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A New Ontology-Based Approach for Human Activity Recognition from GPS Data

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Abstract
Mobile technologies have deployed a variety of internet-based services via location-based services. The adoption of these services by users has led to mammoth amounts of trajectory data. To use these services effectively, the analysis of this kind of data across different application domains is required in order to identify the activities that users might need to do in different places. Researchers from different communities have developed models and techniques to extract activity types from such data but they have mainly focused on the geometric properties of trajectories, and do not consider the semantic aspect of moving objects. The current work proposes a new ontology-based approach so as to recognize human activity from GPS data for understanding and interpreting mobility data. The performance of the approach was tested and evaluated using a dataset acquired by a user over a year within the urban area in the city of Calgary in 2010. It was observed that the accuracy of the results obtained was related to the availability of the points of interest around the places that the user had stopped. Moreover, an evaluation experiment was carried out, which revealed the effectiveness of the proposed method with an improvement of 50% performance with complexity trend of an O(n).

Keywords: *Ontology, Data Mining, Activity Recognition, Semantic, GPS.*

1. Introduction

The development of location technologies in mobile devices and wireless communication has led to deploying a variety of internet-based services such as Location-Based Services (LBS) [1]. The application domain for these types of services are typically transportation management, location-aware advertising, and tourism [2]. The widespread use of these applications and services in our daily activities has led to a large number of positioning data that can be represented as trajectories [3]. Moreover, spatially distributed networked systems with thousands of energy- and resource-limited mobile devices (i.e. “thin” devices, e.g. smartphones, PDAs, tablets, RFIDs), all capable of acquiring and communicating in real time, cause an ever-increasing volume of heterogeneous data streams [4]. With such an increase in the trajectory data, there is a need for improving the existing methods to efficiently handle and investigate user activity types out of such a large amount of data. In this regard, some researchers have investigated some analytical techniques [5,6] and computational methods [7,8,9] for the analysis of movement data; yet, they mainly concentrate on the study of the geometric view of raw trajectory data and do not consider the semantic aspect of moving objects. Therefore, the extracted patterns are classified based on a set of geometric properties. For example, when considering only the geometric properties, one could discover a dense area where trajectories meet. However, without semantics, it is hard to find out why the trajectories meet, and consequently, what might attract the users. Furthermore, mined results can be made more meaningful when the nature of movement data is considered as a context within the recognition process [3]. Geographic data recognized as

context can provide the possibility of activity identification based on GPS trajectories. Therefore, trajectory data is required to be reconsidered not only from the geometric view but also from the meaningful semantic view in order to interpret and understand their meanings.
The main idea of this paper is to propose a new ontology-based approach to recognize human activity types by considering ontology in order to explore and interpret the extracted semantic patterns. This study investigates various extracted features and background information based on the model ontology to extract different activity types. To accomplish this, it is required to define a semantic conceptual data model and a number of computing techniques to integrate various sources of data and reconstruct meaningful trajectories from the movement data. The remainder of the paper is organized as what follows. Section 2 presents a summary of various research studies in particular studies on analyzing mobility data. Section 3 describes the proposed methodology and illustrates each component. First the proposed conceptual data model is described in order to develop an ontology based model and then the activity recognition process is presented. Section 4 illustrates the experiment conducted on a dataset. Moreover, a summary of the results is presented and the implications of the evaluation outcomes are discussed. Finally, section 5 concludes the paper and describes the future research works regarding further developments.

2. Related works

Activity recognition studies usually use spatial distance-based and statistics-based methods. The basic idea of spatial distance-based method is to assign the closest POIs to the stops where activities have happened. Bohte et al. [10] have defined rules to restrict the candidate POIs and possible activity types, and then they have detected the POIs with the smallest distance to the activity centers in trajectories. Xie et al. [11] have proposed the influence and influence duration of POIs on trajectories. This method actually selects the POIs closest to the polyline geometry of the trajectory. Some researchers have extracted regular activity patterns in trajectories to identify the activity types. For instance, Huang and Li [12] have introduced a multivariate analysis approach to identify activities using vehicles trajectories. Time constraints, network distance, activity chains, and POIs were used as four inputs. Scores for candidate POIs were selected around the locations where vehicles stopped were calculated using a neural network framework. Some works [13,14] used Markov networks to classify activities into six pre-defined types. This technique was an extension of the Markov networks for sequence matching. Moreover, Liao et al., in [15], have proposed machine learning and probabilistic reasoning methods in particular conditional random field method to identify daily activities using the GPS data.
Studies like Alvares et al. [16], Xie et al. [11], and Moreno et al. [17] have designed relevant spatiotemporal join methods to infer activities from trajectories by computing the topological relationships between the trajectory data and a small set of predefined activity hotspots together with the time constraints. Spinsanti et al. [18] have proposed a series of rules to detect the overall activity of the trajectory. Considering a trajectory whose stops are annotated with possible activities and common sense IF-THEN rules, the authors annotated the trajectory with the most probable global activity. A similar approach has been proposed by Renso et al. [19]. This work annotated trajectories with activities such as tourist, home-to-work commute using an ontology, and an inference engine.
The majority of the mentioned activity recognition works still have unresolved questions. The key idea of these approaches is to extract the location history of the individual, in conjunction with knowledge about the semantics of the locations, in order to infer the activity of a person. Therefore, they only discover the stops and moves of moving objects and annotate them with contextual data. However, it can still be difficult to identify the activity type of the moving object [20]. For instance, if two stops are identified for a moving object, one on a residential land use and the other on a commercial land use, it is difficult to determine whether the residential stop is the residence of the moving object or if the commercial stop is a work place. The moving object could, for example, be visiting a friend or shopping. To draw stronger inferences, one needs not only to identify stops but also extract some associated semantic features such as stop begin time, stop duration, and also stop frequency from the trajectory data.

3. Methodology

This section illustrates the proposed ontology-based approach to recognize human activity types. As depicted in figure 1, it consists of two main parts, namely semantic trajectory ontology modelling and activity recognition.

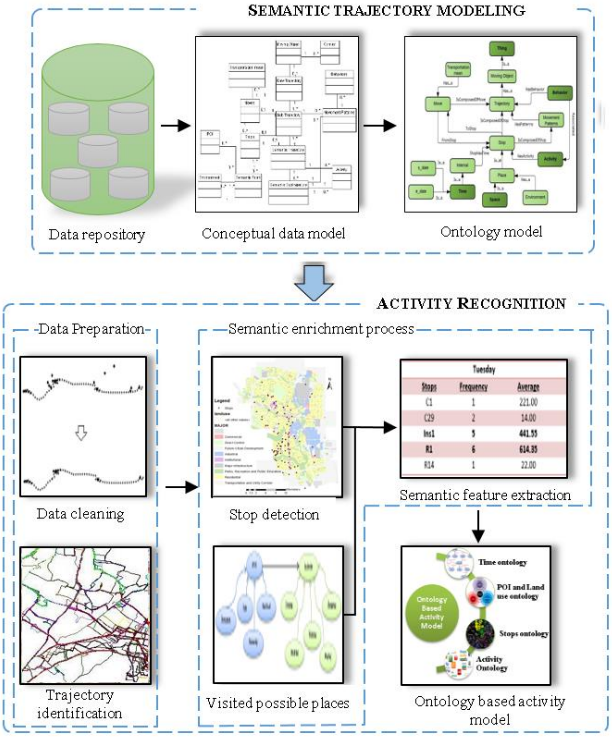

Figure 1. Proposed methodology.

