A Review on Continuous Clustering and Querying of Moving Objects with a Special focus on Spatial-Temporal and Semantic Properties

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Abstract

Large amount of mobility data is getting generated from wide range of location sensing devices. Due to proliferation of these gadgets storage and analysis of moving objects has been an active area in data mining research over the years. Unlike snapshot data the storage, clustering and retrieval of spatio-temporal data requires particular approaches for processing due to the accumulation data stream. In this paper we are surveying state of the art techniques for the clustering and querying of moving objects. Some of the related concepts in moving object data storage is also discussed for the continuity. As a proposal we are briefing a semantic based dynamic clustering approach for moving objects and queries. The suggested framework encapsulates objects and queries together for efficient pattern extraction.

Keywords: Dynamic Clustering, Moving Object Clustering, Spatio temporal objects,

1. Introduction

Real time mobility data is getting accumulated in to network database from various sources such as context sensing devices, social networking sites, geo tagged multimedia elements etc. Host of applications exist that utilises mobility pattern of objects. Being an established data mining tool moving objects clustering attracts research attention. Clustering provides general behaviour of objects where objects in same clusters exhibit common behaviours, these behavioural features are defined in accordance with the purpose of our application. Since the moving objects continuously change its spatial and temporal properties clustering of moving objects requires special attention. Compared to static objects moving objects processes number of unique features like location, time, the direction of movement, change in speed, destination reaching time, maximum speed, average speed, meeting and revisiting points of different objects, behaviours of objects moving adjacently and the like. Specifically, the moving objects data consists of spatial, temporal and non-spatial attributes.

Visited points of moving objects are effectively represented in the form of trajectories that can be defined as the time-stamped which provides history of the traces. Though trajectory clustering is relevant knowledge extraction tool in this field we restrict our discussion in moving objects clustering. Majority of the existing moving object clustering techniques focuses on the static data. But if we extend the clustering towards each updated location in regular interval of time deeper insights can be exploited about the movement patterns, trends etc. of moving objects and spatial-temporal networks. As the number of objects being monitored and GPS sampling rate increases volume of spatio-temporal data also increases and processing becomes difficult. At this context for efficient and scalable pattern extraction dynamic clustering approaches like incremental clustering are adopted.

Moving micro clusters is another paradigm that describes the clustering of closely related individual moving objects in current time and in future.

Evaluating queries from the moving objects is another area of focus. The relevance of queries expires as the object that fires query approaches its destination. Time and location of query generated are important parameter that determines its scope and relevance. There are some important works that consider moving object and queries together for providing time bounded results. Apart from the latitude, longitude and time moving objects also hold lots of contextual information. Semantic trajectory processing is an area that concentrates on such kind of data extraction. This paper aims to examine some of the mentioned clustering and querying techniques developed for moving object data. We are proposing an effective method for clustering of moving objects and queries for aggregate queries.

2. Moving Objects

Traditional database systems are equipped to store static data such as inventory on a specific date, academic record of a student etc. The data are constant unless it is explicitly updated using required DML queries. Maintaining the details of moving objects in snapshot database is not feasible due to the requirement of continuous updating and network overheads. Moving objects are represented in the form of trajectories which can be expressed in form of triples (x, y, t). Where (x, y) represents latitude and longitude and temporal factor t represents the time at which the object resides in a particular location. Representation and indexing of spatio-temporal data plays crucial role in retrieval and processing. There is a number of studies reported in the representation moving objects in the database [6] [1] [2] [3] [4].

Moving Object Spatio Temporal (MOST) is one of the widely accepted data models that provide facility for storage and retrieval of Spatio Temporal features of Moving objects [5], [6]. The dynamic nature of continuously moving object is updated in the database using time varying functions. In order to represent continuously varying attributes this model introduces three sub attributes, A. value, A. update time and A. function, where A is the object in consideration. The value of dynamic attributes depends on time and is updated with a single variable function A. function. Indexing in database avoids searching of the entire row for to locate particular information. Traditional way of indexing in a continuously changing context is not feasible as it will brings bandwidth and network overheads. In MOST indexing of dynamic attribute is managed by plotting a trajectory with time against value of dynamic value. This paper also presents a language for querying and triggers specification of spatial-temporal data. Future Temporal Language is designed over the non-temporal query language but adds the flavors to administer spatial (clauses such as DIST, INSIDE) and temporal (clauses such as UNTIL, NEXTTIME) traits of mobile data. This language permits a natural specification of future states in the query construct.

