

Online recognition of people's activities from raw GPS data: Semantic Trajectory Data Analysis

Mehdi Boukhechba , Abdenour Bouzouane, Bruno Bouchard, Charles Guin-Vallerand, Sylvain Giroux

LIARA Laboratory

Universite du Quebec a Chicoutimi (UQAC)

Chicoutimi, G7H 2B1, Canada

{ Mahdi.Boukhechba1, Abdenour_Bouzouane, Bruno_Bouchard }@uqac.ca, {charles.guin-vallerand }@teluq.ca,
{sylvain.giroux }@usherbrooke.ca

ABSTRACT

The widespread use of GPS devices leads to an increasing availability of people traces. The GPS trajectory of a moving object is a time stamped sequence of latitude and longitude coordinates. The analysis and extraction of knowledge from GPS trajectories is important for several applications domains, ranging from traffic management to advertisement and social studies. We present an approach capable of incrementally extracting semantic locations from people's trajectories and inferring the activity done by users. We associate the places visited by people during their movements to a meaningful human activities using a novel algorithm that cluster incrementally user's moves into different type of activities. Studies using GPS records from a confined spatio-temporal region demonstrate that the proposal is effective and is capable of inferring human activities without depleting the phone resources.

Categories and Subject Descriptors

H.2.8 [Database Applications]: Data Mining

General Terms

Algorithms

Keywords

GPS Data, Human activities, Semantic enrichment, Online clustering.

1. INTRODUCTION

Human's activity recognition represents an active topic of research since several decades ago. However, only in the recent years, with the increasing availabilities and facilities of collecting movement datasets from GSM or GPS equipped devices or even network wireless technologies like WI-FI [6] and RFID [18], we have the possibility to study people's activities from their movement traces.

Mobile wearable tracking devices, e.g., phones and navigation systems, sense the movement of people and vehicles represented by GPS records that capture geo-location, time, and a number of other attributes such as bearing and speed.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from Permissions@acm.org.

PETRA '15, July 01 - 03, 2015, Corfu, Greece

© 2015 ACM. ISBN 978-1-4503-3452-5/15/07...\$15.00

DOI: <http://dx.doi.org/10.1145/2769493.2769498>

In fact, real-time recognition of people's activities offers the possibility to understand what people are doing in the present moment, and estimates their actions in the future. We are going to use this concept in further work to assist people with special needs like persons suffering from Alzheimer disease in their daily outdoor tasks with absolute security. Assuming that we have some beforehand knowledge about people's destinations, our system can be used to detect every anomaly in their behaviors and start assistance processes like reminders, suggesting a new destination or home back roads. We bring a novelty to the manner of resolving the problem via 3 points:

1-The majority of related works are based on the classification of historical records of people's trajectories using density based approach (See [7] for example) where we try to identify the most visited place with post treatment processes e.g., end of day, every week ...

These methods fail in their ability to deal with less visited places by people but important in their trajectories e.g. cemetery, airport ..., and cannot be used to fields like assistance where we need a real-time access to person's activity. That's why we propose a new online solution which answer to those difficulties.

2-This work handles not only stationary behaviors but also moving activities like shopping. We introduce the speed and the variance of the orientation of people's trajectories as a new variable in our system.

3-Our classification method is based on a new version of online K-means, where we propose a temporal data window with variable size in function of person's moving behavior.

In this paper, we will demonstrate an innovative method to real-time switch raw GPS data to meaningful human activities using only a mobile device without network or historical records requirement and consuming a minimum of mobile resources. The approach presented aims at enriching people's movements, represented in real time during her/his travel trajectories, with semantic information about the places visited. Our method is based on the real-time recognition of points of interest "POI" (A Place of Interest, is a (urban) geo-referenced object where a person may carry out a specific activity) in people's trajectories, what clearly increase the use of this contribution, contrasting from economic uses like traffic management, public transportation, commercials and advertising, to more serious uses like security and police, risk evacuation management.

The following sections detail our contribution: Section 2 briefly reviews related work; Section 3 presents our approach in terms of

three major components, i.e. trajectory classification, spatial recognition and activity discovery; Section 4 describes the experimentation by highlighting two dimensions: memory usage and accuracy. Finally, conclusion and future focus, as well as the expected contributions, are summarized in Section 5.

2. RELATED WORKS

The emerging concept of semantic trajectory is a new topic for trajectory data analysis; however, research community's efforts are increasing day by day to carry clear definitions and common understandings. Spaccapietra et al. [11] propose a conceptual model for trajectories using two alternative approaches for trajectory modeling, based respectively on data types and design patterns.

Trajectories are defined as a spatio-temporal function that record the changing of the position of an object moving in space during a given time interval. Each trajectory include a list of sample points that implement the function of the time-varying point; A list of stops; A list of moves, that lies between two consecutive stops (or between the beginning of the trajectory and the first stop, or between the last stop and the end of the trajectory).

