Trajectory Data Analysis in Support of Understanding Movement Patterns: A Data Mining Approach

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ABSTRACT

Recent developments in wireless technology, mobility and networking infrastructures increased the amounts of data being captured every second. Data captured from the digital traces of moving objects and devices is called trajectory data. With the increasing volume of spatiotemporal trajectories, constructive and meaningful knowledge needs to be extracted. In this paper, a conceptual framework is proposed to apply data mining techniques on trajectories and semantically enrich the extracted patterns. A design science research approach is followed, where the framework is tested and evaluated using a prototypical instantiation, built to support decisions in the context of the Egyptian tourism industry. By applying association rule mining, the revealed time-stamped frequently visited regions of interest (ROI) patterns show that specific semantic annotations are required at early stages in the process and on lower levels of detail, refuting the presumption of cross-application usable patterns.

Keywords

Trajectory, Spatiotemporal, Data mining, Semantics, Framework, Design science

INTRODUCTION

Moving objects equipped with digital devices that transmit or receive information through network infrastructures enable the collection of data that represents their corresponding movement in space and time. One type of data that may be observed from such digital traces is trajectory data. Trajectories are generally comprehended as the digital traces collected after moving objects through an established wireless network infrastructure, forming a certain path (Giannotti, Nanni, Pedreschi and Pinelli 2007; Güting, Almeida and Ding, 2006).

Trajectory data is collected in vast amounts every second, with every movement. The increasing volume of data is regarded as a burden to organizations unless they can extract useful knowledge and insight from within that can support them in enhancing the quality of their decisions. Extracting knowledge is the primary goal of data mining and the interest in the field has been developing and maturing through the last decade following an impressive pattern. The discovery of previously unknown patterns on moving objects and the ability to understand and interpret them to support organizational decision-making processes is an open research problem in different application domains.

Storing, querying and analyzing trajectories are among the problems recently investigated. Data management techniques and data mining algorithms are the main areas investigated to address the relevant research problems. However, most of those areas deal with trajectories in their raw format and with the extracted patterns in their numerical forms (Yan, Chakraborty, Parent, Spaccapietra and Aberer, 2011). Thus, semantic enrichment and analysis of trajectories has gained much attention lately, with a call for investigating the techniques and approaches by which semantic patterns can be extracted.

In this paper, we present a conceptual framework (Sem-TP) for extracting semantic trajectory patterns using data mining techniques. Semantic enrichment takes place in three levels according to the different evolutionary state of the data and the corresponding ontological module appropriate in such level. Sem-TP is generic and proposed to support a range of applications. Presenting this framework is part of a design science research approach where it is evaluated using prototyping and tested within the Egyptian tourism and travel industry.

PROBLEM STATEMENT

Current research on the analysis of trajectories either focuses on specific data mining techniques and algorithms and enhancing their computational performance while applied on raw trajectories, or on semantic annotation algorithms used with trajectory data. Moreover, semantic enrichment of trajectories focuses on annotations of individual trajectories rather than that of the extracted patterns. This approach creates a high level of dependence between the proposed solutions and the semantics of a specific application domain, which deprives us from reusing the solution in other contexts. Therefore, there is a call for a generic framework that would allow the application of data mining techniques on semantic trajectories as well as enabling the semantic enrichment of extracted patterns.

BACKGROUND

Trajectories have different definitions in the literature, whereas the following definition is the one followed throughout this paper: an instance that represents the spatial evolution of a certain object moving in space to achieve a certain objective in a given time interval. This definition is associated with the underlying purpose of the application domain where – in other words – the trajectory is the trip that starts with *begin* and terminates with the *end* of the journey, passing by multiple *moves* and *stops* (Spaccapietra, Parent, Damiani, Macedo, Porto and Vangenot, 2008). In addition, a trajectory *section* is composed of two stops and the move in between (Oueslati and Akaichi, 2010). Thus, trajectory ontology is defined in terms of the following five concepts; begin, end, stop, move and trajectory section.

