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Review article

A systematic review on moving objects' trajectory data and trajectory data warehouse modeling

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ABSTRACT

The development of mobile technologies has paved the way for new and various applications taking advantage of trajectory data resulting from moving objects activities in their associated ecosystems. Such data can be mainly handled either by real time applications or by oriented decision-making tools going from trajectory data warehouse technology to data mining classical advanced instruments. Indeed, applications dealing with moving objects encompass hidden significant knowledge that can be made visible through analytical and mining tools. This precious knowledge could not come properly in hands only if, the trajectory data problem modeling is global, precise, and concise. The aim of this paper is to investigate the appropriate literature on moving objects, trajectory data, and trajectory data warehouse modeling going from classical to ontological existing patterns. A comparison will be made between them, through which strong and limited contributions will be shown. This work aims to be valuable for researchers aiming to select and use modeling approaches in mobile objects ecosystems.

Contents

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1. Introduction

The increasing development of positioning technologies and remote sensors is leading to huge amounts of mobility data generated from moving object called trajectory data [1]. Those latter must be retrieved, represented and interpreted in order to extract knowledge from them. In fact, moving objects and their trajectories play an important role in applications dealing with tracking animals, traffic control, tracking environmental phenomena, forecasting based on vehicle paths and so on. Modeling the trajectory data warehouse of moving objects is the key to perform analysis and mining processes e.g. location prediction, moving object behavior analysis, path discovery and so on. The modeling phase plays an important role since it proposes a high grade of abstraction while designing the trajectory data warehousing project. In fact, it rests functional in case of technological evolution. Furthermore, it allows determining analysis possibilities and completing mining and prediction processes.

Four steps are to be followed by the designer to model a trajectory data warehouse. In fact, the first step is the modeling of the moving object properties. The second step is the modeling of the moving object trajectory. The third step is the modeling the moving object semantic trajectory data. The fourth and the last step is the deriving of the moving object trajectory data warehouse from the semantic trajectory data model. The principle is the following: each step has as result a model which is considered as output of this step or activity. This output will constitute the input for the next step and will in turn have an output. This process is repeated until the last model is obtained, which is the moving object trajectory data warehouse. Modeling the moving object means that we have to identify the properties of the moving object. Modeling the moving object trajectory refers to identify the components of its trajectories (begin, stop, move, end) and to determine the different relationships between them. Thus we obtain the geometric facet of the moving object trajectory. The moving object trajectory model is generic. That means that it is independent of the application domain's components. It can be exploited by different applications that are concerned with the modeling of moving objects' trajectories by attaching it to other elements of any field of interest. Once we have the moving object trajectory model, we can model the moving object semantic trajectory data model by adding the semantic facet to the geometric facet (moving object trajectory model). The purpose of this step is to link the geometric facet or the generic facet to the semantic facet that is composed of application domain components in order to have a specific and personalized i.e application dependent moving object trajectory data model. The semantic facet contains semantic annotations and moving object application domain thematic information. The trajectory data warehouse model can be easily derived from the trajectory data model. Actually, the class trajectory of the trajectory data model will be the trajectory fact table of the trajectory data warehouse model, the components of the trajectory and the thematic information classes will be transformed into dimensions that are attached to the trajectory fact table. The following Fig. 1 illustrates the process to follow to obtain the trajectory data warehouse model.

Modeling trajectory data and trajectory data warehouse either based on classical conceptual modeling or based on ontological modeling is still challenging due to the complexity nature of moving objects trajectory data and the intricate factors involved in the business choices about a domain's consensual knowledge.

In this paper, we conduct a systematic survey on the major research into moving object trajectory data and moving object trajectory data warehouse modeling to serve as background for the designers and the research community that are interested in the field of modeling trajectory data and trajectory data warehouses. To do this, we have as a first step to define some concepts related to moving objects such as moving object trajectories and moving objects movements types. It is important to know that to model a trajectory data warehouse, we must identify the moving object properties and specificities, then to model moving object trajectory data model. The Fig. 1 illustrates the process to follow to obtain the trajectory data warehouse model.

The methodology used to collect and select articles is the following. We used various published sources publications to analyze different research works for moving object trajectory data and trajectory data warehouse modeling. The selection of research papers was based on some criteria that are the citation of the paper, the date of publication, the name of the known authors in the field of moving objects trajectory modeling and the publisher. In fact, we looked for relevant research papers using for that a set of publication databases like Elsevier, ACM, IEEE, Springer. To refine our selection, we used some key words in the google scholar academic platform such as moving object, trajectory data, conceptual modeling, ontological modeling, trajectory data warehouse, network constrained movement, unconstrained.

The rest of this paper is organized as follows: in Section 2, we define the different types of moving objects trajectories (moving point, moving region), then we enumerate the moving object movements' types, after that we describe the evolution of trajectory data from raw data to semantic data. In Section 3, we present different research works on trajectory data modeling from conceptual modeling to ontological modeling. A comparative study between presented researches is conducted and discussed. In Section 4, we discuss trajectory data warehouse modeling researches and compare them according to some criteria. In Section 5, we conclude the survey and investigate some future works.

2. Toward moving object trajectories semantic modeling

Thanks to device networks, GPS-enabled devices, and specially mobile sensors and satellite, data about moving objects is being collected in various application domains. Moving objects [2] are entities that change position in space and in time. These objects can be considered as moving points such as vehicles, persons, animals or moving regions such as natural phenomena (Hurricanes, forest fires, floods, tsunami, air pollution...) and diseases (cancer, Alzheimer). Each moving object either point or region has a sequence of positions between two or more time-varying stops ordered temporally, characterized by a starting position and an arrival position. We call this sequence of position a trajectory. In fact, a trajectory consists on the description of the evolution of the position of moving objects at a given time interval [3]. It is a spatio-temporal path of the ongoing moving object. Consequently a trajectory is a series of points that trace the moving object's path. Each point has a position in the spatial dimension (X, Y) and a time interval in the temporal dimension (T). The point is considered as a stop and the changing position between two successive points is considered as a move. As illustrated in Fig. 2, the trajectory of a moving object has a begin, a set of stops, a set of moves and an end.

Each moving object has a trajectory. Exploiting moving objects trajectories is the key to discover knowledge about moving

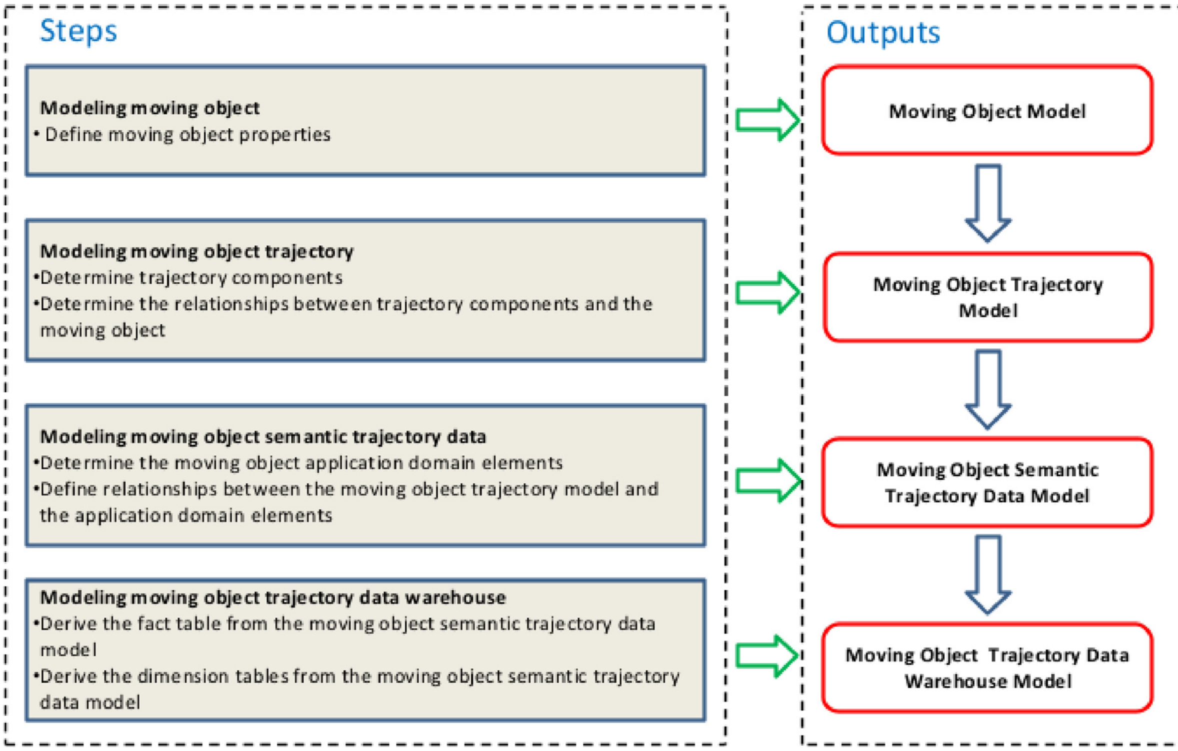

Fig. 1. From moving object model to trajectory data warehouse model.

objects behaviors that help in the decision making process. To exploit moving object trajectories, it is necessary to determine the moving object properties. To do so, we have to distinguish between moving objects types. In fact, each type has its specificities. There are two types of moving object: moving point and moving region. The major difference between them is the change of the shape and the behavior. In fact the moving point do not change the shape while moving but the moving region can change its shape while moving and then change the behavior too. This difference must be taken into account in the modeling phase because it allows to add some specificities that can enrich the trajectory data and the trajectory data warehouse model and strengthen the querying process later. For this reason, we tend to introduce in the next subsections some trajectory basic definitions, then the applications of moving objects that are either moving point or moving region. We describe different types of moving objects movement related to some case studies. Then we present the evolution of trajectory data types from raw trajectory data, over structured trajectory data to semantic trajectory data.

2.1. Trajectory basic definitions

At the best of our knowledge, the first work that was interested in trajectory modeling is presented in [5]. Authors gave the following definition of a trajectory:

•**Definition 1 A trajectory:** is the user defined record of the evolution of the position (perceived as a point) of an object that is moving in space during a given time interval in order to achieve a given goal.

According to this definition, authors of [5] presented three kinds of trajectories that are metaphorical, naive geographical and spatio-temporal:

•**Definition 2 The metaphorical trajectories:** The concept trajectory is occasionally adopted in a metaphorical sense to represent an evolution of non physical movement. In this kind of trajectory, the object is moving in an abstract space (example: I went from a poor life to a wealthy one then back to poor life). Trajectories can be described by defining a time-varying attribute (e.g. life-level) for the traveling object (person).

•**Definition 3 The Naïve geographical trajectories:** this kind of trajectories is a special case of the first one. In fact, geographical trajectories can be described using a time-varying attribute. In this kind of trajectory, stops have a strong geographical connotation (e.g. I went to Sfax then to Sousse then to Tunis). Similarly, moves can be defined in terms of means of transport names.

•**Definition 4 The Spatio-temporal trajectories:** In this kind of trajectory, spatial coordinates are used to show the position of the traveling object that is geometrically represented as a point. In the spatio-temporal trajectories, a trajectory has two facets: a geometric facet and a semantic facet. The geometric facet is represented as a continuous function from a given time interval ([Tbegin, Tend]) into a geographical space. The semantic facet includes two types of semantic characteristics of trajectories. The first type is specific to the requirements of the application and the second one includes the semantics whose are standard and used to give a meaning to trajectory components such as: stops, moves, begin and end of the trajectory.

Authors of [6] defined a trajectory and its components (trajectory section, stop, move) as follows:

•**Definition 5 The trajectory:** is considered as a travel of a moving object in the space and the time. It is composed of a set of trajectory sections. It is characterized by an identifier and a set of attributes. Trajectory = id-traj, t-begin-traj, t-end-traj, duration-traj.

