Spatio-Temporal Outlier Detection Techniques

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Abstract: The improvement in mobile computing techniques has generated massive spatio-temporal data. Mining spatio-temporal data and especially spatio-temporal outlier detection is an attractive and challenging topic that fascinated many researchers. Spatio-temporal outlier detection is used widely in several applications, including climate conditions to detect abnormal changes in the weather, urban safety management, transportation, and traffic management. In this paper, we review the methods of spatio-temporal outlier detection and classified them into four main categories: distance/density-based outlier detection method, pattern outlier detection method, supervised or semi-supervised learning method, and statistics or probabilistic method. This classification is based on the technique used for identifying outliers. We also show when each approach was employed.

Keywords: Spatio-temporal data, Outlier detection

1. Introduction:

The magnificent advances in GPS devices maintained gathering a tremendous number of spatio temporal or moving object data smoothly and rapidly. Consequently, mining of those moving objects data is insistently required to reveal and discover some mysterious insights that could be employed to achieve intelligence in the Urban city smart transportation systems. Generally, outlier detection in data mining refers to detecting an object that is contradictory with Other neighbor objects [12]. Moreover, outliers are different from noise; noise data is improbable data but exists in a dataset but outlier is unusual data that disappeared behind it an outstanding knowledge. Spatial outliers are objects or instances that perform irregular behavior concerning their spatial neighbors [2]. Spatial data has two sorts of attributes: behavioral and contextual attributes. Behavioral demonstrates the non-spatial characteristics of a moving object. Suppose we have data obtained by a sensor connected to a buoy. In this case, behavioral attributes could be some things like wind direction, air temperature, water temperature, and wind speed. The contextual attribute is the location of the buoy. Spatial outliers in this situation could be unusually low air pressure registered by a buoy relative to its neighbors. In this case, meteorological scientists may recommend the formation of a hurricane in an early stage and save many humans lives.

In spatio-temporal outlier detection, a major task is to distinguish objects that display irregular behavior either spatially [6]. As a spatial outlier detection is a sub-type of spatio-temporal outlier detection, so any technique employed in spatial outlier detection can be extended for handling a spatio-temporal outlier detection problem [28]. Spatio-temporal data has several kinds the famous of them is a trajectory [16]. A trajectory is a sequence of reading points of a moving object in each timestamp [48]. An outlier trajectory is a trajectory that has numerous differences from the most utmost of the trajectories in a specified time interval based on some similarity evaluation method. The intention behind trajectory outlier detection (TOD) methods is finding the trajectories that do not behave like the usual behavior of the other trajectories in a dataset [28]. TOD belongs to the category of spatio-temporal outlier detection because trajectory has spatial and temporal features. As pattern mining concentrates with patterns that are popular in the trajectory dataset, outlier detection focuses on rare patterns (e.g., following a path different from the common path followed by most of the other trajectories) [7]. Sometimes abnormal trajectories tend to carry critical information about potential problems that require immediate consideration and need to be resolved at an early stage. Meng et.al. [40] classify trajectory outliers depends on the application situations into five categories: distance-based outlier, density-based outlier, feature-based outlier, sub-trajectory outlier, and activity outlier.

In spatio-temporal (ST) applications, outlier detection acknowledged as an interesting topic because it can be used for identifying unusual events: e.g. discovering the change in the environment over the years, identifying the change in the animal habits by following up their movement, catching a taxi drivers misbehavior that takes anomalous paths to get extra money, and traffic flow detection which is an essential responsibility in the plan of a smart city and smart transportation management [16]. In this paper, we categorize spatio-temporal outlier detection techniques into four main categories: distance and density-based outlier detection methods, pattern outlier detection methods, supervised and semi-supervised learning methods, and statistics and probabilistic methods. The distance and density-based outlier detection method addresses a distance or density abnormality in ST objects. The pattern outlier identification technique, on the other hand, is constructed based on a sequence. The spatio-temporal outlier detection method is based on supervised or semi-supervised learning. Statistic or Probabilistic Method has used a probability for building a model for identifying spatio-temporal outliers objects.