Applying computer-based analysis and learning techniques and methodologies with the purpose of discovering non-trivial patterns from data is defined as data mining (Kantardzic, 2011). Data mining strategies are based on either supervised learning (deduction-based or confirmatory) or unsupervised learning (induction-based or exploratory) (Jain, 2009). In addition, a third strategy emerged in the literature and later became a focused theme in data mining research, which is frequent pattern mining (Roiger and Geatz, 2003; Han and Kamber, 2006; Han et al, 2007).

RELATED WORK

Frameworks presented on trajectory mining ranged in focus, but are mostly driven by the knowledge discovery process and the tasks performed to analyze moving object trajectories. Examples of these frameworks are Alvares et al.'s (2007) framework for trajectory pattern extraction and modeling, Yan et al.'s (2011) SeMiTri and Ong et al.'s (2010) movement pattern interpretation framework. Even existing prototypes and their system architectures have their process tasks reflected in their components and layers (e.g. MoveMine by Li et al, 2010; and GeoPKDD integrated system by Nanni, Trasarti, Renso, Giannotti and Pedreschi 2010). While the latter layer-based architectures provided a fine insight on the whole knowledge discovery approach, they did not address the problem of semantic enrichment, which makes the interpretation of the patterns such a challenging task to the beneficiaries.

Alvares et al. (2007), on the other hand, tackled the problem of semantics by modeling the extracted patterns in geographical databases. However, this only provided one aspect of the available semantics. To cover most of the other aspects, Yan et al. (2011) proposed their framework for a comprehensive approach to semantic annotation of trajectory data. As a result, trajectories are richly annotated with all aspects of available semantics whether application dependent or not. Although this approach is expected to yield easily interpretable patterns, it has two major shortcomings. First, it only considers annotation on the individual trajectory level rather than the pattern level. This was addressed by Ong et al.'s (2010) framework but on a very limited scale of five attributes. Second, there is a very high level of dependence between the solution and the application domain, which limits its flexibility to be reused in other domains.

In addition, current research efforts appear to be directed towards solving specific problems in one or more of the following four phases; (a) trajectory storage, indexing and querying, (b) preprocessing and semantic annotations of individual trajectories, (c) mining techniques and algorithm enhancement and optimization, and (d) visualization of patterns/models. However, a comprehensive approach towards mining and interpreting semantic patterns that is generic and able to support a wide range of applications is missing.

In the light of these limitations, the value of the proposed framework is two-fold. First, it is expected to provide a holistic approach to trajectory data analysis, by means of using data mining techniques. This holistic approach facilitates the coverage of the four above-mentioned phases, in order to reach the best possible utilization of the data and technologies available. Second, the application-dependent semantic enrichment of trajectory patterns would be delayed in the process, allowing for higher flexibility in the solution and support to wider range of applications. This "loose-coupling" between the enrichment of the data and the mining solution is described in details in the framework, among the complete process in the coming section.

A FRAMEWORK FOR EXTRACTING SEMANTIC TRAJECTORY PATTERNS (SEM-TP)

In this section, we present the framework proposed to extract semantic trajectory patterns. This framework is expected to include the process, technologies, data, people and decisions as the main aspects formalizing this approach towards knowledge extraction. Sem-TP is expected to establish the grounds for developing an integrated solution that is able to support a range of applications while meeting the requirements of specific ones. The process outlines the detailed tasks to take place at each phase and is mostly aligned with the generic knowledge discovery process. It also highlights the main layers through which data passes through to be transformed into knowledge. The process is considered the most significant component of the framework, which governs the other components. The technologies used in each layer or by the tasks are also presented. Alternatives of technologies may be present; thus proper selection criteria are set at each stage. In the coming sections, each of these aspects is further described in details.

It is important to note that semantics are defined through three types of ontological components, following Yan et al. (2008). Geometry trajectory ontology (GTO) is the first type, and is composed of several concepts outlining the structure of the trajectory both spatially, temporally and semantically. The two other types are concerned with the surrounding spatial and non-spatial semantics, namely geography ontology (GO) and application domain ontology (ADO), respectively. In the following subsection, the uses of these ontology-based semantics are presented within the process outlined by our framework.

