objects can cause substantial differences in the results of visualization and analysis (Hornsby, 2001), it is a critical parameter for visual data exploration as well as data mining and statistical summarization. This temporal resolution is often called *time granularity*. Adding functionality to change time granularity gives us the possibility to explore the data at different time scales. Visualization with coarse time granularity is more appropriate to explore broad scale movement while visualization with refined time granularity is more suitable for detailed movement of the mobile objects. This indicates that time granularity can affect the visualization results of the movement of the mobile objects dramatically (Hornsby & Egenhofer, 2002). Although Hornsby and Egenhofer (2002) presented a conceptual model for this issue, there are few practical methods available for mobile objects.

In this research, two time components determine time granularity in order to aggregate the trajectories of mobile objects; *time range* and *time interval* (Figure 3.2). Time range is the time period that is queried from databases and visualized. For example, if the user wants to visualize parts of trajectories for the time between 10:00 a.m. and 11:00 a.m., then 'one hour' is the time range. On the other hand, time interval is the time granularity, the minimum time unit that divides time range equally. For example, if the time range is 1 hour and the time interval is 10 minutes, the number of time stamps is six. Time range determines the scale of the visualized time period and time interval works as a variable of time granularity.

The user can change these two time parameters for data visualization and exploration. Assume the actual trajectories from the database as in Figure 3.2-a. As the time interval increases, the three trajectories become exactly the same, as shown in Figure 3.2-c. This occurs because the three trajectories start and end at a similar origin and destination. This example shows the impact and importance of selecting an appropriate time resolution for visual data exploration.

3.3.2. Similarity Functions

In addition to the capability of exploring time components, aggregation methods with respect to spatial similarity functions and shape similarity functions measure the similarity of trajectories. They are *locational similarity*, *directional similarity*, and *geometric similarity*. The similarity functions aggregate some trajectories before visualization. Each similarity function returns a value that represents the similarity of two or more trajectories. The user of the toolkit manually determines the threshold value to detect similar trajectories so that the degree of aggregation is left to the user: this is another interactive property of this visualization toolkit.

Once the similarity functions calculate the similarity index values, a density-based clustering method, DBSCAN (Density-Based Spatial Clustering of Application with Noise) (Han & Kamber, 2006), algorithm discovers the clusters of trajectories – these clusters determine the number of groups that contains more than two trajectories that are similar to each other. DBSCAN is a hierarchical clustering method that discovers clusters with arbitrary shapes. This method is described below.

3.3.2.1.Locational Similarity

This function measures the locational difference between two trajectories, quantifying the similarity of two trajectories in terms of the spatial component. It enables the user to aggregate the trajectories that are close to each other. One method is to calculate the Euclidean distance between two locations of mobile objects at the same time stamp (Steiner et al., 2000). In addition, the technique of Spectral Angle Mapper (SAM) has potential to measure the locational difference in the sequence of time (Dennison, Halligan, & Roberts, 2004). Another example is to apply clustering analysis to create generalized space-time paths (Shaw, Yu, & Bombom, 2008). This research utilizes the Euclidean distance method proposed because of its simplicity:

$$\begin{aligned} D_{(a,b)} &= \sum_{i=1}^{n} d_i \\ d_i &= \sqrt{(x_{ai} - x_{bi})^2 + (y_{ai} - y_{bi})^2} \end{aligned} \qquad (3.1)$$

where x and y are coordinates of nodes of the trajectories, a and b are the identifiers of trajectories, i is the order of the nodes, d_i is distance between the node of trajectory a and the node of trajectory b, and n is the number of nodes. Since the number of nodes in each trajectory is same, which is defined by time range, the locational difference in distance at each time stamp is measured (Figure 3.3). The sum of the distances is the locational distance, which is $D_{(a,b)}$. If $D_{(a,b)}$ is zero, it indicates that two trajectories are exactly same.

Once calculation of the similarity values for pairs of trajectories is complete, a density-based clustering method DBSCAN discovers the clusters of trajectories. The user changes the value of $D_{(a,b)}$ – the threshold value – for data exploration. The DBSCAN algorithm calculates a $D_{(a,b)}$ value for each pair of trajectories and if more than two vectors are similar, the algorithm combines those two vectors into one vector. The location of the aggregated vector is the average location of the two trajectories (Figure 3.4, Figure 3.5).

In the example of Figure 3.5, locational aggregation of two trajectories A and B are represented. The calculation for more than three trajectories is as follows;

$$c_n = \frac{\sum_{i=1}^{k} a_n^i}{n} \qquad A_i = \begin{bmatrix} a_1^i \\ a_2^i \\ a_3^i \\ \vdots \\ a_n^i \end{bmatrix} \qquad C = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ \vdots \\ c_n \end{bmatrix} \tag{3.2}$$

where A_i represents vectors for trajectories that contain timestamps, C is the vector for the aggregated trajectories, a_1^i through a_n^i are each timestamps of the ith trajectory of A_i, c_1 through c_n are each timestamps of C, and n is the number of trajectories to be aggregated.

Figure 3.4 illustrates this aggregation process. In Figure 3.4-b, there is one cluster with two vectors aggregated into one vector, visualized as a wider trajectory (Figure 3.4-c). This aggregation makes visualization clearer so that the trends of mobile objects can be detected intuitively.

3.3.2.2. Directional Similarity

Another measure of similarity is the direction of each trajectory. Directional statistics measure the similarity among trajectories. Directional statistics are a collection of methods to discover the trends with respect to direction. Several research fields such as the wind direction analysis (Klink, 1998) and ecological field surveys (Cain, 1989) utilize this method. Directional statistical measurements such as mean direction, variance, and mode direction provide the overall tendency and variability of directional trends of the datasets (Klink, 1998).

Furthermore, there are two different directional models in directional statistics, namely, the cardinal directional model and the egocentric model (Klippel et al., 2004).

The cardinal directional model describes directions used mainly in cartography such as north, south, east, and west; it is an objective view, or absolute view, to define the direction. In contrast, the egocentric directional model describes an individual object's heading based on directions such as straight, left, right, back, and so on, which provides object-centered directional information. As is obvious in Figure 3.6, these two directional models provide different outputs even when the dataset is same.

This research utilizes both cardinal direction and egocentric direction – the user of the toolkit can choose either of the directional approaches. The directional statistical approach classifies trajectories and highlights the trajectories in the same group in the same color. The average cardinal direction of each trajectory is the sum of the degrees at each segment between one timestamp and another timestamp (Figure 3.6). This requires two steps. First, each segment of a trajectory converts itself to be a unit vector to extract the directional information only. Second, the algorithm calculates the sum of all of the unit vectors. The degree of the summed vectors is the average cardinal direction. On the other hand, the algorithm calculating the average egocentric direction uses two segments from two contiguous timestamps of a trajectory, calculating the change in direction from the first segment to the second (Figure 3.7). This sum is the average egocentric direction.

Directional statistics help to see the similarity of directions of vectors. After classifying vector directions in several groups, the vectors in the same group will be rendered in the same color. This functionality extends the range of data exploration to examine directional trends and spatial distribution of vectors.

3.3.2.3. Geometric Similarity

The third and last measure of similarity is the geometry of mobile objects. According to Vlachos et al. (2002), there are several issues involved in measuring geometric similarity. They are as follows:

- Different sampling rates or different speeds
- Similar motions in different locations
- Outliers
- Different lengths
- Efficiency

The first issue relates to the sampled data. There may be some missing portions of the data in sampling, leading to an inconsistent sampling rate (Vlachos, Kollios, & Gunopulos, 2002). Moreover, the speed of one mobile object can be faster than another one. The similarity function, therefore, has to deal with the missing values or inconsistent speeds. The second issue refers to the fact that the geometry may be similar but the locations of two or more mobile objects are different, i.e., one trajectory may be a simple displacement of the other. The similarity function should be consistent regardless of the locations of mobile objects. The third issue deals with outliers. Anomalies in the sensors of location-aware devices or human failure can cause this problem. If there are some outliers, some measures may return extreme values, even though there are only a few outlier observed locations (Vlachos et al., 2002). The fourth issue, length of the mobile objects, is a problem that relates to scale. Even though the geometry of mobile objects is similar, their scale might be different due to differences in trajectory lengths. Therefore, the similarity function should be a scale-free function, so that it can calculate the similarity of mobile objects with different scales. The fifth issue is the efficiency of the similarity function. The similarity function has to be adequately expressive but sufficiently simple, so as to allow for efficient computation.

There has been much research to cope with these challenges. This includes Dynamic Time Warping (DTW) (McIntosh & Yuan, 2005) and the Longest Common Subsequence (LCSS) method (Vlachos et al., 2002). DTW focuses on the most dissimilar parts of the objects, resulting in high sensitivity to noise in the data. On the other hand, LCSS considers the common portions of the objects. In spatio-temporal analysis, DTW stretches portions of the sequences to compare transition of locations along the temporal axis, so the dominant features, patterns of high and low values, are optimally aligned (McIntosh & Yuan, 2005). Since one of the trajectories always has its location so that the two trajectories overlap each other for calculation, it is not suitable for large volume datasets because it is computationally expensive.

There are some other techniques to tackle the issue of measuring similarity: fractal analysis and shape-based analysis for time-series datasets (Kim, Yoon, Park, & Kim, 2002). Analysis of the movements of animals and insects often use fractal analysis (Bascompte & Vila, 1997; Turchin, 1996; With, 1994). In addition, although the latter kind of research deals with shape-based retrieval, it only deals with time-series analysis for non-spatial data, such as stock data – it is not applicable to mobile objects.

Another method to extract geometric similarity is to integrate multiple indices of the object of interest. The combination of characteristics derived from the spatial or spatio-temporal objects generates new perspectives for pattern detection in data. For example, McIntosh and Yuan (2005) developed six indices that characterize spatio-temporal objects. They applied the DTW method to temporal sequences of the six indices to examine the similarity among spatio-temporal events. Another example is Wentz (2000) that proposed three indices to identify and differentiate one spatial object from others. Identification and differentiation of spatial objects based on indices of their shape provides more flexibility to measure shape since those indices address the specific definition of shape.

This research proposes a geometric similarity function with five indices that characterize the trajectory of a mobile object. This geometric similarity function requires three steps: calculation of five indices, conversion of the trajectory into a single point in an attribute space, and measurement of similarity with a simple distance function. First, the function extracts five characteristic values of trajectories. They are *sinuosity*, *direction*, *velocity*, *locality*, and *spatial range*. All five indices are essential since a single index cannot differentiate one trajectory from others. Second, the five indices transform the trajectory from a polyline into a single point in an attribute space. The attribute space has five dimensions corresponding to each index, which simplifies the representation of trajectories. Third, the geometric function calculates the Euclidean distance between two points: this distance represents the similarity or dissimilarity of trajectories. Figure 3.8 illustrates this in a three-dimensional space for clarity.

If D_g is zero, it indicates that two trajectories are exactly the same in terms of geometry. In the toolkit, minimum D_g values can be set by the user as the threshold value to detect groups of similar trajectories for aggregation. Movements of mobile objects that are similar to each other are rendered in the same color in the visualization (Figure 3.9).

Since this similarity function remains unaffected by differences in location, scale, and the length of travel, this method of calculating geometric similarity can resolve some of the research challenges stated above. Moreover, this method is simple and efficient because the basis of this calculation is to measure the Euclidean distance among points that represents trajectories. The calculation of five indices is also computationally efficient. The following sections describe the five indices.

3.3.2.3.1. Sinuosity. Sinuosity measures the winding nature of the movement. It is the ratio of the total length of the trajectory and the Euclidean distance between the origin and destination. Therefore, the definition of sinuosity is:

$$S = \frac{d_E}{d_p} \tag{3.3}$$

where S is the sinuosity, d_p is the total length of the trajectory and d_E is the Euclidean distance between the origin and the destination. If the trajectory is a straight line, the value of S will be one, indicating the trajectory is not sinuous at all. If the origin and the destination are the same location, sinuosity value is zero. The lower the value is, the more sinuous the trajectory. The minimum value of this measure is zero and the maximum value is one.

3.3.2.3.2. Direction. This is the egocentric direction discussed in the section on directional similarity. Average egocentric direction indicates where the mobile objects are heading as a whole from an object-centered view of the mobile object. Calculation of directional property a trajectory is:

$$Direction = \frac{\overline{D}}{360} \tag{3.4}$$

where $\overline{D}$ is the average direction of a trajectory. The value of *Direction* ranges from zero to one since the value of egocentric direction is normalized.

3.3.2.3.3. Velocity. Velocity indicates how fast a mobile object moves during the time period relative to the maximum velocity in the dataset. Definition of velocity of each trajectory is as below:

$$Velocity = \frac{\overline{V}}{V_{\max}} \tag{3.5}$$

where $\overline{V}$ is the average velocity of a trajectory, and V_{max} is the velocity of one of the fastest paths in the sample. This value ranges from zero to one. If the value is close to one, it suggests that the object is moving faster over space relative to the sample.

3.3.2.3.4. Locality. Locality is the ratio of the distance between the origin and the destination, and the distance between the origin and the farthest location from the origin. This measure provides information on how far a mobile object moved from the origin in the whole movement of a trajectory relative to the origin-destination distance (Figure 3.10). This could help distinguish between different types of movements such as purposeful trips and leisurely tours. It can also distinguish trips that begin and end at the same location from ones that do not. In detail, it represents how far the objects moved from the origin compared with the distance between origin and destination:

$$Locality = \frac{L_{OD}}{L_{OF}} \tag{3.6}$$

where L_{OD} is the Euclidean distance between the origin and the destination, and L_{OF} is the distance between the origin and the farthest recorded location from the origin. If the value is smaller, it indicates that the locations of the origin and the destination are close to each other, and vice versa. As for the cases of other indices, this value ranges from zero to one.

3.3.2.3.5. Spatial range. Spatial range measures the spatial extent of the movement. This measure tells how much space is covered by a trajectory. The value is the area of a convex hull that contains a trajectory divided by the area of the convex hull that contains all the trajectories that spread all over the study area. The definition of spatial range is as follows:

$$Spatial\ Range = \frac{A_{path}}{A_{all}} \tag{3.7}$$

where A_{path} is the area of a convex hull that contains an individual trajectory (Figure 3.11) and A_{all} is the area of a convex hull that contains all the visualized trajectories (Figure 3.12). The value ranges from zero to one since this value is normalized by the area that contains all the trajectories. Therefore, for example, if the trajectory is a straight line, A_{path} is zero; if A_{path} is as large as A_{all}, the value is one. A spatial range closer to zero indicates that the trajectory covers relatively little territory, while a spatial range closer to one indicates a more expansive territory for the object. A convex hull provides a relatively accurate measure of spatial range (relative to other measures such as the minimum bounding rectangle) with reasonable computational cost. The Graham scan algorithm has the worst-case time complexity of 0(n log n); this is scalable (Sedgewick, 1990).

3.3.2.3.6. Clustering algorithm for similarity measures. Trajectories that are considered to be similar to each other are aggregated based on a clustering method. The trajectories in one cluster are considered to be trajectories with similar characteristics in either location, direction, or geometry. In the locational similarity function, the average distance between two trajectories is calculated: the two trajectories are aggregated if the average distance is smaller than the clustering threshold, which is defined by the user of the toolkit. In directional and geometric similarity functions, the trajectories are considered to be in one cluster (or similar movement group) if the directional value or geometric similarity value is smaller than the clustering threshold. The clustering algorithm used in this toolkit grows clusters according to a density-based connectivity analysis – it is called a density-based clustering method (DBSCAN) (Han & Kamber, 2006). The DBSCAN procedure is as follows:

- The neighborhood within a radius ε of a given object is called the ε-neighborhood of the object.
- If the ε-neighborhood of an object contains at least a minimum number, *MinPts*, of objects, then the object is called a core object (Figure 3.13).
- Given a set of objects, *D*, we say that an object *p* is directly density-reachable from object *q* if *p* is within the ε-neighborhood of *q*, and *q* is a core object.
- An object *p* is density-reachable from object *q* with respect to ε and *MinPts* in a set of objects, *D*, if there is a chain of objects p_1, …, p_n, where $p_1 = q$ and $p_n = p$ such that p_{i+1} is directly density-reachable from p_i with respect to ε and *MinPts*, for $1 \le i \le n$,

$p_i \in D$.

- An object *p* is density-connected to object *q* with respect to ε and *MinPts* in a set of objects, *D*, if there is an object $o \in D$ such that both *p* and *q* are density-reachable from *o* with respect to ε and *MinPts* (Figure 3.14).

This dissertation customizes DBSCAN in three ways. First, the distances for finding neighbor points are the values calculated between pairs of trajectories by three similarity functions (location, direction, and geometry). For example, the locational similarity function calculates the average difference in location between two trajectories. In this way, the value of locational similarity between two objects is the distance to be used in DBSCAN. Second, ε, one of two parameters to run the algorithm (*MinPts* and ε), is a user-defined value – as stated above, these two parameters are arbitrary values in DBSCAN and affect the results dramatically. ε is the threshold value to detect similar trajectories: the user can try arbitrary values to explore similarity. In data exploration, the user may not know the appropriate values for this threshold value ε. Thus, simple statistical values – maximum *x* coordinate value, minimum *x* coordinate value, maximum *y* coordinate value, minimum *y* coordinate value – are provided for the data to help guide the user. On the other hand, the algorithm in this research sets *MinPts* as one by default, indicating a cluster can be created by at least two objects – even a pair of trajectories that are similar to each other can be a group. Third, another parameter is utilized in DBSCAN in this research – maximum searching radius, *MaxE* (Figure 3.15). This *MaxE* determines the farthest distance to generate clusters from core objects – it is set as a double value of ε by default. The shape of clusters is constrained by this parameter to include objects that are within *MaxE* in one cluster. These parameters, with a combination of similarity functions that are explained in next three sections, provide the interactivity of the visualization toolkit in this research.

The DBSCAN algorithm requires parameters, the radius ε and *MinPts*, to be determined by the user of the algorithm. This is regarded as a disadvantage of DBSCAN in comparison with other density-based clustering methods such as OPTICS (ordering points to identify the clustering structure) of which the algorithm determines those parameters, and DENCLUE (clustering based on density distribution functions), which requires a set of density distribution functions that require longer computation. However, since ε is the threshold value of similarity functions in this dissertation, this parameter can be left as a user-defined parameter, which fits perfectly with the purpose of this dissertation. The parameter *MinPts* is set at two because this is the minimum number of trajectories that are considered to be in one cluster. DBSCAN algorithm is the most appropriate clustering method for this dissertation.

