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Spatio-Temporal Outlier Detection: A Survey of Methods

Chunrui Wu[1], Junfeng Tian[1,*]

[1]*school of Information Sciences and Technology, Jiujiang University, China*
[*]*Corresponding author e-mail:28737970@qq.com*

ABSTRACT:*With the advancement of mobile device and localization technology, the collection of Spatio-Temporal information from moving objects become much easier and easier than before, and outlier detection for Spatio-Temporal data is becoming increasingly attractive in data mining community. Frankly speaking, aSpatial-Temporal outlier is an observation whose attribute value significantly differ from those of other spatially and temporally referenced objects in a Spatio-Temporal neighbor.Discovering STOD is an important problem with many applications such as geological disaster monitoring, geophysical exploration, public safety and health etc. This paper has a briefly introduction of most popular Spatio-Temporal outlier detection methods in recent two decades and list, explain two most useful algorithms to STOD. We also discuss the methods of the spatial outlier detection and temporal outlier detection before the main content for the aim of having a better understand of data outlier detection field. Three tables show the visualized result of our research.*

KEYWORDS:*Spatio-Temporal data; outlier detection; survey; data mining*

1. Introduction

Data outlier detection is an important branch of data mining that is a new field in recent ten years. Many researchers have devoted a lot of energy to it. A Spatio-Temporal object can be defined as an object that has at least one spatial (such as location) and one temporal (such as timestamp or time interval) property, it usually contains spatial, temporal and thematic or non-spatial attributes. The most common examples of Spatio-Temporal data are moving cars, hurricane and forest fire. And Spatio-Temporal data set produced by modern device (such as wireless sensor) mainly record changing values of spatial and thematic attributes over a period of time.

This paper is organized as Section 2 aims to define every category. Section 3 is designed for readers to be familiar with spatial outlier detection. Section 4 emphasis on brief introduction of temporal outlier detection and Section 5 focus on a survey of

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methods about Spatio-Temporal outlier detection. Last, Section 6 summarize various algorithm about outlier detection from different dimension.

2. Category definition

This paper introduces the main outlier detection methods in the form of spatial, temporal, and Spatio-Temporal. The sum of paper we collect in the three forms respectively are 15, 7 and 58. All the methods in every forms are classified by most popularity or useless. This paper start with the introduction of spatial outlier detection methods. These methods are divided into two categories namely cluster and others. Then temporal outlier detection methods are shown and divided into cluster method and deep learning method. Last the most important part, the introduction of Spatio-Temporal outlier detection methods, is summarized. Four categories are used to distinguish these methods. They are cluster method, classification method, deep learning method and others. Follows are brief explanation of above categories. And a summarized graph of the methods introduced in the paper is also shown in the last of this section.

1) Cluster-based approaches are that using existing and popular cluster algorithms to divide the set of data into several data clusters according to similar attributes of data to find outlier.

2) Classification-based approaches which are dividing data set into normal data and outliers via existing classic classification algorithms.

3) Deep learning approaches are which using various existing deep learning algorithms to find abnormal values of data set.

4) Other approaches are which detect outlier detection in an individual or unique way and these approaches are likely contains above categories.

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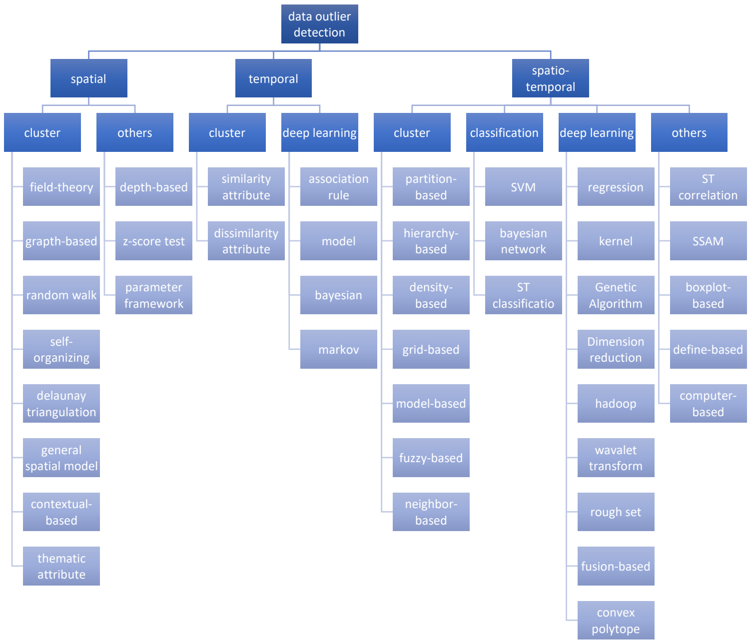