Sem-TP process design

The process presented is comprised of four main phases; *storage*, *preprocessing*, *analysis*, and *post-processing and interpretation*. In addition, data collection is performed prior to the storage and the decision making process is resumed after interpretation. Spatiotemporal trajectories may be collected from many sources; GPS-equipped devices, cell phones communicating via GSM networks and RFID-tagged objects to mention a few. Raw trajectories captured by these different types of networks are then collected and initially stored in operational databases. Then, for the purpose of knowledge discovery and based on the application, specific data sets are selected and cleansed in order to be loaded into the main data storage area.

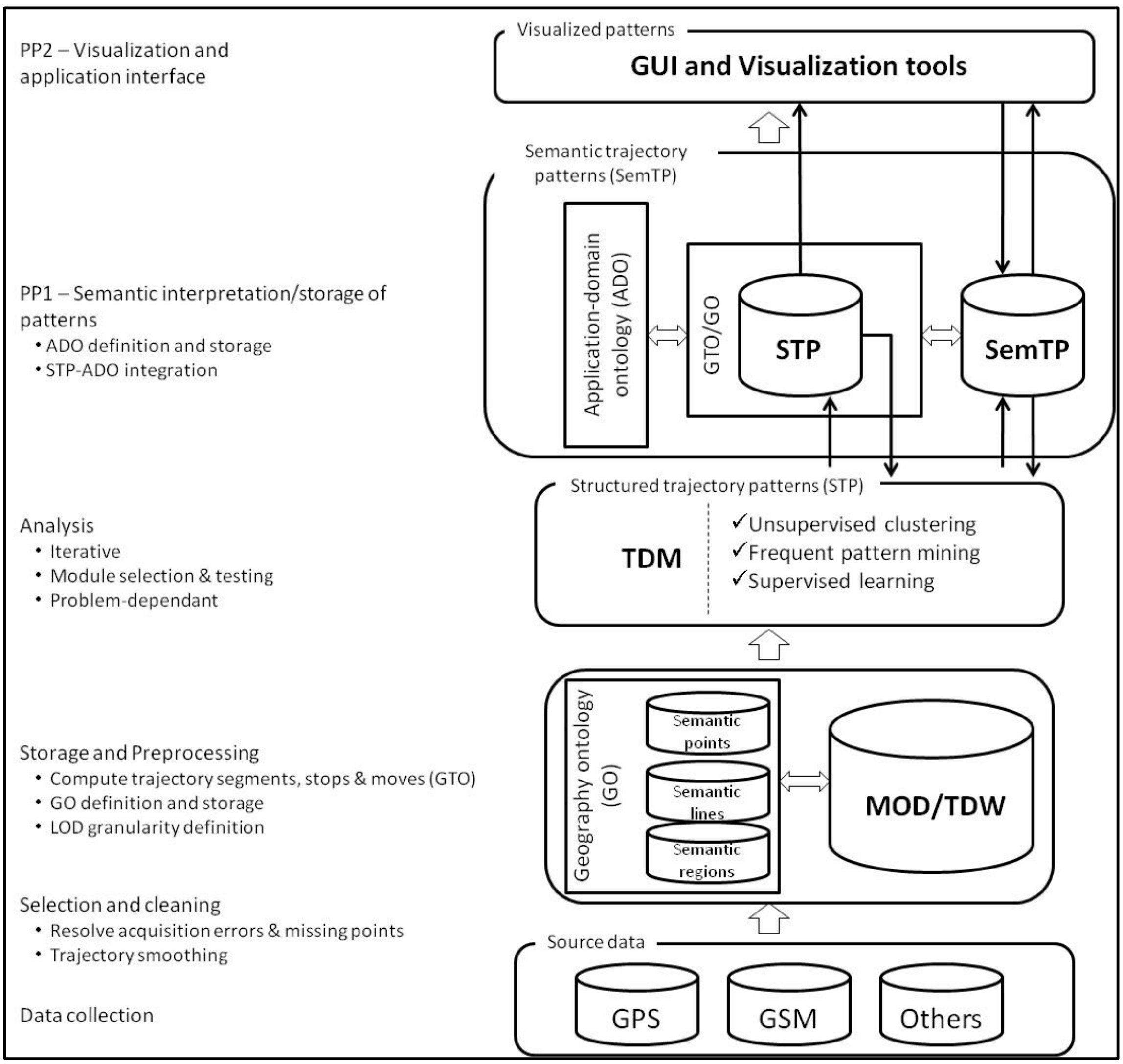

Figure 1. Framework for extracting Semantic Trajectory Patterns – Sem-TP

This initial cleaning task includes smoothing trajectories as well as dealing with missing points as a result of acquisition errors. Once raw trajectories are loaded into the main storage area, a moving objects database (MOD) or a trajectory data warehouse (TDW), preprocessing begins by two main tasks; defining thresholds that will help us identify the relevant trajectories (e.g. density and velocity thresholds), and defining the temporal and spatial separations of segments of trajectories (i.e. sections, stops and moves). The latter is considered to be the very first step in having semantic trajectories, where the GTO is introduced.

Additionally, the geography ontology is defined using concepts from the geographical environment in which the objects move. The degree to which the GO concepts are general or application-specific depends on their level of details (LOD). Regions, lines and road networks are generic and form coarse granularity and high LOD, whereas points are application dependant and form fine granularity and low LOD. In addition, some preprocessing tasks of attribute selection and data reorganization would be required, according to the chosen data mining technique and that will take place in an iterative fashion along with applying the respective algorithm.

The next layer hosts the trajectory data mining functional modules. Having the problem and the types of decisions in mind, the apt learning strategy is selected as well as the technique and algorithm to run. The analytical module to be used is initially tested for suitability and the preprocessing-mining layers are iteratively revisited. The output of this layer is what we call structured trajectory patterns or STP. They are stored and then used by the next layer of semantic enrichment and interpretation of patterns, which is considered one of two steps within the post-processing phase.

