Does Ambient Intelligence for Mobile User Assistance dissolve in Privacy Oriented Policies?

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***Abstract*— *We are developing and testing concepts for an Ambient Intelligence Experiment evaluating embedded mobility analytics to support mobile users within a strong data privacy paradigm. The first part of the project discussed in the paper addresses user profiling based on stay area detection and point of interest disambiguation to feed an on-the-fly recommendation system.*

***Keywords*—*Privacy, Ambient Intelligence, Mobility, Point of Interest, Profiling.*

I. Introduction

A. Context

User data analytics for improving Search and Recommendation has been intensively developed over the past decades with one key driver: selling products or services that best fit users' needs at the time they need it. This objective has been built around one paradigm which is collecting, aggregating, and analyzing as much data as possible on every user piling up a growing number of contextual features. Internet companies which have popularized their search and recommendation engines are the best example of the success of this paradigm. They provided efficient, convenient and free tools to users in exchange of their private data.

However, recent affairs related to the access of user data by third parties for commercial or political reasons have generated a growing trend for privacy protection such as the General Data Protection Regulation (GDPR) put in place in the European Union. This trend implies a paradigm shift both economic and technical. Data should remain a user property which means they may no longer be available for centralized analysis. Prediction models may be compelled to be built and to run locally on users' devices without the benefit of big data analytics (e.g. context sharing, similarity calculus, collaborative filtering).

In this paper we discuss some challenges related to this new paradigm, and the architecture and concepts developed in an experiment to deliver ambient recommendation services for wandering people in a privacy protective environment.

B. About Ambient Intelligence

Traditionally search and recommendation (S&R) systems aim at being as seamless as possible, making use of user behavior (e.g. navigation history) and context (e.g. social connections) to support the decision making process. Whereas previously confined to web navigation the current trend is to move this monitoring to the physical world including instant localization. A whole set of sensors now embedded on smartphones give access to satellite based positioning, acceleration, rotation, magnetic environment, wireless connectivity, temperature, pressure, light intensity, providing valuable direct and indirect information to perform user profiling based on mobility analytics. Our goal is to experiment Ambient Intelligence [1] to achieve context awareness and deliver user centered services through the use of pervasive and ubiquitous computing. Recent smartphone enhancements in terms CPU, GPU and storage capability open the door for such profiling and recommendation without relying that much on externalized resources.

C. About the user privacy protection paradigm

Data Protection Regulations give more rights to users. They must now be informed about what sort of personal data is collected and should be able to access, redact and even delete it which raises some issues for S&R systems making use of data aggregation and matrix factorization for instance.

Popular techniques such as collaborative filtering methods [2] now add similarity among users to existing data models taking into account similarities upon user's history and targeted objects [3]. Whatever specific method is used in this domain (memory-based [4], model-based [5], dimensionality-reduction [6], generative-model [7], spreading-activation [8] or link-analysis [9]) it intensively relies on data aggregation and cross-references. This as a consequence creates some cold start issues [10]. In a paradigm where users are anonymized and history or preference data is not kept server side this is a major technical problem. New deep learning approaches [11] which demonstrated huge improvements in result relevance are even more data greedy to support multi-layered architectures.

To increase privacy protection still preserving data aggregation, new techniques explore obfuscation of private data to support ranged queries [12]. But even though users' data still need to be collected and compared, which ends-up in being a question of trust.

In our experiment we are testing concepts and methods to provided user centric, customized services, taking into account history, taste, constraints and context still preserving privacy. Our proposal is to make use of ambient monitoring and decentralized S&R to achieve this objective.

D. The Ambient Wanderer Experiment

The Ambient Wanderer project (AW) aims at developing and experimenting a recommendation system for people unfamiliar with their environment (e.g. travelers in a new city) willing to spent some time exploring and discovering interesting places. One noticeable aspect is that it is not a search engine. People do not request the system for a place, but rather, depending on their availability, are suggested near-by points of interests (POI). It means that AW must know, depending on the context (e.g. time, place, availability) with limited user interaction, what suggestion best fits current tastes or interest. This particular aspect of the project relates to the ambient intelligence concept introduced earlier in this paper as it means that AW should discover through mobility data analytics both user's profile and on-the-fly opportunities. Suggested activities can cover permanent POI (such as restaurants) and temporary events in permanent POI.