•**Definition 6 The trajectory section:** is a component of the whole trajectory. Each trajectory section is composed of two

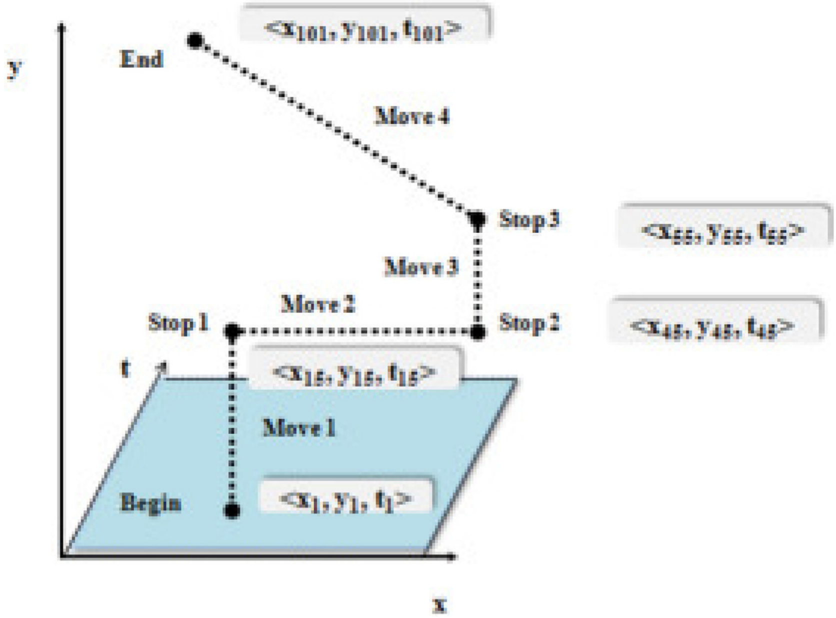

Fig. 2. A moving object trajectory [4].

successive stops and one move. It is characterized by an identifier and a set of attributes.

Traj-section = id-traj-section, t-begin-traj-section, t-end-traj-section, duration-traj-section.

•**Definition 7 The stop:** is a component of a trajectory section and the whole trajectory. It is characterized by an identifier and a set of attributes. Stop = id-stop, tbs, tes, duration stop.

•**Definition 8 The Move:** is a component of a trajectory section and the whole trajectory. A move is delimited by two successive stops. It is characterized by an identifier and a set of attributes. Move = id-move, t-begin-move, t-end-move, duration-move.

2.2. Moving point trajectories

There is a large amount of work of researchers dealing with moving point trajectories. The work of [7] described trajectories as new data source that are massively available and delineate movement paths and behavior in high detail. They concentrated on interpretation in order to extract relevant, implicit information. Revealing implicit information requires sophisticated analysis procedures that take the characteristics of the data into account. The paper presented three types of applications which are extraction of road structure and road regulations, extraction of anomalous behavior, and detection of group patterns in SOCCER where each application needs different treatments. Those applied examples showed that GPS trajectories produced by cars have the potential to delineate not only the road geometry, but also reveal behavioral patterns, that can be used to infer traffic regulations or behavior indicating when a driver needs assistance or help. The last example showed that not only individual behavior is of interest, but also group patterns can be extracted from trajectories. They can be beneficially exploited in the sports context, but also in other applications such as animal ecology. In [8,9] the authors handle trajectory data generated by an important moving object, perceived as a moving point. It is an ambulance. In [8] authors extended UML class diagram with stereotypes and expressive icons in order to explicitly represent the semantic of trajectory concepts and the constructors of multidimensional paradigm at the conceptual level. To validate the proposed conceptual model, authors implemented an ambulance trajectory data warehouse and maintained some OLAP operations on the stored data using SQL. This allows to discover possible hidden relationships between space, time and some issues in emergency medical services, in order to help managers in the strategic decisions making in the medical field. The proposed algorithms facilitate and accelerate complex OLAP analysis on trajectory data in order to extract useful knowledge helping managers to make competitive decisions to ameliorate emergency medical services in general and ambulance services in particular. The case study of [10] is a mobile hospitals which allow to decision makers such as physicians to make scientific discoveries like the detection of the breast cancer disease at an early stage by analyzing trajectory data. Authors in [11] have proposed a partition-and-summarizing framework using semantic locations terms such as landmark that represents a geographical point in the space, which is stable and independent of trajectories. They conducted extensive experiments on a real-life trajectory car data set.

2.3. Moving region trajectories

A moving region is an object that change the position and/or the shape in a continuous manner. Many applications deal with the study of moving regions trajectories. They have always been a challenge due to their unstable shape and movement. Their movements could be summarized in five actions that describe their behavior as follows:

•Expanding: A region can expand from one time partition to another. The expansion means that the density has increased. The density is measured by a density factor which is assigned to each region at each time partition.

•Shrinking: A region can shrink from one time partition to another. The shrinking means that the density has decreased. Contrary to the expansion, if the density factor decreases, it means that the region has shrunk.

•Merging: Two regions can merge if their core points merge, i.e. unified. Two regions region 1 and region 2 that merge become one single region.

•Splitting: A region can split into two or more regions. The split means that the regions is broken up into smaller regions.

•Overlapping: Two or more regions are overlapping if their core points are separated and their border points are united. Region 1 and region 2 overlapped by intersecting only their border points at one side.

We present in this section some studies about moving region trajectories and their representation. In [12], the authors explicitly address concepts and methods for moving regions representations as snapshots series. They developed algorithms to interpolate between two snapshots, going from simple convex polygons to arbitrary polygons to model every object moving both discretely and continuously. Based on those concepts, authors [13] presented a new approach to model and to predicate the development of moving regions based on recorded regions trajectories. They proposed a model for moving heterogeneous regions using enclosing boxes. This modal allows predicting the development of moving regions. One of the most important moving region phenomena studied during the past years is the forest fires. In [14] the authors presented a spatio-temporal data model that supports finding paths among moving obstacles for the management of both static and dynamic disaster-related information. They focused on the case of forest fires. They used a fire simulation model to calculate the fire evolution. In [15], authors developed a mechanism to support the implementation of the set operations of intersection, union and difference between pairs of moving regions using a mathematical model called Component Moving Region CMR. In [16], the authors presented an overview on moving regions surveyed the issue of modeling moving regions especially in the medical field. The case study of [16] illustrated the aspect of the movement of the colorectal cancer. The proposed model described the movement aspects of moving cancer cells related to the colorectal cancer.

2.4. Types of moving objects' movements

According to the literature review, we may distinguish too types of moving object movement scenarios: Network constrained and Network unconstrained movement. Constraints can be integrated in the model as properties, or attributes, as classes or concepts and as constraints relationships between classes and concepts of the model.

This differentiation between the moving objects movements types can be of great help in the trajectory clustering process [17]. In fact, the input parameters of the clustering algorithm will depend on the movement type. The clustering algorithms of network constrained movement take into account the network parameters like the density of the network. Whereas the clustering algorithms of network unconstrained movement do not care about the road network parameters. It care about other criteria such as the shape of the moving object, the direction and so on. According to [17], we have to distinguish some criteria for clustering the trajectory of moving object such as network constrained or unconstrained movement. In fact, there are clustering algorithms that are applied specially to network constrained trajectories [17] such as NETSCAN that is inspired from the density based algorithm (DBSCAN). In fact, NESTSCAN considers the network constraint to estimate the network density. This approach consists on knowing the traffic density on the network to guide the trajectories' clustering. The step of clustering consists on finding the most dense road sections and merge them to find the dense paths. Then, classifying the trajectories according to the founded dense paths. For the network unconstrained movement such as hurricanes and birds migration, the similarities between trajectories can be measured according to other criteria such as the shape of the moving object during the trajectory [18], the speed, the behavior and so on.

Network-constrained movement: the moving object's movement is constrained by a specific constraint which is the network [17]. Typical example of moving object with network constrained movement are means of transport Such as planes, trains and automobiles. We found in the literature the first model proposed by [19] for the moving object network constrained movement. Authors in [20] modeled explicitly the network embedded in the space and provided data types for static and moving network positions. The Fig. 3 describes the network constrained movement by [20]. Here the moving object is constrained by the direction and the type of the road (simple or dual).

Authors in [21] proposed a model called MODTN to manage moving objects that are constrained by a dynamic transportation network. The moving object is modeled a moving graph point on a predefined network graph. In fact, the transport network is modeled by a dynamic graph. This latter takes into account the traffic jam, construction projects as, the transport network has a changed state (traffic jam, breakdown) and topology (construction project, insertion or delete of junction). Authors presented a discrete presentation of the moving object or the moving graph point (dmgp). This latter is modeled as a sequence: dmgp = ((ti, (gidi, ridi, posi), vmi)) where ti is a time instant, (gidi, ridi, posi) = gpi. This latter is a graph point describing the location of the moving object at time ti, and vmi is the speed measure of the moving object at time ti. Moving object and transport network are both dynamic. To model the dynamic graph, researchers propose to associate a temporal attribute for each road or junction in order to detect and store their state for each moment. Roads are represented by polylines with arbitrary geometric shape. Fig. 4 describes the MODTN architecture.

Network-Unconstrained Movement: the moving object moves without any network constraints [18]. Example of network-unconstrained movement are animal migration such as birds and seals, natural disaster such as hurricanes, floods, forest fire and natural phenomena such as air pollution, clouds and so on. This type of movement is constrained by factors other than the network. Examples of network-unconstrained movements are birds migration [5] and seals migration [22]. In fact, the movement of the birds (white stork) while migrating is constrained by three constraints. The first one is the environmental conditions such as Weather conditions like the wind direction and strengthens, temperature degree, pressure, sky condition (sun, rain, clouds). The second constraint is the natural hazards such as mountains, water extents, deserts that may be obstacles for the birds migration and can influence their flight behavior particularly their direction. The third constraint is the artificial hazards such as electric lines and antenna. The Fig. 5 shows that the movement constraints of white stork that were mentioned above are modeled as attributes and as classes in the entity relationship diagram. In fact, the constraints weather, wind, pressure, temperature and sky were modeled as attributes in the class trajectory. Whereas the natural and artificial hazards were modeled as classes with a specialization relationship with other sub classes.

2.5. From moving object's raw trajectory data to semantic trajectory data

The trajectory of a moving object has several definitions that have the same meaning. As indicated in [5], a trajectory is defined as the evolution of the position of a moving object that changes its location in space through a given time interval in order to attain an objective. Trajectory data have been used in several fields. Authors in [14] provided a comprehensive demonstration of the use of trajectory data to discover human behavior (Human mobility pattern, anomalous event detection..) travel pattern (Destination Prediction, Route Discovery..) and urban planning. A trajectory is considered as a series of points that describe a moving object's path, i.e evolving position through time. These points can be

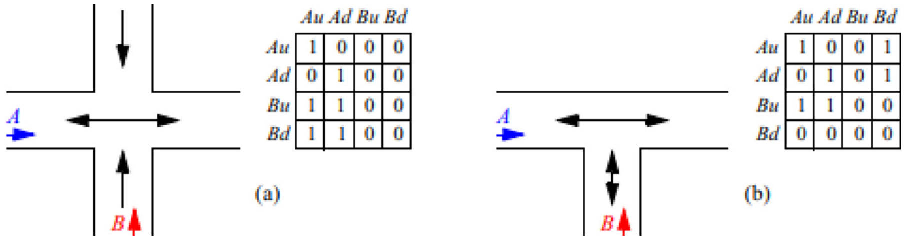

Fig. 3. Network-constrained movement modeling [20].

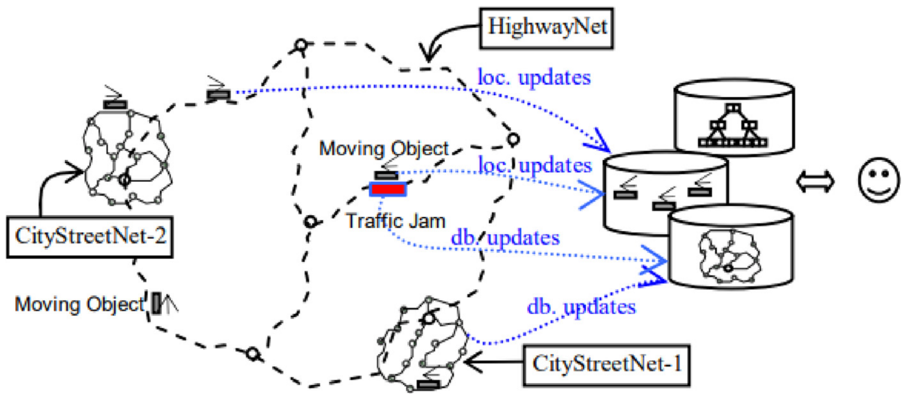

Fig. 4. Network-constrained movement: MODTN architecture [21].