This survey paper is organized as follows. Section 2 presents spatio-temporal outlier detection methods in detail.

In Section 3, we conclude the work presented in this survey paper.

2. Spatio-Temporal Outlier Detection Methods

In this section, the methods for spatio-temporal outlier detection can be classified into four categories: distance and density-based outlier detection methods, pattern outlier detection methods, supervised and semi-supervised learning methods, and statistics and probabilistic methods.

2.1. Distance and Density-based Outlier Detection Method

The distance and density-based outlier methods address a distance or density abnormality in ST objects. For example, a distance-based outlier is an object that distant from its neighbors [15]. On the other hand, a density-based outlier is an object that has not enough near neighbors of moving objects [29]. The two black moving objects in Figure 1 are far distant from the four gray moving objects, therefore they are classified as distance-based outliers moving objects using the distance measure. Furthermore, because the density of the two black moving objects is lower than that of the gray moving objects, they are density-based outliers. The distance-based outlier approach is generally based on the global distribution of points in the dataset. In most conditions, the distribution of points in a sample is not uniform. As a result, this approach has a challenge when having data points with various density distributions. Thus, most of the current models utilized both distance-based and density-based methods to overcome the challenges of using each one of them individually [13].

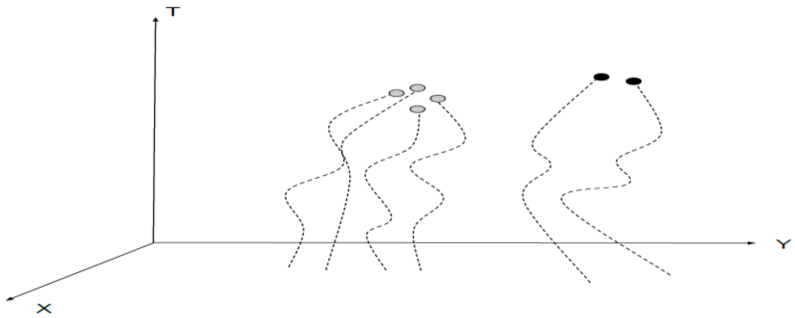

Figure 1. Example on Distance and Density-based spatio-temporal outlier detection method

Kut et al. [4] proposed an expansion of the DBSCAN algorithm for computing the ST-outlier. They utilized a regional query with two values of epsilons (eps1, eps2) to obtained spatio-temporal neighbors. In this method, eps1 was used to recovered spatial neighbors while non-spatial neighbors were retrieved by eps2. After that, the intersection of those two groups employed for detecting spatio-temporal neighbors. This method extends the cluster to detect outliers. Also, Topex/ Poseidon Satellite dataset is used for validating their method. Cheng and Li [9] presented a four-phase multiscale approach for detecting spatio-temporal outliers. The first phase is the classification phase, where moving objects were grouped into clusters. The second phase is the aggregation phase. The scale of each cluster was extended in the aggregation phase, thus objects that did not belong to a cluster in the first phase may now belong to one. The third phase was the comparison, wherever the results of the aggregation phase were associated with the classification phase. Also, the possible spatio-temporal outliers were distinguished in the comparison phase. The last phase is verification, wherever an object that not duplicate in consecutive periods was classified as a spatio-temporal outlier. This method was examined using a coastal geomorphic study in Amerland. This method is more suitable for detecting the change concerning a geographical area over many years. Lee et al. [13] proposed a partition-and-detect framework TRAOD. TRAOD was considered the first algorithm that detected sub-trajectory outliers. As displayed in Figure 2, the thick part in Tr3 is an outlying sub-trajectory because it is different from the other partitions in the trajectory. Contrarily, examining the complete trajectory with its neighbors can ignore those partitions because the differences averaged over the whole trajectory; so, the overall behavior of the trajectory TR3 appears to be similar to its' neighboring trajectories. TRAOD consists of two phases: partitions trajectories into segments, and then detects the outliers. In the partition phase, TRAOD partitions each trajectory into a set of line segments. In the detection phase, density and distance-based measures were employed to discover outlying sub-trajectories. In TROAD, two real trajectory datasets were used: the hurricane track dataset and the animal movement dataset [33]. Despite the efficiency to detect outlying sub-trajectories and outlier trajectories, TRAOD suffered from computational time overhead as well as the high complexity of O(n2). Thus, Guan et al. [8] proposed the R-Tree-based Trajectory Outlier Detection (R-TRAOD) method that used the R-Tree index structure to speed up the outlier detection method. Liu et al. [30] proposed a density-based trajectory outlier algorithm called (DBTOD) that employed a density-based technique to detect outliers and solve the problems in TRAOD to detect outliers when a trajectory is local and dense. Also, the DBTOD algorithm used a dataset generated by the Starkey project (animal movement dataset) as used in the TRAOD algorithm.

