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A Review on Mining Dense Trajectory Pattern Regions of Various Temporal Tightness

Miss.Sumaiya Shaikh [1], Guide: Mrs. Manisha Naoghare [2]
ME Computer
Department of computer engineering,SVIT,Chincholi,
Nashik,Pune University
India

ABSTRACT
Data mining is the process of mining or discovering hidden data from large database. It is the process of identifying relationships among different patterns. It contains the functionalities such as, characterization, partiality, classification, clustering, detecting patterns etc. Data and knowledge mining outputs the best solution for discovering striking and unknown patterns from given dataset. In learning interaction between moving object, a trajectory pattern discovery found very useful. Usually, trajectory patterns arranged in the order of temporal tightness. There are certain research areas such as, animal migration study, ecological analysis, mobility management; traffic analysis etc. required an identification of objects movement that arrives from certain place. Trajectory pattern identification is strategy for discovering object movements. For example, in the bio-metric system based on lip recognition are data, in GPS-tracked animals which required identifying relative motion within groups of moving objects. There are various methods available for discovering trajectory patterns. In existing method some limitations detected as user completely unaware regarding the type of trajectory pattern hidden in large dataset which seems to be an inefficient and inconvenient 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.

Keywords:- *Certification, Cloud Computing, Continuous Auditing, Security*

I. INTRODUCTION

Pattern discovery is most tedious as well as inefficient task as user totally unaware of which type of patterns hidden their dataset. Such as, set of moving objects arriving from multiple locations with different time interval. Therefore, to make classification of such trajectory patterns rigidity of temporal constraints on the pattern consideration is the better way suggested in this paper. It helps to identify capabilities of pattern at different levels with temporal tightness. In this paper author Jae-Gil Lee, Jiawei Han and X.Li discussed about UT-pattern mining for proposed unifying framework mining. It classified the broad range of temporal tightness into three categories namely, a time-constrained pattern, a time-relaxed pattern and a time-independent pattern. There are two phases introduced in this paper to cover these three categories or phases. Proposed two phases are initial pattern discovery and granularity adjustment. Initial pattern discovery phase identifies the detail information (level of details) about patterns and other phase that is in granularity phase patterns are merged together as per their detailing. In this paper author developed a unifying framework of mining trajectory patterns of various temporal tightness. It contains strength of temporal constraints which covers the three phases discussed above. An algorithm known as initial pattern discovery is utilized for the implementation of first proposed phase i.e. initial pattern discovery. To ensure system efficiency a stepwise approach is proposed in which spatial-constrained have been checked. In second phase, pattern forest construction algorithm is utilized for extracting good set of previously identified initial patterns. For efficient discovery of patterns a novel concept known as pattern forest in introduced. It represents the granularity hierarchies. Granularity hierarchy is constructed by spitting and merging of pattern. To construct a pattern forest drill-down and roll-up operations have been performed to discover more patterns.

II. RELATED WORK

G. Lee, J. Han, et al. [1], discussed about trajectory patterns that arranged according to the strength of temporal constraints. The proposed framework in this paper consists of two phases: first is initial pattern discovery and the second is granularity adjustment. In the initial phase detail levels of patterns are discovered. In the other phase patterns are merge together to construct a forest. In this paper, UT-pattern mining algorithm is developed. The algorithm first discovers initial UT-patterns using the intuitive information-theoretic principle of maximizing data compression and then constructs a pattern forest by drill-down and roll-up to discover more patterns. Finally, UT patterns are compared with the floack patterns. Floack patterns are classified as time-constrained. In this author like to claim floack patterns that are sometime too restrictive to find useful pattern. In this paper, use synthetic data sets created by varying four control parameters. Author discussed about, floack patterns, time-relaxed trajectories, sub trajectory cluster etc.

P. Laube and S. Imfeld [2], developed methods for spatio-temporal analysis of relative motion within groups of moving point objects, such as GPS-tracked animals. In this paper, they aim to develop a flexible analysis concept for the integrated analysis of motion parameters of groups of moving point objects. To identify, characterize and categorize the basic types of relative motion within groups of moving point objects also to identify sub-groups according to equal or similar movements. Finding patterns over time means identifying (a) the concerned individuals and (b) their location and extent on the time axis. The concept of REMO analyzes to detect interrelations in any kind of observation data of moving point's objects.

In paper [3], author P. Laube, Marc van Kreveld et al. discussed about REMO model. The proposed approach considered object's motion properties in an analytical space as well as spatial constraints of the object's lifelines in geographic space. In this paper, author discussed about geometric properties of the formalized patterns with respect to their efficient computation. In[4], author discussed about the development of a generic approach for geographic knowledge discovery (GKD) in geospatial lifeline data. It contains some crucial steps such as, Data reduction and projection, exploratory analysis and model selection, Visualization etc.

In[5], research on reporting floack patterns have been conducted by Marc Benkert,J. Gudmundsson et al, in this research they were determining that tree-based algorithm can well suitable for identifying flock patterns. However they very much depend on the characteristics of input set.

Similarly in [13] author, M. Nanni and D. Pedreschi defined a time-focused clustering for mining trajectories of moving objects. A new approach to the trajectory clustering problem, called temporal focussing, is sketched, having the aim of exploiting the intrinsic semantics of the temporal dimension to improve the quality of trajectory clustering. They implemented a density-based clustering method is utilised for moving objects trajectories.

Petko Bakalov, Marios Hadjieleftheriou al.[6] discussed about time relaxed trajectory joins manifested on basic symbolic join algorithms. Existingly, there was two kind of solutions or approaches are available, from that first approach is based on notion of multiple origins and the other is hueristic solution based on “divde and conquer” method[6]. This approaches are suitable where there is limited memory resources. The problem of computation of longest duration flock patterns is discussed in[9],. There are many problems in trajectory pattern mining such as, propose and design techniques for more complex patterns and implemented techniques that can manage spatio-temporal data with errors and missing values.

