A Brief Survey on Online Analysis of Movement Data

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Abstract—**The increasing availability of mobility data and the awareness of its importance and value have been motivating many researchers to the development of models and tools for analyzing movement data. This paper presents a brief survey of significant research works about modeling, processing and visualization of data about moving objects. We identified some key research fields that will provide better features for online analysis of movement data. As result of the literature review, we suggest a generic multi-layer architecture for the development of an online analysis processing software tool, which will be used for the definition of the future work of our team.**

Moving objects; data warehousing; on-line analytical processing; movement data analysis

I. Introduction

A moving object is a pervasive object that can change it position or size in time. New applications of mobile data are emerging as the collection of mobility data increases. Satellite positioning technologies and location aware devices are being used to gather data about people, animals, vehicles and other moving objects. The available data can be exploited by multiple applications, such as, finding human mobility patterns, vehicle traffic planning, leisure purposes, optimization of vehicle trajectories, or Location-Based Services (LBS).

The current top Database Management Systems (DBMS), such as Oracle DBMS, Microsoft SQL Server or IBM DB2, supports spatial data applications, but is not well appropriated for representing spatiotemporal data [1-3]. On the other hand, current Geographic Information Systems (GIS) were conceived to process traditional, static or slow changing, geospatial data, but are unsuitable to represent dynamic spatial data, as is the case of the movement of objects [2]. New data models to represent moving objects have been proposed to deal with movement data; spatiotemporal access methods have been developed for increasing efficiency of movement data manipulation.

To explore this vast amount of raw data in order to transform it into useful knowledge, researchers are proposing the use of data warehousing (DW), Online Analytical Processing (OLAP) and data mining techniques. The data warehouse was conceived to be the enterprise's data repository, working as an integrated data repository that is organized around the main subjects of the organization. The implemented model is usually easy to understand and is optimized to query operations [4]. Online analysis is performed by the use of an intuitive and responsive software tool, such as OLAP, for the appropriated visual analysis of the data. The OLAP concept was proposed by E. F. Codd *et al.* [5] to enhance the querying of the data stored in data warehouse systems. OLAP systems include a set of tools and algorithms that enable easily and efficiently querying data warehouses with huge amounts of data.

However, traditional DW and OLAP systems are not able to cope with the spatial or geospatial dimension of movement data. Several works have proposed data warehouse systems for support the online analysis of movement data [6-8]. . In order to provide the analysis of data with spatial and temporal characteristics, OLAP systems should integrate spatial analysis features, which can be obtained by the integration of GIS features in OLAP systems. Because moving objects can generate huge amount of quite complex data, data mining techniques are being used in the aggregation and summarization of movement data [9,10].

The main scientific contributes of this paper are a brief survey about methods and tools for the analysis of movement data and a generic multi-layer architecture for the development of an online analysis software tool for movement data. The paper is organized as follows. Section 2 presents the fundamental concepts associated with moving objects. Section 3 focuses on mobility databases and data warehouses, while section 4 is dedicated to online analysis for moving objects.

The generic multi-layer architecture is explained in section 5. Last section presents a brief conclusion and the future work.

II. MOVING OBJECTS MODELLING

The most relevant research works about moving objects we found are based on 2D-space model and represent moving objects as points, lines or regions. Distinct spatial data types can be defined depending on the modelling approach, which can be continuous or discrete. Based in the continuous approach, three kinds of basic abstract spatial data types were defined [11]: point, line and region. To capture time, the initial spatial data model was extended to include two basic data types, *mpoint* and *mregion*, defined as mappings from time into space (see Fig. 1). Forlizzi *et al.* [12] stressed the fact that these abstract models are needed but are more difficult to implement, and proposed a discrete data model for the abstract data model proposed in [11]. Forlizzi *et al.* presented a correspondence between abstract and discrete data types. The transformation into discrete spatiotemporal types was made using a time *sliced representation*, i.e., through the decomposition of a continuous value into fragments, called "slices".