User profile can off-course be defined manually but our assumption is that it generally does not support or adapt smoothly to contextual changes. In AW, user profiling makes use of trajectory analytics to discover significant places and time constraints. However, an additional dimension is required to explicit the meaning of these places: a data warehouse of point of interest (POI). The role of this database is twofold: for the profiling part to provide structured and standardized information about visited POI then for the recommendation part to provide a list of nearby POI along with contextual information. For our experiment we mapped information from 4 different Geographic databases (HERE, FourSquare, Grand-Lyon, IGN), and 9 different social and cultural events databases (PreditHQ, International Showtime, Evenbrite, Songkick, Allevents.in, Meetup, Sportradar, 10times).

With respect to the privacy protection aspect, our proposal is to run the profiling part on the device (which means no centralized processing). However, some data need to be exchanged with the data warehouse (i.e. position and POI details) but as no recommendation or ranking as to be performed by the data warehouse, no user identification is required. To a larger extent, for increased privacy protection intermediate network routers our virtual private networks can be used without impacting query results.

This paper discuss experiments made to test the concept of local profiling thanks to user mobility analytics.

II. Mining trajectories for profile inference

A. *Knowledge Acquisition through Trajectory Analysis and POI Discovery*

Trajectories contain a wealth of information about users, about their favorite places, habits, schedules, constraints, transportation modes and to some extent their tastes. But inferring such meta information requires to process raw data. Trajectories are typically sets of way points $WP_i = \{ \varphi, \lambda, \sigma, \tau \}$ where φ is a latitude , λ a longitude, σ the altitude and τ a time stamp. This information may come from direct sources of data such as Satellite based Navigation Systems (SNS). But other sources of data are also available such as semi-direct (Wi-Fi, Bluetooth, Internet of Thing beacons) via radio maps or indirect ones (e.g. linear acceleration, rotational acceleration, magnetic field, light, pressure, sound environment).

Direct sources are almost unavoidable in terms of precision but they come with 2 major drawbacks. The first one is energy consumption. However, new SNS chips combined with the use of multiple satellite constellations and more powerful batteries should proportionally reduce the relative impact of such computation with respect to other components (such as screen display) consumption within smartphones [13].

The second concern is related to a loss of precision while entering an indoor location. A lot of researches are now focusing on using semi-direct and/or indirect sources to overcome this issue ([14], [15], [16]).

Semi-direct sources are a good alternative to SNS in term of energy consumption but the main limitation is to get access to radio maps. Wi-Fi hot spots are interesting as they offer more accuracy typically for indoor localization and can, in some cases, provide additional information thanks to broadcasted network identification.

Indirect sources of data only provide physical measures [17] with respect to a local referential (i.e. a smartphone). Such information is generally very noisy and un-calibrated but might provide some clues about move patterns typically for indoor locations [18].

As a first implementation of AW we started with SNS positioning. Sampling intervals can be optimized to preserve energy consumption taking into account motion characteristics for indoor and outdoor location such as those detailed in table 1.

TABLE I.

Selected SNS sampling intervals		
Outdoor	***Speed (m/sec)***	***Time Interval (sec)***
	0 < s < 0.5	10
	0.5 < s < 2	5
	2 < s < 15	20
	s < 15	30
Outdoor	-	60

Such settings prioritize precision for walking phases. AW is not a navigation system per se. One salient aspect of the profiling part is to detect to which POI a user walks to. This is why sampling intervals are shortened when entering a slow motion phase where precision is required.