3.4. Data Summarization

Data summarization methods provide summary information of the visualized trajectories in the toolkit. There are two components for the summarization methods – directional statistics and axis conversion. Directional statistics provides overall statistical information about the trajectories while axis conversion allows the user of the toolkit to visualize the data from different viewpoints.

3.4.1. Directional Statistics

Directional statistics provide the overall information of visualized trajectories such as the number of trajectories, mean direction, and mean velocity, which is displayed in the visualization toolkit. These values provide information on trends in the visualized trajectories.

3.4.2. Axis Conversion

Axis conversion allows the user to explore the visualized trajectories from several different viewpoints. Visualization is in a three-dimensional view by default, allowing the user to rotate, zoom-in, zoom-out and pan the visualized trajectories at any viewpoint using three axes – *x*, *y*, and *t* (time). One option is a typical viewpoint for visualizing spatial data – two-dimensional space for *x* and *y* coordinates. In addition, to examine the change of *x* coordinates or *y* coordinates according to *t*, the user can select two more specific viewpoints in the toolkit: an *x*-*t* viewpoint and *y*-*t* viewpoint (Figure 3.16). In this way, if the user chooses *x* and *t* coordinates, the toolkit visualizes the overall movements in the *x* direction according to the time dimension. On the other hand, if the user chooses *y* and *t* coordinates, the toolkit delineates overall movements of the *y* direction according to the time dimension.

3.4.3. Data Mining of Geometric Similarity

Data mining techniques within the software WEKA (Witten & Frank, 2005) utilize geometric similarity indices calculated by geometric similarity functions for further data exploration of geometric similarity. WEKA consists of major data mining methods such as association rule mining, classification, and clustering. There is a component in the toolkit to export the indices from geometric similarity functions, as well as some other values, into the WEKA format. The indices are ID for each trajectory (Trajectory ID), ID for groups of the geometric cluster (cluster ID), sinuosity, velocity, spatial range, locality, egocentric direction, cardinal direction, average value of the *x* coordinate, and average value of the *y* coordinate. The user can choose the variables to be exported by checking the check box in the ‘Export’ section of the toolkit. This option offers the user another perspective for data exploration by providing data mining analyses that can afford the means for pattern detection and prediction of the data from nonspatial data, which will be the integration of Knowledge Discovery in Databases (KDD) and other visualization toolkits.

3.5. Data Exploration Process

3.5.1. Data Preparation and Import Data into Databases

The next six sections explain the basic process of data exploration with the visualization toolkit developed in this research. The first step of the data exploration process is data preparation. There are five required values, namely an ID to identify each mobile object, date and time of the tracked location, *x* coordinate, and *y* coordinate. Data should be in a text format with a tab delimited form. Second, the toolkit imports the text data into databases in SQL Server 2005. The user selects the type of datasets, browses to the text file, and clicks “Import” to store the information in a database.

The database has seven values for each record of locations. These are the following:

- ID: the identifier used to keep all the records in the database unique. This is the primary key for the database. The data type is *big integer*, which can store larger values than *integer*.
- trajectoryID: the identifier for each mobile object. Records that have the same trajectoryID represent records containing locations for one mobile object. The data

type is *integer*.

- DateAndTime: the field to store both date and time. The data type is *datetime*.
- Date: this field contains date information only. The data type is *text* with a maximum length of 15.
- Time: this field contains time of day information only. The data type is *text* with a maximum length of 15.
- xCoordinate: the *x* coordinate for each record. The data type is *real*.
- yCoordinate: the *y* coordinate for each record. The data type is *real*.

The algorithm in the toolkit decomposes the date field in the text data into date and time, respectively, and stores them in the database as independent fields.

3.5.2. Query Data Using Time Aggregation Methods

Query functions with time aggregation methods retrieve data that are necessary for data exploration. This requires three steps. First, the user chooses one of three query types – date query, time query, or advanced query (the combination of date and time query). Second, the user specifies the time range. This determines the start time and end time of the query. Third, the user determines the time interval, which is the resolution of time. After all these three steps are complete, the toolkit starts a query when the user clicks the button "Query." Then, the toolkit will ask the user to save the queried data as a text file.

3.5.3. Visualize Queried Trajectories

The user can visualize queried data in the visualization screen on the toolkit. The user selects queried data as a text file by clicking the "Browse" button. The "Read Data" button starts loading the data onto the visualization screen. Visualization starts with the "Start/Stop" button. The toolkit also provides directional statistical information when the data is loaded. Once the visualization is started, the user is able to use axis conversion with the buttons in the "Axis Conversion" section.

3.5.4. Applying Similarity Functions to the Visualized Trajectories

Similarity functions calculate the similarity values among mobile objects using the queried data from the databases. The user should complete four steps for the calculation of similarity. First, the user browses a text file of queried data by clicking the "Browse" button. The user can acquire information such as maximum *x* coordinate value, minimum *x* coordinate value, maximum *y* coordinate value, and minimum *y* coordinate value by clicking the "Statistics1" button. Second, the user chooses one of three similarity functions. Third, the user specifies a threshold to detect similar mobile objects. Finally, clicking the "Calculate Similarity" button calculates the similarity values. The toolkit asks the user to save the data with similarity information as a text file.

3.5.5. Visualize Trajectories with Similarity Information

The bottom-left components of the visualization toolkit deal with the visualization of data processed by the similarity functions. The user visualizes the data by clicking the "Browse" button, "Read Data" button, and "Start/Stop" button, in this order.

3.5.6. Export Geometric Similarity Values into WEKA Format

The toolkit can export information of geometric similarity into the WEKA data format in three steps. First, in the "Export" section of the toolkit, the user chooses the data by clicking the "Browse" button. Second, variables that the user wants to export are selected by checking checkboxes of each variable. Third, clicking the "Export to WEKA Format" button executes the export action. The saved data are in a WEKA data format with the extension ".arff." The user can import the exported WEKA data directly in WEKA by double-clicking the exported file. The software WEKA is launched, ready to begin data mining.

3.6. Summary

This chapter introduced the components of the visualization toolkit developed in this dissertation. Visualization with vector algebra enables a simple but efficient representation. In addition, aggregation methods for time, location, direction, and geometry, with user-defined threshold values, provide interactivity and flexibility in data exploration in order to detect patterns in terms of similarity among trajectories of mobile objects. Moreover, exporting geometric similarity information to WEKA datasets connects data mining with Geovisualization. The next chapter of this dissertation describes the datasets used to illustrate the visualization toolkit.

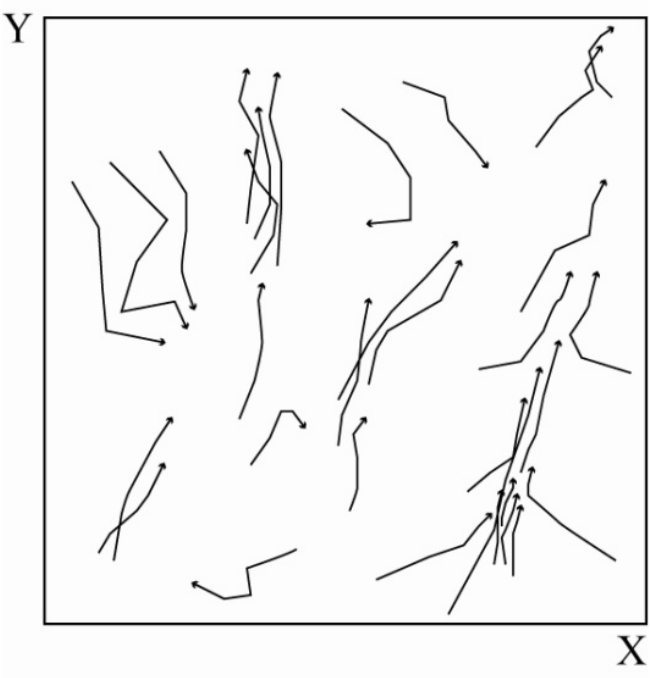


Figure 3.1. An example of visualized vectors in two-dimensional space.

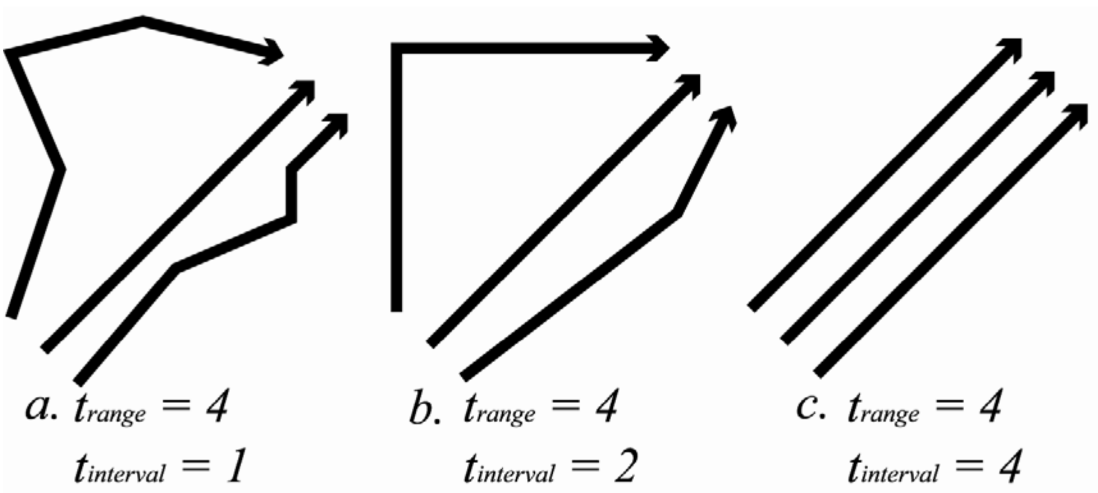


Figure 3.2. Time range and time interval.

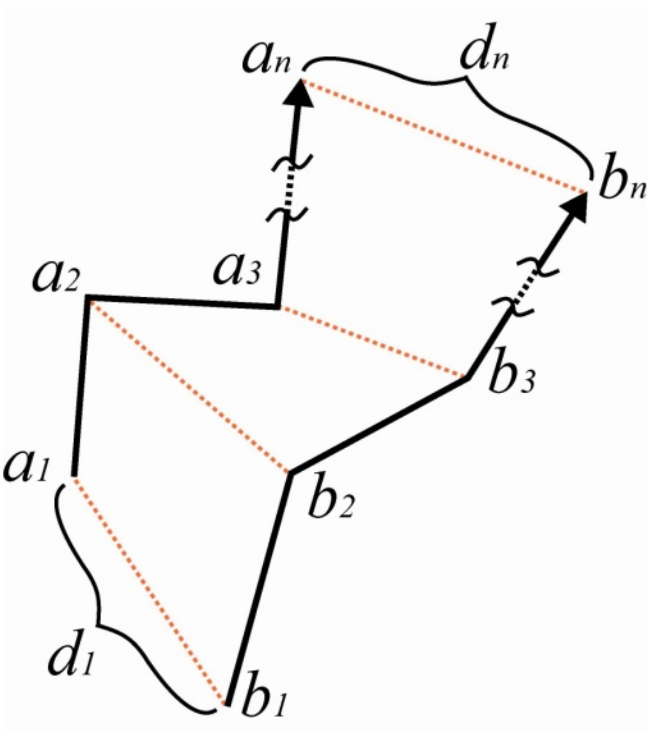
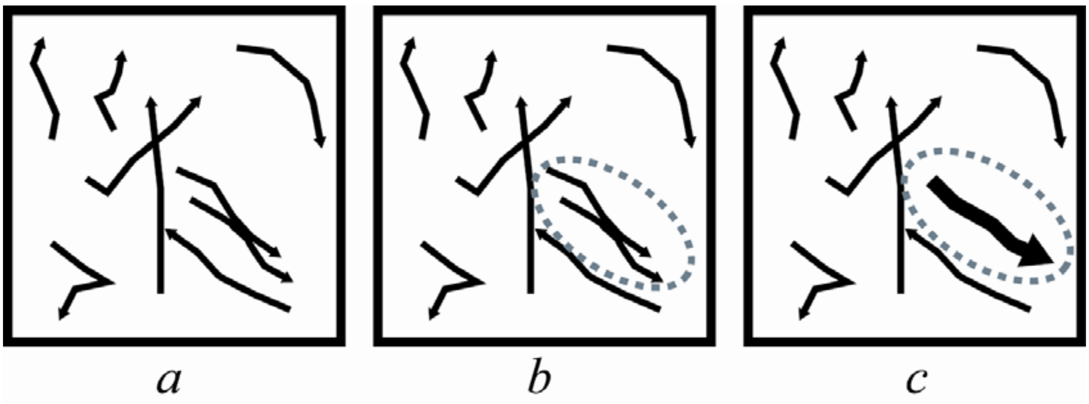


Figure 3.3. Locational similarity.



a. trajectories b. detection of a cluster c. aggregation of trajectories

Figure 3.4. An example of locational vector aggregation.

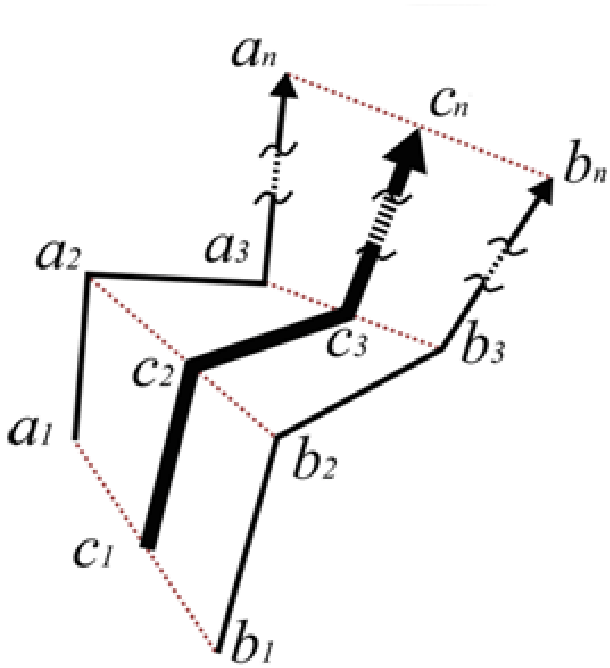


Figure 3.5. Locational aggregation.

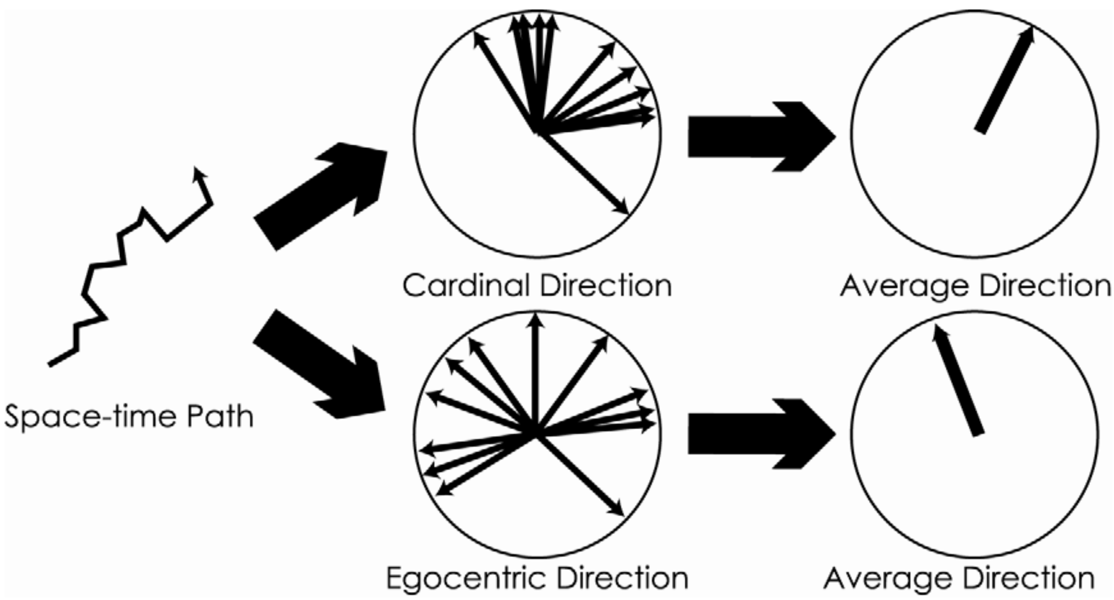


Figure 3.6. Directional statistics and classification of trajectories as vectors.

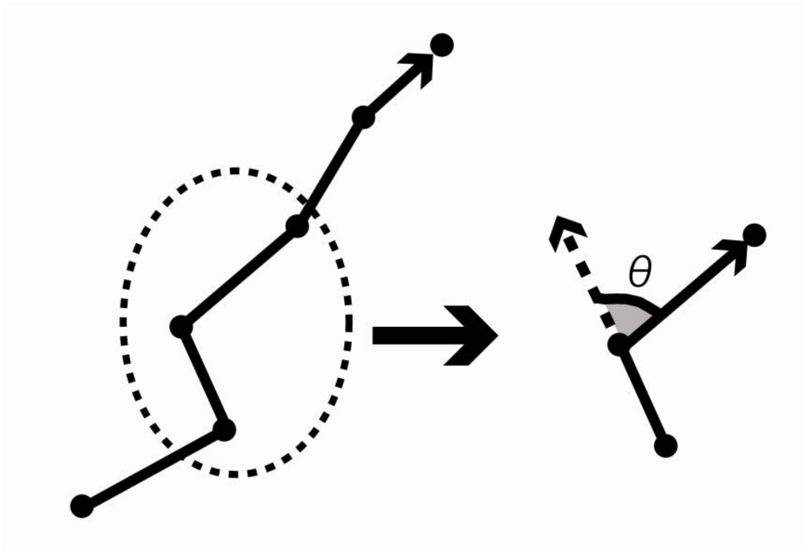


Figure 3.7. Calculation of egocentric direction.