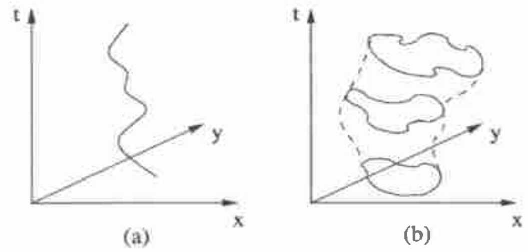

Figure 1. Continuous representation of a moving point (a) and a moving region (b) [14]

Although all these developments, there is no de facto standard data location model for moving objects, which is the core of moving objects modelling. The most obvious approach is to store the location of each moving object periodically. Wolfson identified several problems with this approach, such as query weakness and resource inefficiency, and proposed a trajectory-based location model to overcome it [15]. Current DBMS do not handle moving object type of data very well because it would require too high data update frequency, which could cause serious performance problems. Therefore, indexing moving objects databases was the aim of many works [16,17]. A moving objects database should store predicted data and provide query capability for querying such data [14]. In a comprehensive survey presented in [18], spatiotemporal access methods are classified into four categories: (1) Indexing the past data – are restricted to fixed networks, work by building line- trajectories or are trajectory oriented; (2) Indexing the current data – deal with frequent updates of objects positions; (3) Indexing the future data – predict the future positions of the objects; and (4) Indexing data at all points of time – provide, usually trajectory-based, past, present and future objects positions.

The focus of our research is the online analysis of data that is generated by gathering the position of moving objects through time. This research will not address the problem of how to know, in real-time, the location of moving objects. Therefore, in the next sections, we restrict our study to historical movements of moving points; it will not include the approaches to address the modelling of future movements, as well as moving regions issues.

III. MOBILITY DATABASES AND DATA WAREHOUSES

Spatiotemporal databases support temporal evolution as well as spatial management of objects data and can deal with geometries changing over time. The Event-based Spatio Temporal Data Model (ESTDM) was proposed to assist the analysis of temporal changes by mean of the integration of a time dimension in GIS raster-based systems [19]. Kim et al. [20] designed and implemented a spatiotemporal query-processing prototype, based in a conventional database management system, which was able to answer to spatiotemporal queries. They suggested a logical spatiotemporal database model to represent spatial and historical information within databases, and proposed a spatiotemporal database query language, named STQL, as superset of the conventional SQL language, which can process spatial and temporal attributes. However, all code and data has to be loaded into memory, and no spatiotemporal join, indexing or aggregation issues were taken into consideration.

In the context of moving objects research, several other spatiotemporal database systems have been developed. Here, we highlight SECONDO and HERMES systems. Güting et al. [21] developed the SECONDO system for implementing the moving objects data model they proposed [13]. SECONDO is based in a extensible architecture, consisting of three major components: the kernel, the optimizer and the GUI. The kernel could be supported by different DBMS and is extensible by data models. The optimizer assumes an object relational model and supports an SQL-like language. SECONDO supports spatiotemporal indexing and was designed for support the development of spatial and spatiotemporal algorithms and applications.

In the context of LBS, Pelekis et al. [22] implemented the HERMES system for querying trajectory data. Instead of using the moving object database (MOD) for maintaining the moving objects current position, HERMES provides a trajectory database, which the authors argue is more appropriated for LBS. HERMES is developed as an extension to the Oracle DBMS and supports advanced querying on trajectories, including coordinated-based queries (e.g. range, nearest neighbour queries), trajectory-based queries (e.g. topological, navigational, similarity-based queries) or combination of both.

As we said before, although current DBMS are not appropriated to support the storage and query processing of movement data, top market DBMS already support spatial data types. Therefore current DBMS can be used to store the huge amounts of movement data and are suitable to support the implementation of mobility data warehouses. A spatial data warehouse integrates typically spatial data, and both dimensions attributes and fact measures can be associated to spatial data. According to Han *et al.* [23], a spatial data warehouse "*is a subject-oriented, integrated, time-variant, and non-volatile collection of both spatial and non-spatial data in support of management's decision-making process*". Thus, the spatial data warehouse is an appropriate source for on-line spatial data analysis and spatial data mining. In a spatial data cube, there are three types of dimensions [23,24]: 1) descriptive dimension without spatial attributes; 2) mixed spatial dimension, containing both kinds of attributes; and 3) geometric or spatial dimension containing only spatial attributes.

All the data warehouse systems proposed for support the online analysis of movement data that we analysed [6-8], transform the movement data into trajectories. Trajectory data warehouses aim to provide relevant information about moving objects trajectories, such as travelled distance, average speed, maximum acceleration and presence of distinct trajectories [7].

In spite of competence to handle spatiotemporal data, neither SECONDO nor HERMES can be used as a tool for online analysis of movement data. First, they do not provide an easy and efficient query system for the use of the analysts, such as available on OLAP systems; and second, they do not provide an appropriate interface for the processing of geospatial data, such as implemented by GIS tools. Thereby, the use of spatial data warehouses emerges as a viable alternative for the development of tools that enable analysis of data movements.