Kang et al. in [6] utilized the access point MAC address of a WI-FI network to capture location data on a campus. They developed a time-based clustering algorithm to "extract places" taking advantage of the continuity of the WI-FI positioning. A new place is found when the distance of the new locations from the previous place is beyond a threshold d , and when the new locations span a significant time threshold. This algorithm is simple and works in a novel incremental way on mobile devices. However, the algorithm does not consider the re-occurrence of readings at the same location. More simply, each time it discovers a place, it is a "different" place. This also makes it difficult to discover places that are visited with high frequency but short dwell time. Finally, this method requires continuous location data collection with very fine intervals, and thus large storage.

A clustering method is proposed in [7] called CB-SMoT (Clustering-Based Stops and Moves of Trajectories) to infer semantic information from trajectories, it is a clustering method based on the speed variation of the trajectory. This method first evaluates the trajectory sample points and generates clusters in places where the trajectory speed is lower than a given threshold for a minimal amount of time. In a second step, the method matches the clusters with a set of relevant geographic places defined by the user.

The community has gone further in [1] where authors present a free software called Weka-STPM (Semantic Trajectories Preprocessing Module) that has been constructed into Weka to preprocess raw trajectories in order to transform them into semantic trajectories. As a module of Weka, it allows the user to directly apply the several mining algorithms available in Weka [4] to mine semantic trajectories. Weka-STPM is the first tool for semantic trajectory preprocessing for data mining it use CB-SMOT in first order to generate the semantic trajectories.

The work of [5] aims to infer activities from users trajectories. This paper presents an approach using spatial temporal attractiveness of POIs to identify activity-locations and durations from raw GPS trajectory. The algorithm they propose finds the intersections of trajectories and spatial-temporal attractiveness prisms to indicate the potential possibilities for activities. The experiments use one month of GPS trajectories provided by 10 volunteers, results show an high accuracy of the method.

A different approach is the one of [15], where the focus is not on the single user, indeed users' trajectories and domain data such as POIs and road network topology are used together to define functional regions. The results are region represented by a distribution of topics (functions), where a topic is a POI category. With this work, the authors aim to help people to easily understand the complexity of a metropolitan area. The results are applied to different fields, such as urban planning, location choosing for business, advertisement casting and social recommendations.

In [13], an algorithm is proposed to associate each stop in a user's trajectory to a list of possible visited places and each of these places is associated to a probability. Finally, depending on the kinds of activities associated to the identified place, the trajectory is classified into a (probable) trajectory behavior. In this work they assume the moving object is a person that travels using a transportation means associated to a traceable (GPS) device (car, bus, metro, train). The person gets out of the transportation mean to reach the final destination walking. During this time interval the person is not traceable what justify the use of probability to find the visited place.

While developing a rich body of work for managing moving objects, the research community has shown very little interest in the real-time recognition of POI in people's trajectories, the majority of related works are based on the classification of historical records what exclude problems linked to mobile's performance like battery life and low computational capacities.

Moreover, nearly all approaches are based on the detection of stops in person's moving, neglecting activities with moving behaviors, and only minority of these studies try to automatically identify the background geographic information since generally we request a set of relevant geographic places defined manually by the user.

3. OVERVIEW OF THE APPROACH

We adopt the person is GPS traceable via a cellphone or another smart device. Usually, person's activities are divided into two behaviors: stationary and non-stationary, where the second one is also divided into two categories moving to reach a goal and moving to do a goal.

For example working in the office is a stationary activity, going from work to shopping is non-stationary activity to reach shopping center, shopping is non-stationary activity too but the goal is to do shopping, so it's an activity with moving (see Figure 1). Based on these concepts we introduce 3 types of clusters:

1. Stop concept, represented by "c1" and characterizes stationary activities.
2. Activity with moving "c2" is a non-stationary activities that requires movement over a time interval.
3. Moves, represented by "c3" are a set of actions that aim to move from POI to another.

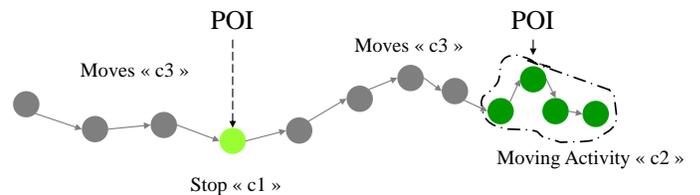


Figure 1: Relation between moves, stops and activities with moving

As shown in the following Figure 2, to deal with all these concepts, we introduced in the first step a real-time classification method based on K-means, to classify every new GPS data according to the three families (stops, moves, and activity with moving), in parallel, we observe the accumulation of type of clusters, after a certain threshold of same cluster's accumulation we conclude that the person is probably doing something interesting. For the second step, we summarize the accumulated clusters to one probably POI and we start a geospatial research for the most meaningful nearby geography entity. If research process succeeds, we declare this point as a POI. The third step is to assign the POI to an activity, like museum to tourism activity and gym to sport activity.