Structured patterns in the interpretation layer are further enriched with ADO-based semantics. By incorporating application-specific semantics into the STP rather than the individual trajectories, we would achieve what we call semantic trajectory patterns or SemTP. These patterns are then visualized – the second step of the post-processing phase – and stored in a pattern-base-like repository to allow for further querying and use. In addition, if the mining output is in the form of models (i.e. clustering) they can be used in other mining problems (e.g. classification).

Sem-TP tools and technologies

At each of the abovementioned phases, there is a specific technology (or range of technologies) supporting the tasks carried out. There are also many tools that make use of the technologies. Existing tools allow the minimization of development efforts and reuse of available solutions. Developing in-house tools is always an available solution, yet known to be lengthy and costly. On the other hand, going for an off-the-shelf solution makes a selection decision necessary at each of the four phases and whenever an extra tool is used. For example, at the data collection phase the specific type of the network, the types of devices used to transmit movements and initial data storage environment are among the technologies to be considered at that phase.

In the storage layer, the platform used and the DBMS are two technologies to be considered. In the preprocessing and mining phases, choosing the aiding tools is a non-trivial task. Furthermore, it is essential to apply the appropriate mining strategy, technique and algorithm that will help answering questions of the specific problem in hand and support the targeted types of decisions. This, too, plays a role in the tool selection process. While storing ontology-based semantics that are used across the layers of the framework, it is important to know how semantics will be stored and what annotation algorithms to be used. Finally, the various techniques and tools available to visualize extracted patterns are the last of the essential technologies that would be investigated.

DATA COLLECTION AND ANALYSIS

Sem-TP framework is the seed of a design science-based research instance, where the framework is provided as an IT artifact that is evaluated and tested for feasibility through prototyping. In order to do so, the research was conducted as a solution-centered instantiation of Peffers et al.'s (2008) six-stage design science research methodology (DSRM), yet grouped into three phases. The first phase used exploratory research methods to identify the specific research problem and the solution objectives. The second phase involved designing and developing the framework, then demonstrating it in a suitable context (i.e. the application domain of tourism and travel – T&T). It was then evaluated in the third phase using a prototypical instantiation in the T&T, where the results and the managerial implications communicated to the potential beneficiaries.