Ralf Hartmut Guting and colleagues developed a generic framework for representing spatio-temporal attributes of moving object [4].Core of this frame work focuses on the spatio-temporal aspects of continuously moving objects. One of the main challenges for designing spatio-temporal database is maintaining compatibility with traditional system. They introduce abstract data types in the proposed model. It postulates five classes of abstract data types and supporting constructors viz. Base, Spatial, Time, Temporal and Range type. The temporal and range types are derivatives of base, spatial and time types. The paper provides complete and precise definition for all operation and embedding query operations.

Integration of complex moving objects is modeled in a progressing project funded by NASA for the efficient analysis of hurricane [8] [19]. Binary Large Objects (BLOBS) are the means of storing large complex structures of moving objects in the database, even abstract data types defined for this purpose, however it represent them as low level binary strings without preserving their structure. The model proposes Type Structure Specification (TSS), which provides a set of high level interfaces, functions and abstract data types that can hold spatio-temporal attributes of data received from different sensors. The Spatio Temporal Query Language (STQL) in the frame work enables the users to pose ad hoc spatio temporal queries on moving objects. The paper also proposes a storage mechanism called intelligent BLOB (iBLOB) unlike the normal BLOB it understand the structure of the application object stored and support fast database operations.

Table1 : Comparative study of moving object storage methods

Sl. No.	Work	Modeling of features	Query Support	Implementation
1	MOST[5],[6]	Three attributes are defined A.value, A.updatetime and A.function. Value of dynamic attribute is updated by the time dependant function.	Future Temporal Logic defined over non temporal query language.	Implemented on top of existing DBMS
2	R. H. Guting et al[4]	Five classes of Abstract data types to represent objects BASE, SAPTIAL, TIME, TEMPORAL and RANGE.	Multiple classes of operations are defined separately for temporal and non-temporal types	Abstract data types can be built over the existing data models.
3	Hadi Hajari et.al[7]	User defined data type GPOINT, GLINE , MPOINT and MG POINT. Object positioning over a constrained network is described using Linear referencing System.	Not addressing queries	Built over OGC Compliant Oracle Data Model
4	Markus Schneider [8],[9]	Abstract Data Types are defined. Stored using iBLOBs	Supports Ad Hoc queries for moving objects	Spatial-Temporal Query Language that provides and SQL like query language for spatial and spatio temporal data.
5	Leila Esheiba et.al [10]	Star Schema to represent moving objects. Moving angle of the object is measured	Direction based queries are defined	

Leila Esheiba et.al in their literature [10] introduces a direction based star schema for moving objects. The motion of the object is represented by its trajectory which represents the path that the moving objects. Spatial cells are defined with specified dimensions and are used to identify which object falls within a given cell at a certain time or during the time interval. The motion angle of trajectory segment is computed using the direction value from which the direction majority of the object and other predictions such as the future position of the object, number of objects moving in a particular direction etc. can be calculated.

A recent study in the field [7] proposes a network based data model for representing spatial data in constrained environment. The location of the moving entity is described using Linear Referencing System (LRS) where, the location is described in terms of a linear element along the transportation network from a starting point instead of coordinates of the points. A change in the road segment is updated by changing the mile points. The transportation network is stored as a graphical structure that supports network specific operations. Basic attributes of the route like starting point, end point, length, intersection of roads, junction, direction of travel etc. are stored in the instances of separate classes. The model proposes user defined data types such as GPOINT, GLINE and MPOINT for representing static positions, regions and moving regions respectively. Operations that support for the data types are also detailed in the paper.

Large number of literatures are available in this field but for the context of our proposal a few of the state of the art techniques are reviewed here. Table 1 gives the concise of different MOD storage approaches discussed.

3. Moving Object Clustering

The clustering of moving objects needs special procedures due to its dynamic nature. As an example GPS tracks of 5,000 online taxi system in a popular city in a day consists of 50.4 million location points [11]. Considering the huge size of streams of points that are added in every specified time stamp, normal clustering methods has to evaluate each point multiple times which is time consuming and not an efficient solution. Another challenge in clustering moving objects is the difficulty in managing two dimensional geographical information with the time domain. One of the well-known scheme for moving objects is incremental clustering. According to this location are clustered upon the updation from different moving objects without re-clustering the entire space time components. Incremental clustering avoids the necessity of storing all location updates that reduces storage requirement. Several constraints arises at this stage, especially associated with the cluster centroid, speed of movement and termination condition etc.