Graph 1. The summarize of the methods in this paper.

3. Temporal

Since a large number of applications generate temporal datasets, this stresses the need for effective methods of outliers with respect to such temporal data. From the table 2 we can see some existing temporal outlier detection methods.

Category	Method	Reference
Cluster	Similarity attribute	[17]
	Dissimilarity attribute	[18]
Deep learning	Association rule	[19]
	Model	[20],[21]
	Bayesian	[22]
	Markov	[23]

Table 2. The summarize of Temporal outlier detection methods.

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3.1 Similarity

Many existing algorithms about temporal outlier detection is always at a single instant in time. In order to make up for this deficiency, a method using similarity trend was proposed [17]. It has an emphasis on historical similarity trends between data points and then calculates outliers that have a drastic change. This method has been applied to traffic data and has an effective result. On the contrast to this case, another case adopts dissimilarity attribute to mine temporal outliers. It adopts a suitable dissimilarity measure to find dissimilarity between input pattern and reference patter then find the outliers [18]. It also define a deviation expression to compute dissimilarity degree.

3.2 Deep Learning

Association rule is a kind of deep learning algorithms. In temporal data mining, it also work. A novel concept, temporal association rules, is defined. The method based on it can infer the normal behavior of objects by extracting frequent rules from a given dataset [19]. Specifically, temporal association rules are combined to generate temporal quasi-functional dependencies that lead to outlier detection. Modeling is a nice way to SOD. An effective two-step procedure using modeling to detect community trend outliers is proposed [20]. First, model the normal evolutionary behavior of communities across time using soft patterns. Second, adopting effective measures to evaluate chances of an object deviating from the model. Experimental results show high effect in discovering interesting community trend outliers. For the task of temporal data mining in a smart home environment, it is useful to draw upon the temporal nature of sensor data and then build a model of expected activities to find anomalous events [21]. Besides, the Bayesian model, Markov model and other deep learning models are applied equally to TOD. Probabilistic inference on the Bayesian model that is automatically inferred form the Petri net representation of a business process case allows the detection of temporal outliers [22]. In another case, the value functions of the Markov reward process are regarded as the anomaly probabilities of sequential behaviors [23]. It uses TD learning algorithms to efficiently construct anomaly detection models of complex sequential behaviors by estimating the value functions of the Markov reward process.

4. Spatio-Temporal

Spatio-Temporal data are constituted by sampled locations at specific time-stamps, typically this kind of data deal with trajectory of moving objects that change their locations over time. Detecting outliers which are grossly different from or inconsistent with the remaining Spatio-Temporal dataset is a major challenge in real-world knowledge discovery and data mining applications. It can be seen from the categories from table 3 that STOD methods are divided into four classes: cluster, classification, deep learning and others.

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Table 3. The summarize of Spatio-Temporal outlier detection methods

Category	Method	Reference
Cluster	Partition-based	[24],[25],[26]
	Hierarchy-based	[27],[28],[29]
	Density-based	[30],[31],[32],[33],[34]
	Grid-based	[35]
	Model-based	[36],[37],[38],[39],[40],[41]
	Fuzzy-based	[42],[43]
	Neighbor-based	[44],[45],[46],[47],[48],[49],[50],[51],[52]
Classification	SVM	[53],[54],[55],[56]
	Bayesian Belief Network	[57]
	ST classification	[58],[59]
Deep learning	Regression	[60]
	Kernel	[61]
	Genetic Algorithm	[62]
	Dimension reduction	[63],[64],[65]
	Hadoop	[66]
	Wavelet transform	[67],[68]
Others	Rough set	[69],[70]
	Fusion-based	[71],[72]
	Convex polytope	[73]
	ST correlation	[74],[75]
	Smooth Spatial Attribute Method	[76],[77]
	Boxplot-based	[78],[79]
	Define-based	[80]
	Computer-based	[81]