IV. ONLINE ANALYSIS OF MOVING OBJECTS

One of the biggest issues with spatial data warehouses is the execution of OLAP queries for analysing and exploring data that have spatial and temporal characteristics. SOLAP was first termed by Bédard, *apud* Rivest et al. [25], who defined it as "a visual platform built especially to support rapid and easy spatiotemporal analysis and exploration of data following a multidimensional approach comprised of aggregation levels available in cartographic displays as well as in tabular and diagram displays". OLAP operations with spatial measures raise challenging issues on the efficiency of the performed implementations. Furthermore, spatial OLAP requires the definition of new concepts, operations and similarity metrics to support the aggregation and summarizing of movement data.

A. Spatial OLAP

To enhance spatial queries performance, Han *et al.* [23] developed a method for selective materialization of a data cube by pre-computing selected spatial aggregations, balancing the cost of on-the-fly computation with the storage overhead of the pre-computed aggregations. The method facilitates both on-line spatial data analysis and spatial data mining, and includes two algorithms for selection of spatial objects able to be merged. In order to enhance the efficiency of spatial queries that require on-the-fly computation, Papadias et al. [26] developed a method that combines spatial indexing with the pre-aggregated results. They propose a data structure, named aR-tree, which combines a spatial index with the materialization technique. The aR-tree is a R-Tree that stores the value of the aggregation function for all objects enclosed in each minimum bounding rectangle (MBR). Therefore, an aggregation query is more efficient, since part of the answer is found in the intermediate nodes of the tree and the query does not need to access all the enclosed objects.

Papadias et al. [27] identified three basic barriers of traditional techniques when applied directly in spatiotemporal applications: 1) no support for ad-hoc hierarchies that are not known at the design time; 2) lack of spatiotemporal indexing methods; and 3) limited support for dimension versioning and volatile regions. Dimensioning versioning allows data cube analysis with dimensions that evolve over time. Volatile regions are those that change their extents over time. To overcome these obstacles, they proposed a solution to these three problems based in the creation of spatiotemporal structures that integrate indexing with the pre-aggregation technique, keeping summarized information inside the index to boost aggregation queries with arbitrary groupings.

Most of the research with Spatiotemporal OLAP focuses in the query efficiency, using computational pre aggregation, index mechanisms or both techniques. An excellent survey on spatiotemporal aggregate computation describes and formalises the different kinds of aggregations over moving objects (Lopez, Snodgrass, & Moon, 2005): aggregation on explicit attributes, temporal aggregation, spatial aggregation and spatiotemporal aggregation.

B. Spatial OLAP Systems

Many research publications describe the implementation of SOLAP systems. Using a SOLAP tool, a user has the ability to conduct the analysis without having to master a query language or to know and understand the underlying structure of the database, which may be very complex in the case of spatiotemporal databases. Based in an SOLAP system prototype, developed previously by the research group, Rivest et al. [25] described an application example to demonstrate the features of a new SOLAP technology, such as the visualization and manipulation of the geometric component of the spatial data, the database navigation operators, the synchronization of the displays and the graphical symbology, and the interactive legends.

The work developed by Bédard and his team on SOLAP concepts and systems is remarkable. They provided a truly easy and useful system for the online analysis of spatiotemporal data, even when in a context of evolving specifications [28]. Based in the same concepts, Bimonte *et al.* [29] went a bit further and presented a use case where spatial measures provide better decision support. They developed a spatial multidimensional data model and identified two requirements for dealing with complex spatial measures: (1) support *n* to *n* relationships between fact and dimensions; and (2) model measures as complex entities with support to inter-dependent attributes and aggregation functions.

The PIET system is another significant SOLAP system that resulted from a loosely coupled integration of GIS and OLAP. In the PIET system both kinds of data are maintained separately [30]. PIET data model provides a formal framework for integrating spatiotemporal data with OLAP and data warehousing. PIET makes use of a two-phase query processing technique: 1) a process called *subpolygonization* decomposes each thematic layer into open convex polygons; 2) the overlay of those layers is computed and stored in a database for later use by the query processor. PIET model and implementation supports standard GIS and OLAP queries, geometric aggregation queries (e.g., "total population in countries with more than three airports") and integrated GIS-OLAP queries (e.g., "total sales by product in cities crossed by a river").

However, in the spite of the extendible implementation of analytical features for spatiotemporal data, we did not found SOLAP concepts and implementations that cope with dynamic spatiotemporal data, such as moving objects data.

