Trajectory Patterns Mining and Activity Monitoring for Wild Life Based on Temporal Tightness

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ABSTRACT

Trajectories are sequences that contain the spatial and temporal information about movements. It is more useful in learning interactions between moving objects. There are multiple solutions defined in the previous methods those are inefficient and inconsistent due to it developed for specific type of trajectory pattern. Usually, user doesn't have an idea about which type of trajectories are hidden in their dataset therefore discovery of pattern get tedious task. Many trajectory patterns are arranged with respect to their potentials and temporal restrictions. Unifying patterns are nothing but mining trajectory patterns of various temporal tightness. It has two phases first one is to discover the detail level of patterns and another is to construct a forest that represent the various patterns..

Keyword : *Trajectory pattern mining, synchronous movement patterns, moving object trajectories, trajectory clustering*

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1. INTRODUCTION

In the domain of data & knowledge mining certain kind of growth seen in the modern positioning technology enables large scale collection of various moving objects data such as animal movement data, vehicle movement data, and mobile tracking data. Data are usually collected from satellite, sensor, and other wireless technologies. For instance, animal scientists attach sensor tags on animal to track their movement and mobile phones have enabled the tracking of almost all kind of data. Generally, patterns can be moved synchronously or asynchronously. In synchronous movement objects are interacting with each other while in asynchronous movement object follows the same path for their movements. UT i.e. unified trajectory patterns are the combination of sub-trajectory patterns. It shows the temporal tightness in object movements. Usually, trajectories are given as spatio-temporal sequences. A set of objects that are nearly related to the location, time or both can be known as, UT-patterns. Majority of applications can benefit from the UTpatterns mining. For example, in animal trajectories, zoologists can learn migration or movement patterns of animals such as deer and wolf. In battleship trajectories, commanders can discover movement of the enemy. In soccer-player trajectories, attack strategies of the opponent team can be guessed by the coaches and so on. Previously existed UT patterns correspond to only one type of broad range type pattern. Such as, in flock pattern geographic data mining approach is used to detect tightness of patterns such as, flocking behavior and co-occurrence in geospatial lifeline data [7]. This tedious because user does not know that which type of trajectory pattern is involved in their dataset. User database may contains, multiple sets movement of objects arriving from various locations with different time interval such as, within one minute interval, one hr. interval and so on. Therefore, classification of such patterns may get into tedious task. One simple way to for classification of such patterns is discussed in [1], such as to build a framework having capabilities of handling trajectory patterns at different levels with temporal tightness. This strategy requires identifying sharpness of temporal suppression on patterns. Author F. Giannotti, M. Nanni[2]discussed about trajectory pattern mining problem with several methods to discover T-patterns from trajectory data. But the T-pattern is generalized technique for spatial-temporal data mining. It includes background information i.e. geographic information. In [3], partition-and-group framework is proposed for clustering trajectories. Using clustering trajectory TRACLUS is developed. For cluster validation visual inspection tool is developed in it. Clustering trajectories are based on partitioning and group strategy which helps to identify sub-trajectories.

2 RELATED WORK

In this section we are going to discussed related work about classification of trajectory patterns. As per the tightness temporal constraints there are three types classified into trajectory patterns.They are explain as following:

2.1 P. Laube and S. Imfeld, "Analyzing relative motion within groups of trackable moving point objects," in Proc. 2nd Int. Conf. Geograph. Inf. Sci., Boulder, CO, USA, Sep:

P. Laube et al [1], represented the concept of REMO analysis. It allows investigating the relative motion of many moving point objects. The proposed REMO analysis is based on two key ideas, first one is the multiple parameters describes the individuals motion organize in the analysis matrix and second is spatio–temporal "behavior" as well as connections in each group of moving bit objects are established as patterns in the REMO matrix. Necessary patterns of relative motion i.e. constant, concurrence is actually be identified and bounded in space-time. Testing of REMO represents its universally applicable layout. It basically helps to identify interrelations in any kind of observation data of moving point's objects. Furthermore, improvement of model is to test and enhance REMO analysis model. They have defined definition of language pattern. In the phase of testing, REMO model construct artificial and additional real observation data sets.

2.2 P. Laube, M. J. van Kreveld, and S. Imfeld, "Finding REMO— Detecting relative motion patterns in geospatial lifelines," in Proc. 11th Int. Symp. Spatial Data Handling, Leicester, U.K., Aug. 2004, pp. 201–214:

M.V. Kreveld proposes topographical data mining approach. It detects generic aggregation patterns such as flocking behavior and convergence in geospatial lifeline data. The proposed approach considers the object's motion properties in an analytical space. There are few methods implemented to detect concurrence processes and static clusters. A generic, understandable and extendable approach is proposed for data mining in geospatial lifelines [2].