Secondary research was dominant in the early phases of the study; however, demonstrating and evaluating the framework in a suitable context demanded in-depth information on the domain. Thus, individual in-depth interviews were held with two prospect beneficiaries of the solution from the T&T industry; the information and monitoring advisor in the Egyptian Ministry of Tourism (MoT) cabinet, and the sales and marketing manager of one of the largest privately owned T&T firms in the industry. Non-probability purposive sampling was applied to narrow down the target sample to those two respondents. The objective of those interviews was two-fold. First, identifying the types of decisions that needed to be supported by the prototype was essential to drive the complete solution instance into the right direction. Second, information collected in the interviews laid the foundations of the three ontological components upon which most of the semantic enrichment of trajectories and patterns was achieved.

On the other hand, for the purpose of the prototype instance, synthetic trajectory dataset was generated based on the specified data model to represent trajectories of 99 moving objects, moving over the period of 7 days in the area of Greater Cairo, Egypt, with an average of a 4-day visit per moving object. Also the time interval was defined from 07:30 till 00:30, which is referred to as the active day. This yielded to a total of 860 cleaned stop-initiating-move trajectories. In addition, 110 potential points of interests were compiled to be used for the GO semantic annotations, which were later clustered to six distinct regions of interest using k-means algorithm. All data generated and collected was stored in PostgreSQL databases with the PostGIS spatial extension. In addition, all ontological definitions were converted from OWL-based documents to relational databases and stored accordingly.

Data mining was used in the core analytical layer, and association rule mining technique was applied to address the main application domain problem in hand. Finally, analyzing the framework was achieved through evaluating the feasibility of the prototypical instance and communicating the results with the prospect beneficiaries for confirmation and/or further suggestions.

PROTOTYPING AND EVALUATION

The prototype constructed is regarded as the practical solution used to evaluate the feasibility of Sem-TP, in which we sought to extract patterns on time-stamped frequently visited points and regions of potential interest to tourists. The objective was to support two main types of decisions. In the public MoT cabinet, strategic decisions like marketing for new touristic attractions was among the decisions of highest priority, whereas tactical decisions of service packaging and trip advising were the targeted decisions to be made by the privately owned firms. Given these kinds of decisions, association rule mining was chosen to discover the relevant frequent patterns. To serve this purpose, RapidMiner was used to apply the chosen technique to data, and the embedded FP-growth algorithm was used to extract the association rules.

According to our data model, generated trajectories were found to be implicitly annotated with GTO-based semantics, where a trajectory as an entity is formed by a sequence of moves and stays, forming sections, having a beginning stay and an ending stay. Additionally, the spatial dimension along the trajectory path was represented by latitude/longitude pairs, which constitutes part of the GO component. Thus, stored cleaned trajectories are passed on to a pilot preprocessing-mining round.

Attribute selection, discretization and variable transformation were among the necessary preprocessing tasks required to achieve the appropriate analytical dataset on which FP-growth can be applied. Running the algorithm against this initial dataset yielded no rules at all. Assuming that this is due to the large number of distinct locations visited and continuity of the spatial coordinates, a modified analytical data set was created where the following two tasks were necessary; (a) Discretization performed over the temporal attribute, and (b) locations annotated with names of their corresponding points of interest (POI) rather than being represented by spatial coordinates.

The first iteration over this modified data set yielded no rules as well, under minimum support and confidence thresholds. Thus, in the second iteration POI were clustered into automatically generated ROI. Partitioning algorithm k-means was used to ensure complete inclusion of every possible point, and this preprocessing task yielded a clustering model of six distinct regions labeled according to application-based knowledge of the respective centroids. The structured trajectories were then enriched using the new LOD, that of regions.

According to the new LOD, the second mining iteration of the algorithm yielded eight rules with confidence range of 50-75 percent. Rules extracted were of the following format: If a moving object visits region R_i within the time range T_x, then it is likely that he/she would visit region R_j within the time range T_y with a specified confidence – a sample shown in Table 1. These rules provided insight on the spatiotemporal dimensions of the movement as well as semantics on the surrounding geography and are referred to as the STP.