C. OLAP for Moving Objects

Several relevant contributions are helping to implement true online analysis of movement data. Damiani and Spaccapietra [31] proposed the Multigranular Spatial Data Warehouse Model (MuSD), which is a formal model based on the concept of spatial measures at multiple levels of geometric granularity. The MuSD model has the following distinctive characteristics: (1) a spatial measure represents the location of a fact at multiple levels of spatial granularity; (2) spatial dimension and spatial measures are represented in terms of OGC features; (3) spatial measures at different spatial granularity can be dynamically computed by applying a set of coarsening operators. A measure of this kind is, for example, the location of an car accident: depending on the application requirements, an accident may be represented by a point along a road, a road segment or the whole road, possibly at different cartographic scales. The MuSD model defined the algebra of SOLAP operators to enable user navigation and data analysis.

In order to facilitate trajectory data analysis in different application domains, Alvares et al. [32] advocate the enrichment of trajectories with semantic geographical information. They proposed a data pre-processing model that adds semantic information to trajectories to simplify queries, analysis, and mining of moving objects data. The complexity of most queries is reduced from a spatial query to a conjunctive query after the execution of an algorithm that extracts *stop* and *moves* from raw trajectories.

Baltzer *et al.* [10] developed an OLAP framework for trajectories analysis that answers aggregate queries with respect to the spatial movements of a set of objects represented in a relational table. A new operator GROUP TRAJECTORIES for group-by operations on trajectories was introduced. It includes three alternative implementations for computing groups of trajectories for group-by aggregation: group by overlap, group by intersection, and group by overlap and intersection. The algorithms assume the objects move on a 2D spatial grid and the results are dependent from several input parameters. No performance issues where taken into account.

Trajectory Data Warehouses (TWD) have been proposed by several authors. Orlando *et al.* [7] followed an approach based on classical data warehouse concepts and the use of a commercial efficient tool and system, the Oracle database management suite. The TDW was aimed to study the trajectory properties such as average speed, travel led distance, maximum acceleration, and presence of distinct trajectories. The granularity of the fact table is given by a regular three-dimensional grid on the spatial and temporal dimensions (x,y,t), where the facts are the set of trajectories which intersect each cell of the grid. The study focused in loading and computation in the ETL (Extract, Load and Transform) process of a complex aggregate measure, the *presence*, which can be defined as the number of distinct trajectories lying in a cell.

Marketos *et al.* [6] implemented a TWD system, based in the HERMES framework, and developed trajectory-oriented ETL processes for the creation of spatial measures. The trajectories are first constructed and stored in the HERMES moving objects database, and then loaded in the TDW. Like in the previous approach, only numeric measures are loaded into a fact table, and conform dimensions cells defined by a multilevel spatial dimension and a time dimension. A third dimension provides the profile of the moving objects. In the ETL phase, the following measures are computed: count trajectories, count users, average distance travelled, average speed, average travel duration, and average absolute acceleration. Like in the previous TDW, the distinct count problem was specifically addressed. The aggregate computation of the presence is not trivial because many indexing techniques suffer from the distinct count problem.

Based in the PIET framework, Gómez et al. [8] developed an extension to trajectory data by the definition of a moving object fact table (MOFT) that stores the id and the position scans for each object. In order to reduce the amount of data generated by periodic position observations, a small MOFT was created by the semantic extraction of *stop* and *moves*. The small MOFT stores all object stops: the object id, the geographic id, the initial *stop* time and the final *stop* time. Both tables are factless fact tables. A query language, based on regular expressions, called RE-SPaM, was developed with the objective to find out sequential patterns in trajectory databases. Aggregation is performed on top of this language, applying aggregate operators to the sequences that are in the query result. The support of rollup functions, it allows performing mining at different levels of aggregation and it is possible go back to the base data, in order to support any kind of queries. Association rule analysis can also be supported by this approach.

V. Generic Multi-layer Architecture for Online Analysis of Movement Data

As a result of the literature review presented in the previous section, we have conceived a generic multi-layer architecture that is organized into four layers (see Fig. 2). The architecture aims to integrate seamlessly GIS and OLAP concepts and encompass both MOD and TDW in order to be able to answer to a broad scope of queries. OLAP and GIS tools seek to improve the data access through easy visual interaction. GIS lacks analytical features and OLAP is unsuitable to analyze spatial data; the integration seeks to get the best of both worlds.