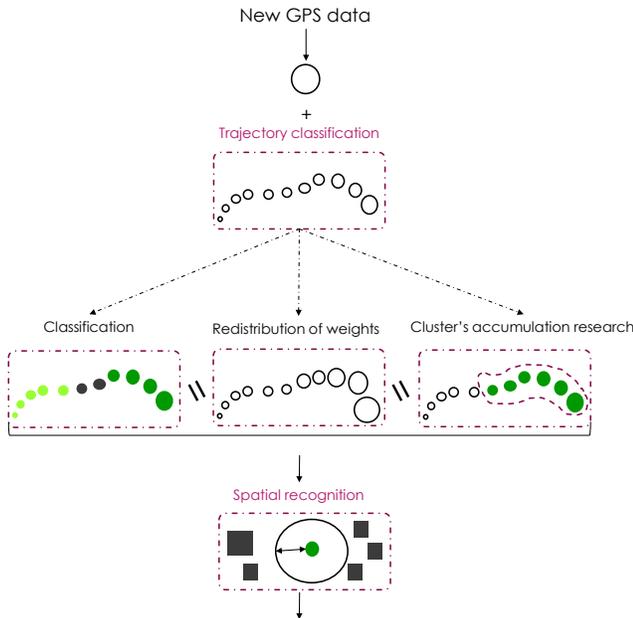


Figure 2: The overall approach of activity recognition

3.1 Step 1: trajectory classification

The aim of this step is to classify the continuous GPS collection incrementally into different kind of activities. The most recent part of GPS collection is stored in a temporal window called TW.

Definition 1: GPS collection is an assembly of GPS points $P = \{P_1, P_2, \dots, P_n\}$. Each GPS point $P_i \in P$ contains latitude ($P_i.Lat$), longitude ($P_i.Lngt$), timestamp ($P_i.T$), speed ($P_i.S$) and bearing ($P_i.B$). We add to these information the variance of bearing ($P_i.V$) of the last l P_i where l is the size of our temporal window TW, and the weight ($P_i.W$) that represents the importance of the point P_i according to the time generation.

Definition 2: temporal window TW is a subgroup of a GPS collection with a variable length l . In fact TW contains all P_i with not null weight $P_i.W$. (see Figure 3 that represents the relation between a GPS collection and TW, every point in the GPS collection is a record row from the database).

To handle this condition we introduced a trigger on every new GPS data record that deletes P_i with null weight.

locationId	latitude	longitude	Time	Speed	Bearing	Variance	weight
614	48.42104953	-71.05172413	Mon Nov 10 12:...	0.75	76.5	49.7	1.0
615	48.42104953	-71.05172413	Mon Nov 10 12:...	0.75	76.5	88.36	0.47
616	48.42104953	-71.05172413	Mon Nov 10 12:...	0.75	76.5	115.97	0.22
617	48.42104953	-71.05172413	Mon Nov 10 12:...	0.75	76.5	132.54	

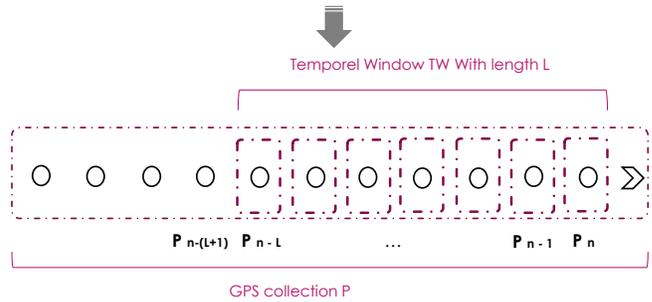


Figure 3: The relation between the GPS collection P and TW

According to person's speed, GPS collections are fed every 10 seconds for speed more than 10 km/h and every 5 seconds for less. Once a new GPS data is received we achieve three parallel processes like below:

3.1.1 Process 1: classification

At the arrival of a new GPS data, P_n is stored in TW. Classification process is not launched on every data arrival but after a threshold called T_{min} that will be exposed in the process 3. We classify the P_i in TW using two variables speed $P_i.S$ and variance of bearing $P_i.V$ applying K-means.

The variance of bearing $P_i.V$ is calculated using this formula: $P_i.V = \frac{\sum(p_i - \bar{p})^2}{l}$ where $\bar{p} = \frac{\sum p_i}{l}$, this calculation is made before recording the new P_i in TW and it represents the variance of user's orientation in the last l P_i (l is the length of TW).

Stops behaviors are characterized by a very low $P_i.V$ and $P_i.S$, moves by important $P_i.S$ and low $P_i.V$ because person's moves using conveyances tend to a quick and straight manner. Moving activities are branded by a low $P_i.S$ and important $P_i.V$ since these activities are pedestrian actions which generally require a frequent shift of orientation like visiting paintings in a museum, shopping in a market or walking in a zoo.