B. *Stay Area versus POI: definition*

One key concepts tested in AW is to build user profiles making use of visited POI. Our assumption is to consider user navigation in the real world similar to navigation on the world wide web. A visited POI is similar to a selected hyperlink. Therefore, we use POI metadata (type, price, ambience, etc) as well as time series and event sequences for content based modeling and recommendation. However, before going further in the analysis, we need to define some concepts first.

A stay area (SA) is a place where a user spent "some" time. It is different from a stay point, where no move is recorded for a given amount of time. To illustrate this, we can consider a stop at a gas station where a user moves around a car, stay still when filling the tank then go to pay and comes back to the car. In AW it is considered as a Stay Area. Shapes, borders, centroids and methods to build SA are discussed in the next section.

A point of interest (POI) at least in its basic definition as implemented by POI databases is a place (a location) associated with a description (e.g. type, price, …). POI share with SA similar questions about size, shape and centroid definition. Typically, is a particular place (such as a bench or a fountain) within a park a POI in itself or should it be the park as a whole. Where the centroid should be located? In databases POI are generally registered as a point (the centroid is typically positioned at the center of the POI surface).

One aspect of user profiling in AW is performed thanks to matching overlap between SA and POI. We use primarily the Harversine distance (*Hd*) among centroids (1) complemented by vertical distance (*Vd*) if available (4). Haversine formulae is a less accurate than Vincenty's formulae [19] but deliver enough accuracy for short distance considered in SA to POI comparison.

$$Hd = 2\,R \arcsin\left(\sqrt{\sin^2(\Phi) + \cos(\varphi 1)\cos(\varphi 2)\sin^2(\Gamma)\ \sin 2(\Phi)}\right) \tag{1}$$

with

$$\Gamma = \frac{\lambda 2 - \lambda 1}{2} \tag{2}$$

$$\Phi = \frac{\varphi 2 - \varphi 1}{2} \tag{3}$$

$$Vd = |\ \sigma_1 - \sigma_1\ | \tag{4}$$

In (1) and (4), φ is the latitude, λ the longitude, σ the altitude and R is earth's radius (mean radius = 6,371km).

C. Stay Area detection method

Standard methods are based on Stay Point detection [20]. A distance comparison is made between an anchor point and its successors to check if it stays below a predefined distance threshold. In such case a second test is performed to measures the time span between the anchor point and the last successor that is within the distance threshold. If the time span is larger than a given threshold, a stay point is detected.

These thresholds can be set manually or dynamically [21]. According to our experiments predefined thresholds are useful when searching for a specific type of stay (e.g. in a restaurant, at work) where a minimal duration can be set. However, when activities are totally unknown dynamic thresholds using change points detection should be preferred as they allow to get a much finer grained analysis. Change points detection techniques [22] identify significant variations in trajectory patterns such as speed. It allows detection of transportation modes and multi-modality interconnection nodes (e.g. switch from car to subway to walk). In the context of AW, change point detection and motion patterns are important for the recommendation system as it allows to filter which POI are reachable depending on considered transportation mode.

However, stay point based methods give partial results which are collections for stops within trajectories. They do not capture the granularity of a stay within a large place. So improved methods [23] apply density clustering as post processing to aggregate close candidates into larger Stay Areas.

Nevertheless, from our experiments we realized that it was insufficient to address every types of stay such as "cloaked areas". It typically occurs when a user enters a place where localization information is lost. For various reasons such as to reduce energy consumption the tracking application may stop recording. We end-up in having a gap (or a significant difference) in time intervals between recorded way points. Therefore, depending on selected thresholds there might not be enough way points to activate Stay Point creation. We developed an adaptation to the standard stay points detection algorithm to detect such disappearance and reappearance within the same vicinity. It makes use of trend analytics. The trend computes the mean time θ over *m* previous way points. Therefore, for 3 consecutive way points (W_{i-1}, W_i, W_{i+1}) a "cloaked" Stay Area is created if:

$$(\ t_{i+1}\ >\ \alpha.\theta)\ \ AND\ \ \left(d_{i+1} < \beta\left(\frac{d_i}{t_i} \times t_{i+1}\right)\right) \tag{5}$$