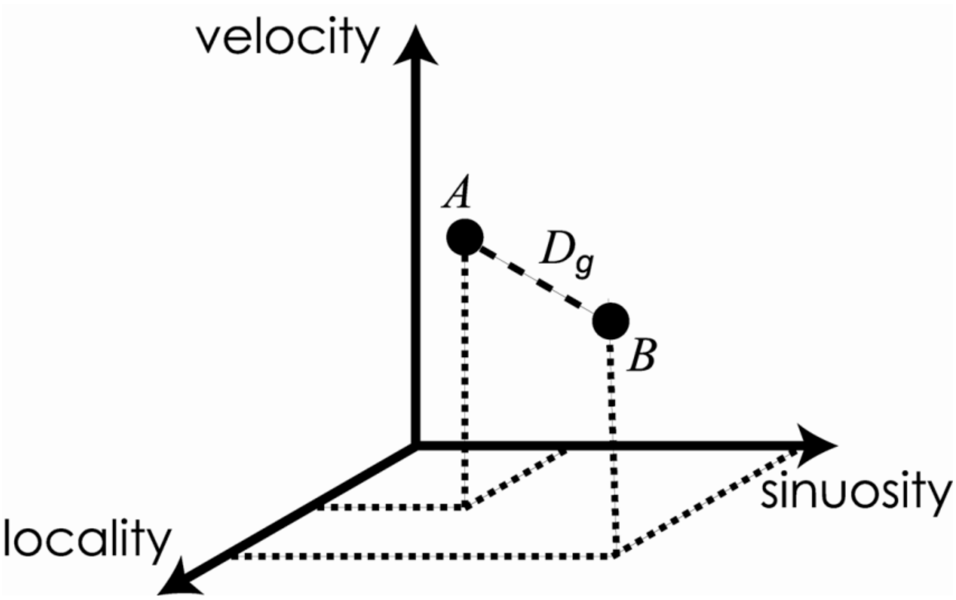


Figure 3.8. An example of a space-time path as a point using three indices.

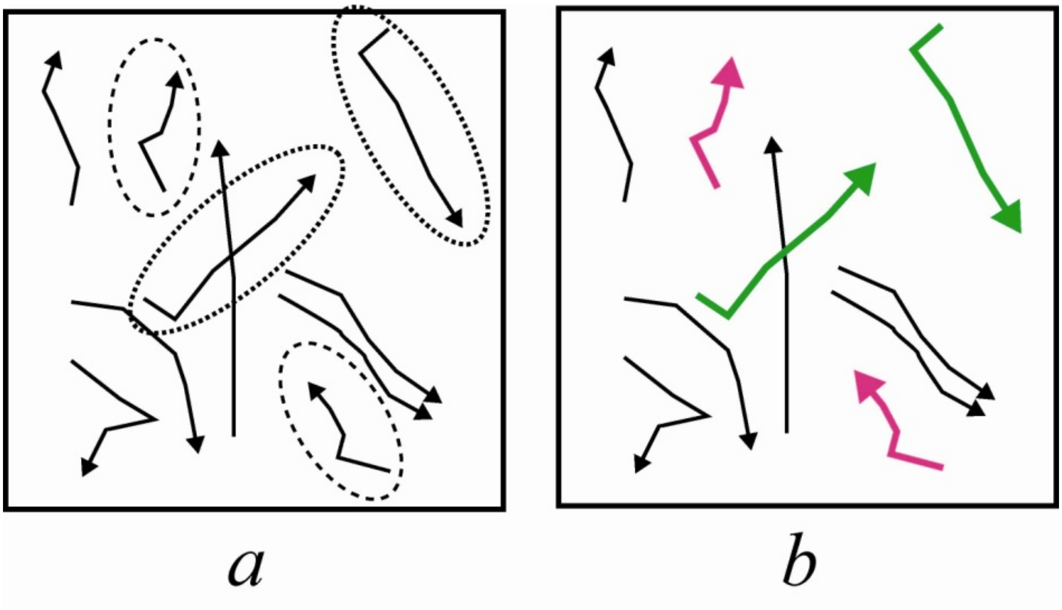
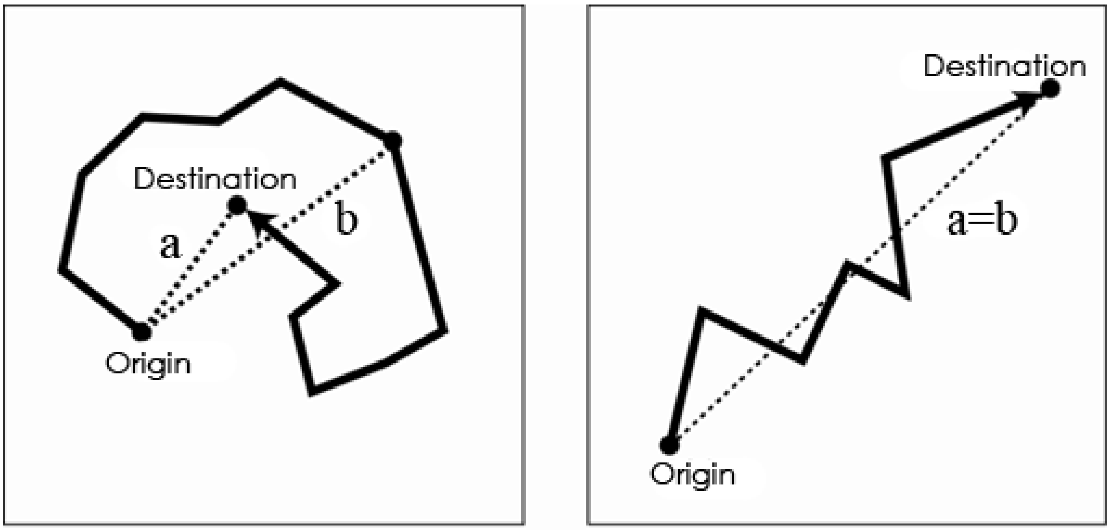


Figure 3.9. Example of geometric vector classification.



a: the distance between the origin and the destination

b: the distance between the origin and the farthest time stamp

Figure 3.10. Locality.

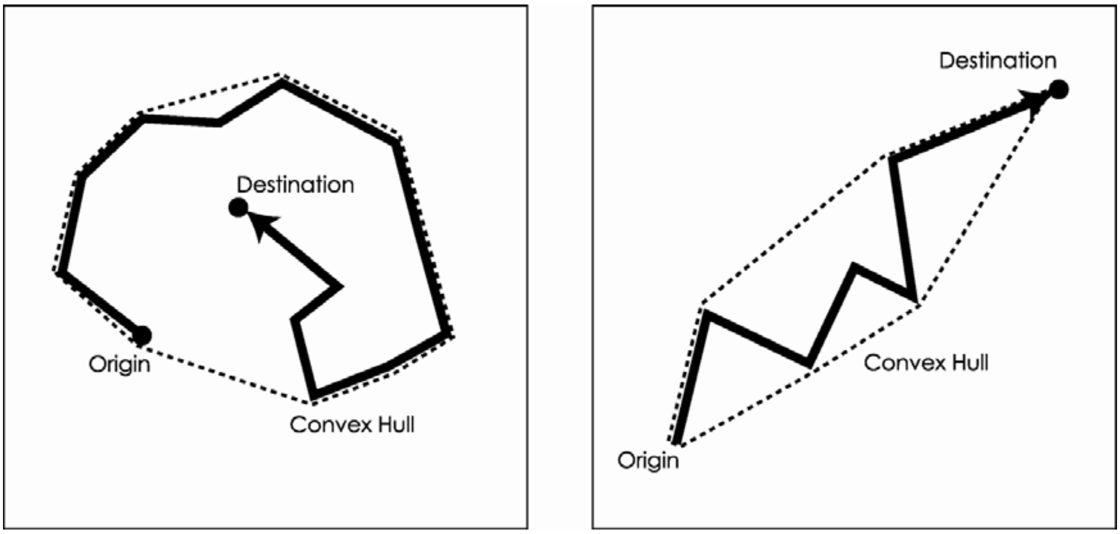


Figure 3.11. Convex hull of paths.

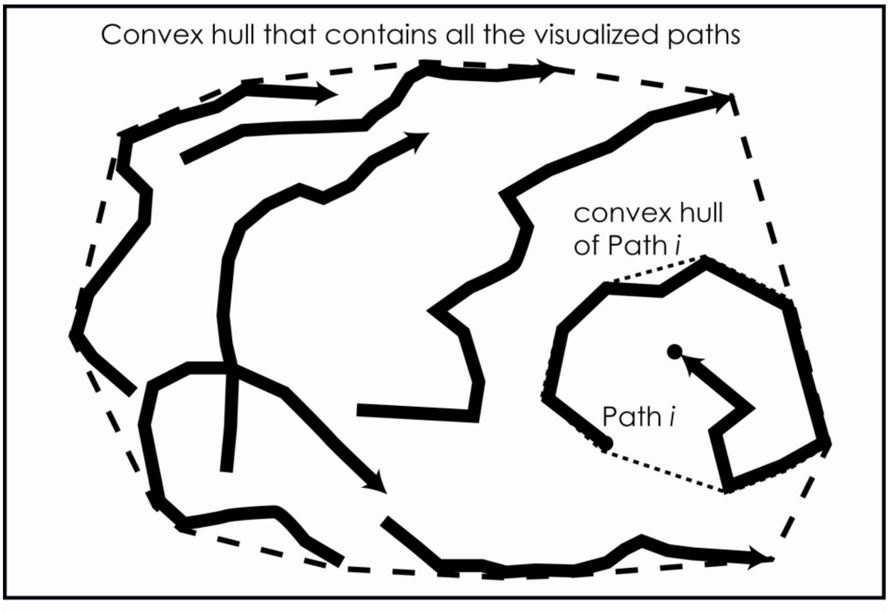


Figure 3.12. Spatial range.

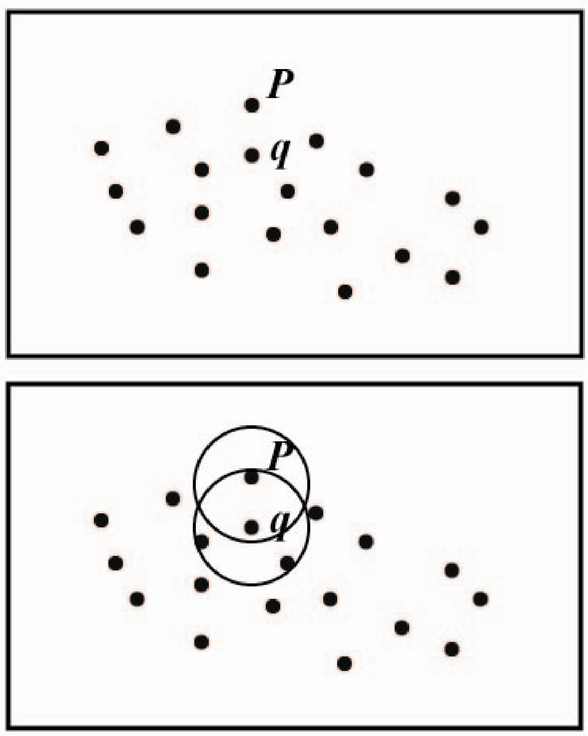


Figure 3.13. Core objects.

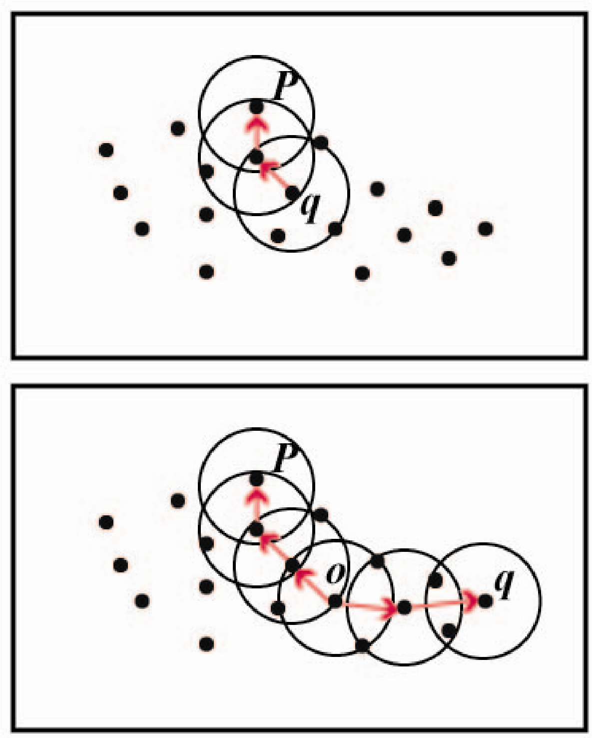


Figure 3.14. Density-reachability and density-connectivity.

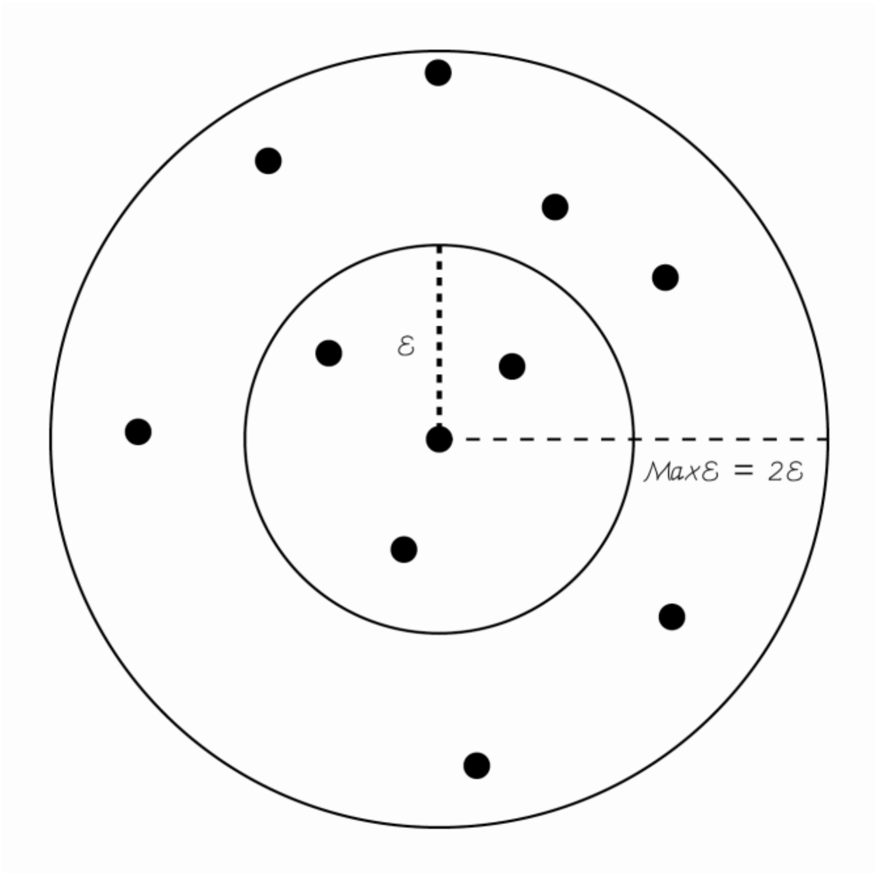


Figure 3.15. DBSCAN in this research.

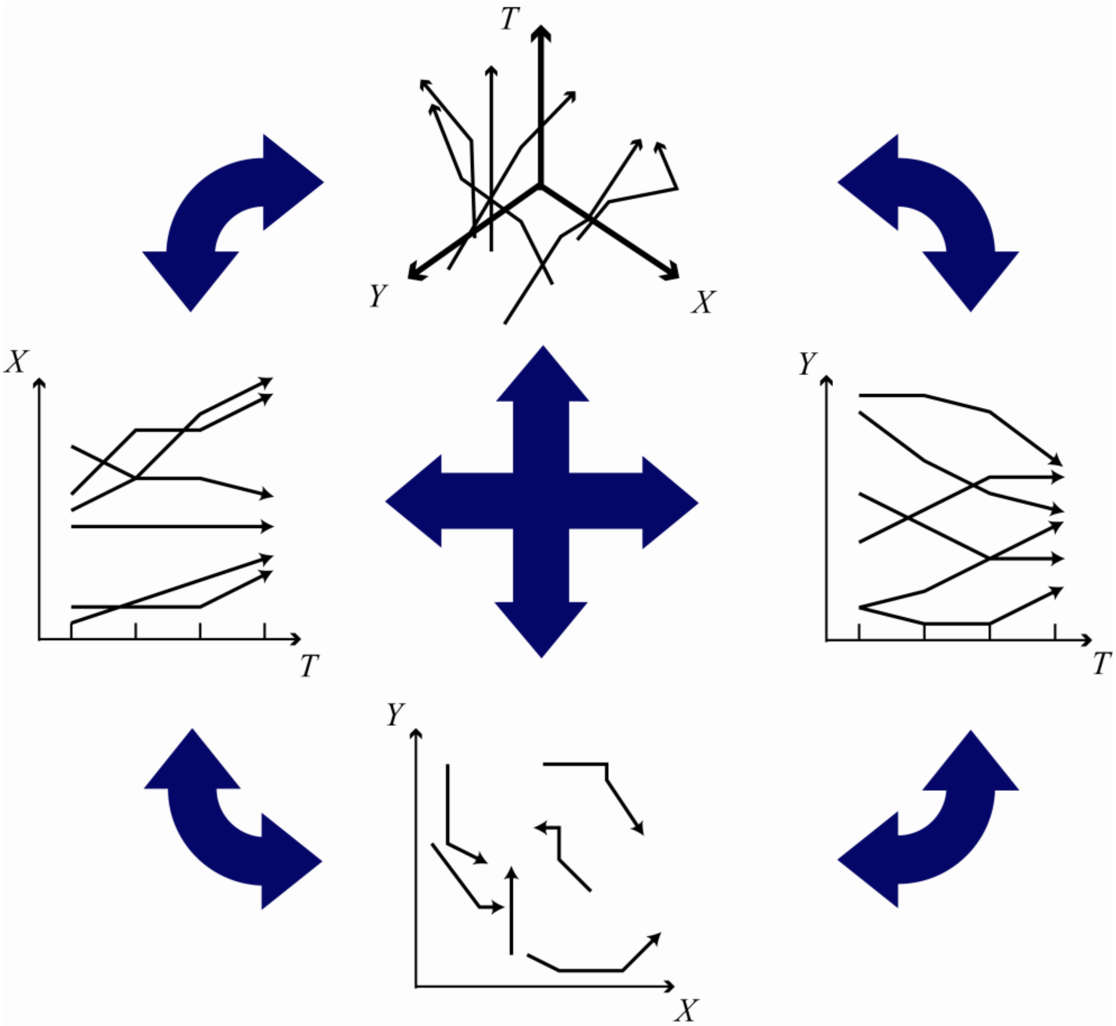


Figure 3.16. Axis conversion.