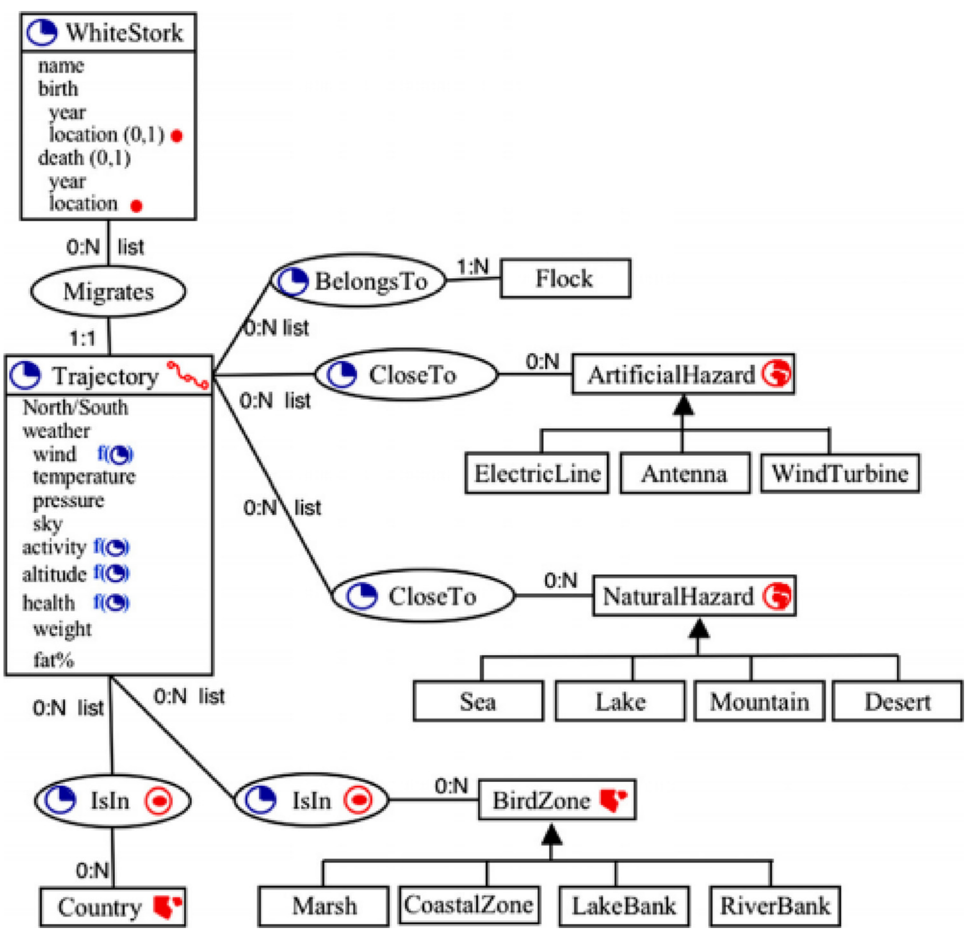

Fig. 5. Network unconstrained movement of birds migration model [5].

acquired from tracking devices such as GPS beacons. The concept of trajectory has evolved. In fact, it started by raw trajectory data then structured trajectory data, pursued by semantic trajectory data. Those latter encompassing useful information in their description.

Raw trajectory: they are an ordered sequences of spatio-temporal positions occupied by a moving object over time. They are directly generated by sensors that capture the position of moving object in time. A lot of studies have been done to turn raw trajectory data into a trajectory data set that is correct and manageable using for that reconstruction methods, techniques and algorithms such as filtering, smoothing, outline removal, missing point interpolation, map-matching, data compression and so on. The authors in [23] defined raw trajectory as a cleaned sub-sequence of raw movement data for a specific moving object in a specific time interval. The work of [11] aims at facilitating human's understanding of a raw trajectory by automatically generating a short text for individual trajectory. Therefore a partition and summarizing frameworks were implemented in a prototype system called STMaker. This latter splits a trajectory into several partitions with similar travel behavior and generates summarizing to describe the most significant features for each partition. The authors proposed to pre-process the raw trajectories using for that semantic locations terms such as landmark to describe a geographical point in the space, that is stable and independent of raw trajectories. Firstly, they defined a set of features for each trajectory segment, then they derived an optimal partition with the aim to make the segments within each partition as homogeneous as possible in terms of their features. Thereafter, in the summarizing phase, they select for each partition the most interesting features by comparing them against the common behaviors of historical trajectories on the same route and generate short text description for these features. This work conducted extensive experiments on a real-life trajectory dataset generated by 33,000 taxis as moving object in Beijing over three months.

According to [24], raw trajectory is a set of points that describe the movement of an object in a spatio-temporal dimensions. It is considered as the basic level of every trajectory since its raw data are directly generated from the sensors capturing the position and the time stamp of the moving object. Points have three coordinates and are represented as xi, yi, ti where xi and yi are the coordinates of the point in the 2D plane while ti represents the time. This type of trajectories lacks semantics and needs more structure and signification.

Structured trajectory: they are considered as a transition from raw to semantic trajectories, since they clarify and structure raw trajectories. Actually, they are considered as the partitioning of raw data into episodes or segments (Methods: various segmentation algorithms, based on spatial gaps, temporal gaps, time intervals, time series, etc.) starting by begin and ending with end with some stops and moves in-between (various stop identification algorithms, based on velocity, density, etc.). Authors of [23] defined a structured trajectory as a trajectory whose list of triples is partitioned into four kind of components: a Begin B, End E, and a sequence of consecutive and alternate moves M and stops S (see Table 0).

Many structured trajectory models have been proposed in recent years, offering different solutions to enrich space–time trajectories. Most of these structured trajectory models are based on different kinds of segmentation proposed for spatio-temporal trajectories. In fact, authors in [25] developed a structured trajectories learning method to extract coherent motion features that effectively captures compact and discrimination motion patterns. The authors applied this method on a novel crowd representations called CROWD MOOD. This latter is established based on the idea that the social emotional hypothesis of crowd behaviors can be revealed by investigating spacing interactions and the structural levels of motion in crowds too. Authors in [26] have proposed a method for human action recognition using discriminate structured trajectory groups. They represented a video as a set of trajectories' groups described by their flow and motion features. They considered the spatio-temporal relationship between each trajectory group.

Semantic trajectory: despite the improvement from raw to structured trajectories, there is still a lack in the semantic aspect. The analysis of both raw and structured trajectories do not lead to sufficient and significant information. For instance, the observation of the trajectory of a tourist recorded using a tracking device without any tags is meaningless. It does not give information about his destination, the places he visited, the means of transport he used, etc. So, it is some how useless. However, when adding geographic annotations and sense to the trajectory, several observations and conclusions can be made. For the same tourism example, semantic trajectory provides meaningful information such as the most visited museums, the most used means of transport. Such information can help in improving the tourism sector. Here came the need for semantic trajectories. In fact, they are the evolution of structured trajectories by semantically enriching the trajectory components (begin, stop, move, end) with annotations and by establishing relationships with application-dependent entities [27]

In [23] authors defined a semantic trajectory as a structured trajectory with added semantic information and annotations: stops, moves as well as Begin and End are linked to objects of Geographic Data and Application Domain dependent Data.

Authors in [28], define a semantic trajectory as trajectory with annotations. In fact, semantic information refers to annotate the trajectory components of the structured trajectory. The authors defined three types of annotations. The first type is annotating trajectories components(begin, stop, move, stop) with points of interest such as office, hospital, home, restaurant. The second type is annotating trajectory components with activities such as working, eating, walking, shopping. The third type is annotating the trajectory components with behavior of the moving object such as the shape, the speed, the direction.

Many semantic trajectory models have been proposed in recent years. Most of them are based on different kinds of segmentation proposed for spatio-temporal trajectories. To make this concept more understandable, authors in [5] have defined a conceptual view on trajectories and proposed two modeling approaches for semantic trajectories that are the design pattern and the data types. They introduced the concept of trajectory as a sequence of moves going from one stop to the next one. This stop–move model has been applied in the work of [23] to transform the initial low-level real world GPS tracking data i.e. raw trajectory data to high-level semantic trajectories by proposing a trajectory computing framework containing three major components that are: trajectory modeling, trajectory computing and trajectory pattern discovery with detailed algorithms. Authors in [29] have proposed a new model for semantic trajectories integrating multiple points of view and explanatory factors in order to enrich the representation of life trajectories by modeling the expectations of an individual.

Fig. 6 illustrates the evolution of trajectory from raw to structured then to semantic one.

The figure begins by the raw trajectory which is represented by a series of GPS points. The next layer is the structured trajectory. It is expressed as a sequence of moves and stops extracted from the GPS points. The third layer is the semantic trajectory describing the journey of a worker. The worker leaves home and goes to his office by can. He then go to the restaurant on walk. Finally he goes back home by car. We can summarize

Table 0
Structured trajectory components.

Begin (B)	A spatio-temporal position where the trajectory starts. It is defined as a tuple h point, instant i, where instant = t begin;
End (E)	Another spatio-temporal position where trajectory ends, with similar definition h point, instant i, where instant = t end;
Move (M)	Defined by a time interval [t beginMove, t endMove] during which the object is moving. A move is defined by a time varying point ;
Stop (S)	Defined by a time interval [t beginStop, t endStop] during which the object is not moving or almost not moving (meaning that the physical movement is irrelevant).

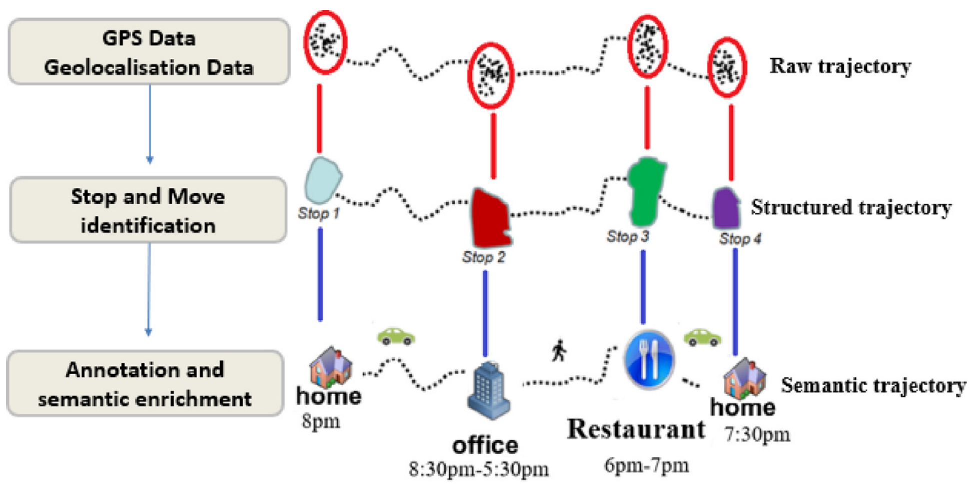

Fig. 6. From raw, through structured to semantic trajectory.

the description of the semantic trajectory as follows: (Begin, home, 8am) → (move, car, 8am–8:30am) → (stop, office, 8:30am 5:30pm) → (move, walk, 5:30pm–6:00pm) → (stop, restaurant, 6:00pm–7:00pm) → (move, car, 7:00pm–7:30pm) → (stop, home, 7:30pm).

3. Trajectory data modeling

The increasing development of position sensors such as GPS and AIS provides a lot of information about the movement of a moving object. This latter is by nature spatio-temporal and requires specific storage and exploitation. This fact, has led to the definition of specific types and functions to model and manipulate the trajectory concept. Modeling the trajectory of mobile objects, is the key to perform behavioral analyzes. Nevertheless, the simple position of a moving object is not sufficient. It is necessary for this to have additional information that will enrich the initial trajectory. In the literature, several models were proposed. In this section, we divide the trajectory data modeling into two categories: trajectory data conceptual modeling and trajectory data ontological modeling.