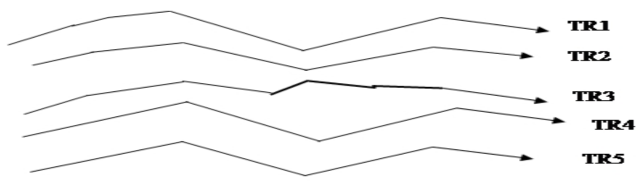

Figure 2. Example of sub-trajectory outlier

Trajectory outlier detection is a kind of spatio-temporal outlier detection. As shown in Figure 3, T1 is an outlier trajectory comparing to its neighbors (T2, T3, T4) as it is far away from them. Ge et al. [46] proposed an evolving trajectory outlier detection approach called the TOP-EYE algorithm. The TOP-EYE approach employed a decay function to quickly discovering outliers moving trajectories. This method cumulatively computes an outlier score. In the TOP-EYE algorithm, an experiment was conducted on a real-world trajectory dataset from the Massachusetts Institute of Technology (MIT). This trajectory dataset was extracted from a video surveillance system and used to monitor a specific area. Moreover, Ge et al. [26] developed a taxi driving fraud detection system that depends on Dempster-Shafer's theory on consolidates two evidence: travel route and driving distance evidence. Furthermore, a routemark was used to represent a driving path from an attractive site to another one. Based on routemark, they employ a generative statistical model to characterize the distribution of driving distance and identify the driving distance evidence. Moreover, used a dataset contains GPS traces of approximately 500 taxi cabs collected around 30 days in the San Francisco Bay Area.

Zhongjian et al. [47] proposed a Prototype Based Outlier Detection (PBOTD) approach for identifying outlier taxi trajectories using a historical trajectory database. Firstly, the routes R are grouped by utilizing the medoids algorithm. The previous step iterated until the summation of the distances from the routes to its center remains stable. Secondly, the set of the centers of the clusters are identified as Representative Routes (RR). A score calculated based on routes in RR For each trajectory t. A trajectory t is considered an outlier if it has a score greater than a specific similarity threshold. The PBOTD approach used a real-world dataset that includes 5,660,692 trajectories in Beijing for validating the proposed method. Yu et al. [36] represent the trajectory outliers by two density-based definitions, i.e., point outlier and trajectory outlier aiming to find outliers from the trajectory stream data. However, it is not able to quantify the degree of an outlier in a trajectory. Also, their parameters are highly dependent on the dataset. Two datasets are used in their experiments: GPS trajectory data generated by 10,357 taxis from February 2 to February 8, 2008, in Beijing [44, 45] , and the GMTI (Ground Moving Target Indicator) dataset that records real-time trajectories. Also, Yu et al. [35] propose a rich taxonomy of innovative classes of neighbor-based trajectory outlier definitions that model the anomalous behavior of moving objects for a great range of real-time applications. Furthermore, a general strategy proposed for efficiently detecting those new outlier classes called the minimal examination (MEX) framework.