2.3 P. Laube, S. Imfeld, and R. Weibel, "Discovering relative motion patterns in groups of moving point objects,", Int. J. Geograph. Inf. Sci., vol. 19, no. 6, pp. 639–668, Jul. 2005:

P. Laube, S. Imfeld et al [3], contributes the development of a generic strategy for topographical knowledge discovery in partial lifeline data. The proposed approach is developed by integrating the crucial steps of KDD such as, data reduction and projection, analysis of exploratory & model selection, data mining and Visualization. Football players tracked on a pitch and data points moving in an abstract ideological space used to demonstrate the generic nature of the approach. The proposed methodology can discovers the set of valid, novel, useful and understandable motion patterns from these datasets. They have represented the reveals of REMO GKD in many more motion patterns.

2.4 M. Benkert, J. Gudmundsson, F. Hubner, and T. Wolle, "Reporting flock patterns," in Proc. 14th Eur. Symp. Algorithms, Zurich, Switzerland, Mar. 2006, pp. 660–671:

M. Benkert et al [4] represented the idea of projecting trajectories into points in higher dimensional space. It is very feasible for discovering flocks in spatio-temporal data. The proposed mechanism is the first step towards the algorithms for finding spatio-temporal patterns, such as flocks, encounters and convergences. In preprocessing step, random projection is used to reduce number of dimensions. A tree-based algorithm is proposed for flock pattern identification which performs very well in small numbers of time-steps the resulting running times are often very small. This method faced with trade-off.

2.5 P. Bakalov, M. Hadjieleftheriou, and V. J. Tsotras, "Time relaxed spatiotemporal trajectory joins," in Proc. 13th ACM Int. Symp. Geograph. Inf. Syst., Bremen, Germany, Nov. 2005, pp. 182–191:

P. Bakalov et al. [5], defined "Time Relaxed Spatiotemporal Trajectory Join" query. In this they first demonstrated the symbolic join algorithm but it is inefficient solution. Two heuristics have introduced which totally reduces query time for the TRSTJ query. Symbolic join algorithm is based on multiple origins notions that can reduce the number of false positives effectively. Another heuristic solution was based on the principle of "divide and conquer". It proved to be very efficient for situations where the memory resources are limited. In future work they planned to extend their work for the "best-match" trajectory join problem. It looks for the best match between two trajectories over their whole lifetimes.

2.6 D. Sacharidis, K. Patroumpas, M. Terrovitis, V. Kantere, M. Potamias, K. Mouratidis, and T. K. Sellis, "On-line discovery of hot motion paths," in Proc. 11th Int. Conf. Extending Database Technol., Nantes, France, Mar. 2008, pp. 392–403:

D. Sacharidis et al [6], proposed a framework for on-line maintenance of hot motion paths. It is used to discover frequently traveled trails of numerous moving objects. In this they considered a distributed platform with administrator and manage hotness and calculations of these paths in a spatiotemporal index, and many moving clients that issue updates only for important changes in their positions. They were focused on motion patterns that discarding obsolete paths that expire from a sliding time window. Freely moving objects are assumed by them. An observational reproduction exhibits the ability of our methodology to provide a dense representation of objects' movement, as well as its efficiency with respect to on-line maintenance of significant motion patterns.

2.7 J.-G. Lee, J. Han, and K.-Y. Whang, "Trajectory clustering: A partition-and-group framework," in Proc. ACM SIGMOD Int. Conf. Manag. Data, Beijing, China, Jun. 2007, pp. 593–604:

J. Lee et al [7], proposed a partition-and-group framework for clustering trajectories. It partitions trajectory patterns into a set of line segments. Then, group's identical line segments together into a cluster. Its main benefit is to discover common sub-trajectories from a trajectory database. Based on this strategy, they have developed a trajectory clustering algorithm known as, TRACLUS algorithm. It consists of partitioning and grouping phases. This algorithm is based on minimum description length (MDL) principle. The proposed algorithm has some properties such as, Extensibility, Parameter Insensitivity, Efficiency, Movement Patterns and Temporal Information.

2.8 J. Gudmundsson and M. J. van Kreveld, "Computing longest duration flocks in trajectory data," ," in Proc. 14th ACM Int. Symp. Geograph. Inf.. Syst., Arlington, VA, USA, Nov. 2006, pp. 35–42:

J. Gudmundsson et al [8], considered the problem of computing a longest duration flock or meeting. They provided several exact and approximation algorithms. It has some variants are as hard as MaxClique to compute. Divide-and-conquer is performed on τ and then test same O(n/(mε2)) vertical columns. In this paper, they have determined all entities the time intervals that they are within the sweeping disk. Recursion is applied to discover a longest interval containing an at least m interval, which is done before and after tˆ independently. Distinct from flock pattern this problem is not NP-complete and below we will give a polynomial time algorithm for fixed-meet (m, max, r), followed by a faster radius approximation algorithm.