3.1. Trajectory data conceptual modeling

Several works were interested in the conceptual modeling of trajectory data. Some of them have extended spatio-temporal data models and moving object data models. This section focuses on the trajectory data modeling. In particular, a conceptual modeling approach research approach will be presented. The work of [5] were concerned in the conceptual modeling of trajectory data with the Entity Relationship (ER) diagram. According to authors [5], a trajectory has two facets: a geometric facet and a semantic facet. The geometric facet is represented as a continuous function from a given time interval ([Tbegin, Tend]) into a geographical space. The semantic facet includes two types of semantic characteristics of trajectories. The first type is specific to the requirements of the application and the second one includes the semantics whose are standard and used to give a meaning to trajectory components such as: stops, moves, begin and end of the trajectory. After defining the different types of trajectories, the requirements for the trajectory modeling are to take into account the characterization of trajectories, their components and the different types of constraints (semantic, topologic, ...) in order to fix a conceptual view of the concept of trajectory. The conceptual model is seen as a direct support and an explicit representation of trajectories' components (stops, moves, begin, end). Two solutions were proposed in [5]. The first solution was the Trajectory Design Pattern, and the second one was the Trajectory Data Types. Both proposed solution have used the icons defined in MADS [30] to represent the geometry and the relationship between entities at the conceptual modeling level. In fact, MADS supports both spatial and temporal objects and their relationships. It supports objects and relationships that have a geometry attribute describing their spatial extent and have a life cycle attribute describing their temporal extent (the lifespan) and their activity status like active, suspended, disabled. MADS represents spatial attributes (whose value domain is a spatial data type), time-varying attributes to record their values over time, topological and synchronization relationships by using spatial and temporal constraining the linked objects, derived attributes, and allows multi-representation at the schema level as well as at the instance level.

The trajectory design pattern and trajectory data type approaches [5], were driven by different modeling goals and can be combined if needed. For the first approach, the design pattern is a predefined generic schema that can be connected to any other database schema by the designer and can be modifiable. In fact the designer can modify the design pattern by adding new

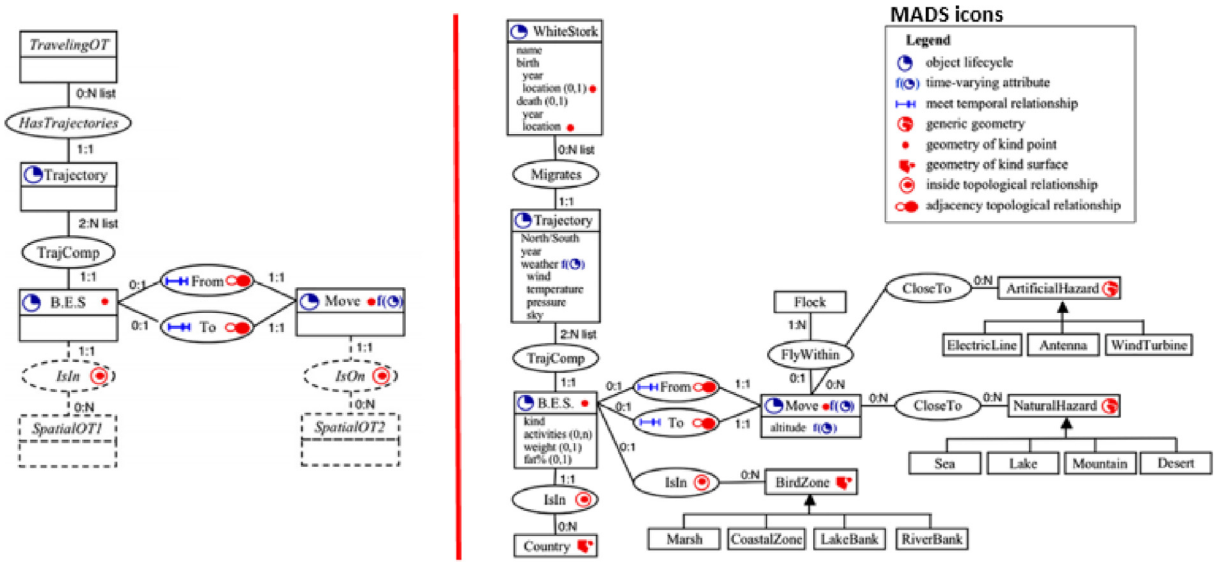

Fig. 7. A trajectory data personalized conceptual model derived from the generic design pattern.

elements or semantic attributes, deleting other ones to adapt it to the requirements of the new application. The predefined generic schema is composed of a moving or traveling object, its trajectory and its trajectory components such as Begin, End Stops (BES) and Moves. It can be adapted to model any moving object trajectory data.

To demonstrate the reuse of the trajectory design pattern, authors have personalized it to a bird migration (white stork) case study. They modified the generic design pattern by adding and deleting new elements and semantic elements respectively to the requirements of the application of birds' migration. The Fig. 7 illustrates the passage from a generic design pattern to a personalized one for white stork trajectory data [5].

For the second approach that is the Data Type approach, authors hold the idea that much semantic information are specific to application and cannot be collected into a data type, but has to be defined by the database designer. On the other hand, the authors proposed to define a generic data types to hold the trajectories' components such as the beginning, the end, stops and moves…and to define the functions of interpolation. Among the data types defined in [31], we cite:

•Data type TrajectoryType: each element of TrajectoryType describes a single trajectory and it is composed of a time varying point to represent the spatio-temporal trajectory, a set of sample points, a list of stops, a list of moves.

•Data type TrajectoryListType: each element of TrajectoryListType describes a list of trajectories which is composed of a list of element of type TrajectoryType. Authors [5] deleted the two entities B.E.S and Moves which represents the components of a trajectory and combined their attributes with those of the Trajectory entity. In fact, the definition of the data type TrajectoryType holds the two notions stops and moves. Each Data Type supports a set of methods. In fact, for the TrajectoryType we found several methods like begin (), end (), SamplePointsVarying (), StopAt (t Instant), AverageSpeed (), NumberOfStops (), Orientation (n Integer)…and for the TrajectoryListType we found two methods which are TrajectoryAtInstant (t Instant) and DurationBetween (n Integer). Furthermore other works were interested in the conceptual modeling of trajectory data. The STER Model (Spatio-Temporal ER) [32] is an extension of the Entity-Relationship model for modeling spatio-temporal trajectories. Authors have defined a small set of spatiotemporal conceptual modeling constructs. They employed the ER model as the concrete context for presenting the new constructs. The resulting Spatio-Temporal Entity-Relationship STER model captures more conveniently spatiotemporal aspects of moving object.

STUML model [32] is an extension of UML in order to satisfy spatiotemporal requirements by using a clear, simple and consistent notation to capture alternative semantics for time, space and change processes from discrete to continuous. The aim is to provide support for different categories of spatio-temporal data. These include temporal changes in spatial extents, changes in the value of thematic (i.e., alphanumeric) data across time or space, and composite data whose components vary depending on time or location dimensions. PERCEPTORY model [33] is a CASE tool that comprises UML based conceptual schema to build a geo-spatial conceptual models and an object dictionary database. It aims at capturing and managing the representation of user's perceptions in the most natural way of thinking and to facilitate the development of the database supporting these perceptions. Perceptory uses the stereotypes of meta-model UML. These stereotypes enrich UML for particular areas by creating new modeling elements, and possibly the definition of a particular graphic representation. Therefore, authors in [33] have developed their own stereotypes through two separate Plug-in for Visual Language (PVLs):

- The spatial PVL: To represent purely spatial data. It contains three basic symbols representing respectively, the spatial element as point, line or surface. Their graphical combination allows designers to express the spatial types.
- The spatio-temporal PVL: to represent spatial and/or temporal data. It provides the basic types of time Instant and Period that are spatial and spatio-temporal. This allows to represent alternative temporalities or multiple temporalities.

These PVLs are pictograms that are added to the UML models. In Table 1, we present the initial version of the visual language Perceptory, which used pictograms based on the letters of the Greek alphabet to model the spatial and temporal dimensions

Authors in [34] have extended the model based on stops and moves concepts of Spaccapietra in order to propose a new conceptual framework for modeling and mining trajectory data. In fact, the proposed framework facilitates the data mining process since it focuses on frequent trajectory patterns, sequential trajectory patterns and association rules. CONSTAnT model by [35],

Table 1
Spatial and temporal pictograms in Perceptory.

Pictogram	Description
β	Object represented by a point.
ω	Object represented by a line.
ε	Object represented by a surface.
γ	Object represented by any geometry.
τ	Object represented by a complex geometry.
ψ	Object represented by an unknown geometry.
ζ	Object whose existence is represented by a moment.
χ	Object whose existence is represented by an interval.
α	Object whose existence is of any temporal type.
δ	Object whose existence is represented by a complex temporal type.
ι	Object whose existence is unknown.

the model includes the concepts of semantic sub-trajectory, semantic points, geographical places, events, goals, environment and behavior, to create a general concept of semantic trajectory. Every semantic sub-trajectory may have transportation means, goals and behaviors. The transportation means represents the method that allows the object to move. The model is divided into two main parts. The first part contains information related to the moving object, the devices that generate the trajectory data, the semantic trajectory and the semantic sub-trajectories. The second part of the model is more complicated. In fact, this part includes the goals of the semantic trajectories and semantic sub-trajectories, the transportation means, and the behavior of the semantic sub-trajectories. The proposed model was applied in two different application domains, based on real trajectory data set. The first example is related to a tourist application, while the second one is related a bird migration application. Authors in [36] have proposed a system planning and case study for a heterogeneous moving-object trajectory meta-model using generic sensors. So as to afford a unified meta-model and strong structure for trajectory's services, the proposed trajectory's data model has profit from benefits of both conceptual and ontological space and time. Further, the presented method is well-known by providing a framework for handling with mobile object trajectory in an inter operable way, using sensors that traditional data model unable for this goal. Authors in [37], manipulate a trajectory as a rich semantic object. They proposed a conceptual model of trajectory data resulting from mobile hospitals by a class diagram. They extended UML and created a Trajectory UML profile to enrich the model with stereotypes and icons and to propose relationship constraints between the different element of a trajectory components. They divided the trajectory data modeling into two respective models: the moving object trajectory components' modeling and the application domain moving object modeling. The first model described each class that models the trajectory components and the different relationships between them. Consequently the proposed model is a generic. In fact, it is independent of the application domain and can be exploited by different applications that are concerned with the moving object trajectory data modeling. To do so, authors in [37] defined a trajectory as a set of trajectory sections where each trajectory section is composed of two successive stops that are delimited by a move. Fig. 8 illustrates the proposed generic conceptual model for a moving object trajectory data.

To have a personalized moving object trajectory data conceptual model, the designer have to add domain application entities. In fact, in [37] authors were interested in the conceptual modeling of a mobile hospital trajectory data. To do so, they added application dependent elements to the generic trajectory data model (Fig. 8) such as mobile hospital, patient, medical staff, prescription, drug and so on. Fig. 9 illustrates the combination of the generic model with the application dependent entities that refers to medical domain. Such combination constitutes the trajectory data conceptual model. The red part is the application dependent elements and the green part is the generic trajectory model.

To conclude this subsection, we mention some examples of specialized application for trajectory data and trajectory data warehouse conceptual modeling:

•Trajectory-UML profile [37]: it allows to enrich the model with stereotypes and icons and to propose relationship constraints between the different element of a trajectory components. Trajectory-UML permits to model both trajectory data and trajectory data warehouse at the conceptual level.

•MADS [30]: it is a framework for spatio-temporal modeling. It represents of orthogonality between the three dimensions: structural, spatial and temporal. This allows to obtain a model that is both simple (since the concepts are independent) and powerful (since these concepts can be combined with flexibility). The orthogonality makes possible to mix in an application dependent data with spatio-temporal data to constitute trajectory data.

3.1.1. Comparative study between trajectory data conceptual model approaches

The proposal [38] is intended to be a part of a data warehouse design methodology, however, it does not cover the implementation step. Semi-automatic generation tools should be built to derive the physical implementation from the conceptual model and transformations rules should be defined to generate the specific logical models from the starER constructs.

The proposed model by [33] needs validation through geospatial repositories via the Internet. Furthermore, translating data dictionaries into XML files is a path to explore. The proposed conceptual model is concentrating on the UML static diagram. Integrating dynamic diagrams in the conceptual model is mandatory to consider the geospatial context.

In [32], the representation of application-defined temporal dependencies between associations, attributes, and objects is a major step toward standardization and consistency.