The first part contains raw trajectory data, maps/layers, and an application domain. In this part, a conceptual data model is defined, and based on that, a semantic trajectory ontology model is designed. In the activity recognition step, first the raw trajectory data is cleaned and the trajectories are reconstructed. In the semantic enrichment process, stops are identified and annotated with the probable visited places. Next some semantic features are extracted from the annotated stops. Then the model ontology is populated with the extracted features and some predefined axioms. Finally, the ontology inference engine is executed and the axioms are interpreted to classify the ontology instances using the appropriate concepts on the activity types.

3.1. Semantic trajectory modelling

In this research work, an application was developed to gather the user's trajectory data [21]. The background knowledge database includes land use, road network, and POI layers.

3.1.1. A conceptual data model for semantic trajectories

Figure 2 describes a conceptual model that addresses the modelling requirements with the goal of analysis of semantic trajectory data. The aim of this model is to represent the concepts and relations of the movement domain, where the trajectory data and semantic movement patterns are to be interpreted along with the activity types.

This model is an extended version (green colored box) of the conceptual framework introduced in Spaccapietra et al. [22], which relies on the conceptualization of stops and moves in trajectories. The conceptual model contains information related to moving object, raw trajectory, sub-trajectory, semantic sub-trajectory, semantic trajectory, semantic place, stop, move, activity type, and behavior type.

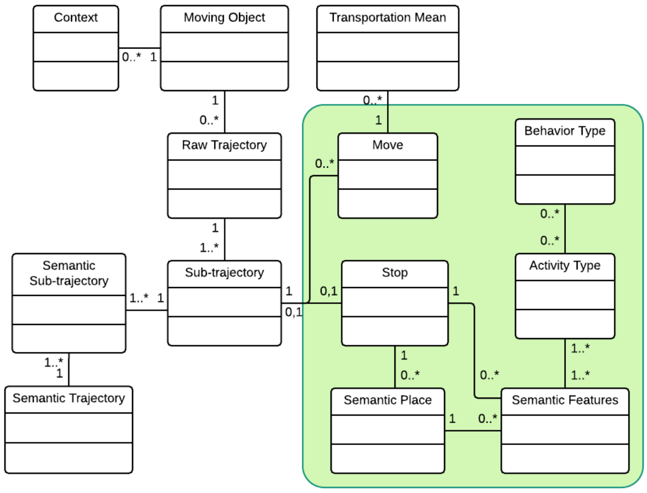

Figure 2. Extended conceptual model of semantic trajectory used in this work.

A moving object generates raw trajectory that, based on different criteria, can be divided into sub-trajectories. By giving meaning to these sub-trajectories, the semantic trajectory becomes a combination of different semantic sub-trajectories. Each sub-trajectory is composed of stops and moves. Every stop is connected to an interval that represents the time of the stop. It includes the start time and end time concepts, which anticipate when the trajectory starts and ends. Each stop, as shown in figure 2, could have different semantic features, as what follow.

Definition 1 (Semantic features): Semantic features are extracted from the stops, and are divided into five different types including stop frequency, average duration, stop land use type, stop POI category type, and stop start time.

Definition 2 (Semantic place): A semantic place consists of a set of positions where a stop is located. It includes land use type and POI type, which would cover environmental information related to a stop.

Definition 3 (Activity): An activity is what the moving objects are going to do during their movement. In other words, it is the objective of the movement, which has a start time and an end time, and it can be relative to the entire trajectory or part of the trajectory (the semantic sub-

trajectory). Activities can be represented as taxonomy, from the more specific to the more general. It is classified into four different major activities including recreation, profession, shopping, and other activity types.
Profession activity types could be working, getting involved into different jobs, etc. Shopping refers to the time spent at different stores for buying food, drinks or groceries required, in general, for one's daily needs. Recreation might include going to the theatre, pub, gyms, and other places related to leisure. Other activity types might include relaxing at home, cultural or religious activities, etc.
The inference of the activity types is based on the semantic features. Activity types are highly influenced by the users' location. For instance, if a person is close to a university, the most probable activity types would be studying, teaching or working. In order to capture this dependency, first it is needed to model which activity types can be performed or hosted within or nearby every place (e.g. eating is possible in a restaurant, while shopping is possible in a mall). Therefore, there is an association between places and activity types and, according to the conceptual model, an activity is typically performed in a place.
For example, the restaurant is both a place for eating and a working place expressing the fact that a restaurant may be a kind of work place for people working there (the cook, the waiter, etc.) or a place to represent the fact that typically restaurants are attended by people for dining. Therefore, activity types are also correlated to time and, in particular, to the time of day and the duration that a user spends at each place. Different activity types might have different timetables and durations.
For instance, if the place is a restaurant, different time periods may be interpreted as different activity types. As an example, the period of 15 to 30 minutes would be interpreted as a delivery since there is not enough time to stay in and eat. If the time period is between 30 minutes and 3 hours, it would be interpreted as dining, and if the time period is between 3 hours and 8 hours, it would be interpreted as working.
Also stop frequency and average duration are important features to find out the type of activity. As a general example, if the stop frequency is more than five days a week and the average duration is more than eight hours, it could be inferred that the place would be either where the person works or lives. Therefore, this research work hypothesizes a functional relationship (1) for Activity Types (AT) based on different features, as shown below:

$$AT = f(P, L, S_f, T_b, S_d) \quad (1)$$

where:
- P is the POI type that is around the stop
- L is the land use type where the stop has occurred
- S_f is the frequency of the stop in a week
- T_b is the start time of the stop in the place
- S_d is the average duration of the stop in a week

For instance, for a specific stop, if the land use type is residential, the POI type is null, the begin time is evening, stop frequency per week is more than six, and the average duration is more than ten hours per week, then the moving object is 'spending time at home', i.e. AT= Return Home. At this step, some rules can be defined on the captured data in order to extract different activity types.

3.1.2. Semantic trajectory ontology model

Semantic Trajectory Ontology Model (STOM) is built based on the proposed conceptual data model. Figure 3 shows a very partial version of this ontology with only the most important concepts and relationships. Shapes represent the main concepts, whereas arrows represent relationships between two concepts.