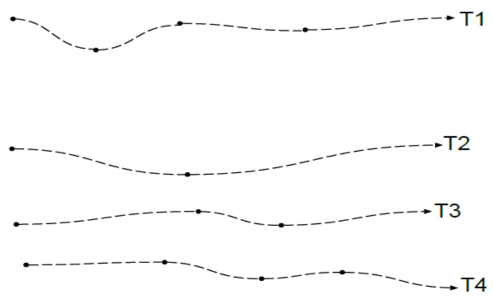

Figure 3. Example on trajectory outlier

Recently, an unsupervised spatio-temporal contextual collective anomaly detection was introduced [27] Firstly, it classified the spatio-temporal outliers. After that, they group the spatio-temporal outliers that share similar anomalous behavior to discover anomalous events. For validating their proposed framework, two types of data were used: South Pole AVHRR ski temperature data collected from July 24, 1981, to June 30, 2005. Also, the SSM/I data which is a primary resource for estimating sea ice concentrations and classifying sea ice types. Kumar et al. [17] developed a Visual Assessment Tendency (ClustiVAT) to identify outlier trajectories. Trajectory clustering is performed by applying the iVAT algorithm [14]. A non-directional similarity measure is used for grouping trajectories with common paths and opposite directions. Further, a directional similarity measure is employed for dividing trajectories moving in a reversed direction in each cluster. Then, if trajectories are far away from others in the same cluster or clusters with a fewer number of trajectories are recognized as outliers' trajectories. The ClustiVAT approach practices the MIT trajectories dataset [41] in their experiments. In [7], , a TODCSS algorithm was proposed that depends on the common slices sub-sequence for identifying outlier trajectory. Firstly, they compute a direction-code sequence of each segment in every trajectory. Secondly, they used the common slices sub-sequences as a distance measure between two trajectories. Eventually, the slice outliers and trajectory outliers are detected based on the new distance computation. The TODCSS algorithm used three datasets: Atlantic hurricane track dataset, GPS coordinates of approximately 500 taxis collected in the San Francisco Bay Area during May 2008, and synthetic labeled trajectories using the publicly available trajectory generator program written by Piciarelli [31].

Djenouri et al. [22] proposed another method that used the flows distribution of the flows in a given time interval for discovering abnormal spatio-temporal traffic flow. Firstly, they constructed the flow distribution probability (FDP)databases from the traffic flows using spatial and temporal information. Secondly, they used the inliers are collected to enhance the FDP databases, and outliers are eliminated from the FDP databases. Furthermore, a k-nearest neighbor was used as a distance-based outlier detection mechanism for FDP outlier detection. Two traffic flow data are used from Odense in Denmark and Beijing in China for validating their proposed algorithm. Also, Kong et al. [42] proposed a long-term traffic anomaly detection (LoTAD) approach. The LoTAD approach mainly divides into three steps. Firstly, a spatial and temporal segment database was build using the bus trajectory database and the bus station line database. Secondly, the anomaly index was estimated for each path section. After That, the lrd and LOF values were computed of each path section depends on the density values by employing the LOF algorithm [29]. Then they applied the K-means algorithm on the bus station database for obtaining regions as each cluster represents a region. Next, anomaly scores were defined for each region. After that, those anomaly scores were ordered in decreasing order. Finally, regions that had a high score were determined as outliers' regions. The LoTAD had been tested on a real crowdsourced bus trajectory dataset in Hangzhou from October 2014 to March 2015. Recently, Duggimpudi et al. [6] proposed two algorithms: Spatio-Temporal Behavioral Density-based Clustering of Applications with Noise (ST-BDBCAN) and Approx ST-BDBCAN. They adjusted the ST-BDBCAN algorithm by using the LOF algorithm for calculating a factor for the outlier for spatio-temporal behavioral (ST-BOF). Furthermore, the data was partition into blocks, and a parallel mechanism is applied for enhancing scalability in the second algorithm Approx ST-BDBCAN. Also, they validate their proposed algorithms by using buoy datasets. Distance and density-based techniques for detecting spatio-temporal outliers have simple calculations. Although, each of them suffers from overhead computations, mainly when dealing with large amounts of moving objects data.