The approach proposed in [37] is validated using a unique case study which is not sufficient to demonstrate the applicability of the proposed conceptual model in different contexts. In addition, the only enriched diagram is the class diagram. More dynamic diagrams are needed to represent the behavior of represented systems.

In [5], the relation between the proposed trajectory modeling strategies and the different network models it not studied in the work. Moreover, the extraction of spatio-temporal and semantic patterns from trajectory conceptual modeling needs to be explored to allow spatio-temporal data mining.

The model proposed [35] needs further studies and representation, toward a more structured behavior taxonomy. In future

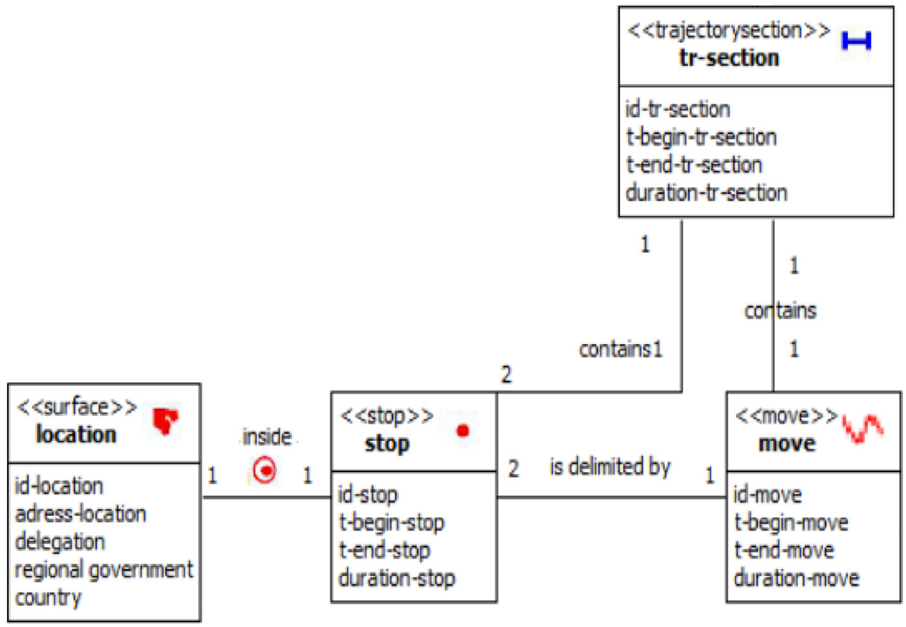

Fig. 8. Generic trajectory conceptual model based on Trajectory-UML profile [37].

work, authors are planning to extend the goal entity, for instance, to develop a taxonomy of goals and activities.

The proposed model [36] could be enhanced and refined by the introduction of a multipath fading submodel that quantifies the disadvantages of using the system in an enclosed space. The amount of data generated by such systems opens up many new issues such as the integration of a machine learning-based function to detect anomalous trajectories within the terminal or a recommendation system to support personalized advertisement platforms in the airport are examples of projects that can rely on the system proposed.

In the following Table 2 we compare between the above mentioned trajectory data conceptual approaches by considering the major criteria diversely handled in all of them mainly the model representation, the trajectory representation, the relationships and the case study.

3.1.2. Discussion of trajectory data conceptual model approaches

We strongly believe that the proposed models provide the basic concepts for trajectory data conceptual modeling and are the baseline rock for future research on semantic trajectory data warehouses. However, work is still needed to further explore the interaction between trajectory modeling strategies and the multiple network models that have been proposed in the literature, in view of enriching, if applicable, the modeling of network-constrained trajectories. Real scenario validation should also be carried out for the validation of different proposals. The extraction of spatio-temporal and semantic patterns will be performed using data-mining techniques. In this context, the investigation of the interplay between trajectory conceptual modeling and spatio-temporal data mining should be studied. Conceptual representation of extracted patterns may therefore call for an adjustment of the different approaches. A related line of investigation concerns the specification of operators for the aggregation of trajectories. An example operation on components is an aggregation replacing a set of stops in a region with a unique stop accounting for the whole time spent in the region. An example operation on trajectories as a unit is an aggregation replacing a set of trajectories with the average trajectory (somehow) computed from the set. Exploring aggregation functionality is a well-known research direction in spatio-temporal warehousing and we intend to extend current techniques to cope with our new concept of semantically enriched trajectories.

3.2. Trajectory data ontological modeling

The representation of moving object's trajectory data, as well as the associated reasoning approaches, is a big challenge imposed by the growth of moving objects application domains such as the management of road traffic and the prevention of natural disasters, etc. Therefore we review, research works that addressed the ontological modeling of trajectory data. In [39] the authors were concerned with the design of ontologies to facilitate the information exchange and sharing processes among applications dealing with moving objects. This application area ranges from fleet management systems to the monitoring of the users of mobile phones to provide location-based services. This work is based on the comprehension and registration of the fundamental mobile ontologies that can be used to exchange useful information. In particular, they analyzed the movement concept, its properties and its relationships within the spatio-temporal considered environment. They described, represented and interpreted common parameters for all mobile object applications. The proposed approach is generic enough to cover different types of moving objects, such as mobile phones, moving taxis, or even migrating groups of animals and specific enough to integrate data involved in a specific application domain. The authors defined the mobile ontological domain that includes the following components: Trajectory: the central and fundamental concept of ontology; The objects of the trajectory: these moving objects can be the moving vehicles, moving devices as shown in the following figure Fig. 10.

They used of mobile object ontologies for location-based services (LBS), to analyze, comprehend and model LBS data semantics. The analysis of trajectory data leads to the domain, content and application data categories. Modeling the semantics of the three data categories leads to the creation of three different ontologies: the Domain Ontology, the Content Ontology and the Application Ontology as shown in Fig. 10 A major contribution

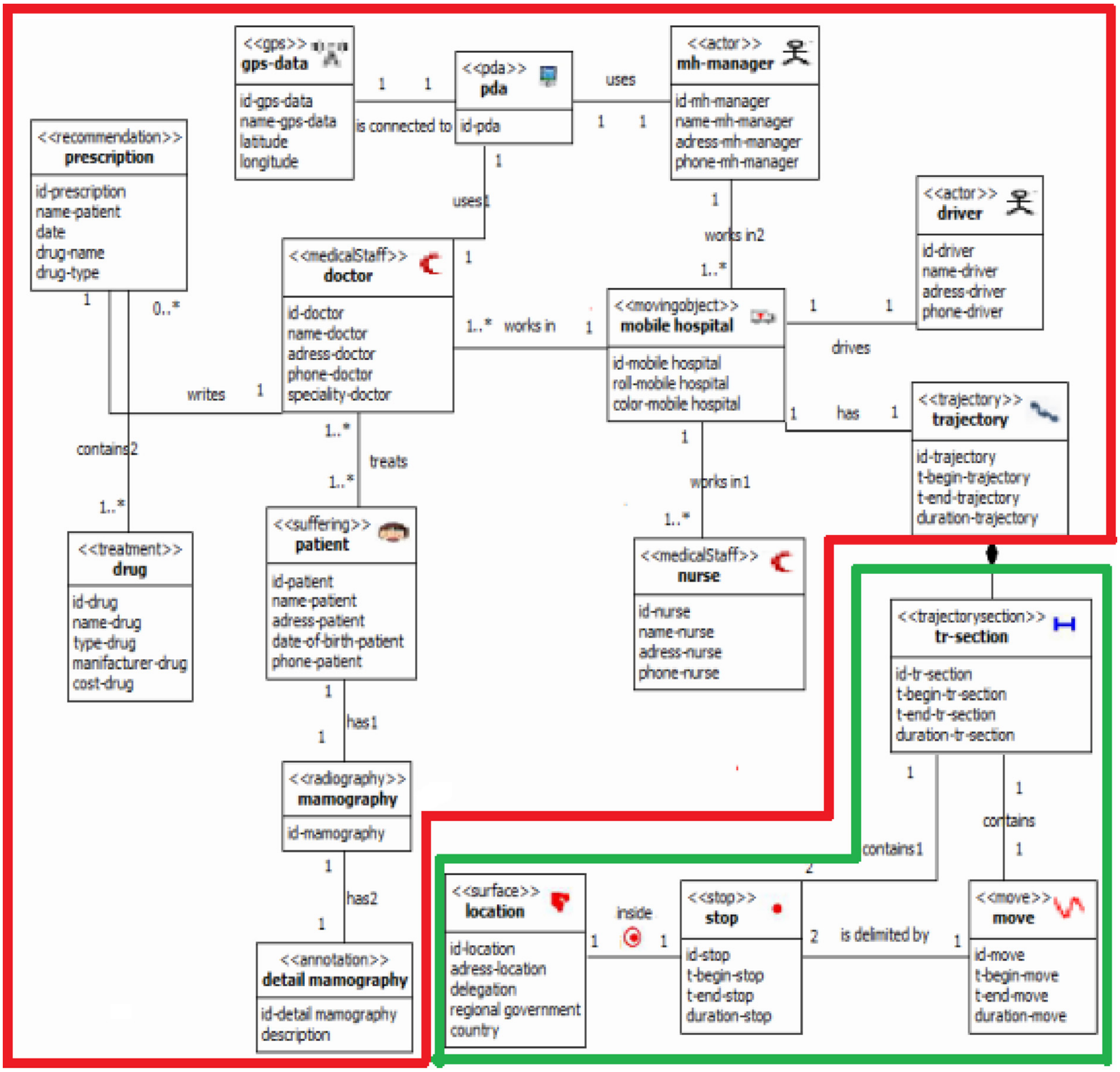

Fig. 9. Trajectory data conceptual model for mobile hospital based on Trajectory-UML profile [37].

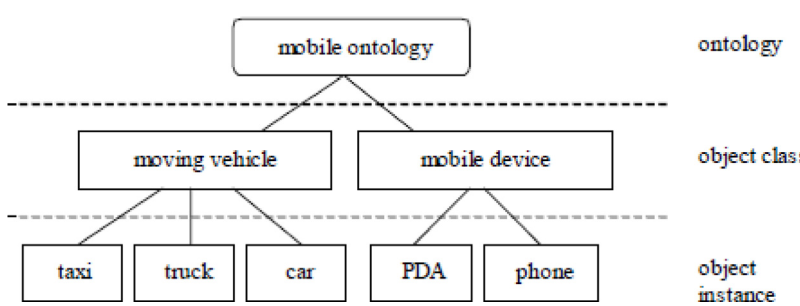

Fig. 10. Mobiles Ontology according to [39].

of this work, is the creation of ontologies to explain, share and interchange the concepts of location, position, movement and time through location-based applications.

In [5,23], authors proposed an ontological framework for modeling and querying trajectory data. They have provided three ontological modules: a trajectory geometric module, a geographic module and application domain module as shown in Fig. 11, where each one defined respectively as:

- The geometric trajectory ontology: defines the generic concepts of the trajectory. It involves spatio-temporal concepts used to specify the spatial, temporal and spatio-temporal characteristics of the application data;

Table 2
A comparative study between trajectory data conceptual models.

TD Conceptual model	Model representation type	Trajectory representation	Relation-ship	Case study
Tryfona et al. [38]	Based on ER model	Semantic	Association: One to one One to many Many to many	Codastral application navigational system.
Brodeur et al. [33]	Based on UML notation	Semantic	Association Aggregation Composition Generalization Specialization	Geo-spatial application databases.
Tryfona et al. [32]	Based on UML notation	Semantic	Generalization Association Composition	Regional health application.
Oueslati et al. [37]	Based on extended Trajectory- UMl	Structered Semantic	Association Aggregation Composition	Healthcare application Mobile Hospital.
Spaccapietra et al. [5]	Based on ER model	Semantic	Many to many Many to one Animals application	Migrating birds.
Bogorny et al. [35]	Based on UML notation	Semantic	Aggregation: Many to many Many to one	Tourism application. Bird migration application.
Boulmakou et al. [36]	Based on UML notation	Structured Semantic ROI Space time path	Association Composition Specialization	Tracking airport security.