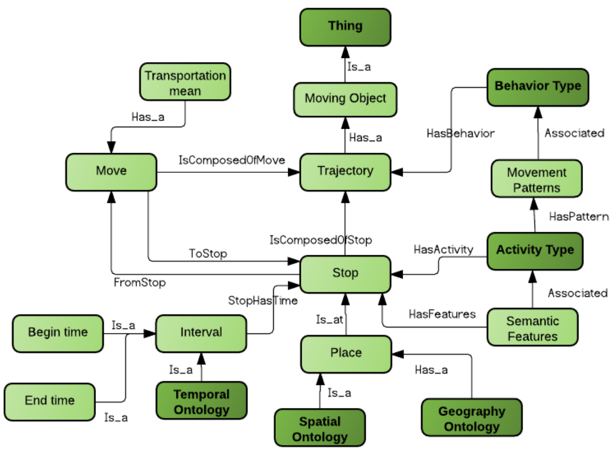

Figure 3. Semantic trajectory ontology model.

The main concepts of STOM are listed below:
- Moving object is a user object, who is equipped with an enabled-GPS device;
- Trajectory is a logical form to represent a set of stops and moves;
- Stop is the spatial part in trajectory ontology;
- Move is defined as the maximal subsequence between two consecutive stops;
- Place is a description of the location that user visited/stopped;

- Transportation mean refers to the type of transportations that objects use to move from one stop to another;
- Start time is the time when the activity starts, the time when user arrived at the location;
- End time is the time when the activity is finished, the time when the user leaves the location;
- Activity is the semantic part representing user activity types for a stop;
- Movement patterns are the regularities and common things that happen in the movement data;
- Behavior is a pattern among different activity types.

STOM consists of different ontologies such as spatial ontology, temporal ontology, geographic ontology, and thematic ontology. The spatial ontology holds generic concepts for the description of the geometric component of a trajectory. The temporal ontology is another source of information that integrates time concepts and rules for modelling semantic trajectories. OwlTime ontology [23], which is being developed by the World Wide Web Consortium (W3C) is chosen. Geographic ontology describes the places where people move through, and includes a variety of land use types, road networks, and POIs layer. POI represents the specific categories such as shopping center, park, etc. The road network represents the interconnections of different road types designed within urban areas. The land use represents different regions and their utilization such as agricultural, residential, recreational or other types. Therefore, this ontology is used to aid potential interpretation of each stop, i.e. why the moving object stopped. The thematic ontology model gathers a wide range of application-dependent concepts. The understanding of trajectories profoundly depends on their relationships to application objects and not just the moving object itself. The model describes the concept of activity type that includes the stop, trajectory, semantic features, movement patterns, activity type, and behavior type concepts. The activity type is composed of stops and their features. Therefore, integrating these ontologies together provides the semantic description of application-relevant trajectories with their domain specific semantic meaning. These ontologies are integrated into a unique ontology by setting up rules between them.

3.2. Activity recognition

As shown in figure 4, the activity recognition consists of three steps. The first step is the data preparation, where the GPS data is cleaned and the daily and weekly basis trajectories are identified. The second step is the semantic enrichment process, which includes stop detection, finding probable visited places and extracting semantic features. Once stops are detected, they are annotated with the POI and land use types. Next, several semantic features such as the stop start time, stop frequency, and average duration are extracted. The final step is the ontology-based activity model. The information retrieved from the previous steps is used to populate STOM for reasoning the activity type. Each step is explained in more details in the following sub-sections.

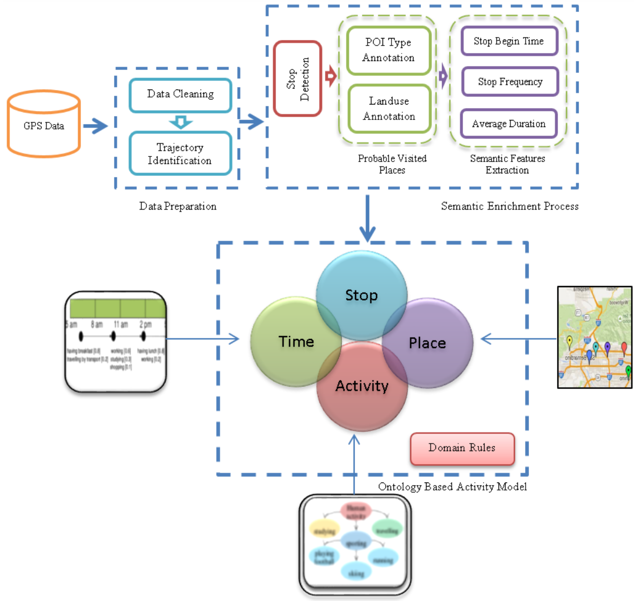

Figure 4. Activity recognition process.

3.2.1. Data preparation

Due to the problems in GPS data collection and sampling errors from mobile devices, the recorded positions usually contain errors [24]. Therefore, data has to be cleaned from any inconsistencies such as empty values, duplicates, and outliers. Moreover, in order to index the data, semantic indexing technique, introduced in [25], which is a suitable method for ontology data, was applied in this research work. Generally, this step helps eliminate unrealistic attributes such as trajectories with a travel time that is too short (e.g. 10 seconds duration) and also improbable speed (by defining thresholds). Next, trajectory identification is applied for dividing the cleaned GPS data into daily and weekly basis trajectories. Time constraint is used to identify these two types of trajectories.

3.2.2. Semantic enrichment process

The enrichment process aims at extracting stops from the cleansed trajectory data and annotating them with the environmental information around them, in particular, by exploiting nearby POIs and land use types.

3.2.2.1. Stop detection

As mentioned earlier, stops are the portion of trajectories where people stop for a given time duration and where it is assumed that they are performing activities. In this research work, the GPS data, which was collected by users using our application contains temporal gaps (the application was turned off automatically or manually when users did not move for a certain time or when they entered a building).

Therefore, considering the format of the GPS data, the TVB algorithm is used to extract stops. Algorithm 1 provides pseudo-code for determining stops. Given the speed threshold Δ_{speed} and time interval $\Delta_{duration}$, for any two consecutive GPS records $p_i(x_i, y_i, t_i)$ and $p_{i+1}(x_{i+1}, y_{i+1}, t_{i+1})$, if the speed of p is lower than Δ_{speed} and the temporal gap $t_{i+1} - t_i > \Delta_{duration}$, then p_i is the end point of the current trajectory, while p_{i+1} is the starting point of the next trajectory. Therefore, p_i is considered as a stop.