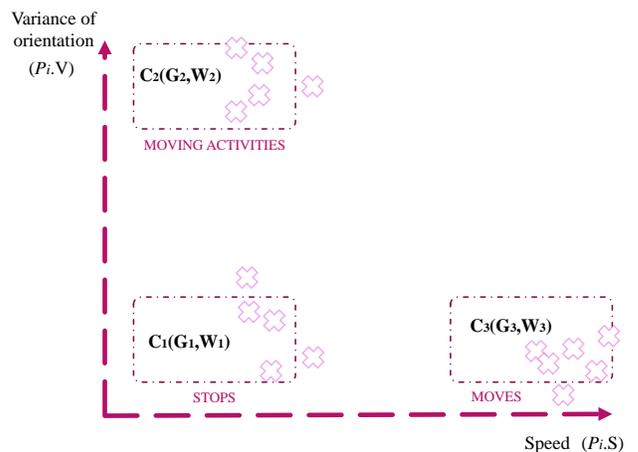


Figure 4: Inferring activity's type using speed and the variance of orientation

3.1.2 Process 2: distribution of weights P_i . W

Every P_i has a weight which determines the degree of resemblance of P_i 's class to the current activity. Our methodology is inspired from work in [3], the weight of each data point decreases exponentially with time t via a fading function $w_i = f(t) = 2^{-\lambda t}$, where $\lambda > 0$. The exponentially fading function is widely used in temporal applications where it is desirable to gradually discount the history of past behavior. The parameter λ is called exponential decay constant, the higher value of λ the lower importance of the historical data compared to more recent data. And the overall weight of the data stream is a constant, $W = \sum_{t=0}^{t=t_c} 2^{-\lambda t} = \frac{1}{1-2^{-\lambda}}$ where t_c ($t_c \rightarrow \infty$) is the current time.

Unlike [3], we chose a variable value of λ between 0 and 1 depending on the nature of data that already exist in TW (class of every P_i). We noticed that λ has a link with the ability to make a decision, when we are sure that an activity is performing, we need less data to make a decision so λ tend to 1, and λ tend to 0 when we have issues to find what type of activity is executing, therefore we need a maximum of points (see Figure 5).

Based on these observations we found a mathematical representation of λ using the entropy of Shannon, the entropy is a measure of unpredictability of information content, or in another term it measures the disorder in a set of information. Consequently, λ of the new P_n is calculated using the entropy of the old data set in TW.

The value of λ is calculated as follows, $\lambda = 1 - H_2(p_i) = 1 - \sum_{i=0}^{n-1} p_i \log_2 p_i$ where $p_i = \frac{w_i}{W}$.

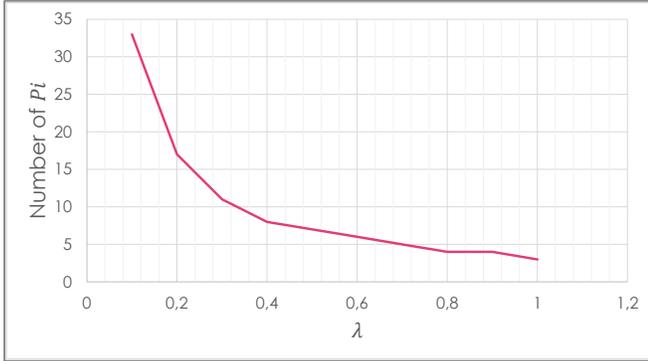


Figure 5: The impact of varying λ on TW's length

3.1.3 Process 3: cluster's accumulation research

The algorithm recognizes that someone is doing an activity if the weight of its cluster W_j exceeds a value μ , where $\mu = \frac{W}{k}$ with k representing the number of clusters (activities) used by K-means to classify TW, in our case $k=3$ because we try to identify three family of clusters :Stops; moves; moving activities.

The most important question is "when do we search for a cluster accumulation?" To minimize the use of device resources, it is recommended to handle this step carefully. The research process is not launched on every data arrival T but after a time called T_{min} in which it is expected to have an activity.

Proposition 1: T_{min} is the time from which $w_i = f(t) = 2^{-\lambda t}$ reaches μ , this is verified in this following condition $2^{-\lambda T_{min}} \mu + 1 = \mu$, after development $T_{min} = \frac{1}{\lambda} \log \frac{\mu}{\mu-1}$.

Consequently, on every T_{min} we check if there is any activity that its weight W_j exceeds μ , if found we summarize the points P_i to one point $C_j (G_j, W_j)$ where $G_j = \frac{\sum P_{ij}}{n}$, n is the number of points in this cluster and P_{ij} represent the points P_i in the cluster j . $W_j = \sum_{i=0}^n w_{ij}$, after that we move to step 2, spatial recognition of C_j .