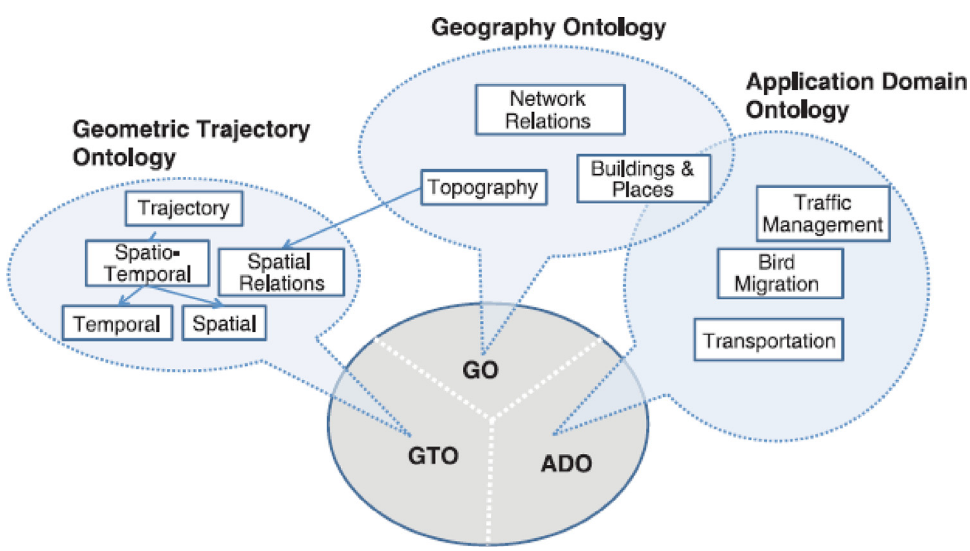

Fig. 11. Ontological model for trajectory data management.

- The geography ontology: presents the concepts that participate in the description of the geographical coverage such as the network of the moving object and topologies. This module is connected to the geometric trajectory and the application domain trajectory modules.
- The application domain ontology: it gathers all the application dependent concepts. For example, ontologies for traffic management, bird migration and transport ontologies.

In both [22,40], authors worked on a marine mammal trajectories case study. In fact, they considered trajectories of seals in order to understanding their behavior and identify their foraging areas. To model semantic trajectory data, an ontological approach was defined to represent trajectory concepts. This approach takes into account thematic and temporal rules. The inference mechanism is needed for queries on the semantic trajectory OwlSeal-Trajectory mapped to the time OntologyOwlTime. An extract of the declarative part of this ontology is shown in Fig. 12. A new approach was proposed in [41] to describe Ontology Design Patterns that are derived from the common conceptual patterns that emerge in different domains when solving different tasks. They introduced a Geo-ontology design pattern for semantic trajectories. The pattern is the result of a joint effort between domain experts and knowledge engineers. It can be used to semantically annotate trajectory data from a range of different domains such as navigation and wildlife monitoring.

Recently, authors in [4] have presented an ontology-based trajectory pivot model. The innovation of this work consists on

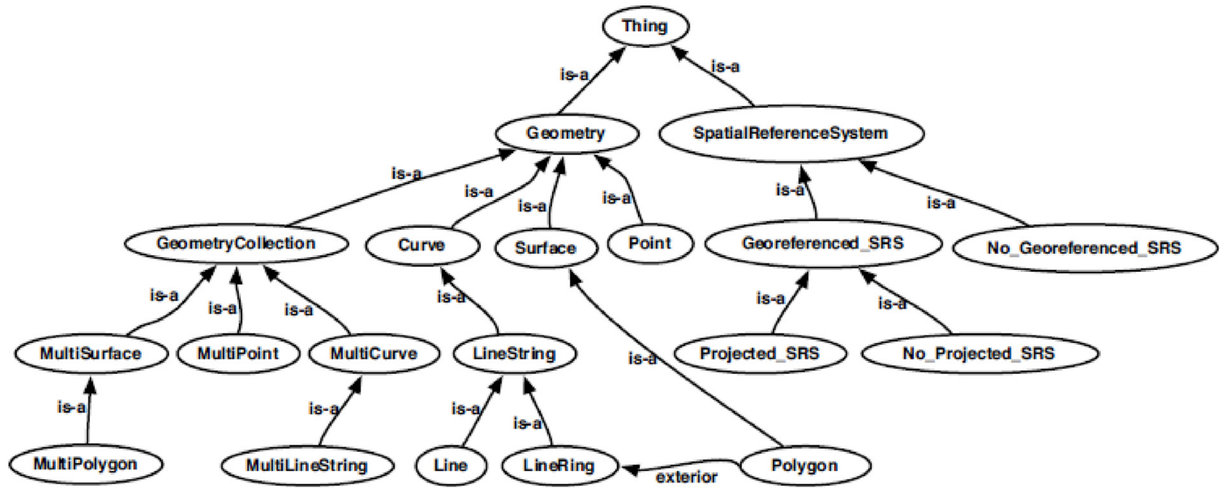

Fig. 12. A view of owlOGC Spatial ontology.

offering a generic semantic approach that turns trajectory sample points into semantic concepts and afford various ontological models of trajectory. The proposed approach is based on two steps: (i) the first step is to design a trajectory pivot model where they present a pivot model with a great expressive power for heterogeneous trajectory data sources. It guarantees completeness of reasoning and desirability in a finite time. The second step is to structure the generic semantic trajectory design approach that holds the geometric trajectory module, the geographic module and the application domain module. These approaches differ generally in the trajectory representation since there are raw trajectory, structured trajectory and semantic trajectory. Authors of [32,41] proposed modular ontology that holds sub-ontologies to guarantee the re-usability and the maintenance tasks [4,40]. In [42], authors defined three ontology modules to support moving object trajectory data modeling. A module is a sub-ontology of a larger ontology. The three modules are the geometric trajectory module, the geography module, and the application-domain module.

•The geometric trajectory module (GTO): it holds generic concepts for the description of the geometric component of a trajectory. It includes spatio-temporal concepts used to specify spatial, temporal and spatio-temporal features as follows:

•The geography module (GO): it holds the concepts that participate in the application description of land coverage. Concepts are likely to include those describing the topography of the land, natural (e.g. hydrological) and artificial (e.g. routes, trains, facilities) networks, buildings, landmarks, vegetation and anything else that is of interest to the application. This module is tightly interrelated with the geometric trajectory module as each application element that has a spatial connotation is to be linked to the type of geometry that is used by the application to specify the corresponding spatial extent. The module is also tightly interrelated (or overlapping) with the application domain module as its concepts may also have a thematic description providing application information beyond the geographic and geometric facets.

•The application domain module (ADO): it gathers all application dependent concepts. Examples of such modules include traffic management ontologies, bird migration ontologies, and transportation ontologies.

Now Combining the Geometric Trajectory Ontology, Geography Ontology and Traffic Management Ontology together leads to the final overall Semantic Trajectory data Ontology as illustrated in Fig. 13.

To conclude this subsection, we mention some examples of specialized application for trajectory data and trajectory data warehouse ontological modeling:

•BAQUARA [43]: it is an ontological framework for movement data which enables semantic enrichment and analysis of trajectories of moving objects with vast and growing collections of linked data available in the Web.

•FrameSTEP [44]: it is a framework for annotating semantic trajectories based on episodes. It allows combining spatio-temporal ontology with annotation algorithms to create instances of the trajectory data or trajectory data warehouse model.

We have to mention that designers can build semi automatically an ontological trajectory data model from a given dataset. Taxi Trajectory data, Drone Trajectory data, Trajectory inference, Trajectory data from building are open datasets. Those latter are CSV files. According to the literature, we can create an ontology semi automatically from CSV files. In fact, we have two alternatives [31,45]; the first one is to transform csv files into relational database and then create an ontology from the database [31]. The second alternative [45] is to transform CSV files into XML files and then create ontology from XML documents. In fact, a systematic study of the tags of the XML document and their nesting made it possible to determine how to identify concepts, conceptual relations and properties.

3.2.1. Comparative study between trajectory data ontological model approaches

The approach [39] proposes a Data Manipulation Language but does not focus on a Query Language at an abstract level which is also essential. Furthermore, after the deep study of the mobile domain and the needs of mobile ontologies, it is convenient to also adopt ontological languages to enrich the proposal with mobile features. The proposal of [22,40] lacks an evaluation on real data and a comparison with other approaches. Moreover, we are highly interested in defining new notions of semantic trajectories and the integration of data mining algorithms with ontological rules. The presented work [41] combines different patterns developed independently without an overarching structure. The work is a first initiative in the field of geospatial semantics research which lacks a common platform for geo-ontology design patterns, documentation, best practice, examples, and so forth that

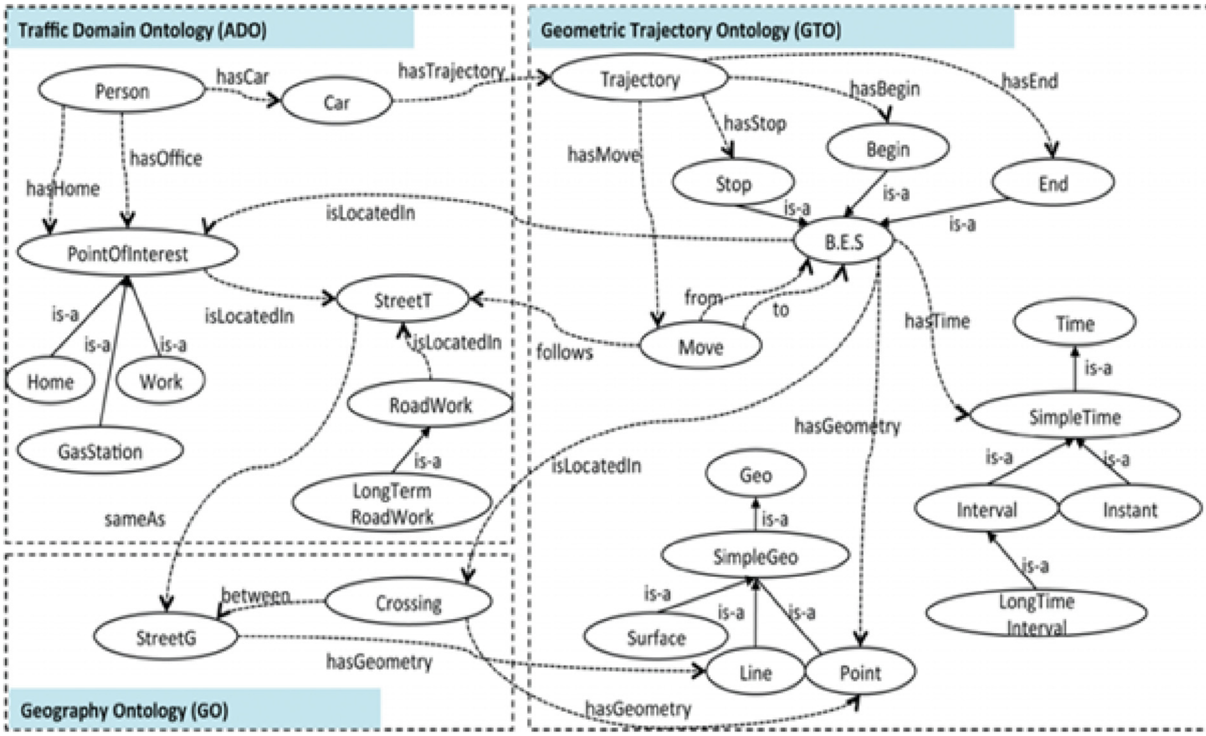

Fig. 13. Semantic Trajectory Ontology for a Traffic Management Application [42].

Table 3
A comparative study between trajectory data Ontological models.

TD Ontological model	Ontological temporal representation	Ontological spatial representation	Case study	Ontology platform	Type of movement
Tryfona et al. [39]	Not treated	Not treated	Traffic management system Mobile agents	DBMS Oracle 8i	Network-constrained
Yan et al. [42]	OWL-PRIME	Simple GEO	Traffic management.	Oracle's DBMS	Network-constrained
Wannous et al. [22] [40]	OWL-TIME	OWL-GC-SPATIAL	Seal trajectory	RDF OWL	Free-movement
Hu et al. [41]	OWL-TIME	Not treated	Human trajectories Wildlife monitoring	RDF	Constrained-movement
Manaa et al. [4]	TIME-OWL	GEO-ONTOLOGY	Pedestrian activities	Oracle's DBMS	Constrained-movement

would significantly lower the initial hurdle for domain scientists interested in semantically annotating their data. In [4], reasoning mechanisms should be adopted to deduce new information and to detect semantic gaps that can hold between heterogeneous trajectory data sources. The adoption of an ontological approach to integrating different trajectory data sources in a trajectory data warehouse by using the global trajectory ontology is also necessary. To summarize all the described works concerning trajectory data ontological modeling, we elaborate a comparative study in Table 3. As evaluating criteria, we considered: the Ontological temporal representation, the ontological spatial representation, the trajectory representation, the case study, ontology platform and finally the moving object's movement type.