4.1 Cluster

Cluster method is mainly divided into seven categories in Spatio-Temporal outlier detection. There are partition-based, hierarchical-based, density-based, grid-based, model-based, fuzzy-based and neighbor-based method. The following are described separately. Now begin with partition-based cluster. Since several existing trajectory outlier methods such as the partition-and-detect framework can only deal with the trajectory data but not for ST data. Based on tradition, an

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enhanced partition-and-detect framework to detect the outliers of Spatio-Temporal trajectory data was adopted [24]. Based on this enhanced framework, it use a congestion outlier detection method to solve the problem. In another case, the trajectories of the same starting and ending points were extracted from the trajectory data, and were partitioned into segments firstly. And then calculating similarity before clustering to achieve the detection task [25]. Another version is the soft computing approach based on rough sets, it modified the basic k-modes algorithm to incorporate the lower and upper approximation properties of rough sets [26]. Besides partition-based clustering methods, hierarchical clustering method is also widespread used. In a motion-based anomaly detection, the notion of "Super-trajectories" based on hierarchical clustering of dense point trajectories was adopted and regarded it as an efficient and robust representation of motion patterns [27]. In the visualization of traffic observation, outliers were flagged in the hierarchy via highlighting [28]. In another hierarchical-based approach, the frequency based analysis is performed to automatically discover regular rules of normal events at each level [29]. As mentioned above, detecting spatial outliers can make use of DBSCAN method which is density-based clustering method. In Spatio-Temporal database, it also does work [30]. A measure known as Local Outlier Factor (LOF) gives a quantitative measure of outlines to each object, where a high LOF score means it is potentially an outlier. Researchers combined LOF and DBSCAN in an ensemble method to find Spatio-Temporal clusters of anomalous measurements [31]. According to Spatio-Temporal context, an algorithm, Spatio-Temporal Local Density-Based Clustering of Applications with Noise (ST-LDBCAN), which has been developed [32]. This novel method can handle multivariate data. However, Because of the limitation of the existing conditions in the LDBSCAN algorithm, some outliers may not be detected effectively [33]. Two new concept were figured out which are Spatio-Temporal Behavioral Density-based Clustering of Applications with Noise (ST-BDBCAN) and Approx-ST-BDBCAN based on traditional notions. And it adopted improved ST-LOF, which is a Spatio-Temporal extension to LOF. Moreover, a density-based local outlier detection technique, mainly uses the Spatio-Temporal similarities among multiple-time-instant synchro phasor measurements, was also be implemented [34]. STOD can also be conducted using grid-based cluster. For example, after developing Exact Grid Top-k and Approx-Grid Top-k, an algorithm named Outstretch was used to detect top-k outliers [35]. In the field of Spatio-Temporal outlier detection, the model-based cluster method is more popular. In video analysis field, mining detection in extremely Crowded Scenes is a big challenge. A solution that modeling the local Spatio-Temporal motion pattern behavior of extremely crowded scenes to characterize the overall behavior of the scene was proposed and effectively found anomalies [36]. In order to capture scene dynamic statistics together with appearance, it is also proper to use dense Spatio-Temporal features for the aim to STOD. It was performed using a non-parametric modelling and an unsupervised or semi-supervised approach to achieve [37]. Besides, the task can be done in gradual modeling. This method modeling all kinds of attributes of observed data over time and spatial: mean, heteroscedasticity, non-local space-time interaction, and local space-time interaction. After forming the combined model, multivariate control

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charts were constructed to detect outliers [38]. Other similar methods are, for instance, using a graph based random walk model to discover anomalous behavior without contextual information in space and time [39] or mine at most top-K% ST outliers [40]. Another case describe the definition of the dispersion of data around a central tendency, which is good for outlier detection and understanding the spatial density of point clusters [41].