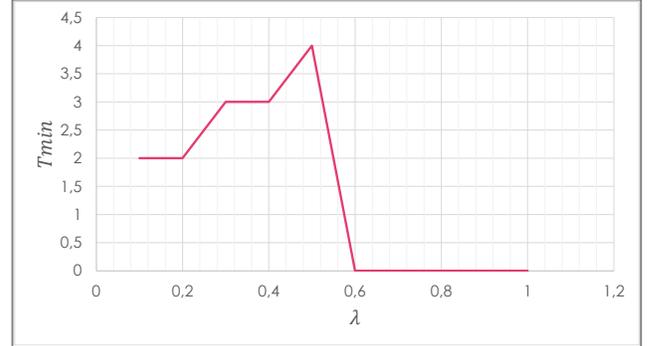


Figure 6: The relation between λ and T_{min}

As said previously, λ is not a static value and it varies between 0 and 1 depending on the disorder of data in TW. From the relation between λ and TW in Figure 6, we note that T_{min} is also affected by the disorder of data in TW. For example, assuming that our TW contains 10 P_i , and 9/10 of them are clustered as 'c1'. In this case λ will tend to 1 because $\lambda = 1 - H_2(p_i) = 1 - \sum_{i=0}^n p_i \log_2 p_i$, where $p_i = \frac{w_i}{W}$ so T_{min} will tend to 0.

Subsequently, when we have a certitude about an activity performed in TW, the minimum time for the next calculation T_{min} will be 0, this means that our algorithm stands ready for a change in activity type. Contrariwise, when we have some difficulties to make a decision about the activity performed in TW (because of the high disorder), the length of TW will be extended to take more points that may help us to decide and the value of T_{min} will automatically increase.

Algorithm 1: trajectory classification

Input:

A GPS point P_i ;

Output:

The activity of the person;

- 1: **For each** T
 - 2: Store P_i in TW ;
 - 3: **End for each**
 - 4: **For each** T_{min}
 - 5: Classify every point in TW ;
 - 6: Update λ ;
 - 7: Update the centers of clusters $C_j (G_j, W_j)$;
 - 8: Calculate the threshold μ ;
 - 9: //Cluster's accumulation research
 - 10: **If** ($\max(W_j) > \mu$) **then**
 - 11: POI = spatial recognition (G_j);
 - 12: Activity = activity discovery (POI);
 - 13: **End if**
 - 14: Update T_{min} ;
 - 15: **Return** Activity
 - 16: **End for each**
-

Algorithm 1 achieves two process, the first is to only store every GPS data P_i when it arrives, the second performed every T_{min} to reduce the calculation. First step is to classify every point P_i in TW, then update the value of λ depending on the disorder of the activities types in TW. After calculating the center of gravity C_j of each cluster and the threshold μ , we start to search for an accumulation of a cluster that is verified by the condition $\max(W_j) > \mu$, we use the max of clusters' weight to avoid the case where two clusters exceed μ in the same time, if condition verified we start to recognize the geographic environment of C_j . Finally we update the value of T_{min} that will determine the next repetition of the process.

3.2 Step 2: spatial recognition

This task aims at further understanding the movement behavior for trajectories, in terms of more semantically meaningful POI.

We search for the closest and most significant geographical feature compared to C_j , it is performed using a spatial query in a spatial database. Our database is powered by OSM¹ and stored in the users device for local usages. This technique aims to discard network uses offering offline services that will save user's money and phone's battery.

Many techniques exist to extract geographic data from OSM, the easiest way is to download and extract it from a website. There are various web services that provide data extracts for a geographic area, for example GeoFabrik is a company which specializes in working with OpenStreetMap. They provide a variety of free extracts in Shapefile² and raw OSM format on their download website³. After downloading raw OSM Data, and storing it in a spatial database, we use algorithm 2 to search the nearest spatial feature to C_j .

Algorithm 2: spatial recognition

Input:

A centers of clusters C_j ;

Output:

POI, Date;

- 1: **If** (there are some geographic entities in 50 m) **then**
 - 2: //search in the geographic database
 - 3: POI = the nearest geographic entity;
 - 4: Date= Get current date();
 - 5: **Else**
 - 6: POI = null ;
 - 7: **End else**
 - 8: **Return** POI, Date
-

3.3 Step 3: activity discovery

Activity discovery is based on the exploitation of tags nations in OSM. A tag consists of 'Key' and a 'Value'. Each tag describes a specific feature of a spatial data element (see [10] for more details).

Each tag has only a key and value. Tags are written in OSM documentation as key=value.

The key describes a broad class of features (for example, highways or names).

The value details the specific feature that was generally classified by the key, for example the geographic entity that contains a tag "building= apartments" represents a building arranged into individual dwellings, often on separate floors.

We assume that each tag represents an activity and each activity belongs to an activity family (see Figure 7).

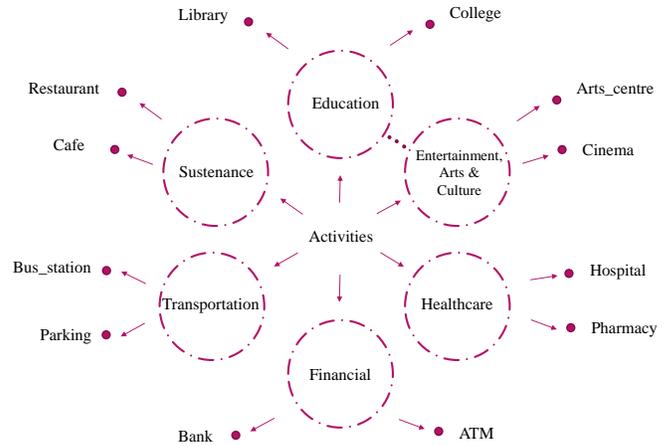


Figure 7: The taxonomy of activities

Activities are organized in a taxonomy which generalizes the kinds of activities of interest for the movement analysis (see Figure 7). For example, the "going to college" activity can be specialized in "education", and so on.