In[7], author Dimitris Sacharidis and K. Patroumpas discussed about hot motion path i.e.time relaxed trajectory joins to detect frequently traveled trails of numrous moving objects. Thery considered distributed settings,having co-ordinators maintaining hotness and geometrics of this paths. This wotk is only limited to freely moving objects. Sub-trajectory clusters: A new framwork called as partitioning and grouping framework. It is utilised for trajectory clustering. TRACLUS algorithm is introduced by D. Sacharidis, K. Patroumpas et al. for trajectory clusters. Main intension of TRACLUS algorithm is to detect sub-trajectories from large trajectory dataset. Sub-trajectory cluster can be defined as the set of clusters moving to similar direction.

J. Gil Lee, J. Han et al[8], discussed about trajectory clustering algorithms to group similar types of trajectories. They focused on discovering common sub-trajectories. In this paper, they proposed a new partition-and-group framework for clustering trajectories, which partitions a trajectory into a set of line segments, and then, groups similar line segments together into a cluster. The primary advantage of this framework is to discover common sub-trajectories from a trajectory database. Based on this partition-and-group framework, they developed a trajectory clustering algorithm TRACLUS. This algorithm consists of two phases: partitioning and grouping. For the first phase, they represent a formal trajectory partitioning algorithm using the minimum description length (MDL) principle. For the second phase, they represent a density-based line-segment clustering algorithm. Experimental results demonstrate that TRACLUS correctly discovers common sub-trajectories from real trajectory data.

Thomas Brinkhoff[10], suggested a Framework for Generating Network-Based Moving Objects, to evaluate spatio-based temporal database, as many applications dealing with the spatio temporal data. It is used to defined benchmark.
Sub-trajectory clustering utilizes hueristic solution based on divide and conquer method. Clustering moving objects is an interesting approach to catch regularities of the moving objects.

Y. Li, J. Han et al. [11], 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.

C. Bohm, C. Faloutsos, et.al [12], 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.

III. PROBLEM FORMULATION

-Multiple methods have been proposed in literature (Section II) 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 pattern

IV. SYSTEM ARCHITECTURE

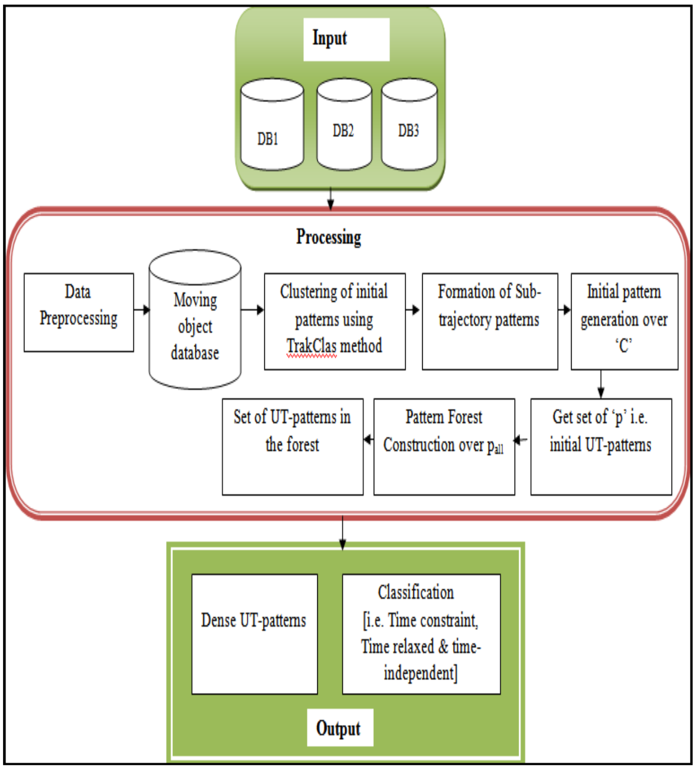

Figure 1: System Architecture

Above figure 1 represents the system architecture of UT Framework. It contains the large database of various object movements such as, animal data, vehicle data etc. Firstly pre-processing is applied on it for refining dataset and to extract the movements of objects. The object movement dataset is given as input to the phase I to discover the detail levels of patterns. The phase I for initial pattern discovery forUT-pattern identification is given as:

1. Initial pattern discovery

2. Sub-trajectory clustering over I using TRACLUS method
3. Collect all sub-trajectory clusters i.e. C_{all}
4. Initial pattern generation over C
5. Get set P of initial UT-patterns

The output is then passed to Phase II to adjust the different levels of patterns. It is further used for classification according to time restricted patterns, time delayed patterns etc. And after successful classification of patterns they are used for various applications ecological analysis, mobility management, traffic analysis, planning and control etc.
The phase II of pattern forest construction is given as:

1. Get all initial patterns P_{all}
2. Apply roll-up approach
3. Apply drill-down approach
4. Construct pattern forest
5. Classify pattern i.e. time constrained pattern and time relaxed patterns

IV. CONCLUSION

In this review paper, we have studied the existing techniques of trajectory mining. Trajectories are nothing but the movements of an objects. We have studied some existing techniques of pattern mining. There are several techniques available for trajectory pattern mining but they have some limitations such as, It is the process of identifying relationships among different patterns. It contains the functionalities such as, characterization, partiality, classification, clustering, detecting patterns etc. Multiple methods introduced in the literature to discover trajectory patterns. It has some limitations as user completely unaware regarding the type of trajectory pattern hidden in large dataset which seems to be an inefficient and inconvenient task. Many trajectory patterns are arranged with respect to their potentials and temporal restrictions.

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