© 2016 IJSRSET | Volume 2 | Issue 3 | Print ISSN : 2395-1990 | Online ISSN : 2394-4099
Themed Section: Engineering and Technology

A Joint approach of Mining Trajectory Patterns according to Various Chronological Firmness

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ABSTRACT

Analysing the trajectories of moving objects is most complex and challenging work when dealing with the real time data. These trajectory patterns play a vital role in getting various kinds of information's about the moving objects. Those information and patterns explains the behaviour of the mobility devices. Generally trajectories contain spatial and activist information about the movements. Various kinds of trajectory patterns were discussed in the literature to get a clear cut and better learning about the patterns, but existing methods can be only applicable for specific type of trajectory patterns. This drawback and inconsistency raise the pattern analysing a most discussing field in global industry. Since the inefficiency of the users to obtain which kind of trajectory pattern behind the data set grabs the attention of the researchers deeply to find a better approach in learning the patterns. Our major work involves in arranging the huge trajectory patterns according to the strength of temporal constraints. In this paper, we propose unifying trajectory patterns (UT-patterns) which is developing a modern framework for mining the trajectory patterns according to its temporal tightness. It has two phases such as initial pattern discovery and granularity adjustment. The initial pattern discovery is the concept of covering initial pattern set and granularities is adjusting like split and merge according to the levels of details obtained. By the obtained result a structured is constructed known as pattern forest to show various patterns detected from the data set. These phases guided by an information-theoretic formula without user intervention and the experimental results shows the efficiency of our proposed work on discovering the patterns from the real-world trajectory data.

Keywords: Trajectory pattern mining, moving object trajectories, trajectory clustering, synchronous movement patterns, UT patterns

I. INTRODUCTION

Data mining is the methodology of extracting information from the huge amount of data. The major to be concerned is memory size and time taken for retrieving the required information according to the user concern. Data mining is a wide area which has various fields in which trajectory mining is a peculiar filed dealing with learning of patterns among the moving objects. These data are not easy to understand and comes to get a conclusion from the result gained by trajectory mining. These trajectory mining had patterns the task is which pattern belong to which from the object and how to form a cluster accordingly. In general various synchronous movement patterns were tracked during the communication or interaction with each other. It happens sequent with minimum time delay from one another; it may also include asynchronous movement patterns which are derived from same path.

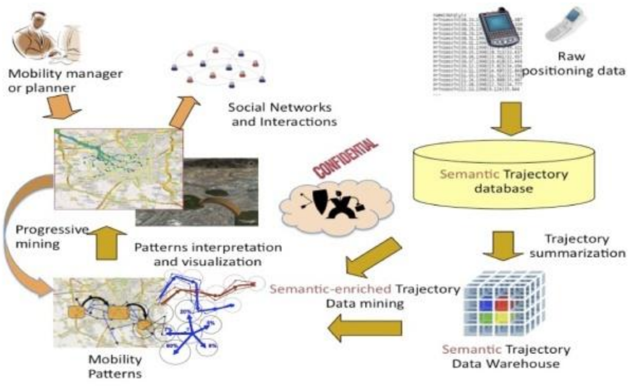


Figure 1 : Sample Trajectory patterns

The above fig1 shows how the trajectory patterns and how they are collected from the various source as in the real time environment. As state before during communication trajectory patterns are gained like social networking and other mobile devices. The mobility manager organized the patterns and stored in the database. From which the pattern are study according to which data set. These tracking of huge data are still difficult which raise the intention and importance of actual pattern. For this below section shows various raise and growth of approaches dealing with trajectory patterns.

II. METHODS AND MATERIAL

A. Related Works

In which Sharma et al [1] proposed two step processes which is based on nearest neighbor forming pre-processed training trajectory data and it is classified by using label. In this technique the important issue is distance similarity which does not process patterns effectively during training set. Most of the literature works deals in studying the data mining and computational geometries such as flock patterns convoy patterns swarm patterns moving clusters, time-relaxed trajectory joins, hot motion paths, and sub-trajectory clusters [2] – [12]. These work are succeeded in dealing one specifying type which are fail to handle multiple types of trajectory data. According Akasapu et al [13] he developed DBSCAN algorithm for dealing uncertain positions into account but density-based line-segment suffers from time management and suffers from computation of distances between the neighborhoods. Lee et al [14] proposed in his work partition and group frame based trajectory, he uses in his work Minimum Description Length (MDL) based on the principle of discovering common sub-trajectories from a trajectory database. According to papers [15], [16],[17],[18] it sates the working of network based generator of moving objects dealing with large trajectory patterns but the code length is huge and not that much effective in dealing pattern unity. Next to this Hidden Markov Model (HMM) [19][20] is proposed in which time-series classification is discussed by using the traditional methods which are dealing with shapes of trajectories but class labeling of new samples and whose class is unknown as a major issue still in developing stage.

B. Background

The existing system deals with three major divisions on trajectory patterns such as flock patterns, temporal variation and sub-trajectory clusters. These three factors depend on the tightness of the trajectory patterns.