where t_i and d_i are respectively the time and distance intervals between W_{i-1}, and W_i, and t_{i+1} and d_{i+1} the time and distance intervals between W_i, and W_{i+1}. The size *m* of the trend window depends on the default sampling interval used for data collection. In our experiments, considering 5 way points with a 10 seconds sampling interval and a walking speed of 1.5 m/sec it allows computing a mean values over 60 meters which is enough to build the trend. α can be set either dynamically or statically depending on the targeted goals. In our experiments we create as Stay Area if the disappearance is longer than 10 times the mean time interval (α = 10). As for setting the maximal radius allowed from W_i, the idea is to keep the reappearance position (W_{i+1}) close enough from the disappearance position (W_i) and therefore much below the distance that could have been made in the meantime keeping the same mean speed). In our experiment we used the following setting: β = 0.2.

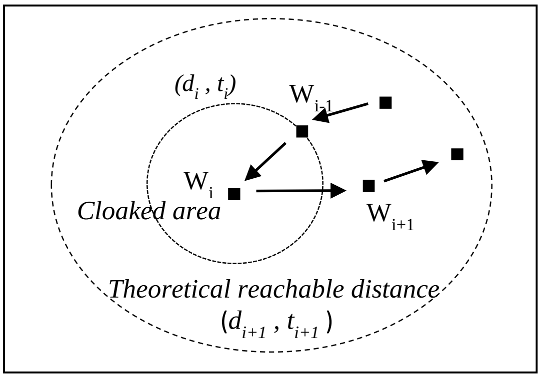

Fig. 1. Cloacked Area Detection

Also, as a stay area is a sequence of way points, for convenience when computing a distance with respect to another location (such as a POI), we define the centroid as a temporal barycenter where each way point W_i gets as weight the value of the time interval t_i between W_i and W_{i+1}.

$$G_j = \frac{\sum_{i=1}^{n} t_i\, W_i}{\sum_{i=1}^{n} t_i} \tag{6}$$

As for the shape of a SA we use the convex hull [24] which provides a closer fit to the covered surface.

III. Experiments

A. Datasets

In order to test our hypothesis, we performed several data collection campaigns monitoring users moves around cities such as Lyon and Grenoble in France. We developed a data recording application deployed on Android phones to capture various direct (SNS), semi-direct (Wi-Fi) and indirect (acceleration, gyroscopic rotation, magnetic field, footsteps) sources of information.

We collected 35 days of data (Fig.2) that have been annotated to build a ground truth. This annotation focused on identifying "significant events" (*E*) which have a minimal duration of at least 5 minutes. We used 10 days of data for our developments, then 25 days for our evaluation. The size is limited to test cold start profiling starting with small amount of observations. The ground truth is a set of labelled events characterized as E={C_E, T_E, D_E, P_E} where C_E is the event centroid, T_E the starting time stamp of the event, D_E a duration and P_E the event type (which may be related to a registered POI). As a convention in our ground truth the centroid C_E has been positioned at the entrance of the event area. In comparison, *POI*={C_P, P_P} reflects a registered point of interest within our data warehouse where C_P is the centroid location as defined in the database and P_P the name of the POI. A={C_A, T_A, D_A, P_A} is a detected area where $P_A \leftarrow P_P$ if $C_A \approx C_P$.