As to fuzzy-based cluster, there are two representative methods. A concept, a new index called the fuzzy outlier index (FOI) which expresses the degree to which a spatial object belongs to a Spatio-Temporal neighborhood was adopted [42] to achieve the task. In addition, an algorithm based on fuzzy rule-based analysis was performed to detecting and preventing fraud in ATM data [43]. Neighbor-based Cluster is also a good method to solve the problem [44]. In common, it usually is one of three steps including clustering, checking spatial neighbors, and checking temporal neighbors [45]. A method named as a Dual non-spatio-temporal attributes Deviation-based STO Detection (DDSTOD) has been carried out, which is depending on “k standard deviation” rule [46]. The rule is employed in SN and TN to mine ST outliers. In addition, a novel method that employs two phases (discovering homogeneous regions and evaluating these regions as anomalies based on their statistical difference from a generalized neighborhood) is proposed to detect localized homogeneous anomalies [47]. It also does work that employing a method that measuring ST neighborhood according to time series similarity [48]. As an author said in his essay, many previous outlier detection methods have focused primarily on only one non-spatial numerical attribute and have not successfully dealt with multiple dimensions and assume a Gaussian distribution of the data which were considered as significant error in STOD [49]. Therefore, he proposed a novel, simple and well-performed method. This method only requires the input of two parameters: the statistical confidence level and the number of nearest neighbors to detect outliers. Surprisingly, it supports all kinds of data such as high-dimensional data, noisy data, and data with or without clustering information. In the Massive-Scale Trajectory Streams data, a rich taxonomy of novel classes of neighbor-based trajectory outlier definitions that model the anomalous behavior of moving objects for a large range of real-time applications is proposed [50]. In another case, after considering both the mutual information contents of neighbor’s nodes when the data is characterized with a graph, outliers are detected with the search of the minimum spanning tree [51]. Another using neighbor-based approach named Spatio-Temporal Shared Nearest Neighbor (ST-SNN) also be proposed which can deal with high dimensional Spatio-Temporal data having different sizes and densities and also capable to identify arbitrary shaped cluster[52].

4.2 Classification

Wireless sensor networks (WSN) providing fine-grained Spatio-Temporal observations have become one of the major monitoring platforms for geo-applications. However, the key challenge for outlier detection in these geo-sensor networks is accurate identification of outliers in a distributed and online

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manner while maintaining low resource consumption. Support-Vector Machines (SVM) have received a great interest in the machine learning community since their introduction, especially in outlier detection in Wireless Sensor Networks (WSN). Based upon the traditional supporting vector (SVM) algorithm, one-class hyper-ellipsoidal SVM was proposed to accurately perform detection with making use of spatial and temporal correlations that exist between sensor data [53-54]. The Quarter-Sphere formulation of One-Class SVM (QS-SVM) extending the main SVM idea was proposed, which based on Spatio-Temporal correlations between the sensor nodes. Although performed well, it also has non-ideal performance. Hence, the algorithm named Spatio-Temporal-Attribute Quarter-sphere SVM (STA-QS-SVM) has existed [55]. The novel technique also suggests that the partially online approach is as efficient as the online approach. After long-time studies, researchers found that the STA-QS-SVM algorithm has a significant communication overhead even if its high efficiency. Given that communication is much more expensive than computation is WSNs, a study proposed three partially online novel approaches based on STA-QS-SVM that would lead to a significantly reduction in the communication cost [56]. Moreover, a method using Bayesian Belief Networks captures the conditional dependencies among the observations of the attributes to detect the outliers [57]. Specifically, employing Spatio-Temporal classification method is a common way. For the multiscale or multivariate data, an approach to detect ST-outliers by evaluating the change between consecutive spatial and temporal scales [58]. In the case of detecting outliers in the Air Quality Sensor Networks, a method based upon a Spatio-Temporal classification focused on hourly NO2 concentrations [59]. Sothey divided a full year’s observations into 16 Spatio-Temporal classes then mined likely outliers.