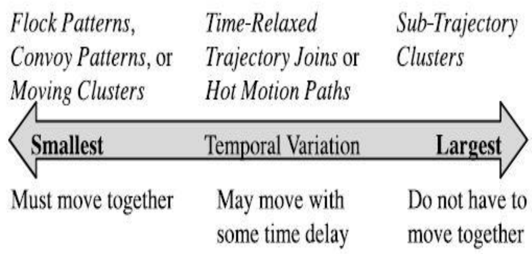


Figure 2: Existing trajectory patterns

These flock patterns are also known as moving clusters or convey patterns which provides the pattern details on movement during communication with each other. These patterns which move together within a small distance are tracked. The next thing is time delay between the trajectory patterns in the same path known as temporal variation. The third one is forming cluster with sub-trajectory clusters that not need to move together. The transition time is calculated between the two locations. These systems are not extremely applicable for all set patterns of trajectory patterns which are of different kinds. At the same time the clustering of these patterns are not accurate by the existing system which are successfully applicable for certain kinds of data only.

C. Proposed System

By the overall discussion, in this paper we propose forming a framework of unifying trajectory patterns (UT-patterns). The proposed system discusses the initial pattern and adjusts as per levels, which forms a cluster by means of information-theoretic formula without user intervention. The UT-patterns covers three phases such as time –constrained, time-relaxed and time-independent patterns. The granularities are based on adjusting levels as per shown in the below figure.

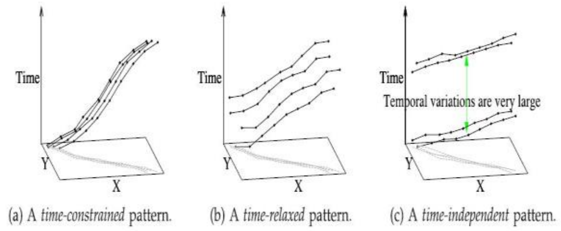


Figure 3 : Three types of UT-patterns

The proposed work is carried by dealing with dataset extracted from [21][22][23][24][25], which are processed under the guide of information-theoretic formula and the data set has details of moving objects. By which navigating the patterns at all different levels were noted and forms clusters.

Clustering in Trajectory Data

The related data are collected from the dataset is portioned and grouped according to its pattern. In other words, we can say grouping of similar patterns by calculation distance length between them. Before this Minimum Description Length is used in finding the shortest length and forming sub-trajectory clustering results in UT-Pattern clustering.

Figure 4 : Architecture of proposed system

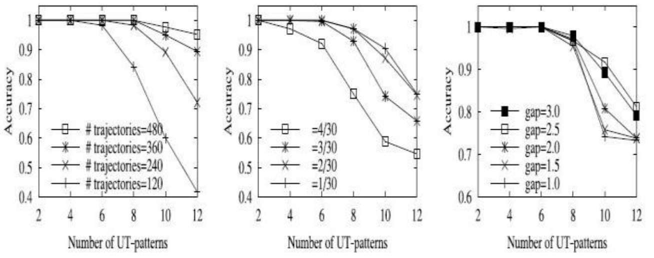
The fig 4 shows the working mechanism of proposed system in which from the collected data the unified frame work has the UT patterns. This has the thousands of pattern which are not belonging to specific type but multiple as discussed; it is one of the major drawbacks of existing system. It undergoes filtering by means of following information-theoretic formula basis on set of reference movements according to its location, time and space. This principle maximizes the data compression and thus an optimize data compression is derived as result. Below works shows the algorithm used in proposed system and results were discussed in the next section.

1. Input set of trajectories $I = \{ST_1, \ldots ST_{num}\}$
2. Output set UT-Patterns
3. $Q = \{UT_1, \ldots UT_{num}\}$
4. /* Phase I:Initial pattern Discovery*/
5. Perform Sub-Trajectory Clustering over I Based on classification-and –group Frame Work[7]
6. Get a set C_{all} of Sub-trajectory Clusters;
7. For each $C \in C_{all}$ do
8. Execute Initial Pattern Generation Over C
9. Get a set $P = \{UT\}$ Patterns Generation over C;
10. Accumulate P into set P_{all}
11. End for
12. /* Phase II:Initial pattern Discovery*/
13. Execute pattern for forest Construction Over P_{all}
14. Return the Set of UT-Patterns In the Forest
15. Classify The Three patterns into three Types

III. RESULTS AND DISCUSSION

Performance Comparison

As per the proposed system and algorithms the extracted data undergoes with UT pattern mine with different movement characteristics based on the control parameters in which the accuracy increases with decreasing in number of UT-patterns.



(a) Effect of the number of trajectories. (b) Effect of the variation of timestamps. (c) Effect of the gap between UT-patterr

Figure 5: Accuracy of UT-Patterns

According to the results obtained the UT clusters were below or equal to 6 which shows the high accuracy level (80 ~100 percent) under various conditions rather than odd cases.

k	2	3	4	5	6	7	8	9	10
m=2	69	50	46	45	44	41	39	38	32
m=3	24	21	16	14	12	10	10	9	9
m=4	5	3	3	3	1	0	0	0	0
m=5	1	0	0	0	0	0	0	0	0
m=6	0	0	0	0	0	0	0	0	0

This proposed work is compared with flock patterns by comparing the minimum number of objects (m) increases or the minimum duration (k) increases, a smaller number of flock patterns were achieved and the below table show that the proposed mechanism is more efficient than the other existing works in the tem of finding the trajectory patterns.

IV. CONCLUSION

By the overall work, proposed unifying framework is developed for UT- pattern which deals with different temporal tightness like time-constrained, time-relaxed, and time-independent effectively and successfully. The data compression is maximized and pattern construction discovers more patterns than the traditional methods. The extracted results from the experiments prove the accuracy is high such as nearly to 100 for various movement characteristics. It achieves accuracy on hidden pattern on the data set and support large data set thus overcomes the real-time issues and proves its performance efficiency.

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