4 DATA

4.1. Overview

This research utilizes datasets consisting of three types of mobile objects data (MOD): 1) GPS travel survey data in the state of Kentucky, 2) wild chicken movement data in Thailand, and 3) self-tracking movement data of the investigator in the state of Utah. Characteristics of movements in each dataset differ from one another because of the difference in tracking devices, spatial and time resolution of the tracking method, study area, and so on. In addition, inherent constraints in movements can cause differences. For example, a road network restricts the movement of vehicles to the network, while an animal's movement is more flexible, indicating more free movement all over the study area. Thus, data exploration with three different datasets identifies the effectiveness of the visualization toolkit.

4.2. Personal Travel Data Survey in Lexington, Kentucky

Two organizations of the Federal Highway Administration – the Office of Highway Information Management and the Office of Technology Application – conducted a project whose purpose was the development and field test of an automated data collection device that included Global Positioning System (GPS) technology. The Lexington Area Metropolitan Planning Organization, the principal planning agency for a two-county area in central Kentucky, volunteered to participate in this project in 1996.

The size of study area is approximately 461 square miles with a total population of approximately 350,000.

The original data consist of four types, namely, activity data, screening interview data, postdiary interview data, and GPS data. This research utilizes GPS data only. The date of the recorded timestamps ranges from September 16th to December 30th in 1996. There are 327,407 timestamps, 89 households, 173 people, and 2,256 trips in total. The DIGIT Lab of the Department of Geography at the University of Utah created databases to integrate the information from the four types of data and eliminated the noisy timestamps for further use. The resulting data contain 290,231 timestamps, 88 households, 163 people, and 1,984 trips. The attribute fields of GPS data in the databases are household ID, driver's ID, trip number, sequence number, date, time, longitude, latitude, and speed in miles per hour. This research uses the driver's ID, longitude, latitude, date, and time information.

4.3. Wild Chicken Movement Data in Thailand

The second dataset in this research is movement data of wild chickens in Thailand. The Human-Chicken Multirelationship Research (HCMR) Project conducted a survey to collect this data in Chiang Rai, Thailand using Wireless Fidelity (WiFi) positioning system (Okabe et al., 2006). A small WiFi tag that bundled a chicken's body recorded the location and time. The report shows that the effectiveness and usefulness of WiFi technology can contribute to the growing need to understand the spatial movement of animals through their trajectories (Turchin, 1998).

The WiFi data tracking system consisted of six devices, namely, tags to stick to the chickens' legs, activator, receiver, Power over Ethernet (PoE), WiFi access point, and a management engine. The functionality of each device is as follows. Tags wirelessly transmited the information of location and time. The weight of the tag was 35 grams and the size was 62mm×40mm×17mm. The receiver caught the signals from the tags and transmited the information to the management engine. Three kinds of antennas were used in the study – 360 degrees, 135 degree, and 60 degrees – due to differences in directional characteristics. The management engine processed the signal information to track the location of tags. Spatial resolution was 1 meter and time resolution was 1 second.

The study area was the 200 square-meters of land under cultivation inside the Chiang Rai Livestock Research and Technology Transfer Center. There were eight concrete one-storied houses in the area: two of them were residential houses and six of them were vacant houses. Two of the vacant houses were used as a room to install the management engine and a preparation room, respectively. The only residents were people who lived in the two houses. Thus, the chickens could move freely all over the study area.

There were 18 chickens used in this survey – they were the chickens that the Chiang Rai Livestock Research and Technology Transfer Center owns. There were three chicken houses in the field: each chicken house contained one cock and five hens. The survey ran from November 2nd until November 9th in 2005. Preparation of the WiFi positioning system took place on the 2nd, 3rd, and 4th until 4:30 p.m., which coordinated the adjustment of the positioning system with the release of the chickens into the field. Actual data collection started at 4:30 p.m. on the 4th until 9:15 a.m. on the 9th. Okabe et al. (2006) reported the locational error in the data, indicating that there are directional patterns in errors. Outliers with extreme locations were eliminated from the data.

This research utilizes the data from November 5th to November 8th. To examine the movement pattern throughout the entire day, this research leaves the data collected on November 9th out of consideration, since movement was only recorded in the morning for this date. The attribute information is *x* coordinate, *y* coordinate, date, and time.

4.4. Self-tracking Data in Utah

The third dataset is the self-tracking GPS dataset of the investigator. It is a collection of daily movement data mostly in Salt Lake County, Utah from January 1st, 2007 until December 31st, 2008. A GPS device (Garmin eTrex C) records the timestamps of everyday movement from the morning until the end of the day. Recording starts when the investigator first leaves his home and ends when he returns home, which is the last travel destination of the day. The time resolution is 2 seconds, meaning the GPS records the location and time every 2 seconds. According to the display on the GPS device, the minimum spatial error in recording is 4 meters. Since it is impossible to track the timestamps when the investigator is inside buildings, the GPS only collects movement outside the buildings. This limitation of tracking causes some issues in data collection.

The GPS device used for this dataset sometimes causes errors in tracking and generates some missing parts in data. Occasionally, the GPS cannot capture the signals of satellites because of obstacles such as the density of buildings, bridges, trees, and so on. Thus, some timestamps are missing or are recorded in unrealistic locations when the investigator stays at an area where the density of the buildings is high, or an area where there are many obstacles above the investigator. This happens mostly in the downtown area of Salt Lake City where tall buildings exist. Another problem is user-error. Some portions of trajectories are missing because either the investigator forgets to turn on the

GPS device or the battery of the GPS device runs out. Thus, there are some days for which only a part of entire movement is recorded.

Due to the errors and mistakes above, data cleaning is necessary to choose only days with complete trajectories. In addition, the movement of the investigator outside of the State of Utah is also eliminated. Elimination of incomplete trajectories and error locations results in 273 days of complete trajectories. The attributes selected are latitude, longitude, date, and time.

4.5. Summary

This dissertation utilizes three different datasets for visual data exploration. Each dataset contains unique movements of mobile objects that can be differentiated from the movements of other mobile objects. Personal travel data in the state of Kentucky collected the movement data of a comparatively large number of people. Since each participant in the survey provided individual movement data for just a few days, an example of effective analysis may be to seek for the overall patterns or dynamics of the entire study area as a collection of individual movement. Self-tracking data recorded the long-term daily movement of one individual. Unlike the other datasets, this dataset contains movement that starts and ends at the same location for more than 2 years. Data exploration to investigate the variation in location at different times of a day is a possibility with this dataset. Although human movements are often limited to road networks, movements of chickens in Thailand are not limited to a road network. It is interesting to find original patterns in flexible movement in contrast to the network-constrained movement. Chapter 5 reports the results of the data exploration with the visualization toolkit in this research.

5 RESULTS

5.1. Overview

This chapter illustrates the toolkit's functionalities by showing results from querying the database at different levels of temporal granularity, and aggregating the trajectories based on trajectory similarity at the specified granularity. This chapter will explore results based on the toolkit components described in the Methodology chapter. Unless otherwise mentioned, this chapter will focus on the Thailand wild chicken dataset, and use the other datasets to reinforce these results. Note that we only focus on the functionality of the visualization toolkit aggregation methods, and not on the behavioral aspects of wild chickens or humans represented by the other databases.

5.2. Aggregation Methods

This section presents results from two aggregation methods: time aggregation and similarity-based aggregation. As described in the Methodology chapter, the time aggregation methods allow the user to state a time interval of interest and a time granularity within that interval to reconstruct individual trajectories at different levels of movement generality. Given these reconstructed trajectories, the user can then apply similarity functions to aggregate individual trajectories based on location, direction, and geometry to generate synthetic trajectories that reflect collective movement patterns at that scale.

5.2.1. Time Aggregation Methods

Figures 5.1 and Figure 5.2 show the effects of time granularity on trajectory reconstruction. Figure 5.1 illustrates the reconstructed trajectory collection for three different time ranges (6:00 –9:00, 6:00 – 12:00, and 6:00 – 17:00) at the native time interval provided by the data (1 second). Figure 5.2 illustrates the reconstructed trajectory collection at three time intervals for a fixed time range from 6:00 to 17:00. As Figure 5.1 suggests, it is difficult to extract distinct patterns at the highest level of temporal granularity. Even at a relatively low time range, the trajectory collection is generally an undistinguished mass. This problem becomes more acute as the time range increases. Figure 5.2 indicates that changing the time interval can mitigate this problem to a substantial degree: the trajectories are more generalized and patterns are more easily discernable as the time intervals become coarser. The visualization toolkit allows the user to visualize the trajectory collection at the time range of interest and interactively change the time interval until an appropriate granularity level is achieved for the data and questions at hand.

This visual simplification is similar with other datasets. Figure 5.3 is the example of Lexington GPS mobility patterns with four different time granularities: 1 second, 10 seconds, 1 minute and 10 minutes. As is the case of Figure 5.2, a coarser time interval simplifies visualized trajectories, except for the central part where trajectories are dense. Although oversimplification with an extremely high value of time interval can obscure the movement patterns, the appropriate time interval value can simplify the visualization and uncover patterns in trajectory datasets.

5.2.2. Similarity Functions

5.5.2.1. Locational Similarity

After the user has selected the time range and interval, the toolkit allows for the aggregation of similar trajectories to detect clearer patterns from the data. In addition to the time aggregation methods illustrated in the previous sections, similarity functions can uncover patterns in the trajectories. Figure 5.4 compares the visualization from Figure 5.1 (three images of the top row) and the trajectory similarities based on a relatively relaxed locational similarity threshold of 10.0 (three images of the bottom row). Note that as the time range increases, visualization of the disaggregated data becomes more complicated, and it becomes hard to detect visual patterns without the use of similarity functions. However, obvious patterns emerge when applying a similarity function. The locational similarity function detects three distinct groups in all three time ranges. To validate the consistency of this trend, we assessed the number of groups of visualized data while systemically increasing the time range by 1 hour in each step. The number of groups of this dataset is constantly three throughout the day, except for 4 groups emerging between 6:00 and 8:00. This implies the stability of mobility patterns across time in this dataset.

Although the locational similarity function facilitates the pattern detection process, it can also oversimplify the visualization since it aggregates similar trajectories into a single one. Figure 5.5 shows the result from the Lexington mobility data of trajectories aggregated by the locational similarity function. As the locational similarity value increases, small and short-length aggregated trajectories in different groups concentrate in one area, which makes patterns difficult to discern. Some datasets are sensitive to the similarity measures, thus the user must carefully choose the threshold value of the similarity functions in order to find nominal patterns.

It is also possible to compare aggregated trajectories across different time ranges to explore for recurrent or stable patterns across longer time frames. Figure 5.6 illustrates mobility patterns across different dates using the same time ranges. The top row shows the movement for 1 day only (November 5th, 2005) with respect to different time ranges, while the bottom row illustrates mobility patterns for those same time ranges aggregated across all 4 days (November 5th, 2005 to November 8th, 2005). This functionality allows the user to explore for recurrent behavior (i.e., mobility behavior that occurs within the same time ranges across different days or similar time periods). In both cases, there are three groups of similar movement that are remarkably stable whether we view these patterns within 1 day or across multiple days. This suggests the existence of recurrent mobility patterns in this database.

The locational similarity function is useful for finding patterns of movement in urban areas. Figure 5.7 illustrates the daily movement of the investigator in the morning and the afternoon time period. In each image, the investigator's house is at the bottom-left location and the University of Utah is at the top-right location. The locational similarity function successfully detects similar trajectories from the investigator's home to the University of Utah, detecting the generic commuting patterns of the investigator. The investigator uses four major routes to commute to the University of Utah. The locational similarity function detects four aggregated trajectories that depart from the bottom-left and end at the top-right. Each aggregated trajectory represents a summarized route for commuting to the University of Utah.

The combination of time aggregation methods and similarity functions enables comparisons of movement at the same cyclical time period in different years. Figure 5.8 is the comparison of the investigator's daily movement over a 4-month period (from September to December) in 2007 (top row images) and 2008 (bottom row images). The locational similarity function is applied to both datasets. Although the time-of-year period is the same, detected patterns are distinctly different: movement in 2007 has several clusters and is wide in the rage of movement, while the movement in 2008 has fewer clusters with simpler movement patterns.

The time range can also focus on detailed movement throughout 1 day. Figure 5.9 shows three different 1-hour periods for the movement of wild chickens. Some clustered movement can be found in the visualization without similarity functions (top row images) while clusters clearly appear with locational similarity functions (bottom row images). Visualization with shorter time ranges enables the user to focus on detailed movement: the user can find patterns relatively easily. Similarity functions, in this case, show the clusters that can also be found in the visualization without similarity functions to reinforce the visual exploration.

The time range can also illustrate interesting patterns of human mobility. Figure 5.10 shows two different 1-hour segments of the investigator's movement. Visualization without applying the similarity function (top row images) already shows the frequent routes on the road network by the density of trajectories at similar locations. In addition, visualization with the locational similarity function (bottom row images) detects clusters, which clearly appear to summarize the movement in each time range.

Figure 5.11 shows the visualization of chicken movement across all 4 days using two different time intervals and two different threshold values for locational similarity.

The four visualizations, arranged as a quadrant at the left side of Figure 5.11, show the movement of chickens at a time interval of 5 seconds. In contrast, four visualizations in a quadrant on the right side of Figure 5.11 show the same data at a time interval of 10 minutes. The upper row shows results from a locational similarity threshold of 0.1 (a value that requires high similarity for trajectory aggregation) while the lower row shows results from a locational similarity threshold of 10.0 (a value that requires less similarity). Figure 5.11 distinguishes trajectories with locational similarity using different colors.

Note the affects of time interval granularity on the ability to discern patterns. The individual trajectories in the upper row are dense and difficult to disentangle into clear patterns. The individual trajectories in the lower row, at a coarser temporal interval level, are more visually manageable. Also note the affects of locational similarity thresholds on the visual patterns. The upper row indicates the difficulty in finding general patterns when requirements for locational similarity threshold are high: no trajectories are candidates for aggregation. However, the bottom row shows three distinct groups that emerge when the locational similarity is less severe. In addition, these similarity groups remain stable across the two levels of temporal interval granularity. This suggests, in this case, we discovered synoptic mobility patterns that are robust and can be effectively summarized using a coarser time interval that provides a simple and more easily understood view of the data, compared to a finer temporal interval.

5.2.2.2. Directional Similarity

The second similarity function is based on directional information. The directional similarity function detects similar trajectories with respect to two types of directions (egocentric direction and cardinal direction) and renders the trajectories in the same cluster into the same color (unlike the locational similarity function, the directional similarity function does not aggregate trajectories). Figure 5.12 shows the comparison of 1-day (November 5th, 2005) and 4-day (from November 5th to November 8th, 2005) directional mobility patterns of wild chickens. Visualization without the directional similarity function (left-most column images) and visualization with egocentric similarity values of 1.0, 10.0, and 30.0 are in Figure 5.12. A relaxed directional similarity value (right-most column images) detects a few clusters at similar locations (mostly in red and green) while a strict directional similarity value detects more clusters with some outliers. Similar patterns can be found in two different time ranges, implying consistency within the movement patterns of chickens with respect to direction.

Figure 5.13 and Figure 5.14 show movement patterns with egocentric similarity in two different time ranges (6:00 – 9:00 and 6:00 - 12:00) in different date ranges. Figure 5.13 illustrates the 4-day (from November 5th to November 8th, 2005) movement patterns while Figure 5.14 illustrates 1 day’s (November 5th, 2005) movement patterns. As time range increases from 6:00 – 9:00 to 6:00 - 12:00 in Figure 5.13, visualization without similarity functions becomes complicated. However, notable patterns appear when a directional similarity function is applied. As is the case of Figure 5.12, a relaxed egocentric similarity value detects a few clusters while a strict similarity value detects clusters in more detail. In addition, data with a longer time range (6:00 – 12:00) have more outliers. Similar results are shown in Figure 5.14, but more detail cluster formation can be detected because there are fewer trajectories. Also, more outliers are detected with a strict similarity value.

5.2.2.3. Geometric Similarity

The third similarity function is based on geometric characteristics. The geometric similarity function renders the trajectories in the same cluster into a same color. Figure 5.15 illustrates mobility patterns of wild chickens in three different time ranges (6:00 – 9:00, 6:00 – 12:00, and 6:00 – 17:30). Geometric similarity function with a strict threshold (0.1) shows both clustered trajectories and outliers (middle row images) while visualization with a relaxed threshold (0.5) shows that almost all the trajectories are summarized by only a few groups. The stricter the geometric similarity threshold, the less the number of clusters that appear. In addition, the trajectories in the same cluster are often moving closer to each other with respect to location.

Figure 5.16 shows the result of Lexington GPS data with a variety of geometric similarity from 0.01 to 0.5. As in the case of the wild chicken data, as the threshold value increases, more clusters are detected, but the number of clusters decreases at a certain threshold value, i.e., visualization with a threshold of 0.05 detects more clusters than visualization with a threshold of 0.5. This occurs because some clusters are integrated into one single cluster as the threshold value becomes more relaxed to create a cluster that contains a higher number of trajectories.

Figure 5.17 shows mobility patterns with the geometric similarity function in three different time ranges: 6:00 – 7:00, 12:00 – 13:00, and 16:00 – 17:00: these are three different 1-hour movements within a day. As the geometric similarity value increases, the system detects more clusters. Although the geometric similarity function colors trajectories in the same cluster, it does not aggregate the trajectories as with the location similarity function. The geometric similarity function successfully displays the clusters that can be easily found by visual exploration. For these data, the summary trajectories are persistent across all three time ranges; this suggests distinct spatial behavior types that are stable across time.