Algorithm 1. TVB

Input:
Cleaned raw trajectory $T_{raw} = \{p_1, p_2, ..., p_n\}$
Speed threshold Δ_{speed}
Time gap $\Delta_{duration}$

Output:
Stops $T_{stops} = \{s_1, s_2, ..., s_m\}$

begin
    for all $p_i = (x_i, y_i, v_i, t_i)$ ***do***
        if $(v_i < \Delta_{speed}\ AND\ t_{i+1} - t_i > \Delta_{duration})$ ***then***
            $T_{stops} = p_i(x_i, y_i, t_i, t_{i+1}, \Delta_{duration})$
    return T_{stops}
end

3.2.2.2. Probable visited places

The objective of this step is to find probable places that can be visited by a user at a stop. This step utilizes available third party data sources such as Open Street Map (OSM) to gather contextual data for each stop. Two different algorithms are applied to annotate stops with the land use types (Algorithm 2) and the POI category types (Algorithm 3).

(1) Annotation with land use types

Algorithm 2 shows the pseudo-code for the annotation procedure, which annotates stops with semantic regions. For this purpose, the topological correlation is measured using the spatial join between each stop and the semantic regions. If a stop either intersects with or is nearby any region, the stop is annotated with that region. If a stop is located out of the boundary of the city, it is annotated as an unknown area.

Algorithm 2. Select Landuse Type

Input:
Stops $T_{stops} = \{s_1, s_2, ..., s_m\}$,
Land use layer $A_{landuse} = \{r_1, r_2, ..., r_q\}$

Output:
Land use type for each stop $L_{Region} = \{l_1, l_2, ..., l_n\}$

begin
    for all $s_i = (x_i, y_i, t_i, t_{i+1}, \Delta_{duration})$ ***do***
        if T_{stops} *intersects* $A_{landuse}$ ***then***
            $L_i = (x_i, y_i, t_i, t_{i+1}, \Delta_{duration}, r_i)$
        else
            find nearest $A_{landuse}$ *to* T_{stops}
            $L_i = (x_i, y_i, t_i, t_{i+1}, \Delta_{duration}, r_i)$
    return L_{region}
end

The different land use types in this research work are Residential, Parks and recreation, Urban development, Commercial, Institution, Industry and Transportation.

(2) Annotation with probable visited POI category types

The following list provides POIs and their category types. The POIs were divided into 9 category types.

- Food: bar, café, pub, dining restaurant, bakery, fast food restaurant, food court
- Recreation: park, sports center, cinema, concert hall, gym, museum, night club, spa, stadium, zoo, bar, casino, theater
- Religious: church, mosque
- Education: school, college, university, library
- Shopping: shopping mall, strip mall, plaza, book store, clothing store, electronics' store, furniture store, pet store
- Daily shopping: grocery store, wholesale store, department store, supermarket, bakery, butcher's shop
- Business services: post office, car rental, gas station, ATM, industrial place, personal business

- Health services: dental office, pharmacy, clinic, hospital
- Accommodation: hotel, hostel

The pseudo-code in Algorithm 3 shows the detailed procedure of retrieving the probable visited POI category types for a given stop. The inputs of the algorithm are a set of stops, a set of POIs, Maximum Walking Distance (MWD), and User Walking Speed (UWS).

Algorithm 3. POI Type Annotation

Input:
Stops $T_{stops} = \{s_1, s_2, ..., s_m\}$,
POI layer $A_{poi} = \{a_1, a_2, ..., a_u\}$
MWD
UWS

Output:
POI category type probability for each stop $\Pr ob_{cat} = \{c_1, c_2, ..., c_n\}$

1generalPOIs=[]
2 probablePOIs=[]
3 prob=[]
4 ***begin***
5 ***for all*** $s_i = (x_i, y_i, t_i, t_{i+1}, \Delta_{duration})$ ***do***
6 ***if*** $dis\tan ce(s_i, A_{poi}) \leq MWD$ *and*
7 $s_i, time \subset A_{poi}, H_i$ ***then***
8 *generalPOI* ← A_{poi}
9 ***for all*** POI_i *in generalPOIs*
10 ***if*** $TE \leq duration_i$ ***then***
11 $probablePOIs \leftarrow poi$
12 ***for all*** $probablePOIs$ ***do***
13 $POI_{cat} = \{p \in probablePOIs : \mu(p) = cat\}$
14 $dist = dis\tan ce(s, p)\ for\ each\ p \in probablePOIs$
15 $mass = length(POI_{cat})$
16 $prob \leftarrow (POI_{cat}, \frac{mass}{dist^2})$
17 ***return*** POI_{cat}
18 ***end***

In order to extract the POI category type for each stop, three steps are required. First, general POIs are selected; second, probable POIs are extracted, and finally, gravity model is used to calculate the probability for each POI category type.

To detect the general POIs, two conditions are taken into account, as seen in lines 5-8.

First, each POI has to be within a certain spatial range, which is defined by the MWD (the distance likely to be accepted for a walk from a stop to a POI). Dijkstra algorithm is used to compute the distance between each stop and the POIs on a road network. Second, the time period of each stop has to be compatible with the opening hours of the POIs. A stop during the closure of a POI cannot be matched with that POI, so, for example, a stop at 11 p.m. can be matched with a restaurant or a pub but not with a museum. In order to find the probable POIs, users need to have enough time to go and visit the POI based on the Minimum Service Time (MST), and return to the stop (lines 9-11). Therefore, TE (2) is the time that a person needed to reach the POI, visit the POI based on the MST, and come back to the stop again.

$$TE = 2*TP + MST \tag{2}$$

TP (3) is the time a person needs to cover the distance, where d is the distance between the stop and the POI, and UWS is the user's speed on a road network.

$$TP = \frac{d}{UWS} \tag{3}$$

Once the probable visited POIs are selected, the algorithm measures the probability for each POI category type (lines 12-16). A method based on the gravity model is considered for this purpose. The gravity model (4) is a model derived from Newton's Law of Gravitation, and is used to predict the degree of interaction between a stop and each POI.

$$Gravity\ law = \frac{mass_1 * mass_2}{dis\tan ce^2} \tag{4}$$

The definition for the gravity model is represented using the principle of bodies' attraction, where $mass_1$ represents a stop, $mass_2$ represents the number of the probable visited POIs in each category, and the distance is the sum of all the distances of POIs associated with the same category type. It means that the POIs associated with the same category type are assigned the same probability of being visited. More formally, for every stop s the probability p of a category type is determined as:

$$P(s_i, c_i) = \sum \frac{|\{p_i \in probable\ POIs(s_i) \mid \mu(p_i) = c_i\}|}{(d_i(s_i, p_i)^2)} \tag{5}$$

where, s_i is the stop, c_i indicates the category of POI p_i, and d_i is a function returning the distance between each stop and the POIs associated with the same category type. Thus using formula (5), a probability is associated to each possible category type relative to the stops.