In a continuously updating system with the assumption that new locations will not influence the clusters distant from the incoming data Li et. al. [11] proposes an incremental clustering framework called TCMM. It executes the operation in two steps. Initially the micro clustering phase is used to generate representative trajectory line segments by comparing an incoming trajectory with the exiting clusters. Similar micro clusters are merged together in periodical fashion, which will avoid unnecessary maintenance of micro clusters.

The framework proposed by R.V Nehme et al. [12] suggests the idea of grouping moving objects and queries in a single unit according to its spatial temporal features. The method utilises concept of moving micro clusters for the effective and less expensive evaluation of spatio-temporal queries. The clusters are updated for its membership incrementally in every time units. During the motion cluster member ship of individual objects may vary due to the change in speed. Hence the abstraction of join between and join within are performed for filtration of redundant data. In order to preserve the performance in the execution of multiple objects, authors have proposed semantic load shedding mechanism that rejects insignificant points. This method doesn’t consider the splitting of moving objects in different clusters. The breakthrough concept in this approach is the grouping of multiple object movements and queries in single cluster.

Another method discussed in [13] proposes clustering of moving objects in spatial networks. The framework CMON performs periodical clustering of moving objects with different criteria. It proposes a structure called cluster block for maintaining the clusters. The distance between two moving objects are measured as the length of the shortest path connecting them in the spatial network. The CMON method also effectively manages split and merge of cluster blocks. In order to manage the termination point it also requires intermediate destinations in the travel path. When the objects in cluster block reaches the destination it departures from the cluster bock, in order to reduce cost of splitting based on the direction of movement and speed the split scheme is managed. When neighbouring cluster block are moving together with minimum distance threshold they merged together which reduces cluster maintenance cost. The CMON framework doesn't manage queries on moving objects.

Jensen, C. S et. al [14] outlines a new scheme that is capable of incrementally clustering moving objects. This proposal employs a notion of object dissimilarity that considers object movement across a period of time, and it employs clustering features that can be maintained efficiently in incremental fashion. A data structure called clustering feature is set and updates incrementally with the key properties of the moving object cluster. An average radius function is used that automatically detects cluster split events, which, in comparison to existing approaches, eliminates the need to maintain bounding boxes of clusters with large amounts of associated violation events.

As indicated in the introduction the micro clustering is suitable data mining strategy for moving objects. It indicates that group of objects that are so close to each other are probably belongs to one cluster. Yifan Li et. al [15] extended the concept of micro-cluster as moving micro clusters. It represents that set of objects that are not only close to each other at current time but also likely to move together in future. Due to the change in velocity and direction of movement the objects in clusters may scatter along the travel path hence the split and merge events are to be executed carefully.

Table 2 : Comparative study of moving object clustering

Sl. No.	Methods	Problem	Method based on
1	TCMM[11]	Incremental clustering on Trajectories	Micro clustering and Macro clustering
2	TKM[16]	K means clustering of moving objects	
3	Jensen, C. S et. al [14]	Incremental clustering	Considers object dissimilarity. It maintains cluster feature data structure
4	CMON[13]	Periodical clustering	Cluster block to maintain updating of clusters
5	MMC[15]	Moving micro clusters, split and collision	
6	Steven Young et. al[18]	Incremental clustering	Starvation and Stabilization process for consistent centroid update of clusters.

K- Means clustering is a popular clustering strategy, there have been number of competitive works describing its application on moving objects. Since the cluster centroid is to be measured during each location update continuous monitoring of moving objects is required that incurs additional. By addressing this overhead Zhang, Z eta. al [16] proposed a threshold based monitoring where each object is assigned with a threshold range, where the location needs to be updated to the server only f it crosses the threshold value . The k means clustering is achieved by optimised Hill Climbing method to reduce the CPU cost.

An extended version of k- means algorithms configured for moving objects for trajectory data is proposed in [18]. This approach deals with the problem of pre-setting the initial cluster centroids and dependence on the number of clusters. It aims at discovering the common sub trajectories of moving object data by considering direction of movement and Euclidian distance as similarity features. Accuracy measured using Silhouette coefficient shows better performance.

Steven Young et. al [18] presents a fast and stable incremental clustering algorithm that forces minimum memory requirement. The method employs a Winner Take All paradigm, a computational model generally applied in neural networks for competitive learning. In order to update the centroid of moving clusters the starvation trace approach is adopted, it allows idle centroids to garner credit over the time when they are not considered as centroid. Once the centroid is updated it loses this credit. Additional statistical measure is adopted to stabilise the input parameters for clustering process. Table 2 provides a Comparative study of moving object clustering discussed.