Figure 5.18 illustrates trajectory collections at a moderate geometric similarity threshold combined with different levels of temporal granularity and spatial projections to the two-dimensional plane. The time range is fixed at 10 seconds. Again, note the affect of temporal granularity on the visual legibility of the individual mobility patterns, even with trajectory aggregations. Mobility patterns at the 10-minute granularity provide an elegant synoptic view of three groups with similar movement with respect to trajectory geometry: these patterns are much easier to detect compared to results at the finer level of temporal granularity. However, in this case, the discovered mobility patterns are substantially different at the two levels of temporal granularity. This suggests a higher sensitivity of geometric similarity to temporal granularity than locational similarity. It also suggests the value of exploring these aggregations at different levels of temporal interval granularity in order to determine the robustness of the discovered patterns. It is also notable that differences are more apparent with respect to movement in the *y*-dimension over time.

5.3. Data Summarization

Data summarization enhances the effectiveness of visual exploration in two components: directional statistical information and axis conversion. Statistical information summarizes the information of visualized data while axis conversion provides functionality to view the data from various viewpoints.

5.3.1. Directional Statistics

The statistical information reported by the system has two parts: geographic extent of *x* and *y* coordinates of visualized trajectories (*statistics 1*), and summarized information of trajectories (*statistics 2*): number of trajectories, number of detected clusters, mean velocity, and mean direction (Figure 5.19). These two components are useful respectively. For example, outliers or errors of recorded location can be found with the combination of visualization and statistics 1 information (Figure 5.20). The user can edit the data to remove the errors and visualize the data without outliers. In addition, numbers of clusters are easily found by statistics 2 information, even though the visualized trajectories appear to be complicated (Figure 5.21). Visual exploration can be leveraged with the assistance of statistical information.

5.3.2. Data Mining of Geometric Similarity Indices

Another functionality of the visualization toolkit is a data mining functionality that enables the user to export geometric similarity indices (sinuosity, velocity, egocentric direction, cardinal direction, locality, spatial range) that can be analyzed in other data mining software. This research utilizes the data mining software WEKA for decision tree analysis, which is one of the classification methods, with the purpose of discovering the rules that describe the movement of wild chickens. The decision tree algorithm J48 is used to create a tree to discover attributes that influence cluster detection with the geometric similarity function. J48 is based on the C4.5 algorithm: C4.5 is one of the most widely used algorithms for decision tree induction (Han & Kamber, 2006).

This decision tree analysis is conducted on datasets with different time aggregation and geometric similarity aggregation settings. For example, Table 5.1 shows the data mining result of wild chicken data in various time ranges: three 1-hour period movements (top three rows in the table, i.e., 6:00 - 7:00, 12:00 - 13:00, and 16:00 - 17:00) and three incremental time ranges (bottom three rows in the table, i.e., 6:00 - 9:00, 6:00 - 12:00, and 6:00 - 17:30). Time interval and geometric similarity threshold are constant in all the time range cases: the time interval is 10 seconds and the geometric similarity threshold is 0.5. The root node identifies the prominent factor in the resulting decision tree: egocentric direction is the root node in all cases. This indicates that egocentric direction is the most significant index to determine the movement patterns. In addition, the percentage of correctly classified instances is higher when the time range becomes longer (bottom three rows): longer time movement may be more predictable than short time movement. Furthermore, similarity tendency is obvious with the number of clusters detected in visualization (this is the number of clusters detected by the geometric similarity function) and the percentage of correctly classified instances. The fewer number of clusters we have, the higher percentage classified correctly.

Table 5.2 summarizes the results of decision tree analysis of self-tracking data with several time ranges: the same decision trees were generated as in the case of wild chickens. The number of observations in this case (88 to 273 observations) is greater than wild chicken cases (18 observations). As with the case for wild chickens, egocentric direction is the root node in all of the examined cases. This is constantly obvious in the cases of the Lexington data in Table 5.3, which summarizes results of the decision tree analysis of the Lexington mobility data with several time ranges. In addition, the percentage of correctly classified instances is constantly higher than 90.00%, except for one case, even though the number of instances and number of clusters detected by the geometric similarity measure are higher. Egocentric direction may be one of the critical variables to be considered in discovering mobile object movement patterns.

Time interval is another variable that can affect the data mining result. Table 5.4 summarizes the decision tree analysis results of wild chicken data with two different geometric similarity thresholds (0.1 and 0.5) and five different time intervals (5 seconds, 10 seconds, 1 minute, 10 minutes and 30 minutes). Table 5.5 illustrates the results with self-tracking data with four geometric similarity values (0.1, 0.5, 1.0, and 2.0). In the results of wild chicken cases, datasets with relaxed geometric similarity (0.5) and with coarser time interval (10 minutes and 30 minutes) did not obtain any results because there is only one cluster as a result of geometric similarity aggregation. In addition, the dataset with a relaxed geometric similarity measure (0.5) received a higher percentage score of correctly classified instances. This similar trend can be found in the cases of self-tracking data. This occurs due to the decrease in the number of clusters as the geometric similarity threshold increases; it is simpler to classify the instances with a fewer number of clusters. Moreover, the dataset with this geometric similarity (0.5) received the same results even though the time interval changed from 5 seconds to 1 minute, indicating consistency in movement patterns. Furthermore, egocentric direction is the root node of decision trees in wild chicken cases. However, other indices such as spatial range and sinuosity are the root nodes in the cases of self-tracking mobility data and the cases of Lexington data (Table 5.6). This implies the possibility of the time interval having a significant influence on the results of data mining.

Examination of the decision tree itself is another important aspect of decision tree analysis. Decision trees of self-tracking data in four different time ranges (0:00 – 9:00, 0:00 – 12:00, 0:00 – 18:00, 0:00 – 24:00) illustrate that the size of the tree grows as the time range stretches with an increasing number of leaves. As is shown in Table 5.2, the root node is egocentric direction. The next most important explanatory factor is sinuosity in all the cases except for the case of the time range of 0:00 – 24:00: in this case, the spatial range is a factor in the second level. This implies the consistency of the mobility patterns because egocentric direction and sinuosity are the two key factors that describe the movement of self-tracking data.

Decision trees for the self-tracking data in another four different time ranges (6:00 – 9:00, 9:00 – 12:00, 12:00 – 15:00, 15:00 – 18:00) show a tendency similar to the decision trees of self-tracking data in four different time ranges (0:00 – 9:00, 0:00 – 12:00, 0:00 – 18:00, 0:00 – 24:00): egocentric direction is the root node and sinuosity is at the second level in most cases. As the time ranges change, the size of the tree and number of leaves varies. For example, the tree shape in the time range of 6:00 – 9:00 and 12:00 – 15:00 are exactly same: there may be similar mobility patterns with respect to geometry occurring in these two time ranges. In addition, the size of the tree in the time range of 6:00 – 9:00 and 12:00 – 15:00 are small in contrast with other time ranges. This may explain why the complexity of the movement differs from one time range to another: the percentage of correctly classified instances in the tree of the time range of 6:00 – 9:00 (96.59%) and 12:00 – 15:00 (96.39%) are higher than the other two time ranges – time range of 9:00 – 12:00 (90.96%), and that of 15:00 – 18:00 (91.01%) (see Table 5.2).

Decision trees of self-tracking data with three geometric similarity thresholds (0.1, 0.5, and 1.0) show that the size of trees becomes smaller since the number of clusters detected by geometric similarity functions becomes smaller: a relaxed similarity function threshold (1.0) includes a larger number of trajectories in one cluster and therefore, the function detects fewer clusters. In these three cases, the shapes of decision trees are quite different from each other: the root node is not egocentric direction all the time. Clearly, threshold values can greatly impact the results of data mining.

5.4. Summary

This chapter described the functionality of the visualization toolkit with examples from three mobile object datasets. Vector algebra, time aggregation methods, and similarity functions provide effective visual exploration of the mobile objects data. In addition, data summarization methods such as axis conversion and statistical information support the user of the toolkit for more comprehensive understanding of the visualized mobile objects. Furthermore, data mining with WEKA enables the exploration of rules that describe the movement patterns. Chapter 6 discusses the contributions of this research, contribution to other research efforts, and future research challenges.

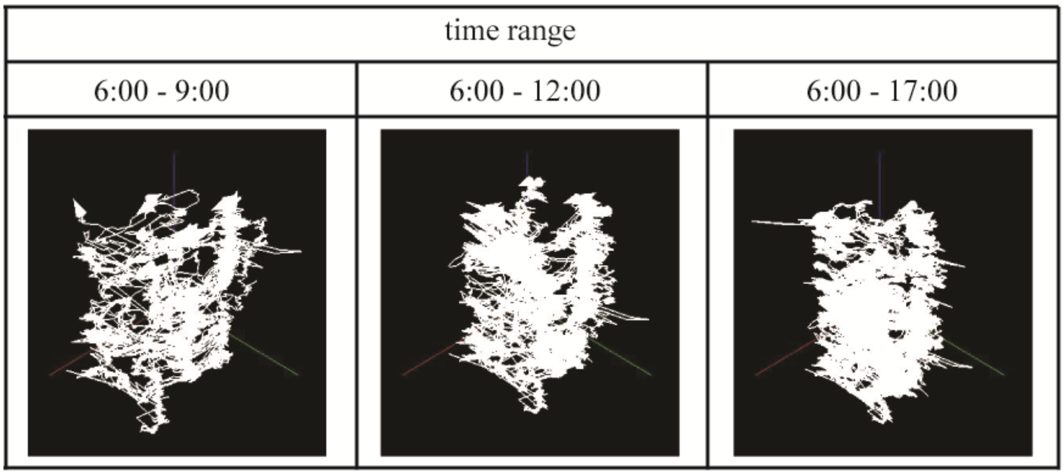


Figure 5.1. Visualization with three different time ranges.

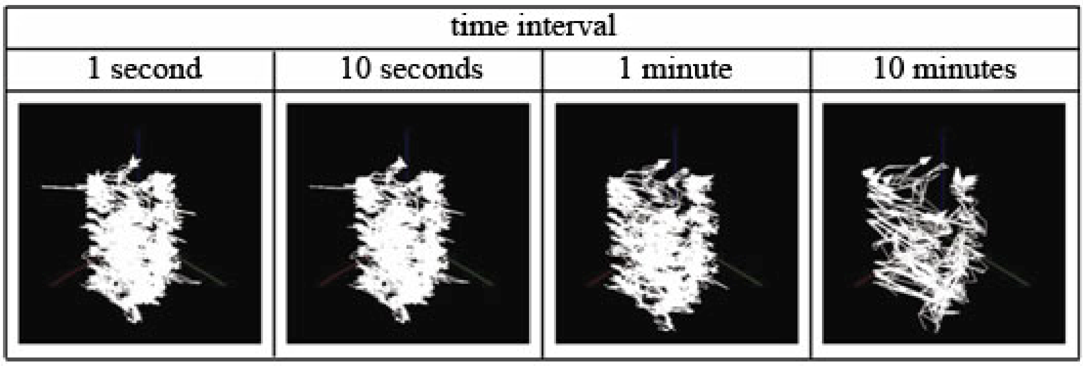


Figure 5.2. Visualization with three different time intervals.

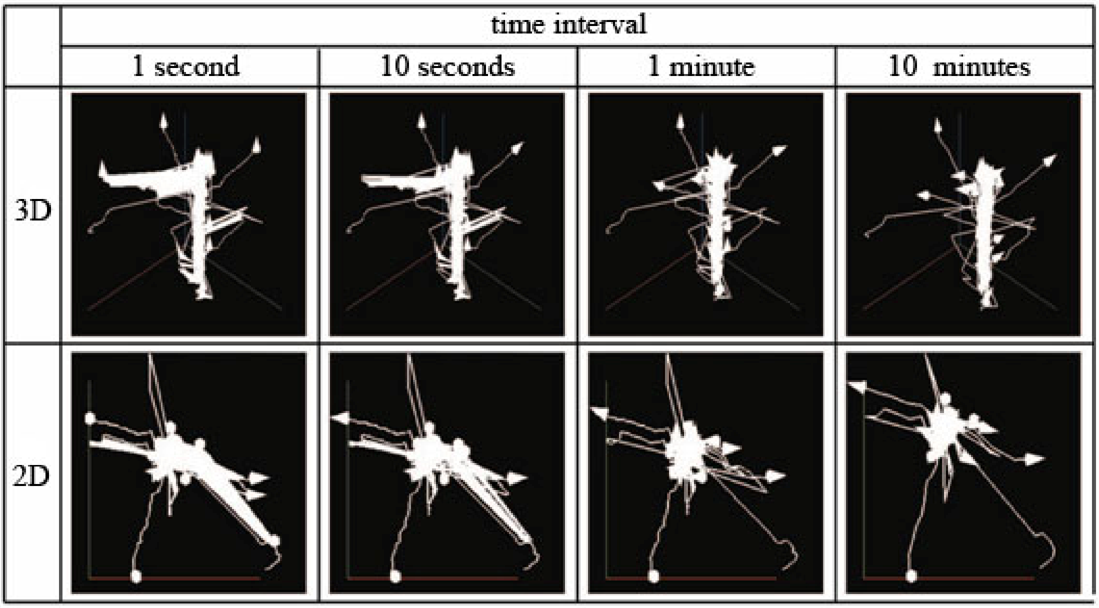


Figure 5.3. Visualization of Lexington data with different time intervals.

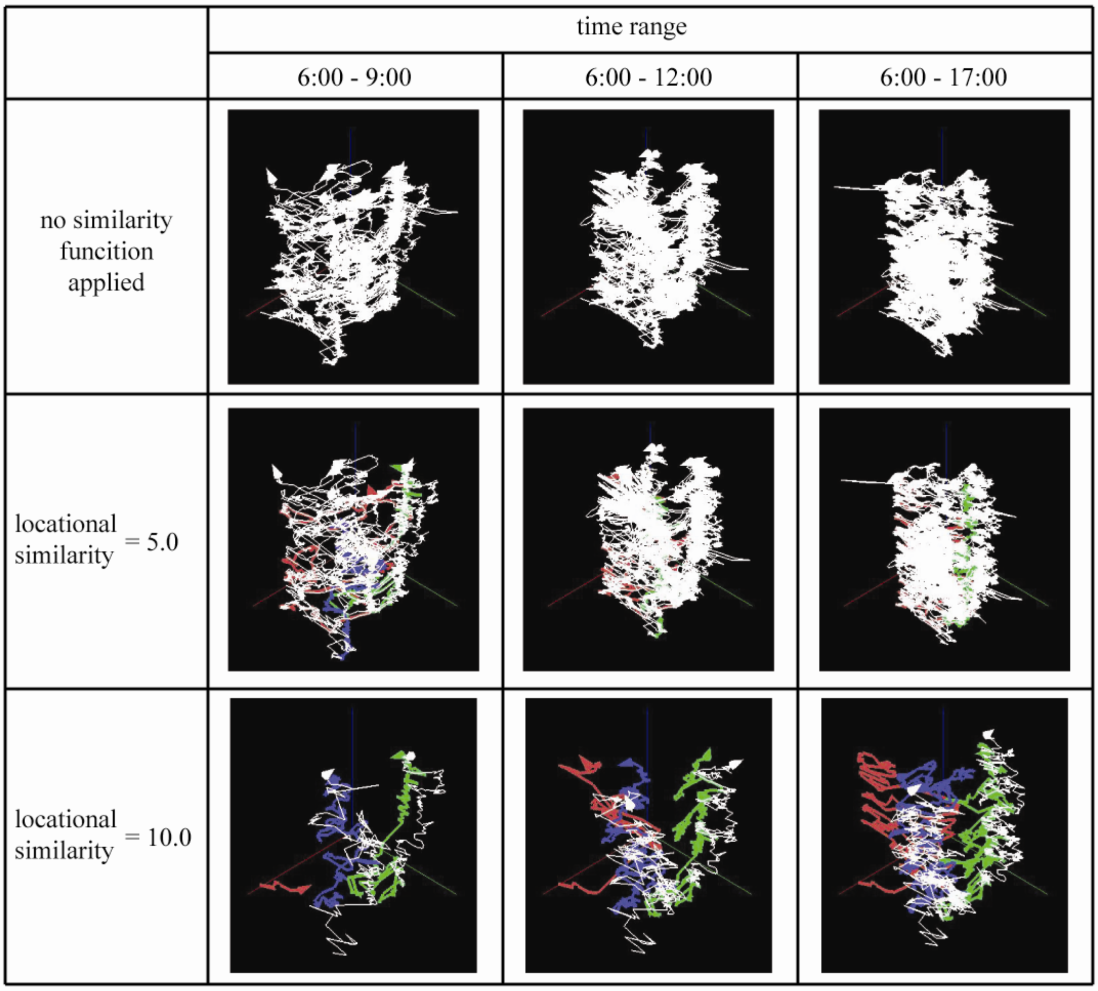


Figure 5.4. Time ranges and locational similarity.

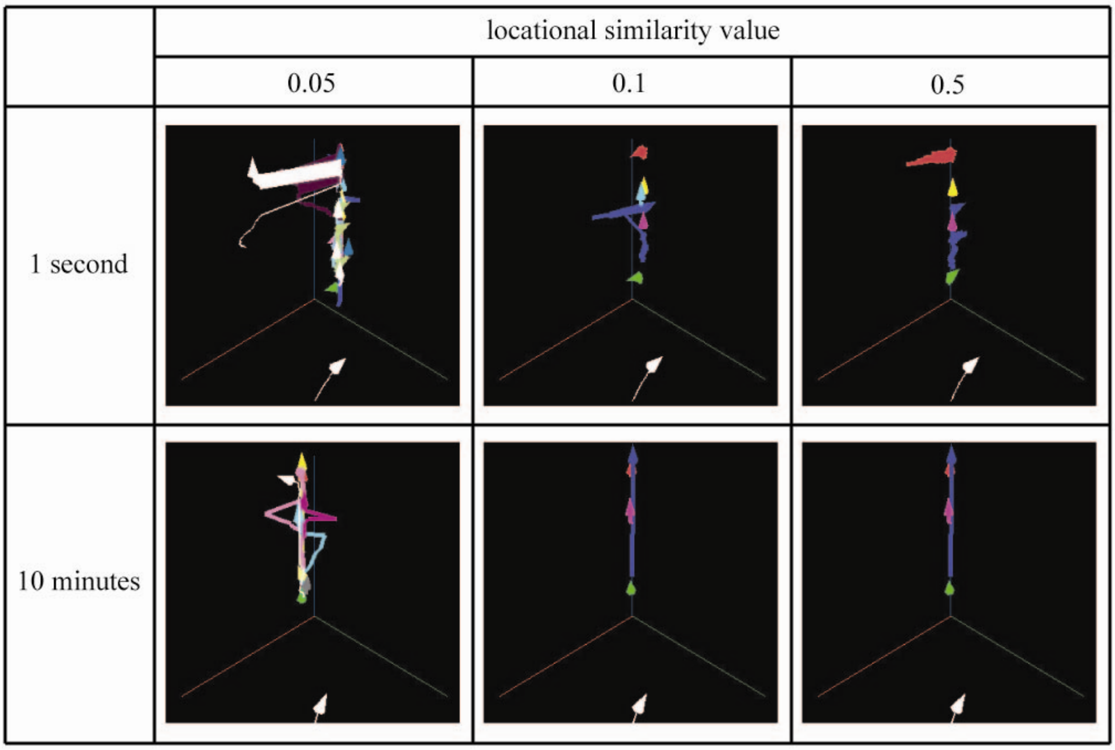


Figure 5.5. Oversimplification with locational similarity.