Subsequently, for example if the nearest geographic entity to C_i has a tag "amenity=library" we deduce that the user is doing an educational activity in the library. This is performed using an algorithm (see algorithm 3) that searches for the nearest geographic entity, and extracts its tag to deduce the activity achieved.

Algorithm 3: activity discovery

Input:

POI;

Output:

Activity;

- 1: **If** (POI = null) **then**
 - 2: Activity = 'no activity';
 - 3: **Else**
 - 4: Tag = Get the tag of POI ;
 - 5: Activity = Search for activity taxonomy (Tag) ;
 - 6: **End else**
 - 7: **Return** Activity
-

¹ Open Street Map (OSM) is a community-driven project aimed to produce a high-quality detailed map of the world. OSM datasets are freely available under the Open Database license terms

² The Shapefile format is a geospatial vector data format for geographic information system (GIS) software

³ <http://download.geofabrik.de/>

4. EXPERIMENTAL EVALUATION

We implemented our approach on Android environment for testing our incremental activity inference. As mentioned before, the geographic process is based on data brought from OSM and stored in a SpatiaLite database, an open source library intended to extend the SQLite⁴ core to support fully fledged Spatial SQL capabilities.

SpatiaLite is simple and lightweight where a whole database simply corresponds to a single monolithic file (no size limits), with no installation needed.

The experimental evaluation will contains two parts: memory usage's demonstration and accuracy demonstration.

4.1 Memory usage

To demonstrate how our approach handles phone's memory usage, we implemented three versions of the real-time activity inference application like below:

Version 1: classification, cluster's accumulation research and spatial recognition steps are accomplished on every new GPS data arrival with a static TW's length using a fix value of $\lambda = 0.5$.

Version 2: classification, cluster's accumulation research and spatial recognition steps are accomplished on the appropriate time T_{min} but with a static TW's length using a fix value of $\lambda = 0.5$.

Version 3: classification, cluster's accumulation research and spatial recognition steps are accomplished on the appropriate time T_{min} but with a dynamic TW's length using a variable value of λ that is updated on every T_{min} in function of person's behavior.

These tests were performed using an Android smartphone from Sony (Sony Xperia S) with 1 GB of Ram and 1.5 GHz dual core processor.

We compared the three versions of our implementation with "Maps", the mapping mobile application developed by Google for the Android and iOS operating systems, and "Waze Social GPS Maps & Traffic", one of the best free navigation applications, it won the best overall mobile app award at the 2013 Mobile World Congress.

Results presented in Figure 8 represent the average of memory consumptions calculated on every application version for six hours. With an average frequency of one GPS point every 5 seconds, our three versions used about 4300 GPS points in this experimentation.

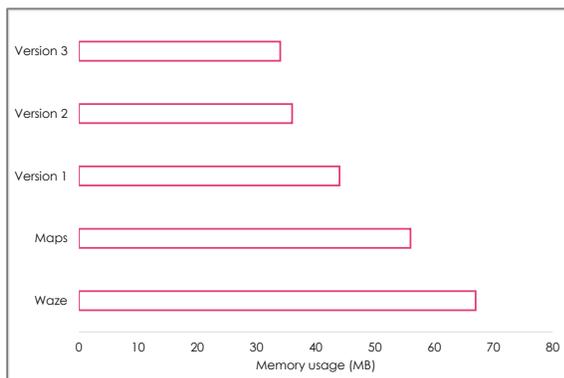


Figure 8: Comparison of three versions of our implementation with two well-known applications (Maps and Waze)

Results show that the activity inference application is globally not very greedy regarding memory usage with average usage of 38 Mo comparing to Maps with 54 Mo and Waze with 67 Mo.

In the other hand, version 3 shows the lowest memory usage rate with 34 Mo, followed by version 2 with 36 Mo and finally version 1 with 44 Mo.

Discussion

Clearly, the version 1 of our implementation is the largest consumer of memory because clustering process, cluster's accumulation research and spatial recognition process are achieved on every GPS data arrivals, which leads to a long calculation time, thus, this technique is not very economic on battery life.

Contrariwise, versions 2 and 3 show interesting results with lowest memory usage. Indeed, the fact of spacing calculation frequency using the notion of T_{min} leads to a shorter calculation time. Additionally, the use of a dynamic TW length (λ variable) in version 3 is more important than version 2 where TW length is fixed, this is illustrated in the example below:

Assuming that we fix $\lambda=0.4$ in version 2, which means that TW will contain 8 GPS points. And assuming that the user is achieving a stationary activity like working in the office. Version 2 will cluster on every T_{min} the same number of points, 8 points.