4. Querying

Querying from a dynamic moving object database is rather different from a static database. Former method strictly adhere to spatial and temporal factions of querying and queried entities. Based on the parameters used for queries and outputs generated queries can be of different types [19] such as distance queries, K- nearest queries, range queries, trajectory queries, aggregate queries etc. Constrained databases and constrained queries are not a new idea, recently these concepts have been studied in new application domain like moving object data management. A constrained database is a generalised relational model for representing infinite relations such as space and time in a compact manner [20]. The key component is first order theories with constraints that defines prescribed semantics. A moving object holds a number of semantic attributes such as the direction of movements, velocity, halt points, meeting locations etc. Based on the constrained databases Mokhtar, H et. al [20] presents three classes of queries : past, continuing and future queries.

Nowadays, semantic based trajectory processing has become a subject undergoing intense study. According to the much discussed concept on semantic trajectory by Spaccapietra et.al [22] the moving object trajectory is considered as a sequence of Stops and Moves. Stops are locations that need to be highlighted due to the reasons defined by the application like meeting point of different trajectories, halt point, slow moving area, turning point and the like. Number of noticeable works are reported in this semantic location clustering. The trajectory enrichment model suggested by Alvares, L. O. et al in [27] performs pre-processing operations for integrating semantic information that is relevant for applications. Authors argue that priori integration of trajectories with semantic/context information details will reduce the complexity of query processing especially for the queries that consists of space and time as major constraints. Trajectories modelled in terms of semantic information can effectively answer queries related to the behavioural motion of objects. An online framework SeTraStream [24] provides real time data cleaning, compression and segmentation over streaming movement data. This model generates meaningful semantic trajectories from raw GPS feeds, which are augmented information about the movement behaviour and can be effectively used for querying. According to this model the pre-processed trajectory is divided in to number of episodes corresponding to distinguishable movement patterns. Correlation coefficient computation is performed for the extraction of movement feature vectors that are used for identifying different trajectory segments. After these segmentation step, different tags are assigned to the trajectory according to the application like distance, duration, density, average speed etc.

Panfeng Zhou et. al [24] presents close pair range queries concept of moving objects that is used to identify pairs of objects closer than specified distance during the specified time interval and within user defined spatial range. Special storage and retrieval trajectories schemes based on Multiple TSB- Tree method have adopted in this. Closed pair queries are particularly applicable in air traffic control, battlefield configurations and intelligent transportation systems etc. The query “Which airplanes were closer to each other than 10 miles during the past month in Massachusetts" neatly illustrates the purpose of this concept.

Already explained method SCUBA [12] efficiently manages moving queries by combining it with moving objects. A continuously running query in SCUBA is represented with different parameters such as id, location, time, speed, destination location and query attributes. Queries generated from multiple moving objects are also clustered based on the attributes. The advantage is that instead of monitoring individual objects answers can be obtained from cluster table that is maintained by periodical uptation. Adjacently moving queries are merged together by two inter related schemes called join between and join within. Once the cluster that consists of moving object and moving queries reaches a destination, SCUBA assumes that it dissolves and the algorithm doesn’t consider possibility of splitting the clusters. It is designed particularly for continuous range queries.

In a recent journal by Gryllakis, F et. al [25] outlines a spatio-temporal database engine Hermes@Neo4j for efficient storage and indexing of semantic trajectories. It provides number of utilities that facilitates hybrid indexing for spatio-temporal and textual data. The framework also suggests special types of queries called Spatio temporal- Keyword pattern (STKP) that will result semantic trajectories over a geographical area.

Ferreira, K. R et. al [26] suggests a flexible query processor for spatio temporal databases using ORDBMS. It is basis is a geographic database which stores spatial and temporal details in static and temporal layers. Each geographic area is described in terms of descriptive attributes. The query processor, Querier, monitors state of database in different time frames. Querier accepts various attributes that defines different combinations of spatial and temporal aspects of data. It is implemented in TerraLib library that permits the use of various DBMS to build generic model of spatio temporal data. Table 3 gives narration of different moving object querying techniques discussed so far.