2.2. Pattern Outlier Detection Method

The detection of pattern spatio-temporal outliers is dependent on sequencing. Because it is the major trend of generating patterns and constraints on the road network, this approach is mainly designed for vehicle trajectories. Zhang et al. [39] proposed the iBAT algorithm by utilizing the isolation mechanism to identify outlier trajectories. The isolation Forest (iForest) function is modified in the iBAT algorithm to separate outliers' trajectories from the normal ones. Additionally, it utilized a few in number and different than the majority as usual features of abnormal trajectories. However, the outlier trajectories recognized using the iBAT algorithm, but sub-trajectories outlier ignored. Also, Chen et al. [5] proposed the iBOAT algorithm as a real-time improvement on the iBAT. It was also used to discover which part(s) of a trajectory is an outlier. In their experiments, both the iBAT and iBOAT algorithms used GPS trajectories collected from more than 7600 taxis in Hangzhou for one year. Lei et al. [18] mainly recognized the basic outlier features for discovering anomalous trajectories. Then they check the flight behavior from historical trajectories and form a model for anomaly detection in the maritime trajectory.

The TPRO algorithm [24] also concentrates on detecting vehicle outliers. It finds the most familiar trajectories in each period for each SD pair. It also calculates outlier scores based on the edit distances between the query trajectory route and familiar trajectories in each period. Zhu et al. [25] proposed the TPRRO algorithm as an enhanced version of TPRO. The TPRRO algorithm is a real-time outlier detection algorithm as it can detect trajectories that are not in the historical trajectory dataset. The TPRO algorithm only detects the outliers in the historical data. However, the TPRO and

TPRRO can compute the outlier score after complete the trajectory. The TPRO and TPRRO algorithms utilized a dataset gathered from about 10,700 cabs in Beijing in 2012 in their experiments.

Bu et al. [11] proposed a framework for monitoring anomalies over continuous trajectory streams. Local clusters build upon trajectories streams. After that anomalies are discovered using a joining mechanism between clusters. Also, pruning strategies are applied without introducing false dismissals. They also develop a piecewise VP-tree (vantage point tree) based index structure and reschedule the order of cluster join to improve their algorithm efficiency. The GPS coordinates of approximately 500 taxis were collected from the San Francisco Bay Area during May 2008 and used in their experiments. Furthermore, Wu et al. [23] proposed a Grid-based approach for detecting spatio-temporal outliers in the South American precipitation dataset obtained from the NOAA [21]. Firstly, they Exact-Grid Top-k and Approx-Grid Top-k algorithms to distinguish the most popular outliers at every stage. Second, using this Top-k, all outlier sequences are discovered throughout time and stored in a tree using the Outstretch method. Finally, the Recursive Nodes method is used to exclude all possible sequences from the list. The resulting sequences are then classified as spatiotemporal outliers.

Zhou et al. [49] proposed the OnATrade algorithm for enhancing the taxi services using GPS big data. The onATrade method consists mainly of two steps: route suggestions and online detection. Firstly, the route candidates are computed using a route recommendation algorithm. Secondly, taxis that deviate from the suggested route are identified as anomalies. The OnATrade algorithm is examined using taxi cabs' mobility traces in San Francisco [32].

2.3. Supervised and Semi-supervised Learning Method

The third category of outlier spatio-temporal detection method is based on supervised or semi-supervised learning. This method depends on the labeled data, or at least one class of data (normal one) is classified.