Inversely, in version 3 TW length will shrink to contain only 2 points as λ will take value equal to 0.9 (the entropy of Shannon of TW will tend to 0). Otherwise, as long as the user is standing in his office, version 3 will cluster only 2 points unlike version 2 that will support in every time 8 points, this difference may seem negligible, but the impact will become more important when it comes to hours of doing the same activity.

Therefore, using the nation of T_{min} and a variable TW's length represent an efficient technique that preserves both the memory usage and the battery life.

4.2 Accuracy

After demonstrating that version 3 of our implementation is the most efficient, we run some preliminary experiments to test the accuracy of our approach using this version. We tracked the movement of one user in the city of Chicoutimi in Canada and we compared the activities inferred using our approach and the real activities.

Note that we used a geographic database from OSM that contains 1368 geographic entity (see Figure 10), every entity contains a set of information like names and tags.

In this process, we used an OSM tool for spatialite database called `spatialite_osm_map` (see [12]) which is intended to parse a whole OSM dataset to a corresponding SpatiaLite's DB-file. The envisioned goal of this tool is to produce a DB-file suited to be immediately used with some appropriate GIS application (e.g. QGIS⁵).

Geometries are reassembled in the canonical form of POINTs, LINESTRINGs and POLYGONs.

⁴ SQLite is a software library that implements a self-contained, serverless, zero-configuration, transactional SQL database engine

⁵ QGIS (previously known as "Quantum GIS") is a cross-platform, free and open-source desktop geographic information systems



Figure 9: Real-time extracting interesting places from GPS data

Following the data organization of OSM, tags are structured in columns where the head of the column is ‘the Key’ and the value in each row represents ‘the value’.



Figure 10: Example of our geographic data shown from our Spatialite database

In the following, we are going to observe the inference process of six activities done during an experimental day. As shown in Figure 9, user starts his day going to the university, after that returning at home, going to the Gym, going to the supermarket, and finally returning at home passing by the pharmacy.

In this experimentation, travel behavior was a mixture of traveling by car and by foot. Results of real moves are presented in Figure 9 via three kinds of points:

- Green: Stationary activity.
- Red: moving activity.
- Blue: simple moves from an activity to another by car or by foot.

Results, presented in table 1, compare inferred and real activities by supporting the duration of the activity (begin time, end time).

Table 1: Comparison between the inferred and real activities

Duration	Activity	Real duration	Real activity
10:32 11:55	University « main pavilion »	10:31 11:55	University Library
12:13 14: 31	Building @ « gegin street »	12 :12 14:30	Home
14:49 17:28	GYM	14:49 17:26	GYM
18:07 18:43	Shopping @ « loblows »	18:05 18:42	Shopping @ « loblows »
	Activity not recognized	19:11 19:12	Pharmacy
19 :49 ...	Building @ « gegin street »	19:48 ...	Home

Our activity process succeeds in inferring correctly five user’s activities with a light duration shift (few seconds). The offset of duration is due to the time required to new activity’s weight to outstrip old activity’s weight in TW.

However, our algorithm had difficulties to detect the activity ‘going to pharmacy’, the reason is that the user didn’t spend too much time there as he passed by the pharmacy just asking for the availability of a medicine. The small duration of this activity did not allow enough time for the algorithm to note that it is a new activity.

Discussion

From previous results, we noticed that our solution represents an efficient technique for dynamic recognition of user’s activity. However we intend to run further experiments to prove the usefulness of the approach, bind it with context-aware assistances

(GIS) application that provides data viewing, editing, and analysis capabilities (<http://qgis.org/>).

and test it with people with special needs (e.g. mild state of the Alzheimer disease).

Like any semantic inference approach, it is difficult to pass automatically from a geographic information to real human practice taking into account all its relational dimensions. For example, algorithm recognizes the activity ‘staying at home’ as ‘staying @ an address’ (see table1, row2) because home is a human interpretation of a dwelling-place used as a permanent residence, machine cannot do such interpretation without human intervention. Clearly, the problem of “Home” can be solved by learning home place, but the issue will quickly rise if we try to introduce more complex human relation like friend’s house or family’s house.

5. CONCLUSIONS AND FUTURE WORK

In this paper we proposed new techniques for extracting semantically and incrementally important geographical locations from users’ moves. We associate the places visited by people during their movements to a meaningful human activities using an algorithm that cluster incrementally user’s moves into different types of activities using two parameters, speed and the variance of the orientation of the moves. After detecting an important accumulation in a cluster’s weight, the cluster is summarized into one point and another process will be launched that aim to search the most meaningfully geographic entity near to this point (POI), when found we associate a semantic activity to it.

Our approach has been experimented in a real case study to test the accuracy of our inference mechanism and to observe the impact of our technique on phone’s memory usage. These tests demonstrate that with a minimum of information, our proposals are capable of real-time inferring person’s activities without depleting the phone resources.