Table 3 : Comparative study of moving object querying techniques

Sl. No.	Method	Querying Approach	Applications
1.	SeTraStream [24]	Online trajectory clustering where semantic trajectories act as the basis for answering the queries	Diagnosing streets for vehicle density, speeding tailgating drivers and Navigation services etc.
2.	Close pair queries[24]	Applies on historical trajectory set to detect the moving objects in a range	Battle field configuration, Air Traffic Control and Ground Traffic.
3.	SCUBA[12]	Incremental clustering, intelligent load shedding to reduce the computational overhead. Applicable to continuous range queries	Continuous movement over constrained networks.
4.	Hermes@Neo4j[25]	STKP queries applies on spatiotemporal and textual data	Querying semantic properties of moving objects

5.	Querier[26]	Query engine built over ORDBMS	Layered approach for processing spatial and temporal features

5. Proposed Model

As seen from previous sections most of the existing moving object clustering methods considers each location updation for processing. As the number of objects and queries increases it becomes difficult in terms of space and CPU constraints. Apart from the explicit spatial temporal features we make use of general behaviour of moving objects such as velocity and direction of movement for clustering. We are adopting the shared execution model in SCUBA [12] where objects and queries are wrapped together and form cluster based on movement parameters. SCUBA is modelled for spatio-temporal range queries, we are extending it to aggregate queries by facilitating some additional features that are not addressed in this. As part of the work we are planning to apply the semantic query analysis on aggregate queries.

An aggregate query is a method of deriving group and subgroup data by analysis of a set of individual data entries. Aggregate data can provide an attribute rich data set, with decreased dimensionality while using in Machine Learning for predictive modelling etc. Aggregate data could provide free access to patterns and trends in data warehouse that wouldn't normally be visible without long running, memory intensive and complex queries. Hence this approach will be more beneficial in decision making. Different queries are asked about moving objects the answers to those represents common behaviour of the movement patterns. As an example, with respect to the constrained road network following are some of the possible questions.

- *Locate the group of slowly moving objects that creates or may cause traffic congestions*
- *Possible number of vehicles that can be accommodated in a toll rout without affecting the traffic.*
- *Average, Maximum and Minimum speed in a traffic network at different time.*
- *Average number of vehicles heading towards a particular direction.*

Individual objects may take different routes as it proceeds towards destination objects leaves one cluster and joins on the other. The split event is to be periodically monitored using appropriate strategy. In order to get clear idea on the percentage of participation of objects in cluster split is important. Following is the different phases in moving object clustering.

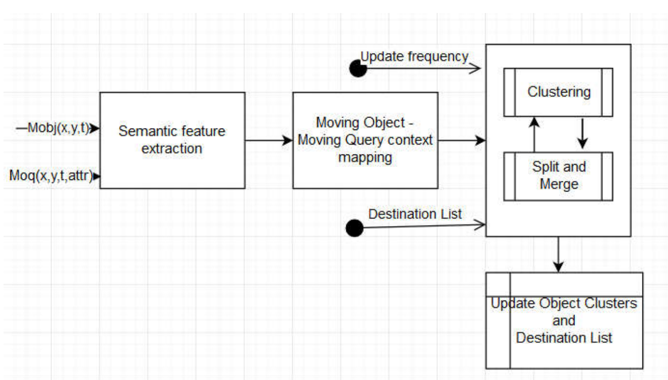

Figure 1 : Components of Proposed Clustering Model

Components of the proposed system is given in figure 1. Moving object data and moving object queries are major inputs given to the system. Explicit information such as latitude, longitude and time are constantly tracked from both moving objects and moving object queries. The semantic feature extraction phase identifies context information such as direction of movement and acceleration in the case of moving objects. Query expiration time is the vital component in the moving object query which are implicit data that can be extracted from the query itself. Queries can be either on static object (E.g. List out all petrol bunks within 5km) or about moving entities (E.g. How many vehicles are moving in the same direction with speed 45kmh). Both type are to be treated accordingly. The context mapping phase probes for a relation between moving objects and queries fired. Followed by the mapping phase clustering is executed. Dynamic clustering and Split and merge phases are executed in parallel fashion. Suitable data structures design is one of the crucial factor for maintaining the clusters.

6. Conclusion

Clustering of moving object data is gaining more research attention due to the generation of huge spatial temporal data from wide range of location sensing devices. In this paper examines relevant approaches in clustering and querying of moving objects dynamically, works still lot to be explored. Considering all the aspects of moving object data incremental clustering is will help in extracting robust features. The notion of k-means clustering is also suitable with some modifications. Querying of moving object is another important paradigm. The concept of SCUBA, ST queries, Close pair queries etc. are examined in this review. We are proposing a combined model for clustering and querying of moving objects. This will take care of spatial temporal and semantic aspect of moving objects.

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