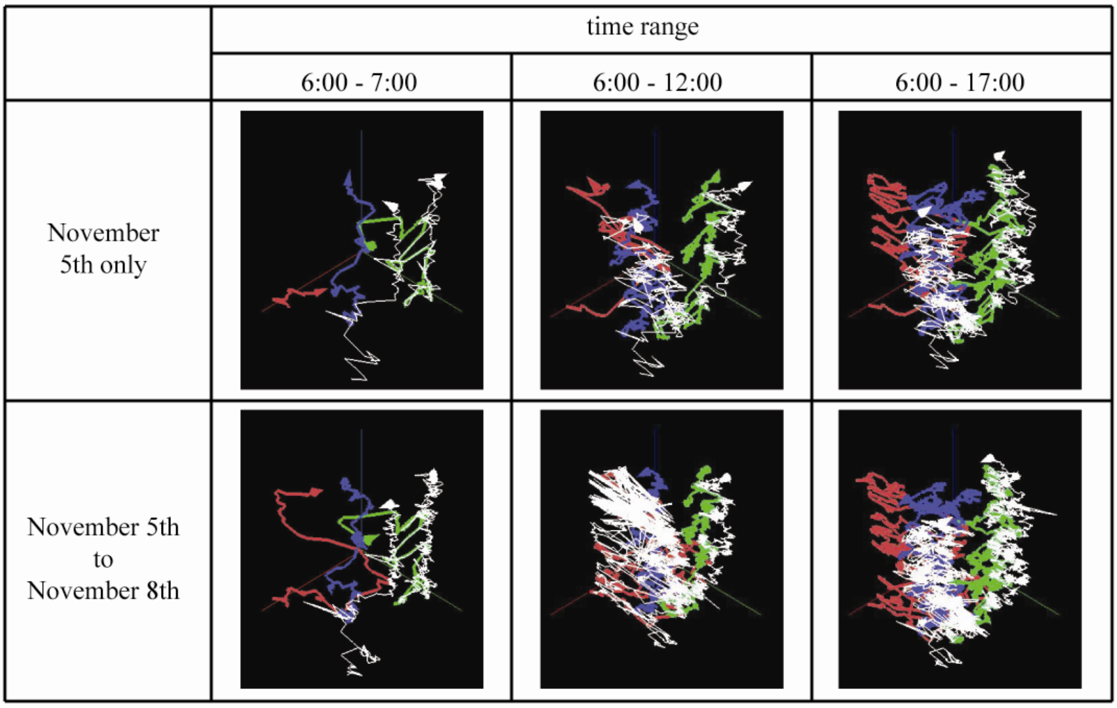


Figure 5.6. Locational similarity and time ranges across different dates.

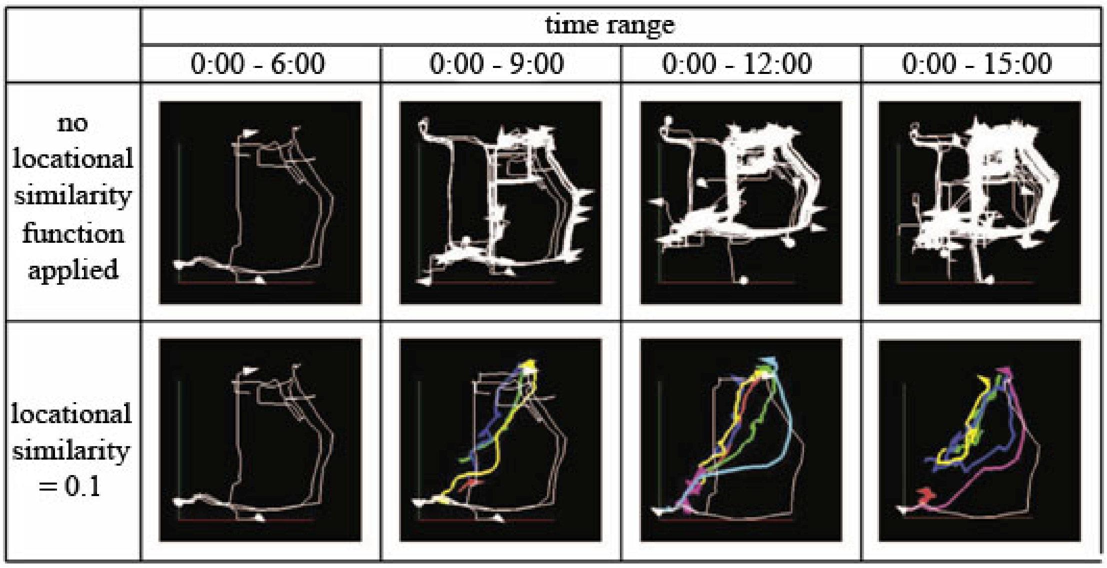


Figure 5.7. Locational similarity with self-tracking data within 1 day.

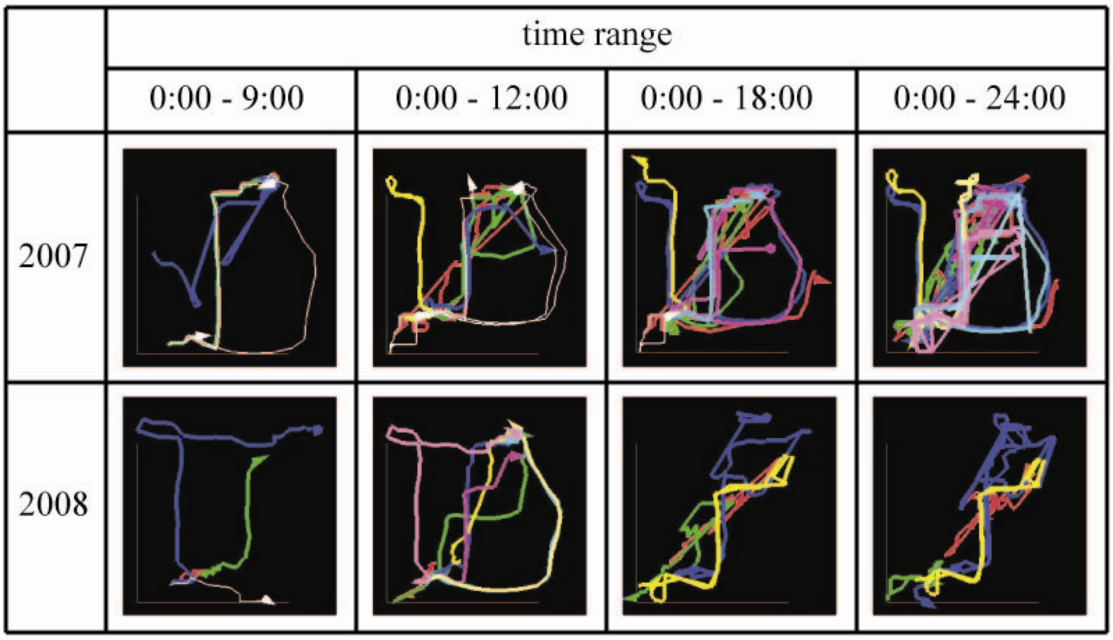


Figure 5.8. Comparison of movement at the same period in 2 different years.

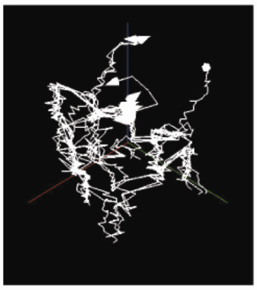
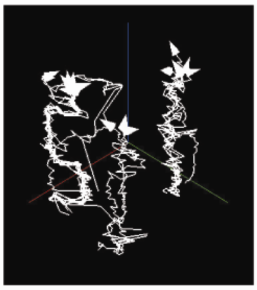
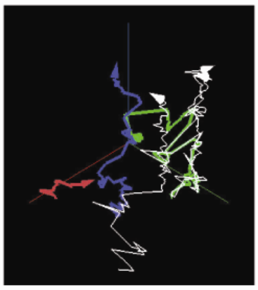
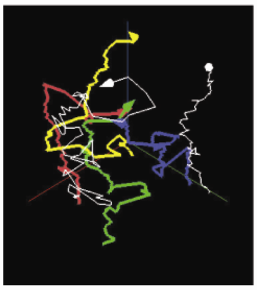
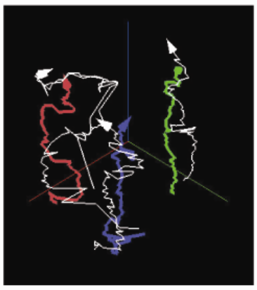
	time range		
	6:00 - 7:00	12:00 - 13:00	16:00 - 17:00
no similarity funcition applied			
locational similarity = 10.0			

Figure 5.9. Locational similarity and time range within 1 day.

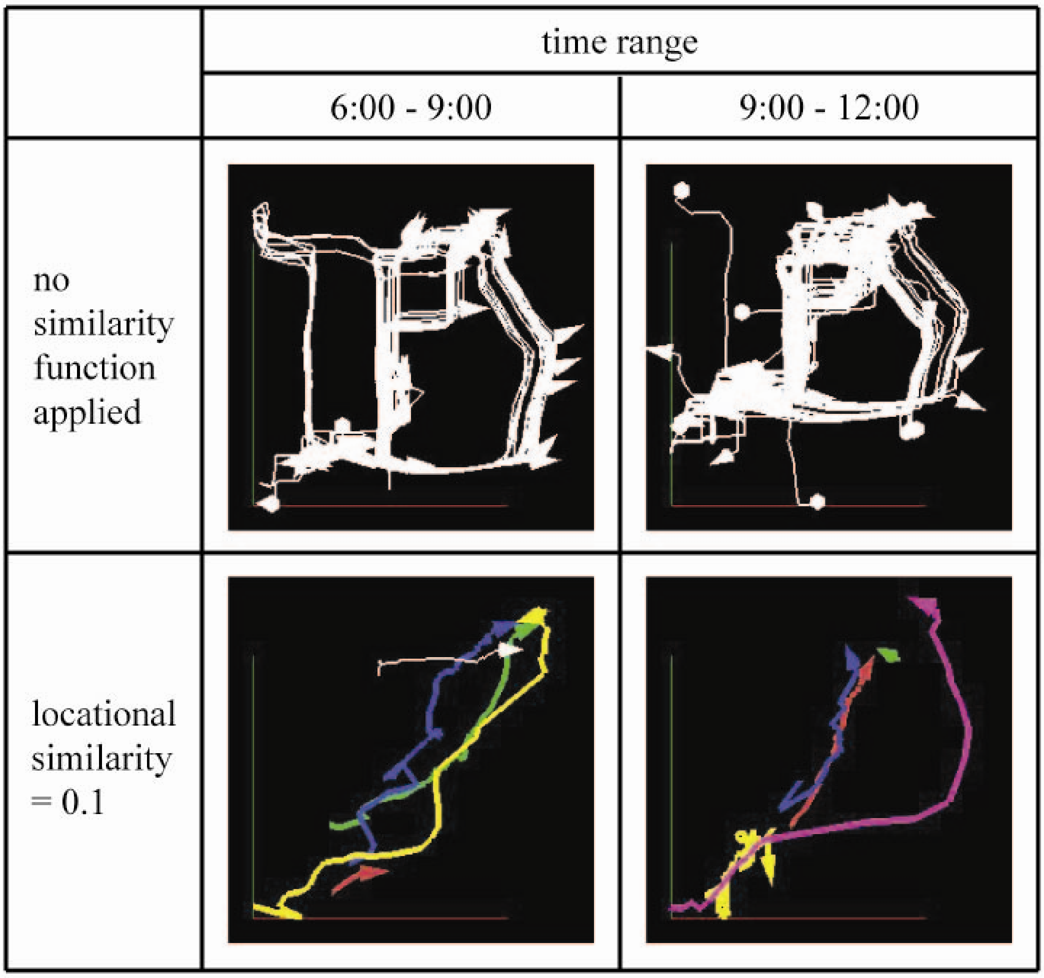


Figure 5.10. Locational similarity and self-tracking movement in the morning time period.

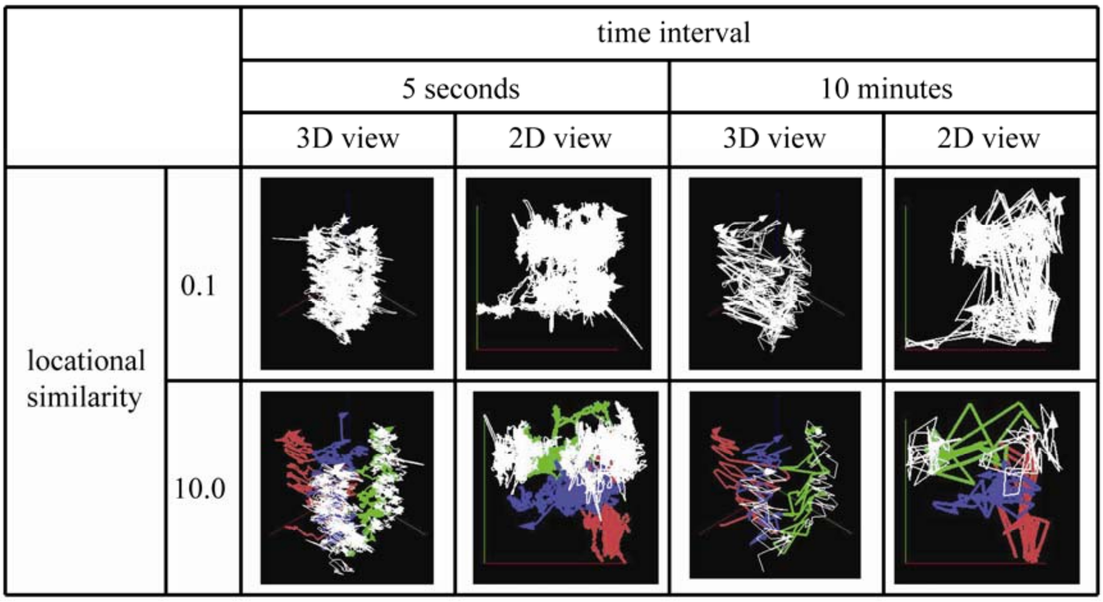


Figure 5.11. Temporal granularity and locational similarity.

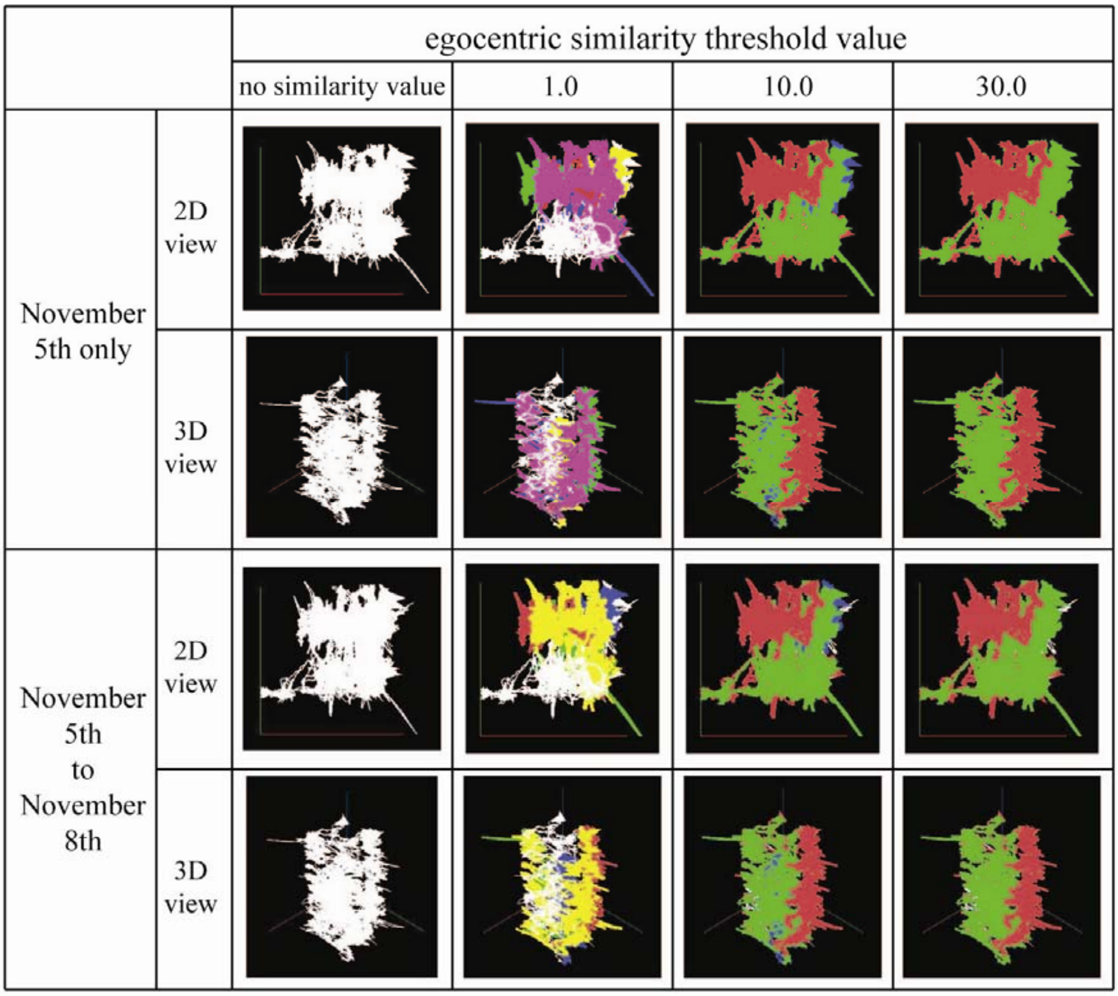


Figure 5.12. Egocentric directional similarity and time ranges across different dates.