2.9 Y. Li, J. Han, and J. Yang, "Clustering moving objects," in Proc. 10th ACM SIGKDD:

Y. Li et al [9], discussed about the clustering analysis on moving objects, which is able to provide some interesting pattern changes and is of extensive interest. They proposed the concept of micro-cluster to catch some regularity of moving objects and manage very large databases. In this paper an efficient algorithms implemented to keep moving micro-clusters graphically small. A superb clustering result could be obtained together with the knowledge about collision. In future work, authors were expecting little modifications to discover interesting clusters of various forms other than being geographically close.

2.10 C. Bohm, C. Faloutsos, J.-Y. Pan, and C. Plant, "Robust information-theoretic clustering," in Proc. 12th ACM SIGKDD:

C. Bohm, C. Faloutsos, et.al [10], proposed a robust framework for determining a natural clustering of a given data set, based on the minimum description length (MDL) principle. The proposed framework, Robust Information-theoretic Clustering (RIC), is orthogonal to any known clustering algorithm: given a preliminary clustering, RIC purifies these clusters from noise, and adjusts the clustering's such that it simultaneously determines the most natural amount and shape (subspace) of the clusters. The proposed RIC method can be integrated with any clustering technique ranging from k-means to k-medoids. RIC framework is very flexible, with several desirable properties that previous clustering algorithms don't have. More importantly, the RIC framework does not compete with existing (or future) clustering methods: in fact, it can benefit from them! If a clustering algorithm is good, proposed RIC framework will use its grouping as a starting point, it will try to improve on it and, it will either improve it.

2.11 J. Lee, J. Han and Xiaolei Li "A Unifying Framework of Mining Trajectory Patterns of Various Temporal Tightness" IEEE transaction on knowledge and data mining vol,27, No.6, june 2015:

Author Jae-Gil Lee,J. Han and X. Li. [11], defined a framework for discovering trajectory patterns. They represent very useful learning interactions between moving objects. There is certain limitation in their defined framework as user doesn't have idea about type of patterns involved in large dataset.

3. PROBLEM DEFINITION

"Mining and classification of UT- pattern regions of different temporal tightness"
-Multiple methods have been proposed in literature which is inefficient and inconsistent as user does not know which types of trajectories are hidden in their dataset, also these methods developed only for specific type of trajectory pattern. Hence to design such system which can construct pattern forest by identifying initial UT-patterns clusters from the test set of trajectories and further, classify them into three types of patterns i.e. Time-constrained, time-relaxed and time-independent patterns

4. SYSTEM ARCHITECTURE

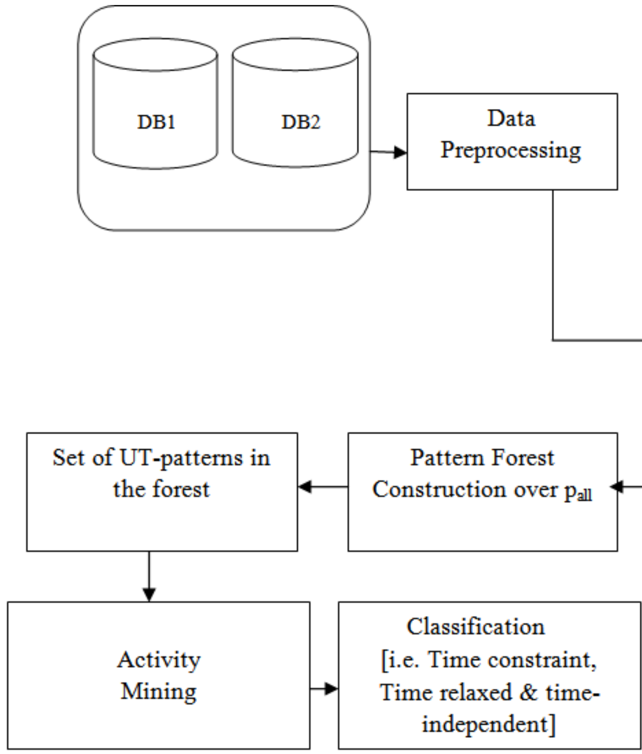

Figure-1: System Architecture

5. CONCLUSIONS

In this survey paper of mining trajectory patterns, we have studied the existing techniques of trajectory pattern mining. Previous techniques only deals with specific type of trajectory patterns. Also there was limitations on discovering patterns as user do not know which type of trajectory patterns involve in their large database. According to our analysis we are aiming to overcome the limitations discussed in literature survey by observing many trajectory patterns that can be arranged according to the strength of temporal constraints.

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