OLAP requires the use of different levels of granularity to allow the analysis of data at different levels of detail. The

OLAP *roll up* operation is based in the summarization and aggregation of the measures, what poses several issues in the case of movement data. Baltzer *et al.* [10] proposed new OLAP operators based in data mining techniques. But, data mining is also very important to provide adequate visual analysis of movement data [9,33]. Data mining aims to map low-level data, usually huge and not easily understandable, into other forms that might be more compact, more abstract or more useful. For that reasons is fundamental to integrate data mining techniques as a fundamental component of the architecture.

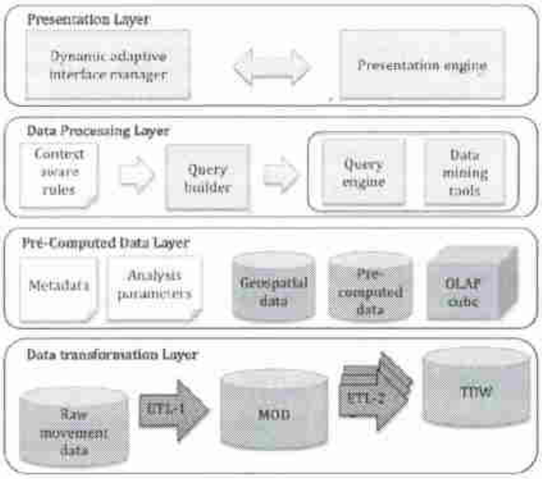

Figure 2. Generic multi-layer architecture

The generic multi-layer architecture encloses the main components that should be integrated in a software system for online analysis of movement data. These components are organized into four layers:

- **Data transformation layer** includes the data sources, a moving objects database (MOD), a TWD, and the ETL processes. ETL-1 represents the ETL process that cleans the raw movement data, converts it to adequate moving objects format and loads the data into the MOD. ETL-2 represents the ETL processes that build the trajectories from data extracted from the MOD. ETL-2 process can be repeated with different analysis parameters and can be used to the enrichment of data with semantics, such as proposed in [32] and according to the analysis parameters. According to Macedo *et al.* [34], the trajectory is defined as a core entity of our TDW data model, while the moving object stands as the core entity of the MOD.
- **Pre-computed data layer** is composed by the OLAP cube, the pre-computed data, the geospatial data repository, the analysis parameters, and the metadata definitions. The analysis parameters will save configurable definitions that could be adjusted by the analyst accordingly with the application context. Configurable parameters can be used to tune the ETL process, as an input to the query builder or even as a context definition in the presentation layer. Pre-computed data, which can be obtained from the OLAP cube, the geospatial data repository, the MOD or the TDW, will be stored, whenever it is opportune, to enhance the queries performance.
- **Data processing layer** has four main components, the query builder, the query engine, the data-mining module, and the context aware rules module. The query builder can submit queries to the distinct databases and call data mining routines. The context aware rules module will bring some intelligence to the system behavior, providing an input to the query builder and the dynamic adaptive interface manager, so the system can automatically choose the more adequate query visualization format.
- **Presentation layer** comprises two main components and is crucial for the successfully implementation of online analysis tools. The dynamic adaptive interface manager will help to configure the interface according to the query results. The presentation engine is the component that will generate the data output.

Many issues arise to fully implement a software solution according to the described architecture. We can find easily numerous challenges, concerning all the four layers, which can be used for conducting scientific research.

VI. CONCLUSION

The potential for the use of online analysis is increasing every day, as a consequence of the augment of the collection of movement data and the emergence of new applications for movement data. So, there is a vital need to develop online analysis tools for movement data, even if those tools are not the more complete and fully suitable. In the literature research, we found several interesting but incomplete analysis tool proposals, which are far from fulfil the complete list components described in the previous section.

All the TDW and (spatial) OLAP systems described previously implement space as a data warehouse dimension, such as time is usually modelled in data warehouses. So, all proposals are constrained to a 2D space grid or hierarchical multilevel space domain. The moving objects data warehouses we found are TDW, because it should be more advantageous as argued Pelekis et al. [22]. In the TDW presented in [6-8], moving object is a dimension entity, space and time are converted in dimensions, the central fact is the position of the moving object, and several nonspatial measures are added, such as distance, speed, bearing or acceleration.

The design of the generic multi-layer architecture, described in previous section, was based in, but not limited to, the presented literature review. Several other research papers have inspired us, but could not be included in this paper. The proposed architecture will be now used as a reference for the development of an online analysis tool.

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