3.2.2.3 Semantic features extraction

The last step of the semantic enrichment process is to extract the semantic features from the annotated stops with the land use types. As shown in Algorithm 4, stops are first divided on a weekly basis, and then different semantic features such as the stop frequency, average duration, and start time for each stop are extracted.

Algorithm 4. Semantic Features Extraction

Input:
Selected land use type $L_i = (x_i, y_i, t_i, t_{i+1}, \Delta_{duration}, r_i)$
Output:
Stop frequency S_f, average duration of a stop S_d, and begin time T_e

1 ***begin***
2 ***for all*** L_i ***do***
3 *compute stop frequency per week (S_f)*
4 *compute average duration of stop per week (S_d)*
5 *extract begin time of a stop (T_e)*
6 ***return*** S_f, S_d, *and* T_e
7 ***end***

3.2.3. Ontology-based activity model

In this section, STOM is used to perform an inference on the most probable activities occurring by users during their trip. Given the extracted features from the previous sub-sections, the ontology model is populated and integrated in a formalism that is capable of reasoning the activity type of users. The activity types are defined as axioms using the domain knowledge. The model is composed of four ontologies: Time ontology, Place ontology, Stops ontology, and Activity ontology.

Activity ontology contains user activity type classes. Description logic is used to formalize the hierarchy of activities with axioms.
Place ontology contains various classes of POIs and the land use types. Each of them denotes a geo-referenced object such as a restaurant, a shop, a lake or other objects. Time ontology contains temporal references, in which the activity types can occur. It is designed for the modelling of time in qualitative terms (e.g. morning, evening). Stop ontology contains places where a user would stay for a period of time including the semantic features such as stop frequency, average duration, and begin time.

3.2.3.1. User activity type axioms

The activity types are defined using axioms based on different semantic features included in the ontology model to express relations between the ontologies (see table 1). For instance, in rule number one, if the land use type is residential, the POI type is null, the start time is evening, the stop frequency per week is more than 5, and the average duration is more than 10 hours per week, then the moving object is 'spending time at home', i.e. AT= Return home.

Table 1. Axioms associated to activity types.

Land use Type	POI Category Type	Features T_b	Features S_f	Features S_d	Activity Type
Residential	-	Evening or night	≥ 5	≥ 9 hours	Return home
Residential	-	Evening or night	≥ 1	≥ 30 minutes	Socializing
Commercial	Shopping	Evening or night	≥ 1	≥ 30 minutes	Shopping
Commercial	Daily Shopping	Evening or night	≥ 1	≥ 30 minutes	Daily Shopping
Any Type	Any Type	Morning	≥ 5	≥ 8 hours	Work Full-Time

Another example is rule number 2: if the moving object stops once within a residential land use type per week, with an average stop duration of more than 30 min and the start time is evening or night, then the moving object is 'visiting a friend', i.e. AT= Socializing. Therefore, applying the axioms outlined above, different activity types can be inferred. The added value of having such an ontology-based approach allows us to define axioms in terms of high-level semantic concepts, abstracting away from the geometry coordinates of the geographical features. Indeed, in this approach, each stop is treated as a semantic concept instead of using spatial coordinates. The assertion of these relationships is an existential restriction, which is specified using the following example axiom expressed in the Web Ontology Language (OWL) syntax as semantic rule number one specifies a typical home activity (Table).

Table 2. Definition of home activity ontology rule.

Concept	Definition in Description Logic
Return home Activity	$\equiv Stop \sqcap$ $HasLanduseType.Residential \sqcap$ $HasBeginTime.Evening \sqcap$ $HasPoiType.null \sqcap$ $\exists \geq 5\ Frequency \sqcap$ $\exists \geq 600\ Duration$

4. Experiment and results

The performance of the approach was evaluated using a dataset, which was captured by a user, who had installed an application (developed based on the prototype for this research work) on his phone, and carried the phone with him while driving a car in the city of Calgary for a year in 2010. The experiment includes 862046 GPS records and 8050 landuse polygons and 17307 POI points. As it can be seen in figure 5, the last six months of the year had more data recorded than the first six months.

Figure 5. Raw GPS data acquired over a year.

It has a total of 862,046 GPS records. The attributes collected include user id, date, speed, heading, mode, and location of the user as shown in table 3. The x and y coordinates are transformed to an attribute called geometry (geometry column).

Table 3. Attributes of collected data.

User Id	Date	Speed	Heading	Mode	Geometry
1	2010-07-06 07:51:18	25.74	24.3	Car	"POINT(-114.133044 50.940534)"
1	2010-07-06 07:51:19	30.19	22.7	Car	"POINT(-114.132991 50.940454)"

Figure 6 shows the routes that the user used to complete the various activity types.

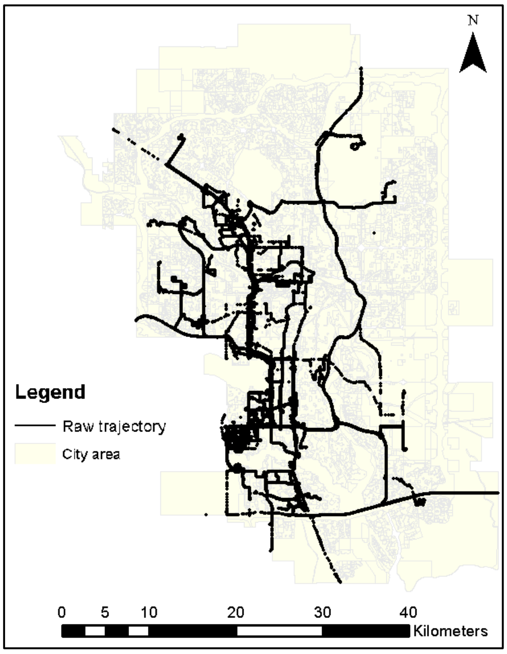

Figure 6. Routes used by user in his history data.

4.1. Data sources

(1) Land use data of Calgary

As shown in figure 7, the land use data includes different types such as commercial, urban development, residential, institutional, industrial, parks, major infrastructure, and transportation. The land use is predominantly residential, with most industrial uses in the eastern half of the city. Commercial and green space land use types are spread throughout the city. Around 35% of the city is covered by residential types, 30% is covered by parks, and 25% is covered by commercial types.