4.3 Deep Learning

Deep learning is a field with many kinds of classic and effective algorithms. In the Spatio-Temporal outlier detection mission, proper using deep learning algorithm can achieve the goal satisfactorily. Existing DL-based algorithms for STOD mainly are regression, kernel, Genetic Algorithm, Dimension Reduction, Hadoop, Wavelet transform, Rough set, Fusion-based and convex polytope. One kind regression based approach is the method based on the partial least squares discriminant analysis and area Delaunay triangulation. It is used to efficiently extract the most important features and detect outliers from the high-dimensional image data [60]. Kernel-based method such as strangeness-based outlier detection algorithm (STROUD) using a measure of strangeness to categorize and comparing the strangeness of a point with the distribution of strangeness of a set of baseline observations before using statistical testing [61]. And another case found a meaningful local outlier pattern by using a genetic algorithm (GA) [62]. The most used method in dimension reduction algorithm is PCA. Based on traditional notion, IPCA-based outlier detection methods were proposed. IPCA is one possible approach for detecting outliers in such type of Spatio-Temporal data streams and mainly used in many real-time applications [63]. Another proposed algorithm consists of collaborative time-series estimation, variogram application, and principle

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component analysis (PCA) is also proposed [64]. Furthermore, a new anomaly detection model that measures the dissimilarity of sensor observations in principal component space was adopted to handle with wireless sensor network data[65]. It is worthy mention that the detection can be performed well with the help of modern device, like computers. Since the calculation involved in calculating weight is significantly large, Hadoop was used to improve its performance[66]. A kind of method using wavelet analysis for scalable outlier detection in large complex Spatio-Temporal data was used recently[67]. The task that detecting blotches in old movies is proceeding to the detection in the wavelet transform domain instead of the spatial domain with using spatial and temporal information of the sequence[68]. And a method called Rough Outlier Set Extraction (ROSE) is widely used. It relied a rough set theoretic representation of the outlier set using the rough set approximations and found top outliers in an unlabeled Spatio-Temporal dataset[69][70]. Besides, it has proposing a non-parametric method rely on a new fusion approach, which able to discover outliers according to the spatial and temporal features[71]. On the other hand, a two-level sensor fusion-based outlier detection technique for WSN also exists[72]. The convex polytope based method is relies on local trajectory based features[73].

4.4 Others

STOD can be performed using spatial and temporal correlations between sensor nodes to distinguish faulty sample data from outlier data[74]. Similar, a method use temporal and spatial trifocal constraints, it was used to track three video streams at once and then perform outlier detection[75]. A method called Smooth Spatial Attribute Method is also appropriate for ST data. One case is that abnormal values can be detected by extreme values of their attributes compared to the attribute values of their neighbors after adopting SSAM[76]. The other case is considering both attribute values and Spatio-Temporal relationships that is based on SSAM[77]. And a new pattern, the Oriented Spatial Box Plot, has been defined for summarizing and visualizing 2D point clusters[78]. It extends the classical one-dimensional box plot. Moreover, an article proposed a simulation-based method to adjust functional boxplots for correlations when visualizing functional and Spatio-Temporal data[79]. For the further operation like STOD, some researchers defined some new notion. Some one proposed the concept of basic element(namely basic data structure) and found that it tent to make it easier and clearer to define meaningful outliers[80]. And in some cases, anomalies were detected in computer-based anomaly detection systems considering that multiple aspects of our life depend on complex cyber-physical systems[81].

5. Conclusion

ST outlier detection is a hot topic and has already been studied extensively. ST data types can be classified into three categories,namely point, line, and polygon. In this paper, the point pattern is most considered. Existing ST outlier detection

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methods are divided into four parts, there are cluster-based method, classification-based method, deep learning method and other methods. Some popular and representative methods are introduced in previous sections. Besides, a brief summary of spatial and temporal outlier mining methods is also made in the previous sections.

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