A Review of Trajectory Data Mining Applications

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***Abstract*—With the rapid development of digital technologies, location-aware technologies have helped increase trajectory data availability that results from tracking moving objects. Through the collection and analysis of trajectory data, the extracted knowledge can be beneficial in many applications. Trajectories are widely known as a series of points that represent geographic locations. The researchers devoted their efforts to many trajectory data mining fields, where the benefit of these data can be gained and employed in many applications. This paper focuses on providing a comprehensive review of trajectory data mining applications such as path detection, urban services, environment services, objects behavior analysis, and so on.**

Keywords—trajectory, data mining, applications of trajectory data mining, review

I. Introduction

The development of technologies has increased in recent years, especially location-aware technologies that geolocate moving objects such as smartphone sensors, radio frequency identification (RFID) devices, global positioning systems (GPS) [1]. In contrast, the moving object can refer to (but not limited to) a human, an animal, a vehicle, or a device [2]. Different application fields can benefit from the extracted knowledge from trajectory data mining, and the increasing use of location-based technology has led to the development of an infrastructure that allows users to take advantage of advanced services such as movement behavior prediction, path discovery, urban services, environmental services, etc.

Applications can provide these services and can provide the correct information at the right time to the service users. Trajectory data are collected from various sources, so the period and rate of sampling the trajectories depend on the applications.

In this paper, we endeavor to review applications and areas where trajectory data mining can be beneficial. The significant contribution is to pave the way for researchers and those interested in the field and clarify their visions regarding trajectory data mining applications.

The remaining sections were arranged as follows: section II explains the concept of trajectory data, section III describes the mining technique, section IV reviews the applications of trajectory data mining, conclusion, and future work are both provided in section V.

II. Trajectory Data

Moving objects that travel in a geographical place can be represented through samples of space and time data called trajectories, considering that trajectories must be expressed with time and space properties.

A trajectory can be defined as a continuous mapping from R to R2 (while R represents time and R2 represents the two-dimensional plane).

This data is generated by different moving objects such as humans, animals, vehicles, electronic devices, etc. These trajectory data can be collected using various sources as well such as smartphone sensors, global positioning systems (GPS), location estimation for 802.11, radio frequency identification (RFID), and so on [2]. An object's trajectory captures its trace for a specific amount of time; for example, an animal's trajectory describes its produced trace by its movements, such as the amount of time of their sleeping, feeding, and running. Generally, trajectory data are timestamped spots where the moving object moves in a spatiotemporal space [2]. We can indicate that a trajectory is a semantic trajectory when it is associated with contextual information.

III. Data Mining

This section provides a framework of the fundamental steps of trajectory data mining, as shown in Fig. 1.

We must notice that not all the steps of trajectory data mining are unavoidable; it depends on the needed requirements and the purpose of collecting the data in the first place.

Firstly, the data will be generated by the moving objects, and it will be collected and stored in the database.

Secondly, preprocessing methods are applied to the collected data, such as sampling [3], [4], [5], cleaning [6], and segmentation [3], [7]. The preprocessing step is a primary step because in this step the quality of data is improved, and the unnecessary data is removed. After that, the management of data begin, the management can include, compression [8],[9], storage systems [10], [11], and index structures [12], [13]. The next step is considered with query processing, retrieve the data from the storage system is a fundamental step. This step aims to find and bring the correct data when needed. Various queries can be used in this step, such as location-based queries [14], nearest neighbor (NN) queries [15], [16], and top-k queries [17]. After this step, the tasks of trajectory data mining occur; these tasks are classified according to each task's type. Tasks can include pattern mining [18], clustering [19], [20], classification [21], knowledge discovery [22], [23]. Finally, in the field of applications, we provide an extensive review of trajectory data mining applications in section V.

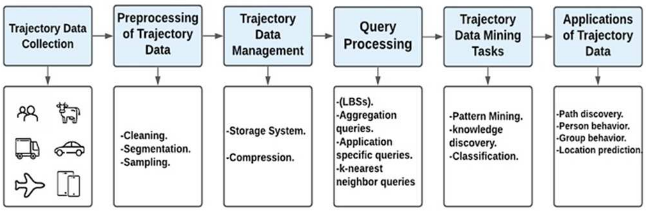

Fig. 1. A trajectory data mining framework.

IV. Applications

The knowledge derived from the trajectory data mining process is beneficial in many application fields. This section presents a review of these various fields and a summary table that contains each application and its relevant work references, as shown in Table I.