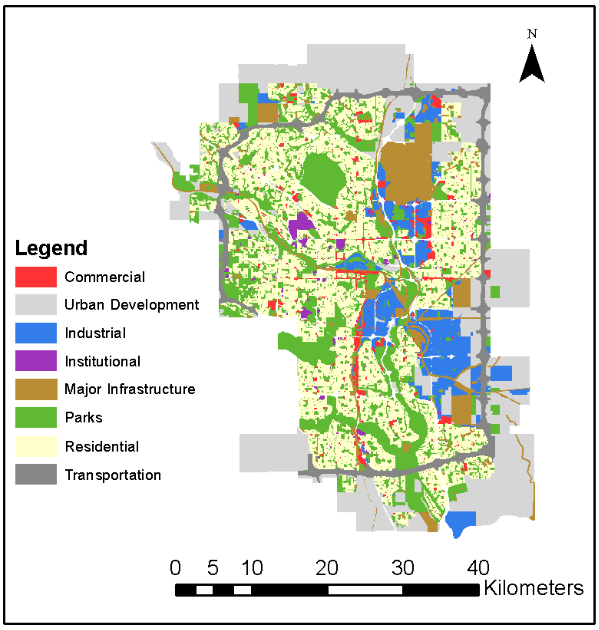

Figure 7. Land use of city of Calgary.

(2) POI data of Calgary

POIs were downloaded from OSM. There are 17,307 POIs, which were divided into nine category types: 2,304 food, 2,213 recreation, 407 religious, 281 education, 1,072 shopping, 996 daily shopping, 1,721 business services, 312 health services, and 7,749 accommodation. Since some of the opening hours were not currently included in the POIs' data, a time table (see table 4) was manually created based on the typical openings of different POIs. Note that the days of the week were divided into Monday-Friday, Saturday and Sunday. Moreover, MST was also added to the table.

4.2. Data preparation

The data preparation procedure was applied to the described collected data. First, the trajectories that were not in the monitored area were removed. Next, the dataset was cleaned from the inconsistencies such as empty values, duplicates, and outliers. In the trajectory identification, 239 daily basis trajectories were extracted. Unrealistic attributes such as trip durations that were too short were removed. Moreover, 28 Weekly basis trajectories were extracted.

Table 4. Opening hours of POIs in different days.

POI	Mon-Fri Opening Hours	Sat Opening Hours	Sun Opening Hours	Category	MST
Bank	9:30 – 17:00	9:00 – 16:00	Closed	Business service	15 min
Shopping mall	9:30 – 21:00	9:30 – 20:00	11:00 – 18:00	Shopping	30 min
Restaurant	11:00 – 23:00	11:00 – midnight	11:00 - midnight	Food	20 min
Post office	9:00 – 18:00	10:00 – 17:00	Closed	Business service	20 min
….	….	….	….	….	….

4.3. Semantic enrichment process

Stop detection

Figure 8 shows the number of stops, which were extracted with different parameters for the dataset. With higher $\Delta_{duration}$ (from two to ten minutes), the number of stops decreased when given a low Δ_{speed}; whilst with a higher Δ_{speed}, the stop number goes up and saturates because stops computed with a higher coefficient Δ_{speed} usually have a longer duration. Therefore, the number of stops decrease as some stops join together. Nevertheless, it is observed that the total percentage of time duration for stops always increases when the minimal stop time $\Delta_{duration}$ becomes smaller or the speed threshold Δ_{speed} increases. Empirical evaluations suggested to use $\Delta_{speed} < 15 km/h$ and $\Delta_{duration} \geq 4\,\text{min}$ to obtain the best accuracy.

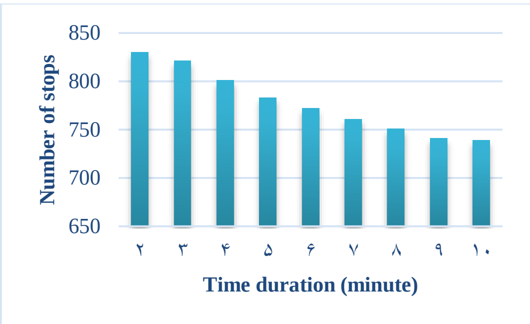

Figure 8. Number of stops based on different time durations (similar graph for speed).

As a result of the stop detection, 1,237 sub-trajectories with 832 moves and 801 stops over the dataset were produced.

Land use Type Annotation

Figure 9 shows the detailed land use type distribution over the trajectories.

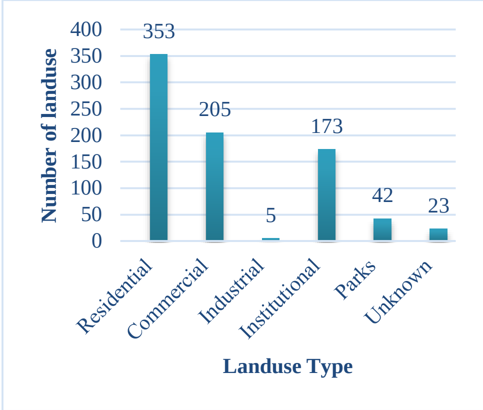

Figure 9. Land use type distribution for user trajectory.

Most of the stops were observed in the residential areas (44.1%), commercial areas (25.6%), and institutional areas (21.6%); and the others were industrial (0.6%), parks (5.2%), and unknown (2.9%).

Figure 10 shows all the stops annotated with different land use types including residential, park, institutional, commercial, out of town, and industrial. As it can be seen, most of the stops have happened in the area where the user lives.

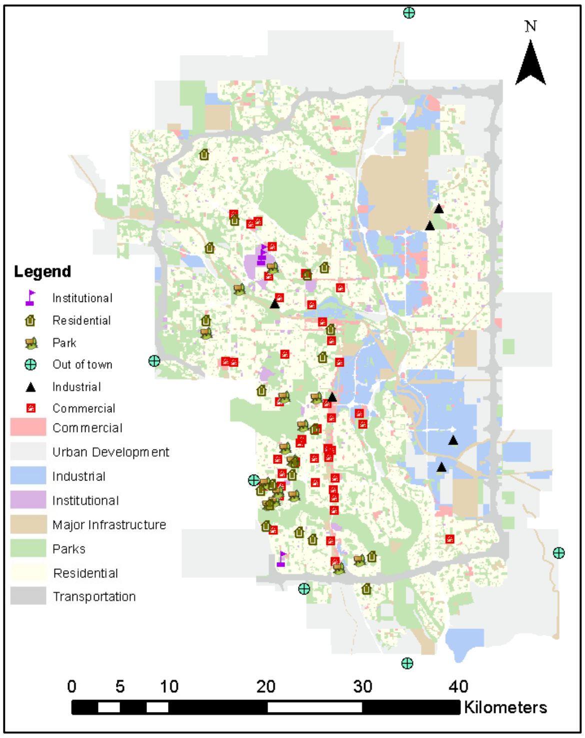

Figure 10. All detected stops in different land use types.

POI Category Type Annotation

In Algorithm 4, UWS and UWD were considered 5 km/h and 100 meters, respectively. As shown in figure 11, most of the stops belonged to the shopping (30.1%), business services (18.9%), and food (17.7%) categories.