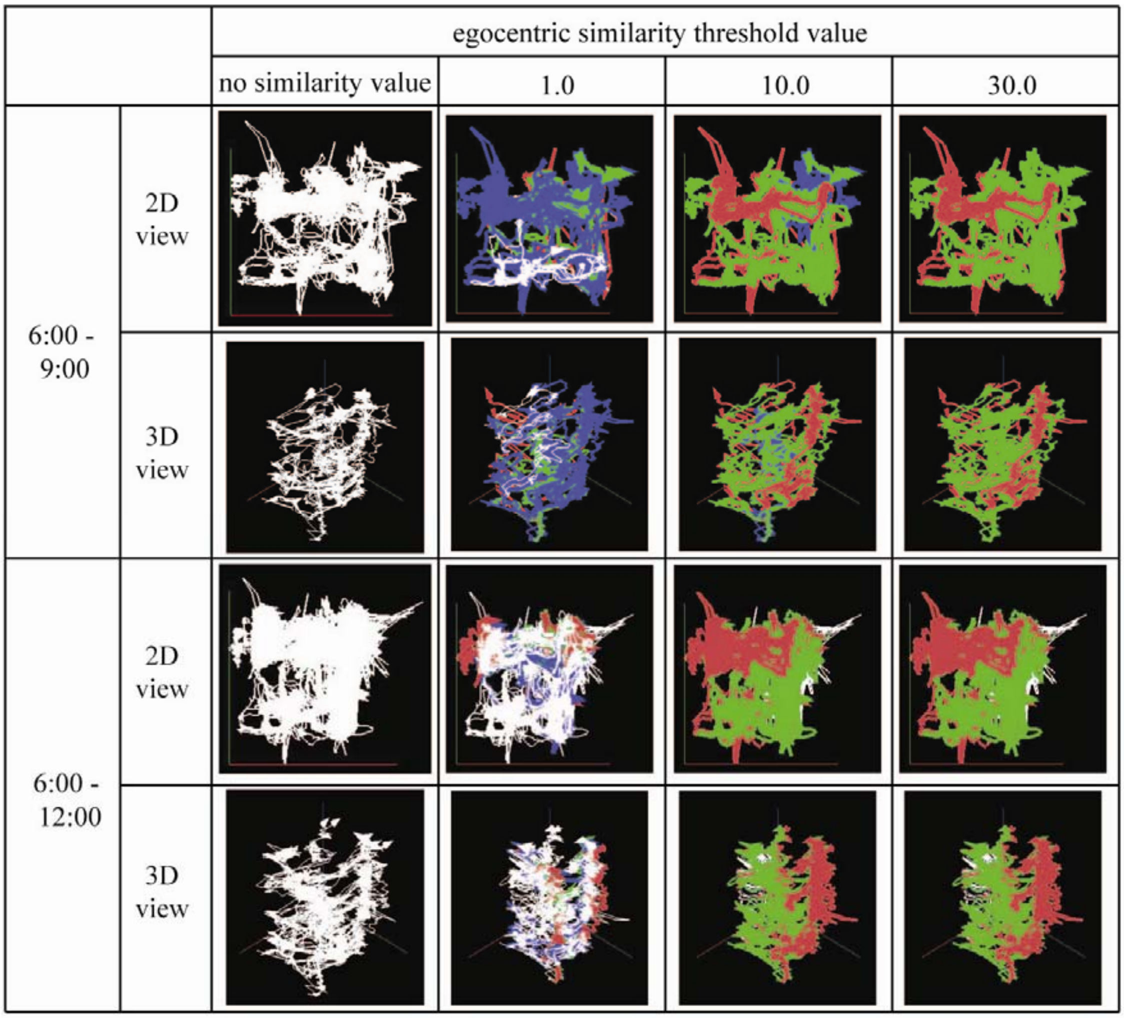


Figure 5.13. Egocentric directional similarity and time ranges in the morning across different dates.

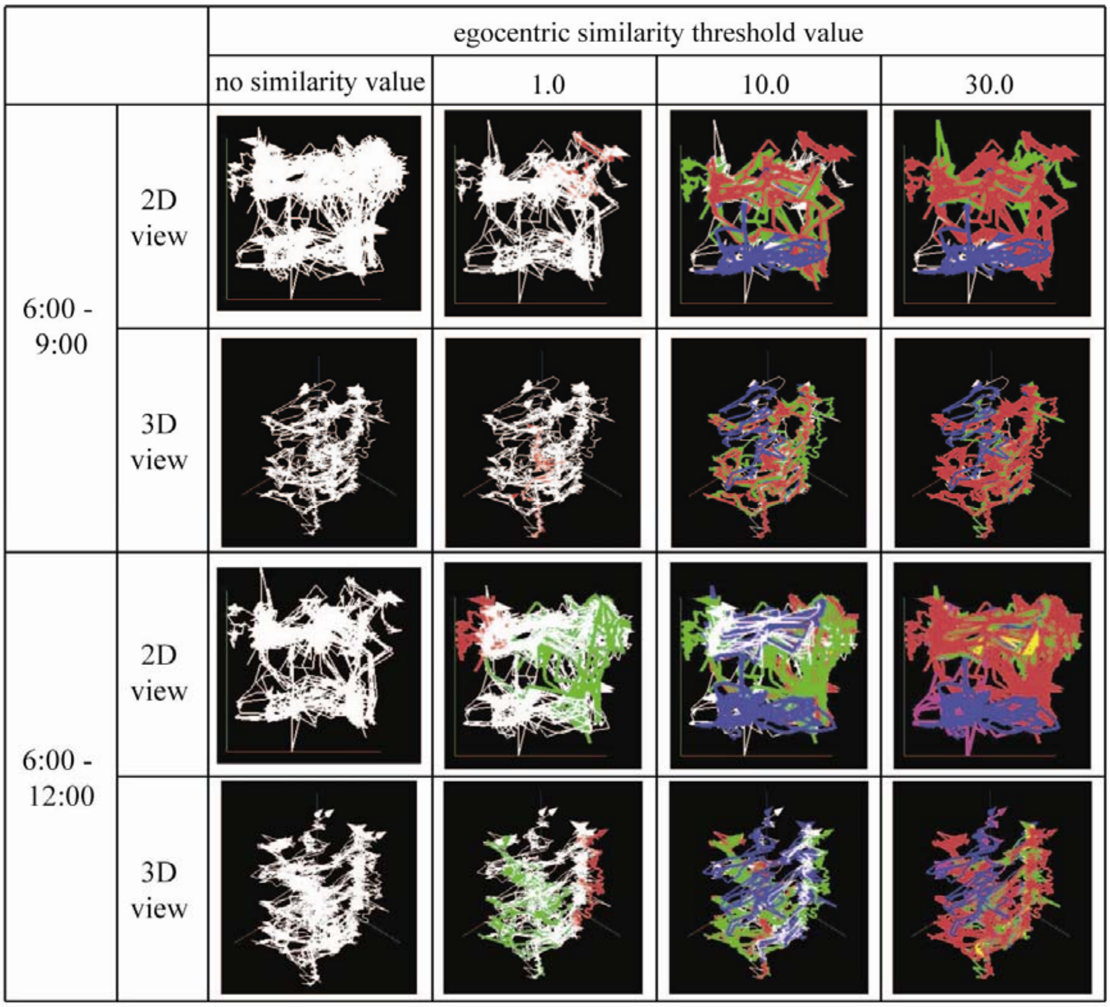


Figure 5.14. Egocentric directional similarity and time ranges in the morning within 1 day.

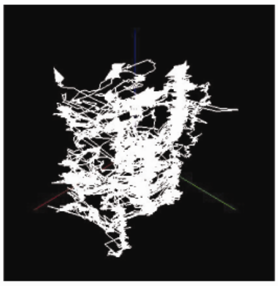
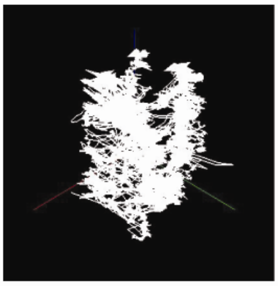
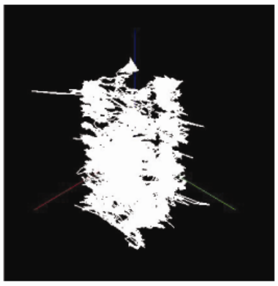
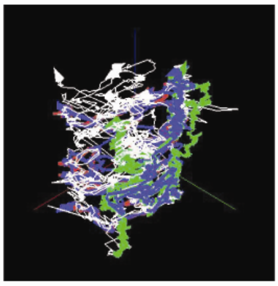
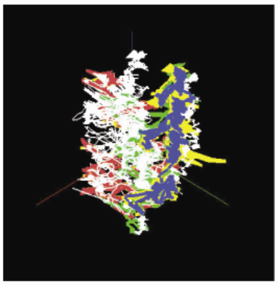
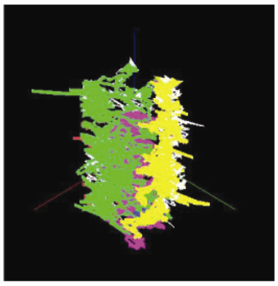
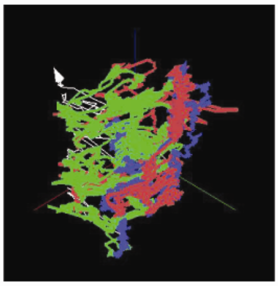
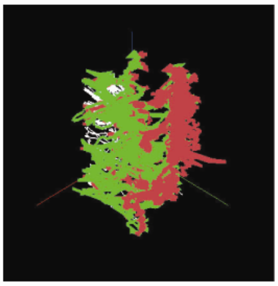
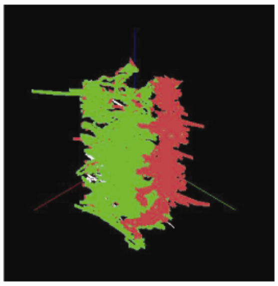
	time range		
	6:00 - 9:00	6:00 - 12:00	6:00 - 17:30
no similarity funcition applied			
geometric similarity = 0.1			
geometric similarity = 0.5			

Figure 5.15. Time range and geometric similarity.

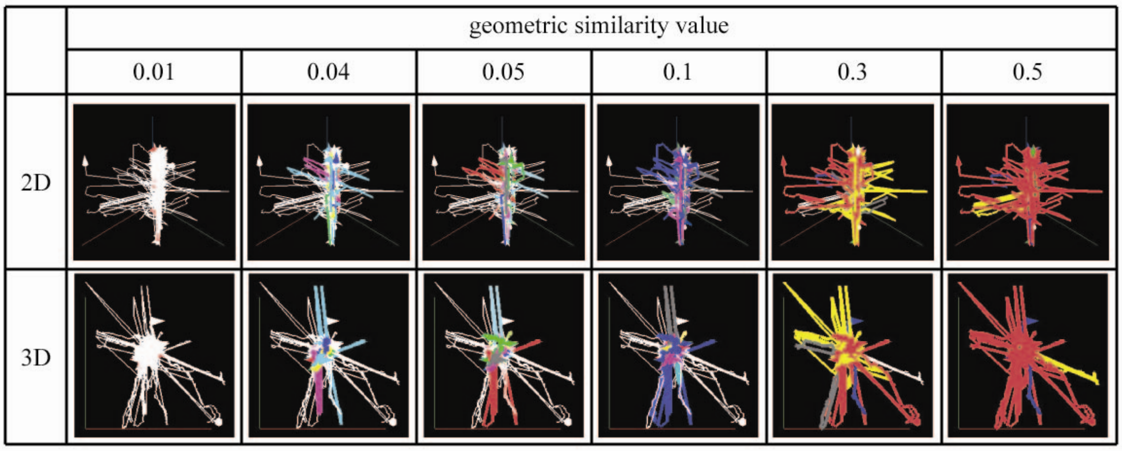


Figure 5.16. Geometric similarity and Lexington data.

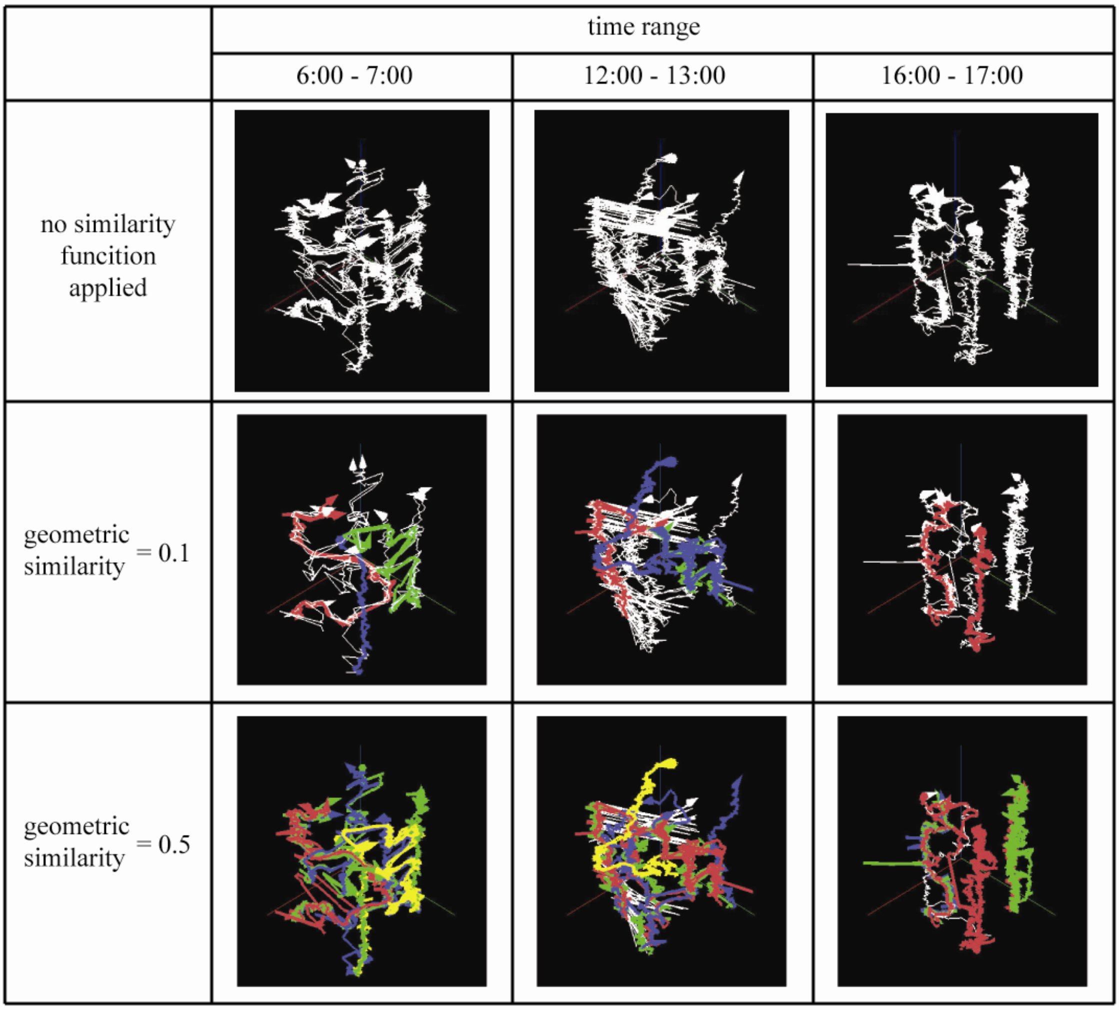


Figure 5.17. Geometric similarity and three different time ranges within a day.

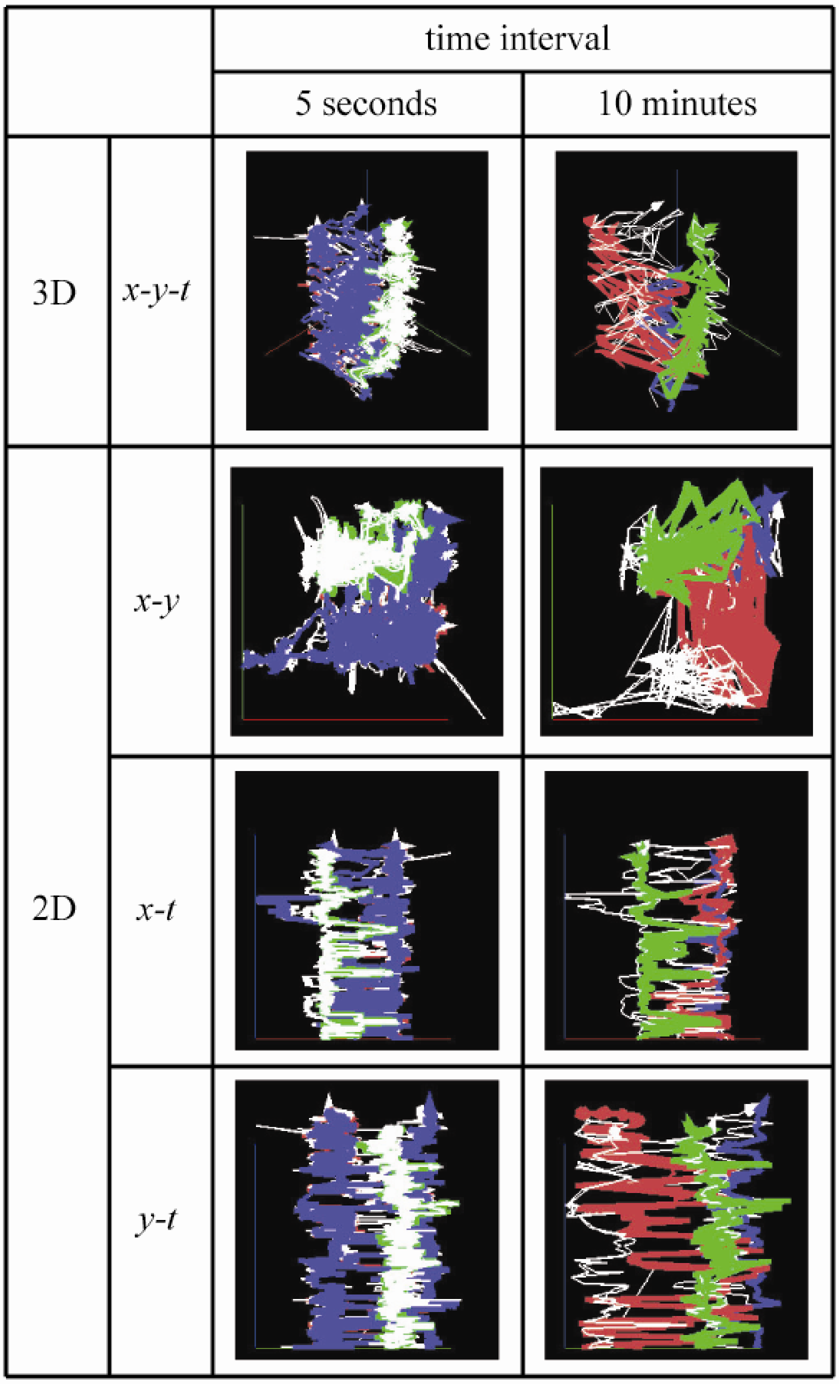


Figure 5.18. Axis conversion and geometric similarity.