A. Path Discovery:

There are many application scenarios, the most common of trajectory detection (route data extraction). Trajectory detection can be the most popular, the quickest, the shortest, etc. Trajectories are derived based on a given trajectory network by finding at least one trajectory satisfying a given goal with a source and a destination much literature has been published in this section [1]. In reference [24], they propose a confusion detection method that detects outliers in GPS paths. They developed a method in a unified framework called iBDD that detects two outlier paths in real-time. Alternatively, we can predict patterns of redundant paths of the same person, such as when she goes to and from work at predictable times. In reference [25], they discovered an ingredient that authorizes the use of geographic context. The ingredient collects chauffeur trajectories and links them to use metadata at GPS. In reference [26], they proposed that within a given period, the most frequent trajectory can be determined by considering the period T, source versus destination, and searching for the most frequent trajectory regardless of the period constraint. There are unconfirmed trajectories in [27], the study addressed the trajectory's creation at a very low meager sampling average for various purposes, such as device and performance limitations and privacy concerns. We can benefit from people with road backgrounds, such as taxi drivers, to find the fastest trajectory to a destination based on their knowledge. In reference [28], They discussed by summarizing the GPS-enabled driving instruction, a massive number of taxis provided the user with the fastest route to a particular destination and departure time. They also designed a two-stage trajectory algorithm to calculate the fastest trajectory practically. Based on a dataset of trajectories from more than 33,000 taxis over three months. We can explore some types of activities that users have in certain domains by semantic domains. To extract them, the study [29] proposed a sequential summarization approach to discover a set of samples as semantic areas of individual trajectories according to spatial and temporal density. They also developed a clustering algorithm based on Nearest Neighbor Sharing (SNN) to discover the recurrent semantic regions.

B. Location/Destination Prediction:

Human mobility has become unusual and therefore predictable, providing suitable ads to target customers requires predicting their location or destinations, and it can be provided through many applications. These are known as location-based services (LBS), which are also known as location awareness services. Destination prediction is intimately correlated to trajectory recognition. The widely known approach for destination prediction is Location/Destination Prediction. Since the destination location is based on historical paths, destination prediction is increasingly useful for people in urban or tourist areas [1]. Most technologies suffer from a data inconsistency problem; the number of available tracks is not enough with the number of historical tracks. In reference [30], they proposed a system called "DesTeller" in a dynamic webpage that simulates how the SubTrajectory Synthesis (SubSyn) algorithm derives site-sensitive information for users. And the problem of inconsistent data, the algorithm has successfully addressed and can predict each query's goals. Since traffic conditions and user preferences can affect the dynamic change of the trajectory in the real world, it is advisable to estimate the possible flight duration by considering the origin location, the destination location, and the time of departure.

In reference [31], they proposed a learning model to represent the problem of estimating the travel time at the origin and destination (MURAT). Location-based applications make it easier for users to find local information (restaurant, gas station, school, or teacher) from their mobile devices.

In reference [32], 63% of local searches were performed on mobile devices. These results are discussed to provide a picture of how location, time, and social context affect local mobile search.

In reference [33], they proposed a hybrid prediction model for user social conformity that considers both regularity and compatibility of human mobility. They have also increased the predictive power by introducing heterogeneous city-wide mobility datasets such as GPS, WiFi signals, and smart cards.

C. Business:

There are recommendations based on trajectory and moving objects to solve business difficulties related to places or areas' characterization. Many organizations take advantage of periodic traffic and movement data in their business. To analyze the movement interactions between these entities of a specific location, trajectory data extraction is recommended. For example, extracted trajectory data have been used for best advertisement page [34], best store design [35,36], and best job website [37,38].

D. Public Security and Safety:

Security must be strengthened by identifying and monitoring location and moving objects that have the potential to cause harm and threats. Trajectory data mining helps detect or even predict these damages or threats promptly as application problems include positioning, the object moving and monitoring, and trajectory-based prediction. An approach was used to detect misconduct [39], explore the movement of aviation accidents and hurricanes [40] and predict their future occurrence [41], and identify and monitor large events and crowd behavior [42].

E. Urban Services:

The quality of life can be noticeably improved in urban areas; with the help of the discovered knowledge of trajectory data mining, that goal can be achieved. Several studies and efforts were spent in this field, a strategic method for deploying charging stations and charging points was proposed [43]; this method helps with preserving and minimization the spent time when a driver wants to reach a charging point; also, it helps with minimal waiting time when a driver looks for available charging points. A recent study [44] was proposed to estimate the pedestrians' traffic extent in closed environments, and the extracted knowledge would enhance the infrastructure.

iPark [45] is a proposed method in parking vehicle issues; it allows the search for parking areas linked with description information about these areas. In references [46], [47] methods were proposed to recognize the areas of different city functions by using and depending on widespread trajectory data.