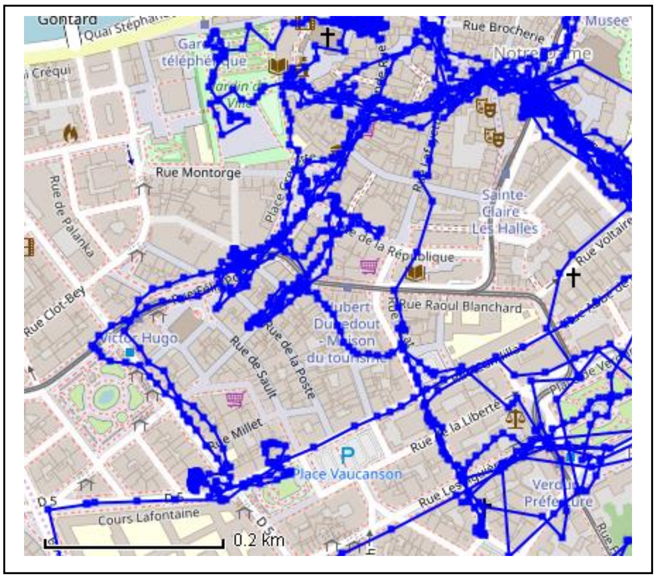

Fig. 2. Aggregated trajectories in Grenoble downtown area

Therefore, from this dataset two different evaluations are performed: the SA detection method and the sematic disambiguation. For the first task (Table 2) a match between A and E is validated if: the Haversine distance between C_A and C_E is below 30 meters and $(T_A - T_E) < 5$ minutes. For the second task (Table 3) a match is validated if : $P_A \approx P_E$.

TABLE II.

Evaluation of Detected Stay Areas	
Labelled events above 5 min (*E*)	208
Detected Stay Area Candidates (A)	194
Correct Stay Area (CA $\approx$ CE)	163
False positive	31
Missed events	16
Recall	0.7836
Precision	0.8402
F1-mesure	0.8109

TABLE III.

Evaluation of POI match	
Labelled events above 5 min (*E*)	208
Labelled (*E*) registered in POI database	115
Valid match ($P_A \approx P_E$)	67
Candidates not in POI database	81
Incorrect candidates	7
Missed events	8

B. Results analysis

For the first task (table 2), the lack of precision in way point localization within trajectories is the main source of false positives. Computed temporal barycenters are located too far away from real event centroids for match validation. Then noise in trajectory data (artificial leaps in way point sequences) also impacts stay points (and therefore Stay area) detection. Exact WP positioning is really critical to increase recall and precision for SA detection (Fig 3.).

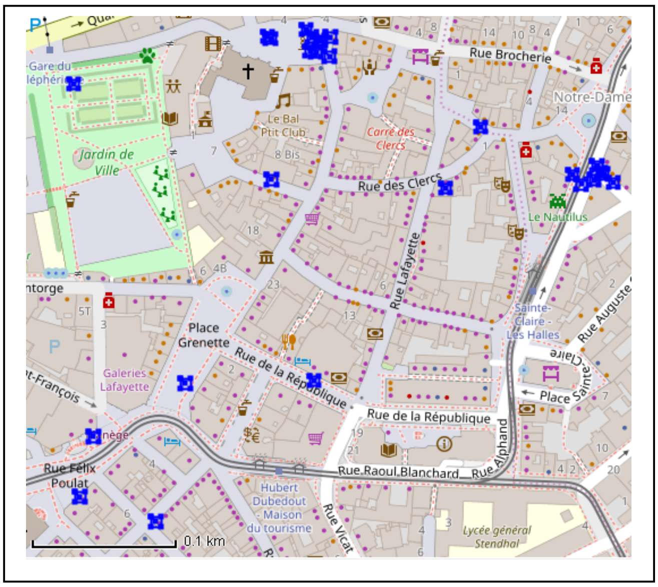

Fig. 3. Detected Stay Areas in Grenoble downtown area

Exact localization of centroids for detected SA, labelled events and registered POI is also a major issue for the second task (table 3.) as it cumulates two problems. The first one is a lack of overlap between centroids. If, due to a lack of a precision, C_A and C_P are not close enough then no alignment is made between *A* and *P*. Furthermore, even if a match is granted it may happen that C_P and C_E are not close enough. In such case it is not possible to align P_A and P_E and therefore to miss some events (Fig. 4).