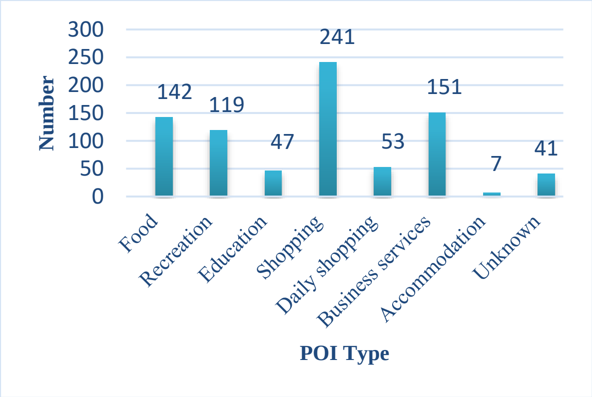

Figure 11. Number of POI types assigned to stop trajectories.

Table 5 represents the POI category type annotation in which a probable activity is returned using the gravity formula. For instance, for the stop S_1, two different category types were computed; food category type with the probability of 0.65 and the business service category type with the probability of 0.35.

Table 5. Most probable POI category type.

Stop	POI Category Type	Probability
S_1	Food	0.65
S_1	Business service	0.35
S_2	-	-
S_3	Recreation	1

4.4. Ontology-based activity model

STOM was populated using the extracted information in the previous steps. The time ontology contained the temporal discretization such as absolute intervals, as shown in table 6.

Table 6. Temporal discretization of time ontology.

Semantic time	Time period
Morning	4:00 AM - 11:59 AM
Afternoon	12:00 PM - 4:59 PM
Evening	5:00 PM - 8:59 PM
Night	9:00 PM - 3:59 AM

The stop ontology included the semantic features, as shown in table 7. For instance, the user had stopped six times a week in a residential land use type named "Residential 1" in the evenings with the average of 614 minutes per week. The place ontology contained the POIs and the land use types, as shown in table 8. For instance, for the stop S1, commercial was assigned as land use type and two different category types were computed; the food category type with the probability of 0.65 and the business service category type with the probability of 0.35.

Table 7. Some semantic features in stop ontology.

Stops	Frequency	Begin time	Average (min)
Commercial1	1	Evening	221
Commercial29	2	Night	14
Institutional1	**5**	**Morning**	**441**
Residential1	**6**	**Evening**	**614**
Residential14	1	Evening	22

Table 8. POI and land use in place ontology.

Stop	Land use Type	POI Category Type	Probability
S_1	Commercial	Food	0.65
S_1	Commercial	Business service	0.35
S_2	Residential	-	-
S_3	Parks	Recreation	1

4.5. Activity inference

The reasoning step was executed by the reasoner using the axioms that had been defined in sub-section 3.2.4.1 for some activity type. Table 9 shows some of the inferred activity types.

Table 9. Some inferred activity types.

Land use Type	POI Category Type	Features			Activity Type
		T_b	S_f	S_d	
Residential	-	Evening	6 days per week	10.2 hours	Return Home
Residential	-	Evening	1 day per week	45 min	Visiting
Commercial	Shopping	Afternoon	2 days per week	41 min	Shopping
Institutional	-	Morning	5 days per week	8.2 hours	Go to work

4.6. Activity type evaluation

Figure 12 illustrates a web interface application to visualize daily semantic trajectories and collecting users' feedback to validate the proposed methodology for activity recognition in this research work. At the bottom of the box, the user is asked to verify if the inferred activity type is correct or not.

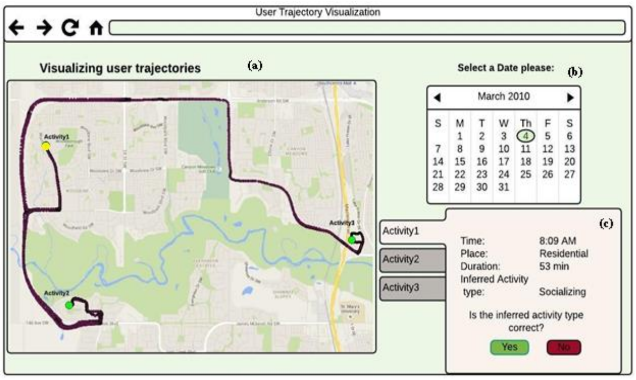

Figure 12. User interface to visualize user's trajectories in order to get his/her feedback.

As shown in figure 12, for instance, a user on March 4th, 2010 had 3 different activity types displayed with green circles on the map. Therefore, the inferred activity types using the proposed method are compared with the collected feedback of the users. The accuracy, as seen in (6), is the number of correctly inferred activity types over the number of total inferred activity types from the dataset.

$$Accuracy = \frac{No.of\ correctly\ inferred\ activity\ type}{No.of\ total\ inferred\ activity\ type\ from\ dataset} \quad (6)$$

The experimental outcome and the evaluation results are depicted in table 10. It shows the accuracies per activities i.e. the percentage of activities correctly identified w.r.t. the number of declared activities (of the same type). For example, good results for activities of type “business services” (the method recognized 97.3% of them) were obtained, while the method was unable to identify “daily shopping” (the method recognized 35.9% of them). It was observed that these results were related to the availability of the POIs around the stops.

Table 10. Accuracy of extracted activities using user’s feedback.

Activity Type	Accuracy (%)
Eating	88.4
Recreational	86.1
Education	69.5
Shopping	91.3
Daily shopping	35.9
Business services	97.3
Go to work	93.8
Trip	88.6
Socializing	90.6
Return home	89.1

4.7. Evaluation
To assess the performance of the proposed method, two different evaluations were performed. First, a reasoning evaluation was performed to show the impact of sematic enrichment of data. Second, a space/time sensitivity analysis was performed to evaluate the performance of the proposed method.

4.7.1. Reasoning evaluation
To measure the impact of the ontology axioms in the reasoning process, two experiments were performed. For this purpose, two sets of data were considered: GPS data and semantically enriched data. For the experiments, as described in table 12, the axiom named “return home” was considered. Figures 13 and 14 show the experimental results for the computation time in seconds and the storage space in triples needed by the inference calculation. The evolution curves are given by the number of stops.

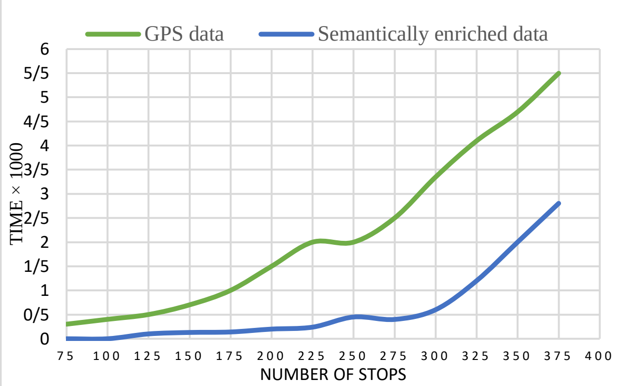

Figure 13. Reasoning computation time using GPS data and semantically enriched data.