Several promising directions for future work exist. First, the enhancement of spatial recognition process with the introduction of probability to assign a cluster to a geographic entity, this probability approach can take advantage of previously recognized activities, for example a person doing tourist activities all the day has more probability to finish his day in a restaurant or in a hotel than in another places. The second enhancement that can be applied to our inferring process is to include users’ profiles. In fact move’s pattern of people varies between young and old persons, healthy and sick, male and female. The implementation of such reflections will improve the accuracy of our inference process.

The privacy aspects may represents an obstacle and in the same time a direction of research. Actually, it has been proved in the literature that the knowledge about the movement of a person may allow to infer the identity of that person and the possible sensitive places she/he has visited. Therefore, privacy-aware analysis methods have to be applied to avoid the disclosing of personal information.

6. REFERENCES

- [1] [Alvares, L.O. , Palma, A., Oliveira, G., and Bogorny, V. Weka-STPM: From Trajectory Samples to Semantic Trajectories, *Proceedings of the XI Workshop de Software Livre, WSL'10*, Porto Alegre, Brazil, 2010, pp. 164-169.](#)
- [2] [Ashbrook, D., and Starner, T. Using GPS to learn significant locations and predict movement across multiple users. *Personal and Ubiquitous Computing* 7\(5\), 275-286.](#)
- [3] [Cao, F., Ester, M., Qian, W., Zhou, A.: Density-based clustering over an evolving data stream with noise. In: *In 2006 SIAM Conference on Data Mining*. \(2006\) 328–339.](#)
- [4] [Frank, E., Hall, M. A., Holmes, G., Kirkby, R., Pfahringer, B., Witten, I. H., and Trigg, L. \(2005\). Weka - a machine learning workbench for data mining. In Maimon, O. and Rokach, L., editors, *The Data Mining and Knowledge Discovery Handbook*, pages 1305–1314.](#)
- [5] [Huang, L., Li, Q., and Yue, Y. Activity identification from GPS trajectories using spatial temporal POIs' attractiveness. *In 2nd ACM SIGSPATIAL Int. Workshop on Location Based Social Networks*, 2010.](#)
- [6] [Jong Hee Kang, William Welbourne, Benjamin Stewart, and Gaetano Borriello. Extracting places from traces of locations. *In Proc. WMASH*, pages 110–118, 2004.](#)
- [7] [Jose A. R. C. Manso and Valeria C. Times , Gabriel Oliveira and Luis O. Alvares, Vania Bogorny. DB-SMoT: A Direction-Based Spatio-Temporal Clustering Method.](#)
- [8] [Krumm, J. et al. Predestination: Inferring Destinations from Partial Trajectories. *In Proceedings of the Ubicomp '03*, \(Orange County USA, September 2003\). Springer Press: 243-260.](#)
- [9] [Li, Q. and Zheng, Y. et al. Mining user similarity based on location history. In *Proc. of GIS'08* \(Santa Ana, CA, Nov. 2008\). ACM Press: 298-307.](#)
- [10] [OpenStreetMap: <http://wiki.openstreetmap.org/> .](#)
- [11] [Spaccapietra, S., Parent, C., Damiani, M.L, Macêdo, J., Porto, F., Vangenot, C.2008. A conceptual view on trajectories. *Data Knowl. Eng.* 65\(1\): 126-146 \(2008\).](#)
- [12] [Spatialite tools:<https://www.gaia-gis.it/fossil/spatialite-tools/wiki?name=OSM+tools> .](#)
- [13] [Spinsanti, L., Celli, F., Renzo, C. Where you stop is who you are: understanding people’s activities by places visited, EPFL, Lausanne, Switzerland b KDDLab, ISTI, CNR, Pisa, Italy.](#)
- [14] [Takeuchi, Y. et al. CityVoyager: An Outdoor Recommendation System Based on User Location History. *In Proceedings of UIC'2006*, \(Berlin, 2006\), Springer Press: 625-636.](#)
- [15] [Yuan, J., Zheng, Yu., and Xie, X. Discovering regions of different functions in a city using human mobility and POIs. *In KDD2012*, 2012.](#)
- [16] [Zheng, Y, et al. Learning transportation modes from raw GPS data for geographic applications on the Web. In *Proceedings of WWW 2008*, \(Beijing China, April 2008\), ACM Press: 247-256.](#)
- [17] [Zheng, Y., et al. GeoLife: Managing and understanding your past life over maps. In *Proceedings of MDM'09*, \(Beijing China, April 2008\), IEEE Press: 211-212.](#)
- [18] [Bouchard K., Fortin-Simard D., Gaboury S., Bouchard B., Bouzouane A. Accurate RFID Trilateration to Learn and Recognize Spatial Activities in Smart Environment , *International Journal of Distributed Sensor Networks, Special issue on Application Development Support for Network Embedded Systems*, Hindawi publisher, pages 1-15.](#)