Li et al. [19] proposed the ROAM (Rule and Motif-based Anomaly Detection in Moving Objects) system as a motion classifier. Object trajectories in ROAM are represented by motifs which are discrete pattern segments with a related time and location values. They have employed a GSTD to produce raw trajectories. Also, ROAM used a data generator to generates motif trajectories. Liao et al. [20] proposed a GPSvas (GPS Visual Analytics System) as a conditional random field-based approach for detecting anomalies from the streaming of GPS traces. A stream of urban taxi GPS data is used for validation in the GPSvas system.

In a video surveillance situation, Sillito et al. [38] proposed a semi-supervised learning system to identify trajectories of anomalous behaviors. In their framework, they respect personal privacy as they required personal permission before connecting any behavior pattern. In their semi-supervised learning framework, two video datasets were used: CAVIAR "INRIA" Dataset (Video clips created July 11, 2003, and January 20, 2004) [1], and Carpark Dataset. Sabarish et al. [37] proposed a Trajectory Outlier Detection Algorithm using Boundary (TODB) algorithm. The TODB algorithm employed a Convex Hull algorithm (Graham convex hull algorithm) to build a boundary of normal trajectories. Later, a ray casting algorithm was used to create a binary classifier and define a spatial trajectory outlier. Two datasets are used in the TODB: the UCI repository (https:/archive.ics.uci.edu /ml /datasets / GPS+Trajectories) GPS trajectories dataset. The second dataset is the Coimbatore-Amrita dataset generated by the authors and containing 43 trajectories. The Coimbatore-Amrita dataset reflects the route traversed by Amrita University students in Coimbatore city. Nevertheless, these supervised/semi-supervised learning-based approaches require manual labeling of the massive dataset which is unreliable for real-world applications.

2.4. Statistic or Probabilistic Method

In this section, a statistical or probabilistic-based method is used for building a model for identifying spatio-temporal outliers objects. Hao et al. [43] proposed a probabilistic model called DB-TOD. The drivers' behaviors are modelled in the DB-TOD using a historical trajectory dataset to detect outlier trajectories. For effective modeling of driving behaviors, the DB-TOD employed an automated feature correction technique. It can also discover the whole and partial outlier trajectories. The DB-TOD was examined on two real-world taxi trajectory datasets: one created by 442 cabs in Porto, and the other by 13,650 taxis in Shanghai. Rogers et al. [34] proposed a spatio-temporal outlier detection model based on the statistics using a Stroud (Strangeness outlier detection) algorithm. In this approach, a strangeness factor was computed for each object in the dataset. This strangeness factor is the sum of the weighted distances of geographic, temporal, and behavioral characteristics termed the kernel of the nearest neighbors' objects. A statistical method was employed for comparing the strangeness of objects with reference objects. The objects were identified as spatio-temporal outliers when there is a big difference. This approach required identifying the standard objects in the dataset, but this earlier data knowledge often unavailable. Three datasets were used in this algorithm: crime data, earthquake data from the southwestern United States, and buoy data from the Gulf of Mexico (weather data recorded from 30 buoys located in the Gulf of Mexico during 2005).

Albanese et al. [3] proposed a Rough Outlier Set Extraction (ROSE) approach for exploring the top outliers in an unlabeled spatio-temporal dataset. Additionally, a Kernel set introduced, a representative subset of the original dataset, significative to outlier detection. For verifying the ROSE algorithm, a school buses real-world dataset consisting of 145 trajectories of two school buses collecting and delivering students around the Athens metropolitan area in Greece for 108 different days [10].

3. Conclusion

Spatio-temporal outlier detection is important in finding anomaly objects or patterns. So, in this survey paper, we summarized the research proposed research methods in detecting spatio-temporal outliers. Moreover, we classify the research methods in spatio-temporal outlier detection into four categories: distance and/or density-based outlier detection methods, Pattern Outlier Detection methods, Supervised and semi-supervised learning methods, and Statistics and probabilistic methods. Also, different applications of spatio-temporal outlier detection are defined. From this survey, we find that spatio-temporal outlier detection is a hot topic in spatio-temporal data mining and still needs more deep research to find solutions to challenges in its especially real-time detection of spatio-temporal outliers.

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