3.2.2. Discussion of trajectory data ontological model approaches

We consider that the different trajectory data ontological models are a part of a project which attempts to allow an information exchange of mobile systems. In this context, many efforts should be done to provide a unified Mobile Editor in UML. Then to define and automate the rules to transform the produced models into ontology. The ontologies' semantic interoperability should be addressed through design patterns, best practice guides, examples, and software. An abstract query language is also essential to allow querying mobility data on the semantic level.

4. Trajectory data warehouse modeling

The data warehousing is defined as the core of decision making system and used to support difficult applications such as planning and forecasting since it provides the useful information always ready, easily and directly accessible for querying as well as for analysis. It stores summarized data, and provides the meaningful information. It is based on a multidimensional structure that supports OLAP and data mining and other exploitation techniques dedicated to transform summarized data into useful knowledge for decision making, planning tasks, prediction processes. Authors in [46] have presented a typical data warehousing architecture (Fig. 14)with the process of data Extraction, Transformation and Loading (ETL). The modeling of trajectory data warehouse (TDW) is very important since it allows determining analysis possibilities. The modeling phase can be conceptual or ontological. In the next sub-sections we present research

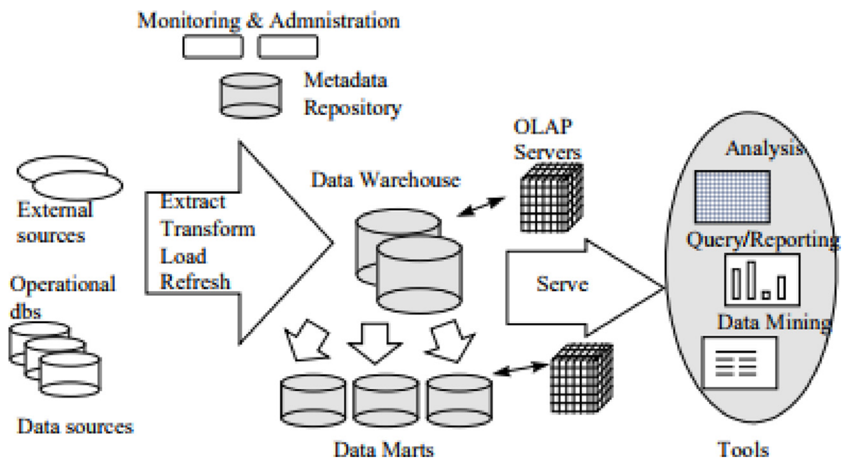

Fig. 14. Data Warehousing Architecture [46].

works that focused on TDW conceptual modeling as well as TDW ontological modeling.

4.1. Trajectory data warehouse conceptual modeling

The multidimensional structure consists on data storage in a cube permitting visualization and analysis of data from different perspectives. The glossary of the multidimensional paradigm is composed of fact, dimensions, measures and hierarchies.

- Fact: The fact table appointed to the fact of interest or the subject of analysis including numerical attributes called measures and other descriptive ones generally the keys of related dimensions. In the context of moving object trajectories, the fact table is the trajectory of the moving object.
- Dimensions: Performed to attributes closely allied to the focus of analysis (fact) and varying axes of measures analysis. Spatial and temporal dimensions are essential in a trajectory data warehouse model.
- Measure: Represents the quantitative aspect of a fact, it is a numeric property of a fact analysis.
- Hierarchies: A finite set of members in a dimension and their positions relative to one another.

Modeling trajectory data warehouse was the focus of many research works. In [47], authors handled the logistic management field in particular truck delivery of goods as a very interesting branch in the economy domain. They extends previous work on the conceptual modeling of trajectories by generalizing the idea of stops and moves introduced by Spaccapietra by defining a set of aggregation functions on trajectory data enumerated by a traveling truck accomplishing its dedicated mission. Indeed, authors proposed two modeling approaches: both of them are based on design patterns using UML graphical notation and stereotype mechanism. This permits to distinguish facts from dimensions and from thematic information. They proposed trajectory data for relational and multidimensional schema and supposed that the trajectory' semantics depends on the application domain. They considered a spatio-temporal path of a moving object as a sequence of trajectories. This latter is a sequence of triples (latitude, longitude and time) generated by a positioning technology. In [48], authors proposed the use of a narrative method as a conduit for systematically explaining the context where the spatio-temporal component of trajectory data is properly integrated with context related information like transportation means, performed activities and mobility patterns. This method is based on the mnemonic 5W1H [49]. According to this model the authors defined a TDW conceptual model with six dimensions to describe the context where objects move (Table 4). In [50], authors introduced a formal framework for modeling a trajectory data warehouse (TDW), and introduced the aggregation function of measure V, which represents the total number of visits in a given spatio-temporal area of several trajectories. A trajectory data warehouse aims to store aggregate information on moving objects' trajectories and offers visual OLAP operations for trajectory data analysis. The trajectory data warehouse conceptual model includes both temporal and spatial dimensions and it is flexible and general enough to deal with moving objects that have free or constrained movement. In particular, the spatial dimension and the associated concept hierarchy reflect the structure of the environment in which the objects travel. The TDW and its visual interface allow to investigate the behavior of objects inside a given area as well as the movements of objects between areas in the same neighborhood.

Authors in [51], have proposed to model a Trajectory Data Warehouse for mobile information collectors trajectories. As a result, they proposed a generic conceptual TDW model for mobile processionals trajectory data. After that, they applied it to the real case study which is the mobile information collector. This method is based on the mnemonic 5W1H [49]. The basic idea of this approach is to apply six narrative questions as mentioned in Table 4.

In fact, authors [51], generated the TDW for the moving object "Mobile Information Collector" (MIC) by answering five narrative questions as follows:

•Who: the dimension mobile information collector (mic) represents the moving object.

•When: the dimension date represents the time when the MIC moves and stops during its trajectory.

•Where: the dimension country and its hierarchy levels regional government and delegation represents the places where the moving object moves to achieve its activities.

•Why: the activity of MIC is to collect information about points of interest that can be artificial dimension (educational company, hospitals, hotels, agriculture companies...) or natural dimension (mountain, lake, sea, desert...) to discover opportunities for implementing new commerce installations, finding new markets for existing and new products.

Table 4
5W1H model.

Narrative question	Description
Who	Addresses the identification of a moving object.
What	Refers to what a moving object is doing and task trying to perform
When	Refers to the time extent related with trajectory points.
Where	This concerns the place where the trajectory point is located.
Why	This represents the motivation for traveling.
How	Identifies both the way the object is moving and the behavior.

•How: the dimension Means of Transportation represents which transportation means the moving object is using for the movement. The Fig. 15 illustrates the trajectory data warehouse conceptual model based on the mnemonic 5W1H [49]

In [37], authors were interested in the medical domain. In fact, they proposed a new trajectory data warehouse UML profile called Trajectory-UML for a mobile hospital trajectory. The extended UML profile is composed of trajectory sequence diagram and trajectory data class diagram with new stereotypes, pictograms and constraints to model the trajectory data warehouse at the conceptual level. The proposed TDW conceptual model was used by other works that focused on moving objects trajectories. In [53], authors proposed a conceptual modeling for trajectory data warehouse related to north wind data. They enriched the conceptual model to support the mobility data and to ameliorate the querying process. Authors in [54] were interested in managing crisis related to flooding by collecting floods' trajectory data. For this aim they proposed a conceptual model for river floods trajectory data warehouse. This can support environmentalists to model, store, aggregate and analyze floods trajectory data. Besides they can use the trajectory data warehouse as a common framework for validation, reproduction and simulation of experimental data analysis. The proposed conceptual model is composed by a fact table that is shared by different dimensions. The fact table is the variable to be analyzed in the immersive analysis later that is the flood trajectory and the dimensions are: time, wavelet and region.

4.1.1. Comparative study between trajectory data warehouse conceptual modeling

In [51], the proposed data warehouse modeling approach does not represent data in a format that allows deep analysis and consequently is not helpful for decision making. In addition, the authors do not propose OLAP to take into consideration the continuity of changes of mobile objects in time and space.

Although authors in [48] proposed a semantic-enhanced data warehouse for trajectories, their work lacks a sophisticated ETL process integrating raw trajectory data with contextual information. The aggregate functions are basic and complex aggregate functions for the measurement points, moreover, representative trajectories are not considered in the approach.

The authors in [50] did not address measurements for frequent patterns and representative trajectories. The approach could be considerably enhanced with the processing of semantically annotated trajectories, in which individual events within the trajectories are linked to semantics. Even if this is feasible with the existing model, a more complicated model is required for a more in-depth investigation of trajectory behavior.

Authors in [37] propose a new framework to model the trajectory of a moving object and its components in a specific way. However, due to the heterogeneity of information sources subject to changes in their content and structures, the schema of the trajectory data warehouse can become obsolete. This may negatively impact the querying process.

Although the proposed system [54] represents an important step toward the closer involvement of users in the analysis driving the decision-making process for developing mitigation and adaptation strategies for the threats of floods, tests were performed in only one case study. Many experiments should be done to prove the feasibility of the proposed solution in different contexts.

The proposed work [47] lacks formal and detailed requirement analysis and in creating a complete and optimized application for a long period of tests in a real corporate environment. Another point that requires deeper investigation concerns the design of aggregation functions for trajectories, which needs a formal and complete study to treat trajectories as complex and first-class objects, including aggregation concerning the semantic information (i.e. events) and other spatial structures, such as polygon geometries (e.g. areas or regions of interest) and points (e.g. clients or truck fleet bases).

This paper [53] studied how DWs can be extended with spatial and mobility data. The proposed work supports only moving points. However, in real case, many other kinds of temporal types exist such as moving regions.

To summarize all the described works concerning trajectory data warehouse conceptual modeling, we present in Table 5, the discussed works on conceptual representation of trajectory data warehouse. As evaluating parameters, we consider in our comparative study: the model representation, the type of movement, the TDW multidimensional structure, the trajectory modeling and finally the implementation platform on which the model is tested.

4.1.2. Discussion of trajectory data warehouse conceptual modeling approaches

In the literature, many approaches shed the light on trajectory data warehouse conceptual models. Most of them are based on a formal basic representation of moving objects. However, many efforts should be done to enhance the moving object models with deeper aggregation functions which should allow a better historical and real-time analysis of the trajectory. Contextual dimensions should be taken into consideration in all models to offer efficient decision-making support. The development of a benchmark for trajectory data warehouse will considerably enhance the verification and the validation of trajectory data warehouse conceptual model proposals.