No	Premises	Conclusion	Support	Confidence
1	Stay_ClassicalCairo= 21:00++	Stay_Downtown= 16:20 – 17:00	0.030	0.500
2	Stay_Heliopolis= 21:00++	Stay_Downtown= 07:40 – 08:45	0.030	0.600
3	Stay_ReligComplex= 14:30 – 15:30	Stay_Heliopolis= 17:00 – 17:50	0.030	0.600
4	Stay_Downtown= 11:00 – 12:00	Stay_ReligComplex= 14:30 – 15:30	0.030	0.750

Table 1. Region-based STPs

However, we were still interested in enriching those extracted rules with ADO-based semantics, one of which is the category of service(s) being offered at the visited location and region. By adding this new dimension to the structured trajectories, the set of rules (Sem-TP) increased in size to include 15 rules with confidence range of 50-80 percent, where a sample is shown in Table 2.

No	Premises	Conclusion	Support	Confidence
1	Stay_ClassicalCairo= 17:50 – 18:30	StopCategory_ReligComplex= HeritageSite	0.040	0.500
2	StopCategory_Downtown= Restaurant, StopCategory_ReligComplex= HeritageSite	StopCategory_ClassicalCairo= Accommodation	0.040	0.571
3	Stay_ReligComplex= 21:00++	StopCategory_ClassicalCairo= Accommodation	0.051	0.625
4	Stay_Heliopolis= 19:10 – 20:00	StopCategory_Heliopolis= ConventionCenter	0.040	0.800

Table 2. Region-based ADO-annotated Sem-TP

Based on those iterations from the prototype and their varying results, the framework was revisited and modified accordingly. The main difference between the originally proposed framework and the modified one is the stage in which semantic annotations take place. Initially, the idea was to establish a complete independence between the extracted patterns and the domain-based ontological components. Yet, through analyzing trajectories in this prototypical instance, it was found that semantic enrichment is a continuous process, where GO and GTO ontological components need to be integrated with individual trajectories prior to analysis. Furthermore, the integration of the ADO component may be postponed to a further stage.

The resulting rules from the three different preprocessing-mining iterations, along with the modified framework, were then presented to the initial respondents in a different set of interviews and in the form of use cases, where four main aspects were evaluated; (a) the willingness to adopt the solution to support their decision making processes, (b) the reasons for accepting/rejecting the solution, (c) what has not been covered by the solution, and (d) further suggestion to enhance the framework.

DISCUSSION

As shown in the previous section, working with low LOD where there are too many distinct values, if not continuous, imposes a challenge during the mining and pattern extraction task. This challenge is essentially amplified if the data mining technique used is not tuned for spatiotemporal trajectories. On the other hand, enriching structured trajectory patterns with ADO-based semantics has exposed a new dimension to the extracted knowledge, enabling enhanced interpretation and usability of extracted patterns, and ultimately decisions of higher quality.

Even though ADO-annotated Sem-TP is characterized by inclusively rich semantics, it does not provide a comprehensive view on the movement of the object. This can be observed from the attributes appearing in a single rule, where the temporal dimension is absent in some cases. Thus, in order to preserve our basic temporal dimension, it is advised to use knowledge from both STP and ADO-annotated Sem-TP in conjunction. The use of this combined knowledge provides an enhanced understanding and better interpretation, without the loss of any of the core dimensions.

This study – as well as similar ones – faced some challenges and have its limitations. Challenges include the availability of data; whether raw trajectories or semantic annotations for the region under study (Egypt), or ontological definitions for the tourism domain. The unavailability of trajectory data mining algorithms incorporated within available data mining tools imposed a challenge on the analysis layer. As a result, it is not clear if non-satisfactory results from initial iterations are due to LOD embedded in the data or due to the inappropriate adoption of the algorithm. Additionally, the large number of tools used caused a seamless flow from data to knowledge along the process to remain as a challenging objective and presents a limitation where the prototype could not be automated at this point.

Nevertheless, feedback from interviewees revealed their willingness to adopt the solution and their readiness to depend on its results if based on a collected dataset. In the MoT, for instance, the resulting rules support decisions on hotel concentration and other trip-advising and planning activities. On the other hand, privately-owned T&T firms use the rules to modify and tweak their vacation packages, excursion plans and personalized recommendations to tourists.

Testing and adopting a visual component to display the results was highly prioritized by the respondents as well. Even though it was out of the scope of this version of the prototype, this prioritization places the visualization on the top of the list of our next versions. In addition, it was suggested to include a new type of semantics, where an events-repository would be integrated with the ADO component and enrich the trajectories on the pattern level.