F. Making Sense of Trajectories:

When trajectory data lacks semantic information, it is considered hard to understand and make sense of. In order to aid the understanding of raw trajectory data, numerous studies were proposed in different areas; in reference [7], an approach that describes, divides, and summarizes the trajectory was proposed, to create a short and simple text that can be readable by humans to describe the trajectory; in order to realize that approach, a proto system called STMaker was proposed [48]. While the semantic information enables the interpretation of raw trajectory data, TOPTRAC [49] was proposed to disclose trajectory data's implicit topic. A method that automatically discovers the personal semantic places was proposed in [50].

G. Ecology:

Solving and characterizing problems associated with living animals' applications can be achieved by determining these animals' behavior and interaction. Various literature has been suggested by those interested in the field, including automatic detection of the trajectory of animals' activities [51], [52], [53], understanding of their environment use [54], and interaction between animals [55].

H. Movement Behavior Analysis:

Predicting human behavior has become necessary in emergencies for disaster management and disaster relief; in reference [56], a model was developed that predicts human mobility, simulates human movements after natural disasters, and collects extensive data to analyze human mobility disasters in Japan. The results proved that prediction after disasters with human mobility could be simulated.

In reference [57], to predict human mobility behavior, a general technique was presented depending on the clustering method to exploit the contextual variable. Multiple models are used to extract the patterns and are combined into a probabilistic framework. The results have demonstrated the possibility of predicting human mobility in the real world. In reference [58], the Athena System was implemented to understand human behavior by interpreting movement patterns and using movement patterns to infer human behavior. In reference [59], the human behavior trajectory is analyzed to represent the path using neural networks by proposing an activity description vector (ADV). Depending on the number of iterations, the activity at a particular point is described to the person. In reference [60], to analyze the trajectory's rationality, a method has been proposed to represent the behavior of the trajectory based on the user's visit to the point of interest (POI).

I. Group Behavior Analysis:

In reference [61], they presented a framework based on grouping for the collective discovery of moving objects that supports discovery through the Internet, which is achieved through an effective discovery strategy.

In reference [62], a framework was presented that simulates the movement's behavior to generate trajectory data from the temporal and spatial movement of people, and a model was proposed to represent the behavior of the individual and the group by algorithms and the experimental analysis proved the effectiveness of the framework.

J. Sports Analytics:

Soccer match analysis has become very important for coaches. Corresponding data is collected to perform player movement analysis, events, and interaction with other players. In references [63], [64] tools were proposed to analyze the player's path and their repeated movements to extract events that may include starting and corner kicks. The results proved that the method is fast and all the tools for coaches have become better team performance.

K. Social Applications:

The excavation of the trajectory data helped to discover human behavior and compare it with different species; in reference [65], a framework has been proposed to measure similarity and search for user files based on the visited site's history. It is called HGSM, where the site records indicate their activities and interests.

Individuals' lifestyles can be understood through their activities, which are identified from the trajectory [66]; an algorithm has been developed to collect publicly available data and connect millions of individuals in social networks.

L. Environment:

To reduce and control pollution that occurs in the world, we need to monitor and determine the level of pollution in many locations and combine data from different sources with pollution data that will help control it. The trajectory data extracted can be used to increase the number of samples collected from Many locations, merging and analyzing them. trajectory data related to air pollution can be obtained by describing and identifying places and regions [67], [68], and there is a lot of literature that helps in monitoring noise pollution in areas. Collecting urban data from various sources [69],[70],[71],[72].

M. Energy:

In determining the energy consumption of individuals and specific sectors, they help identify the problems resulting from that energy. The energy sectors are concerned with the characterization of the area and the moving body, which is addressed by following this approach in the implementation of feedback systems for environmental guidance [73], [74] and for charging electric vehicles a location for infrastructure [75] or by mining paths for vehicles [76].

TABLE I. SUMMARY OF APPLICATIONS IN TRAJECTORY DATA MINING

Application Field	Related Work
Path Discovery	[24], [25], [26], [27], [28], [29]
Location/Destination Prediction	[1], [30], [31], [32], [33]
Business	[34], [35], [36], [37], [38]
Public Security and Safety	[39], [40], [41], [42]
Urban Services	[43], [44], [45], [46], [47]
Making Sense of Trajectories	[7], [48], [49], [50]
Ecology	[51], [52], [53], [54], [55]
Movement Behavior Analysis	[56], [57], [58], [59], [60]
Group Behavior Analysis	[61], [62]
Sports Analytics	[63], [64]
Social Applications	[65], [66]
Environment	[67], [68], [69], [70], [71], [72]
Energy	[73], [74], [75], [76]

V. CONCLUSION

In this review paper, we had provided clarification of trajectory data meaning, the steps of the data mining process were specified, and a detailed review of trajectory data mining applications used in the field and a summary table were proposed in order to facilitate the access and clarify the vision for researchers and those engaged in the field. In future work, we suggest expanding reviewed applications and append the new applications that will appear in the coming times.

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