4.2. Trajectory data warehouse ontological modeling

According to [50] the ontology is a technical term denoting an artifact that is designed to model knowledge about a given real or imagined domain. Ontologies determine what can be represented and what can be inferred about a given domain, using for that a specific formalism of concepts. We present in this section an overview of works in the literature that opted for the ontological modeling of TDW. There exist diverse works in the literature [50] that presented ontology-based methods for the design of semantic TDW [52,55]. In [52], authors proposed an ontology for the design of multidimensional schema. The proposed approach

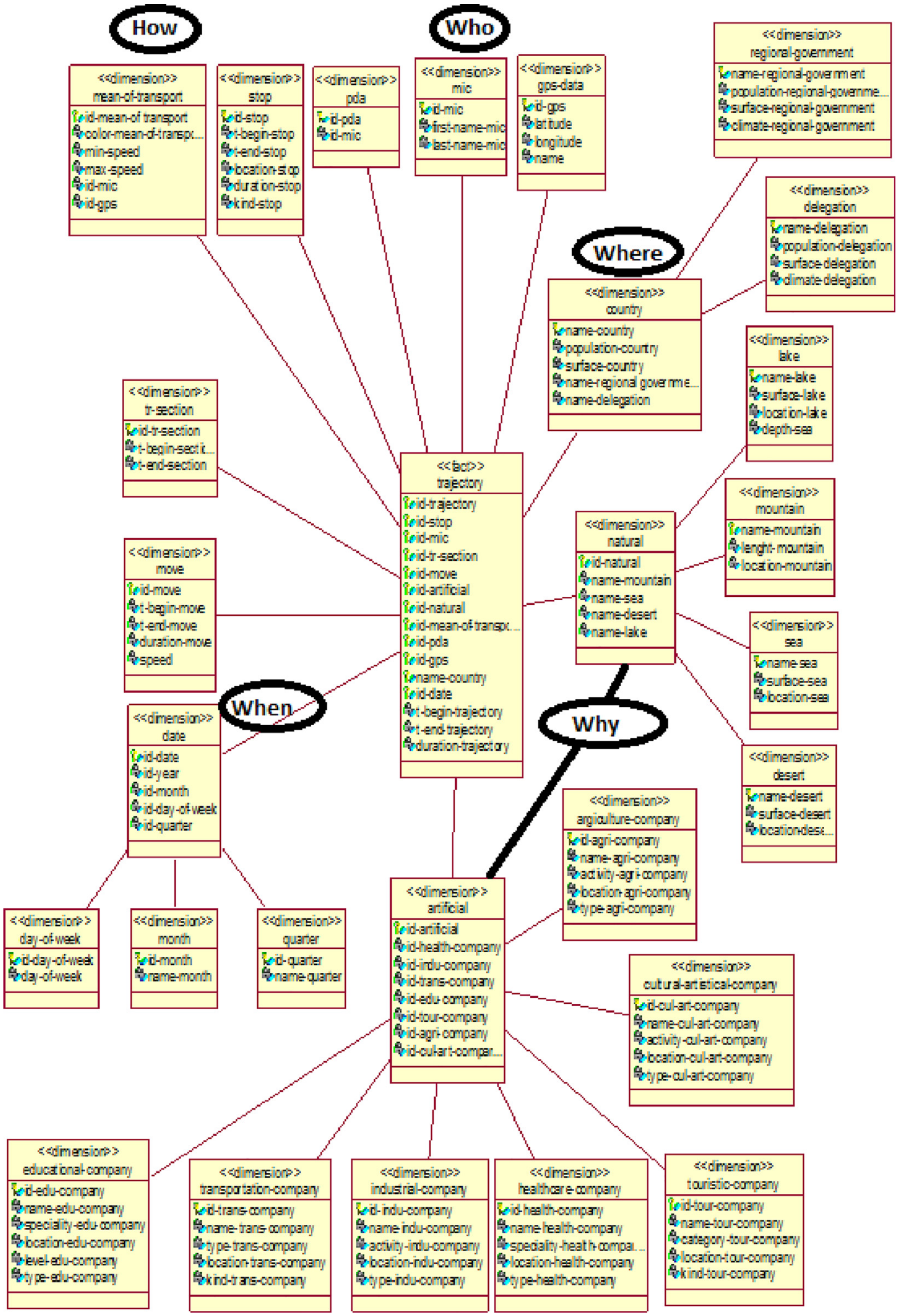

Fig. 15. A trajectory data warehouse conceptual model based on 5W1H [52].

automate the modeling task of identifying facts and dimensions. The multidimensional elements are extracted automatically from the tagged ontology. They identified a concept as fact if it contains ratio of numerical attributes or number of instances greater than the threshold specified by the designer. The numerical attributes become the measures of the fact. For each identified fact, they derive the dimensions by making use of class subsumption and multidimensional principle that n elements of fact are related to at least and at most one element of a dimension through an object property. The work followed the hybrid methodology where the data source and end-user requirements are conciliated at the early stage of the data warehouse design. This allows them to derive only the entities that are of interest for analysis. The requirements of the data warehouse can be represented in

Table 5
A comparative study between trajectory data warehouse conceptual models.

TDW Conceptual model	Model representation type	Movement type	Application scenario	Trajectory modeling	Implementation
Leal et al. [47]	Based on UML notation	Network-constrained movement	Truck goods delivery	Modeled by a set of stops and moves Modeled by a set of aggregation functions	Oracle DBMS
Oueslati et al. [51]	Based on UML notation	Network-constrained movement	Mobile information collector	Modeled by a set of stops and moves	SQL Server MDX query
wagner et al. [48]	Tree-Structured	Network-constrained movement	Transportation means	Modeled by a set of stops and moves	Not treated
Leonardi et al. [50]	Tree structured:fact schemes	Network-constrained movement	Tourist	Modeled by absolute coordinates	Oracle Spatial extension(Oracle™ 11 DBMS)
Oueslati et al. [37]	Based on Trajectory UML notation	Network-constrained movement	Mobile hospital	Modeled by a set of stops, moves and trajectory-sections	SQL Server MDX query
Masaabi et al. [54]	Based on UML notation	Free movement	Floods	Modeled by a set regions	SQL Server MDX query
Vaisman et al. [53]	Based on UML notation	Network constrained movement	Northwind	Modeled by trajectory segments	PostGis and PostgreSQL database

natural-language text format. The concepts in each requirement are matched to the source ontology. The matched concepts are tagged in the source ontology and the multidimensional elements such as fact and dimensions are automatically derived using reasoning.

The application of ontology for the modeling of data warehouses has relieved the burden of the designer to automate the task in a more meaningful way. Thenmozhi and his team has completed their studies with the same idea in [55]. In fact, they proposed a ontological methodology that supports an automatic adaptation of the multidimensional schema when the requirements and sources evolve. The main idea for the data warehouse evolution is that the whole system is specified at the conceptual level. Any changes at the source or requirements are propagated to the data warehouse schema at the ontological level. Hence, the proposed approach analyzes the impact of a given change at the logical level, before it is propagated to the data warehouse schema at the physical level. Based on the evolved data warehouse ontology, the Data Warehouse administrator can make a decision to carry the changes at the physical level. Following the phases of the proposed methodology that are: formalization of inputs, definition of evolution operators, update of changes in requirements or source ontology, extraction of Data Warehouse schema change, propagate change to data warehouse schema and check of the consistency of data warehouse schema. In [56], authors presented a study on how to model a semantic data warehouse for trajectories. In fact, they proposed a SWOT model and offers a dual modeling of ontologies. This proposition enables the separation of the ontology information into two conceptual data layers. The ontologies are namely: Consensual and Interpretation. Consequently, the authors fail to address the addition of much enhanced numerical measures for the fact relationship and did not illustrate a generic ontology model which can be applicable to different domains. In [57], authors presented a Semantic model for TDW (STrDW) related to seal trajectories using an ontological approach. The STrDW is expected to pass through the requirements analysis phase which is expressed by the means of a goal-driven approach. This approach identifies goals that guide decisions of users and it is based on a Goal Model. After identifying users' goals, a connection is made between coordinates of each goal from the one side and the resources of the thematic, spatial and temporal ontologies (denoted as the GO (Global Ontology)) from the other side. In the study of [58], the authors discussed the approach of modeling ontology data using Ontology-Based Moving Object Data (OBMOD) and the efficient ways of storing and querying heterogeneous OBMOD. In their methodology, the authors defined an ontology-based design approach to model and analyze a global trajectory shared ontology and its associated semantics. Moreover, their approach defined the structure of the conceptual model for a semantic trajectory data warehouse based on a formulated algorithm. The authors in [59] discovered the limitations of the works presented in both [58]) and [56]. In fact, they stated that researches of [58]) failed to outline practical query processing on the semantic trajectory data warehouse while [56] failed to address the addition of much enhanced numerical measures for the fact relationship and did not illustrate a generic ontology model which can be applicable to different domains. They attempt to leverage on the prior work by [56,56] and they introduced a novel methodology approach that defines and outlines a generic ontology model for handling the varied semantic characteristics of trajectory objects, events and activities, environmental considerations, as well as, social media interaction. This generic ontology model serves as the background platform for the modeling and design of the thematic constructs for a semantic trajectory data warehouse. In fact, the proposed semantic trajectory data warehouse offers a data repository platform for detailed and enhanced fact attributes and numeric measures. Additionally, the sound generic ontology model enables the semantic trajectory data warehouse to offer descriptive dimensionality attribute representation for the unique characteristic of any chosen application domain. In [60], authors formulate and design a generic framework for trajectory data warehouse ontological modeling. The proposed approach offers a design platform for knowledge discovery and predictive trend analysis. To validate the generality of their approach, they applied the generic model to different case studies such as the tourist movement management, the bird migration movement and the highway traffic and transportation management.

4.2.1. Comparative study between trajectory data warehouse ontological modeling approaches

The feasibility of the proposed approach in [58] for non-traditional applications was not tested. Furthermore, the huge amount of data included in the ontological model generates a paramount need to tackle the optimization issue not only in data storage but also in data retrieval. The proposed system [57] contains a huge amount of data. Consequently, optimization issues should be taken in consideration as well as the performance of the

Table 6
A comparative study between trajectory data warehouse ontological models.

TDW Ontological model	Ontological temporal representation	Ontological spatial representation	Case study	Trajectory representation	Ontology platform
Mick et al. [60]	OWL Temporal instance dimension	OWL Geographical space dimension	tourist bird migration truck delivery	Modeled by a set of activities and behavior during a sequence of trajectory segments	Post Gis(spatial and geographical extension of postgreSQL DBMS)
Sakouhi et al. [57]	Not treated	SDO-Geometry	Seal	GO:Global Ontology	Oracle's DBMS
Manaa et al. [58]	TIME-OWL	GEO-ONTOLOGY	Pedestrians	Geometric Trajectory Ontology	OWL
Mireku et al. [59]	OWL-TIME	Not treated	Generic moving object	Modeled by a set of activities during sequences of stops and moves	Protege Semantic Web Ontology Platform PostGIS DBMS

inference process. Transitions from the design model to logical and implementation models are very important to operationalize the proposed conceptual model. The inherent characteristics of trajectory data such as uncertainty and unpredictability are of paramount importance. The proposed methodology [59] must adopt some privacy-preservation requirements and integrate practical measures for protecting the privacy of trajectory objects such as human beings or social media data. Those requirements should be integrated into the design phase of the framework. The approach proposed in [60] needs to incorporate comprehensive optimization measures for faster and more efficient query processing. In addition, the authors highlight the need to formulate and enforce a framework for the modeling and design of the semantic trajectory.

After presenting different research works in the field of trajectory data warehouse ontological modeling, we elaborate a qualitative comparative study between dissimilar models of ontological modeling (Table 6) according to these criteria: Ontological temporal representation, ontological spatial representation, multidimensional structure, trajectory representation and ontology platform.

4.2.2. Discussion trajectory data warehouse ontological modeling approaches

The proposed approaches offer the baseline rock for concepts for semantic trajectories. Future research should concentrate more on semantic trajectory data warehouses knowledge discovery through data mining techniques. Defining a modeling strategy for trajectory warehousing is also an important issue to be studied. The backbone of the modeling strategy is the aggregation concept which denotes any process somehow collecting a set of data items to produce some global data item that materializes a synthetic view of the collected data items. Different kinds of aggregation are possible, and they can be performed at different levels, distinguishing for example between operators applied to the components of a trajectory and operators applied to trajectories as a unit. Most of the proposed approaches demonstrate the usefulness of their models in one or two case studies. The performance of the approaches should be evaluated on benchmarked datasets gathering real data to allow real scenario validation. The ability to design a scalable data warehouse to handle large sets of trajectory data for an increasing volume of data that will be collected, processed, and stored is an important issue in trajectory data warehouse modeling. Moreover, there is a prominent need to incorporate comprehensive optimization measures for faster and more efficient query processing.

5. Conclusion

In this paper, existing modeling approaches of moving objects' trajectory data and trajectory data warehouse modeling were over-viewed and comparative studies were presented and discussed. Ontologies and data models both represent domain knowledge but are showing some fundamental differences. Useful points of reference to compare between ontological and conceptual modeling are; application dependencies, knowledge coverage, expressive power and operation levels. Although, many researchers have been done in the field of moving objects' trajectory data and trajectory data warehouse modeling either based on conceptual or ontological modeling, each approach suffers from whole genericity. Existing approaches could be improved to fulfill this lack.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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