The first experiment, which used the real GPS data shows the reasoning result with poor characteristics in terms of the computation time and space storage. For example, for 375 stops, the reasoning takes around 5,500 seconds (≃1.5 hours) and generates 220,000 triples.

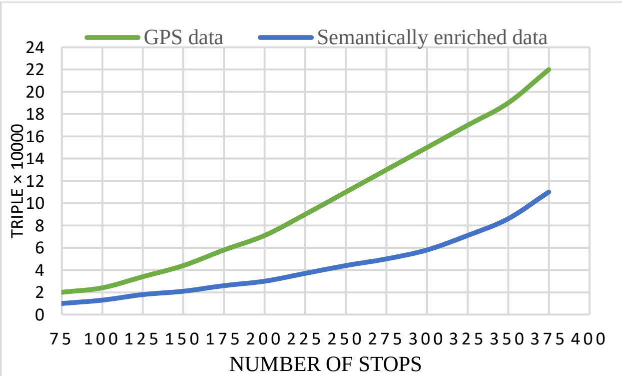

Figure 14. Reasoning storage space taken using GPS data and semantically enriched data.

In experiment 2, semantically enriched data was considered. The computation time and space storage results show the improvement made on the reasoning calculation compared to the first experiment. For example, for 370 stops, the reasoning takes less than 2,800 seconds (≃ 46 minutes) and generates around 110,000 triples. This reveals a reduction about 49% in processing time and 50% in storage space by applying ontology enrichment.

4.7.2. Performance evaluation
To evaluate the performance of the proposed method, a space/time sensitivity analysis was performed. A desktop computer used for the

testing and its configuration (i.e. hardware and software) is shown in table 11.

Table 11. Test system configuration.

Specification	Value
Operating System	Windows 7 Professional- 64 bit
RAM	4.00 GB
Processor	Inter® Core™2 Duo CPU 2.99 GHz
HDD	160 GB (7200 rpm) 8 MB Cache

In this experiment, different values were considered for the Maximum Walking Distance (MWD); from 50m-125m by 25m steps, while the rest of the parameters were left unchanged. The result of this evaluation is shown in figure 15.
As shown in figure 15, the fitted regression model almost follows a linear model, and it can be concluded that the performance trend of the proposed method has an O(n). Of course, due to the dependency of the proposed method on the other parameters, it does not show a complete linear regression.

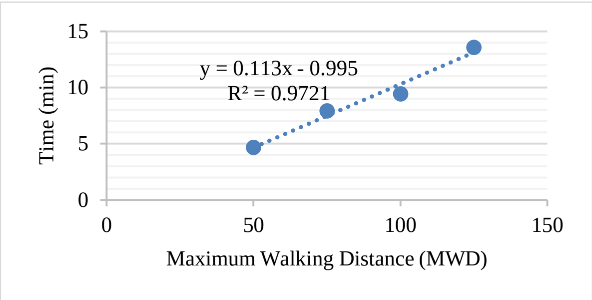

Figure 15. Performance evaluation.

5. Conclusions

This research work proposed a new ontology-based approach to recognize human activity type using GPS data. In comparison with other approaches, the proposed method for activity recognition considered several semantic constraints to annotate stops with the POI category types and the land use types. One constraint was added to relate the duration of the stop to the typical duration of the visits (e.g. a duration of 10 minutes is not compatible with dining in a restaurant). For each POI, a MST was defined to express the minimum amount of time that a person needs to spend to visit the place. Moreover, another constraint was that the amount of time a person could spend in a place is not the complete stop duration but the time needed to cover the distance between the POI and the stop must be taken into account.
With regard to the needs and challenges facing a research work, which is trying to establish an ontology-based approach for computing and understanding human activity types, this paper formulated two major contributions. The first contribution of this study was developing a semantic conceptual data model in order to recognize different activity types. In this respect, several semantic features were added to the model in order to enrich the relationship between the objects in the model. The second contribution was to propose an ontology-based activity model to infer different activity types. The semantic conceptual data model was used to develop the model. In this study, we investigated various extracted features and background information based on the model ontology to extract the activity types. Different axioms were defined using common sense rules so as to recognize the activity types. Finally, two experiments were performed to show the effectiveness of the proposed method. Moreover, a space/time sensitivity analysis was performed to evaluate the performance of the proposed method. In the future works, we shall investigate the usefulness of geo-social network data in the activity recognition process.

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نشریه هوش مصنوعی و داده کاوی

ارائه یک روش بر مبنای هستی شناسی به منظور تشخیص نوع فعالیت انسان از داده‌های GPS

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چکیده:

امروزه تکنولوژی‌های همراه باعث گسترش مجموعه گوناگونی از سرویس‌های اینترنت مبنا، مانند سرویس‌های مکان مبنا شده است. بکارگیری این گونه از سرویس‌ها توسط کاربرها منجر به تولید حجم زیادی از داده‌های حرکتی شده است. به منظور استفاده موثر از این نوع سرویس‌ها، نیازمند تحلیل داده‌های حرکتی با در نظر گرفتن دامنه‌های کاربردی برای تشخیص نوع فعالیت‌های کاربران می‌باشد. محققان از گروه‌های مختلف، مدل‌ها و تکنیک-های متنوعی را به منظور استخراج انواع مختلف فعالیت‌ها از این نوع داده‌ها گسترش دادند، اما آنها بطور کلی بر روی خصوصیات هندسی تمرکز کرده و به جنبه مفهومی یا معنایی اشیا حرکتی توجه‌ای نکرده‌اند. تحقیق حال حاضر یک روش بر مبنای هستی شناسی به منظور تشخیص فعالیت فرد از داده‌های GPS برای درک و تفسیر بهتر داده‌های حرکتی پیشنهاد می‌دهد. کارایی روش توسط یک پایگاه داده‌ای که توسط یک کاربر در طول زمان یک سال در شهر کلگری در سال ۲۰۱۰ جمع آوری شده مورد تست و ارزیابی قرار گرفت. مشاهده شد که دقت نتایج حاصل شده رابطه مستقیم با در دسترس بودن نقاط پر اهمیت در اطراف مکان‌هایی که کاربر توقف داشته دارد. علاوه بر این، یک آزمایش ارزیابی انجام شد که موثر بودن روش پیشنهادی با میزان بهبود کارایی ۵۰ درصد با منحنی پیچیدگی O(n) را آشکار کرد.

کلمات کلیدی: هستی شناسی، داده کاوی، شناسایی فعالیت، مفهوم، GPS.