CONCLUSION

Trajectory data has been of special interest in the data mining field in the recent years, and the volumes in which this data type is collected every second imposes a challenge to organizations on how to gain insight amidst these increasing volumes. Accordingly, discovering previously unknown patterns on moving objects in support of organizational decision-making processes is an open research problem in different application domains. Multiple frameworks and models have been communicated by scholars in this topic, but either focused on semantic annotations on the individual trajectory level or on one aspect of semantic throughout the various layers. Hence, we propose Sem-TP to establish a foundation for a holistic approach that takes the three aspects of semantics into consideration while maintaining an application domain-independent solution.

In conclusion, the contribution of this study is three fold. In one aspect, the proposed framework adds to the body of knowledge a modified approach to semantic enrichment of patterns extracted from trajectory data using data mining techniques. On the other hand, it depicts how existing mining tools and algorithms could be utilized to extract, and illustrates the increasing demand for publicly available tools that accommodate trajectory-specific mining algorithms. Finally, building the prototype has practically given insight to prospect beneficiaries in the tourism industry on the availability and feasibility of such a solution that would enhance their decisions and make them aware of the market in a more updated fashion.

FUTURE WORK

Further research will attempt to overcome the previously mentioned limitations in many ways. First, automating the prototype and developing a unified interface are considered as initial steps towards formulating a single solution instance. Further testing on the various levels of detail is essential to cover the whole framework. Suggested integration of an events repository into the ADO component is also worth investigation and expected to reveal a new level of semantically rich patterns. A module for visualizing the extracted semantic patterns is also one of the main modules to be integrated into upcoming prototypes. Finally, evaluating the framework in other application domains (e.g. Traffic management) may enhance the positioning of our framework in the field.

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REFERENCES

1. Alvares, L. O., Bogorny, V., Kuijpers, B., Fernandes, J. A., Moelans, B., & Vaisman, A. (2007). A Model for Enriching Trajectories with Semantic Geographic Information. International Symposium on Advances in Geographic Information Systems, (pp. 1-8).
2. Giannotti, F., Nanni, M., Pedreschi, D., & Pinelli, F. (2007). Trajectory Pattern Mining. Proceedings of the 13th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, (pp. 330-339).
3. Güting, R. H., Almeida, V. T., & Ding, Z. (2006). Modeling and querying moving objects in networks. The VLDB Journal , (pp. 165–190).
4. Jain, A. K. (2009). Data clustering: 50 years beyond K-means. Pattern recognition letters , (pp. 1-16).
5. Han, J., Cheng, H., Xin, D., & Yan, X. (2007). Frequent pattern mining: current status and future directions. Data mining and knowledge discovery , (pp. 55-86).
6. Li, Z., Ji, M., Lee, J.-G., Tang, L.-A., Yu, Y., Han, J., et al. (2010). MoveMine: Mining Moving Object Databases. Proceedings of the ACM SIGMOD Conference, (pp. 1203-1206).
7. Nanni, M., Trasarti, R., Renso, C., Giannotti, F., & Pedreschi, D. (2010). Advanced Knowledge Discovery on Movement Data with the GeoPKDD system. Proceedings of the 14th International Conference on Extending Database Technology, (pp. 693-696).
8. Ong, R., Wachowicz, M., Nanni, M., & Renso, C. (2010). From Pattern Discovery to Pattern Interpretation in Movement Data. Proceedings of the International Conference on Data Mining Workshops, (pp. 527-534).
9. Oueslati, W., & Akaichi, J. (2010). Mobile Information Collectors Trajectory Data Warehouse Design. International Journal of Managing Information Technology , (pp. 1-20).
10. Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2008). A design science research methodology for Information Systems research. Journal of Management Information Systems , (pp. 45-77).
11. Yan, Z., Chakraborty, D., Parent, C., Spaccapietra, S., & Aberer, K. (2011). SeMiTri: A Framework for Semantic Annotation of Heterogeneous Trajectories. Proceedings of the 14th International Conference on Database Theory, (pp. 259-270).

12. Yan, Z., Macedo, J., Parent, C., & Spaccapietra, S. (2008). Trajectory Ontologies and Queries. Transactions in GIS , (pp. 75–91).