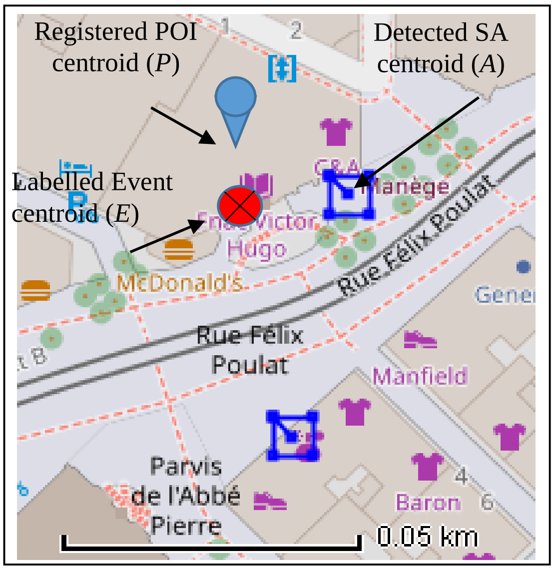

Fig. 4. Centroid inconsistancies for a same event/SA/POI

In order to test the impact of such misalignment between labelled event centroids (C_E) and registered POI centroids (C_P) we started to isolate from our ground truth a set of unique types of events (Table IV). Then, we evaluated distances with registered POI centroids. However, from the 83 unique events in the ground truth we had to remove those not related to a registered POI (e.g. at home or in the countryside), to make things comparable. It leaves 56 unique events (*UEP*) to compare with the database.

We compared C_E to C_P distances using a threshold of 100 meters above which C_P is considered as out of range. From this study 33.9% (19 POI) are registered with a centroid that is located above the 100 m threshold. The mean distance for in range POI is detailed in table V.

TABLE IV.

Centroid Comparison between events and POI	
Unique types of labelled events	83
Unique labelled events registered in POI database (*UEP*)	56
Unique labelled events Not registered in POI database	25
UEP within range	37
UEP out of range	19

To overcome this problem one option could be to increase the distance threshold for matching C_A, C_P and C_E centroids but this has side effects.

Indeed, the second issue relates the lack of completeness of POI databases. If a user visits a friend in an apartment, this place generally is not registered ("candidates not in database") in typical POI database, but if there is a near-by POI (e.g. medical doctor or lawyer's office within close vicinity) then flexibility over centroid distances ends-up in allowing a match between the stay area and the POI. Ruling out these cases is very challenging. It may involve comparing SA and registered POI surfaces, or to consider additional information such as broadcasted Wi-Fi identification.

TABLE V.

Centroids distance comparison for UEP (meters)	
Minimum distance (in meters)	1.9
Maximum distance (in meters)	81.2
Mean distance (in meters)	21.2
Standard Deviation	19.8

Finally, the last main challenge identified from this analysis is related to the semi-indoor problem. A definition of this problem is detailed in [25], but it might be summarized as: for people stopped in front of a POI, exact localization may be jeopardized by SNS noise due to the proximity of tall building walls. In such a case the problem is to detect if people entered the POI or not. Incorrect indoor/outdoor positioning can create a false assignment between the stay area and the nearby POI. In our ground truth for 81 events that do not relate to a registered POI in our database, 18 (22%) are semi-indoor location (less than 10 meters from a near-by registered POI). One way to overcome this issue may relate to the detection of contextual changes [26] such as variation in the magnetic field or a significant precision drop in measured SNS data precision. This is the next step planned for our experiments.

IV. Discussion and Next Steps

We presented in this paper the first phase of an on-going experimental project aiming at testing ambient intelligence to support mobile users in a context of strong data privacy protection. Users' profile and preferences are computed locally, in isolation from the crowd. This is a paradigm shift facing several challenges such as exact user localization (typically when entering to indoor or covered areas) and semantic disambiguation of significant places taking into account a lack of completeness in existing POI databases. The next development phase will address indoor POI detection and the disambiguation of detected stay areas based on the context. Then we plan to compare these results with non-privacy oriented POI detection methods as those performed by central servers to evaluate the loss depending on selected paradigm. The last phase will be to test the usefulness of inferred user's profiles for on-the-fly POI recommendation in the Ambient Wanderer experiment.

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