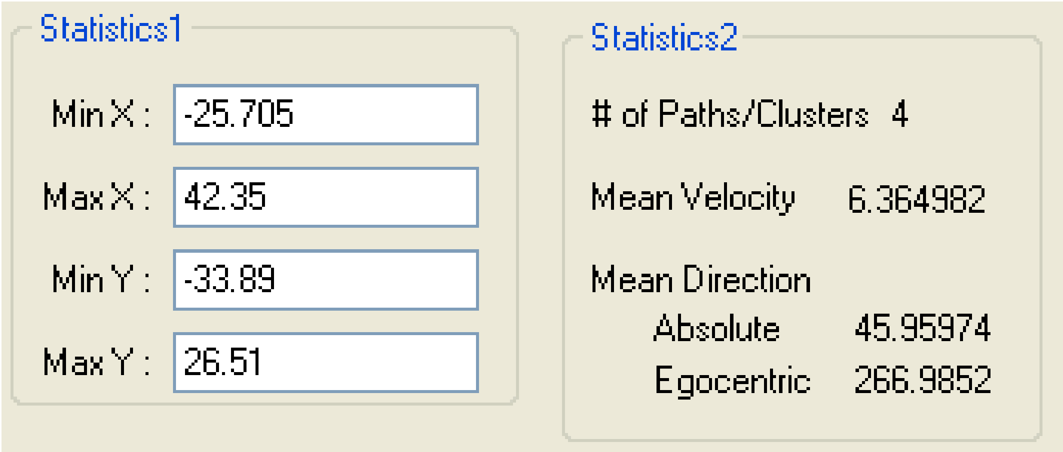


Figure 5.19. Statistical information.

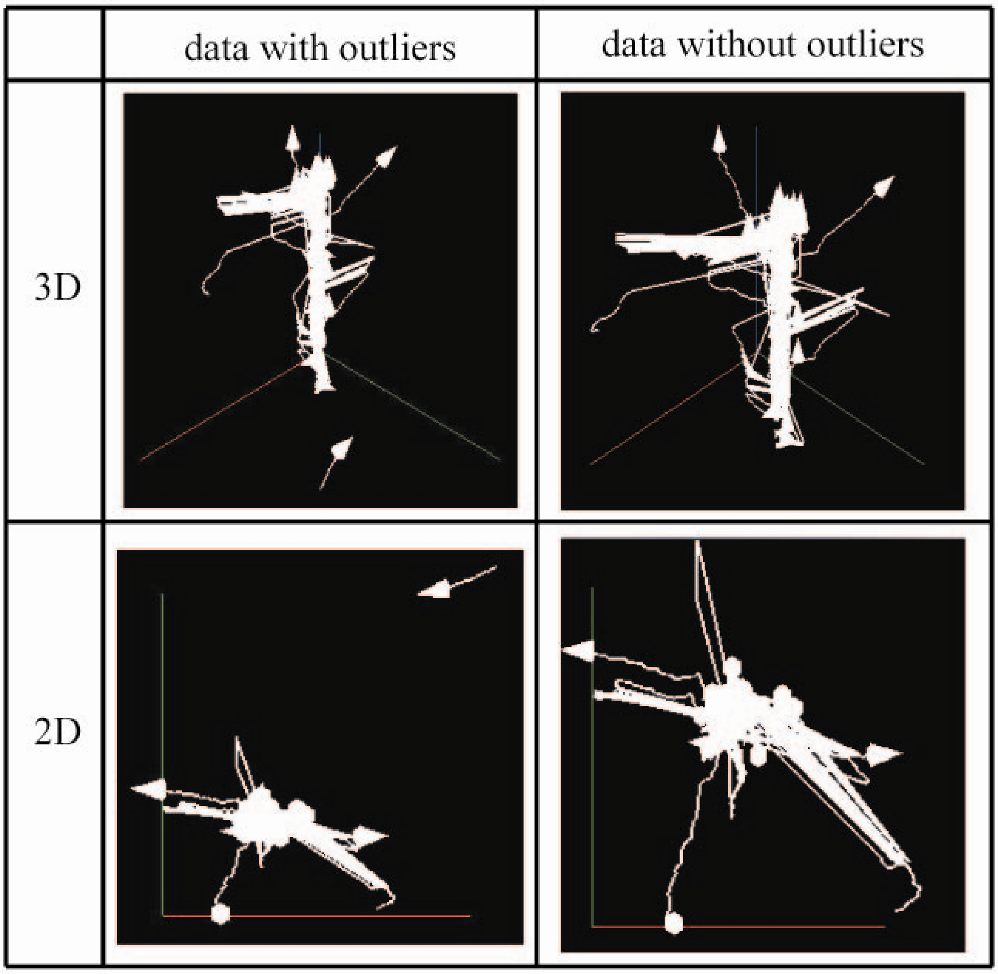


Figure 5.20. Outlier detection and refined visualization.

	geometric similarity value					
	0.01	0.04	0.05	0.1	0.3	0.5
						
number of clusters	1	6	12	13	10	4

Figure 5.21. Number of clusters detected with statistical information.

Table 5.1. Result of decision tree of wild chicken data with various time ranges.

time range	number of clusters in visualization	number of leaves	size of tree	correctly classified instances (%)	root node
6:00 - 7:00	4	4	7	66.66	egocentric direction
12:00 - 13:00	4	5	9	44.44	egocentric direction
16:00 - 17:00	3	2	3	77.77	egocentric direction
6:00 - 9:00	3	3	5	83.33	egocentric direction
6:00 - 12:00	2	2	3	94.44	egocentric direction
6:00 - 17:30	2	2	3	94.44	egocentric direction

Table 5.2. Result of decision tree of self-tracking data with various time ranges.

time range	number of instances	number of clusters in visualization	number of leaves	size of tree	correctly classified instances (%)	root node
6:00 - 9:00	88	4	4	7	96.59	egocentric direction
9:00 - 12:00	155	7	11	21	90.96	egocentric direction
12:00 - 15:00	194	5	4	7	96.39	egocentric direction
15:00 - 18:00	178	8	10	19	91.01	egocentric direction
18:00 - 21:00	182	4	4	7	98.90	egocentric direction
21:00 - 24:00	100	6	10	19	87.00	egocentric direction
0:00 - 9:00	91	4	5	9	91.20	egocentric direction
0:00 - 12:00	173	6	5	9	95.95	egocentric direction
0:00 - 15:00	242	4	4	7	98.34	egocentric direction
0:00 - 18:00	258	5	7	13	94.18	egocentric direction
0:00 - 21:00	268	4	4	7	96.26	egocentric direction
0:00 - 24:00	273	7	7	13	95.23	egocentric direction

Table 5.3. Result of decision tree of Lexington data with various time ranges.

time range	number of instances	number of clusters in visualization	number of leaves	size of tree	correctly classified instances (%)	root node
6:00 - 9:00	60	4	10	19	66.67	sinuosity
6:00 - 12:00	95	3	8	15	54.73	egocentric direction
6:00 - 18:00	134	16	26	51	47.76	egocentric direction
6:00 - 24:00	141	13	25	49	65.24	egocentric direction

Table 5.4. Decision tree analysis of wild chicken data with time interval and geometric similarity threshold.

time interval	# of clusters in visualization	# of leaves	size of tree	correctly classified instances (%)	root node
5 seconds	3	5	9	33.33	egocentric direction
10 seconds	2	4	7	44.44	velocity
1 minute	2	3	5	77.77	egocentric direction
10 minutes	3	5	9	50	velocity
30 minutes	3	5	9	38.88	sinuosity
5 seconds	2	2	3	94.44	egocentric direction
10 seconds	2	2	3	94.44	egocentric direction
1 minute	2	2	3	94.44	egocentric direction
10minutes	1	1	1	-	-
30 minutes	1	1	1	-	-

Table 5.5. Decision tree analysis of self-tracking data with various time intervals.

geometric similarity threshold	number of instances	number of clusters in visualization	numb er of leaves	size of tree	correctly classified instances (%)	root node
0.1	273	10	13	25	94.13	spatial range
0.5	273	7	7	13	95.23	egocentric direction
1.0	273	2	3	5	98.90	sinuosity
2.0	273	1	1	1	-	-

Table 5.6. Decision tree analysis of Lexington data with various geometric similarity thresholds.

geometric similarity threshold	number of clusters in visualization	number of leaves	size of tree	correctly classified instances (%)	root node
0.01	1	1	1	95.00	-
0.05	12	17	33	60.28	sinuosity
0.1	13	25	49	65.24	egocentric direction
0.5	4	8	15	84.39	sinuosity

6 DISCUSSION AND CONCLUSION

Chapter 6 reviews the major contents of this research (section 6.1.) and its scientific contributions to related research fields (section 6.2). Section 6.3 discusses future research challenges and possible improvements and enhancements with respect to the research objectives stated in the beginning of this research. This chapter ends with some concluding remarks.

6.1. Summary

This research aimed to create a highly interactive visualization toolkit to uncover interesting patterns in large volume mobile objects data (MOD). Functionalities such as time aggregation methods with similarity functions synthesize and summarize the overall movement trends in the data. Various combinations of time aggregation parameters and similarity function thresholds successfully detected clusters that extract similar mobility patterns at a specific time scale. In addition, vector representation, statistical information, and axis conversion supported visual data exploration to understand the movement patterns with complicated visualized mobile objects. Moreover, this toolkit connected MOD to data mining software for further data exploration. Results from decision tree analysis vary based on the combination of time aggregation parameters and similarity function thresholds.

6.2. Contributions

The research presented contributes to the scientific and mobile object databases communities in several main areas: 1) high interactivity of visualization toolkit for knowledge discovery in MOD; 2) synthesis of time aggregation and similarity measures; and 3) ability to handle large volume MOD. The toolkit created in this research allows the user to explore MOD in various ways: the user can determine parameters for each functionality of the toolkit. This high interactivity of a visualization toolkit enables visual and geocomputational analysis in flexible and ad-hoc ways. Existing data summarization techniques such as online analytical processing (OLAP) and time aggregation methods (Hornsby & Egenhofer, 2002), and data mining analysis are combined with similarity functions that are presented in this research for deeper data exploration that are especially suitable for MOD.

The second contribution is a synthesis of time aggregation methods and similarity measures. Time aggregation methods and similarity measures are often treated as different topics in mobile objects research. However, it is important to handle both aspects since the analysis mobile objects requires temporal, spatial, and shape information to be analyzed at the same time. Combination of time aggregation methods and similarity functions reveal that the careful choice of time aggregation parameters and similarity thresholds significantly influence the visual results. It is important to utilize both a temporal aspect and a similarity aspect for the advanced and detailed analysis of mobility patterns. In addition, because the geometric similarity function requires geometric components only, it has the ability to compare the similarity of two or more mobile objects at different location and spatial scales. Geometric similarity measure provides a robust way to measure similarity regardless of differences in location and scale: these two elements are major barriers for geographic analysis that are difficult to overcome.

The ability to handle large volume MOD is the final contribution. The visualization toolkit presented demonstrated results for three kinds of mobile objects that are small (18 objects of wild chickens) to large (273 objects of self-tracking data) in size. The visualization toolkit successfully analyzed all three kinds of data, starting from querying the data from the databases and ending with data mining analysis in WEKA software. In addition to the ability to handle datasets computationally, the toolkit facilitated the visual exploration of large volume datasets with time aggregation and similarity functions that provide summarized and simpler visualized MOD. The toolkit provides essential features for the exploratory data analysis of MOD.

6.3. Future Research Development

Future research challenges that derive from this research can be summarized in four categories: 1) consideration of behavioral contexts of mobile objects; 2) development of other similarity measures; 3) validation of visual exploration; and 4) evaluation of the effectiveness of the methods to other MOD.

6.3.1. Consideration of Behavioral Contexts of Mobile Objects

Chapter 5 of this research demonstrated the functionalities of the visualization toolkit and resulting outcomes from the computational and visual exploration. However, this research focuses only on the effectiveness of functionalities in the toolkit to show the ability to find mobility patterns: behavioral contexts of mobile objects that can be explained from the found patterns are neglected. Studying the relationship between behavioral aspects of mobile objects and detected patterns is a broader research question.

It is common knowledge in behavioral science and transportation research fields that specific types of behavior, such as commuting behavior and recreational behavior, have unique characteristics. It is important to analyze the mobility data of specific types of behavior with the toolkit developed in this research to analyze the outstanding patterns in the behavior. For example, time aggregation methods can extract the commuting behavior in the morning time range and the evening time range, respectively, with the time interval of interest. Visualization of each time range will provide the mobility patterns of each commuting behavior in several time scales. In addition, similarity functions will detect similar mobility patterns and outliers in the commuting behavior. There may be certain routes in the urban area that many mobile objects pass at a similar time period. The locational similarity function can detect this behavior. On the other hand, outliers that are not clustered by similarity functions may lead to the discovery of new routes for commuting that can mitigate traffic congestion. Analysis of specific types of behavior is a next step for this research.

Detection of specific types of behavior from large volume datasets is another possible extension with the toolkit described in this research. As mentioned in the previous paragraph, certain types of behavior, such as commuting behavior, occur at the certain time periods, such as in the morning or in the evening. It is possible to assume when those specific types of behavior occur and try to extract them using time aggregation methods. Following analysis with similarity functions can provide the patterns of the extracted mobility data. Functionalities in the toolkit in this research can contribute to behavioral sciences in the new era of data-rich research.

6.3.2. Development of Other Similarity Measures

Although the similarity functions in this research are scalable and effective at detecting similar mobility patterns, there are many ways to assess trajectory similarity. Other ways of measuring locational, directional, and geometric similarity should be explored, as well as other definitions of trajectory similarity distinct from the two dimensions explored in this research.

One possible way is to examine the properties that can be extracted from trajectories. There are other characteristics that can be calculated from trajectories other than the five properties identified in this research, such as average travel distance, average *x* coordinate location and *y* coordinate location of a trajectory, and so on. Behavioral characteristics such as number of activities, number of visiting locations, and activity duration time are also possibilities. It is important to evaluate these characteristics as potential key factors to uncover interesting patterns in MOD.

The investigator has extended this work to create a toolkit that enables visual exploration of trajectory properties in the attribute space in conjunction with the geographic space (see Figure 6.1). This toolkit allows for how the values of each property of a trajectory may change over time (the visualization component at the center in the toolkit described in Figure 6.1). The bottom graphs illustrate the changes of each value with respect to time. Visualization components on the left side show two-dimensional and three-dimensional geographic views of trajectories. The user can incorporate any other characteristics of trajectory to examine the change in values using this toolkit, which may lead to the discovery of key factors that describe mobility patterns of MOD.

6.3.3. Validation of Visual Exploration

In addition, it is difficult to validate the patterns detected solely by visualization because found patterns are based on human visual intuition. Since intuitive comprehension can be misleading, it is urgent to develop methods to validate the detected patterns.

Utilizing geocomputational techniques is one of the solutions to complement the results from visual exploration. Pattern detection techniques such as classification and clustering may be useful to find rules in MOD, which provides a different perspective other than the visual intuitive interpretation of data. In this research for example, data mining analysis with decision trees aimed to find the rules that describe mobility patterns, which provided that the egocentric direction is the most important explanatory factor in many cases. Data mining analysis and visual exploration complement each other in knowledge discovery and validation of the visual exploration.

6.3.4. Evaluation of the Effectiveness of the Methods to Other MOD

Furthermore, it is important to test the effectiveness of the granularity and aggregation methods to other special cases of mobility patterns such as individual people’s movement inside buildings, migrating birds, and so on. Since each mobile object has its unique constraints, unique movement patterns may be detected. Applied analysis using time and similarity aggregation methods will reveal the usability and weakness of aggregation methods in different applications, which can lead to the development of more powerful methods to analyze MOD.

6.4. Conclusion

As the volume and complexity of MOD increases with the growing usage of digital mobile devices, there is a high demand for developing new techniques to handle and analyze the emerging data. Existing techniques are incomplete due to their lack of ability to handle large volume data. This research developed a highly interactive visualization toolkit for large volume MOD for exploratory visual and geocomputational data exploration that can lead to knowledge discovery in individual-based mobility patterns.

Existing research provides techniques to analyze MOD, such as time aggregation methods with OLAP, similarity measures to detect similar mobility patterns, and so on. However, these techniques are often computationally expensive and not well integrated. The toolkit developed in this research responds to a need for a more synthetic way to analyze MOD; it accomplishes this by integrating various techniques into one toolkit. Visualization with computational techniques enhances the range of exploratory data analysis. The toolkit also has the ability to handle large volume datasets, which overcomes one of the major research challenges in the literature.

Although the toolkit detected some interesting patterns, the true success of the toolkit is whether the data exploration will lead to meaningful knowledge discovery for applied fields such as transportation planning, behavioral modeling, and evacuation planning in a time of disaster. These fields can benefit from the pattern detection process proposed in this research for hypothesis generation, model creation, and planning. Development of methods to bridge visualization and knowledge discovery techniques with applied geographic phenomena will facilitate the decision-making processes that lead to better policy making and planning.

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