Smart usage of context information for the analysis, design and generation of power-aware policies for mobile sensing apps

Rafael Pérez Torres

Dr. César Torres Huitzil
Dr. Hiram Galeana Zapién
Cinvestav

Doctoral seminar, 2017

Cinvestav
Unidad
Tamaulipas

Structure

Introduction
Background

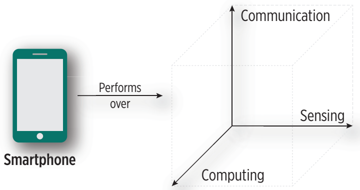


Figure: The advances in the communication, computing and sensing dimensions of mobile devices contribute to their acceptance by society.

Background

- Smart devices, such as the smartphone, become popular after the advances on its underlying technologies.
- The sensing dimension enables *context-awareness* in mobile device, for improved human – computer interaction and enhanced information.
- Battery advances are slower than those of other smartphone components [1], growing 5-10% yearly [2, 3].
- The energy constraint is critical when continuous access to sensors is needed, as in **mobile sensing applications**.

Introduction
Motivation

Motivation

- For the sensing dimension, scientific efforts have been done for achieving the energy efficiency of the GPS location provider.
- The understanding of mobility could augment the location-awareness of the smartphone for many purposes, such as energy savings and the development of Location and Mobility Based Services (LBS, MBS).
- Mobility Based Services are of paramount importance for future Internet of Things (IoT) developments, such as smart cities [4].
- As a high level of abstraction, mobility can be characterized as a sequence of frequently visited places (stay points) using different transportation modes.

Problem statement

- The understanding of mobility is possible at different spatial-temporal scales:

Fine-grain mobility patterns identification

- They refer to the transportation mode employed by user when moving between stay points.
- Given a set of values $\mathcal{V} = \{v_{acc\ 1}, v_{acc\ 2}, \ldots, v_{acc\ n}\}$ obtained from accelerometer in the time interval $[t_1, t_2]$, identify fine-grain mobility information:

$$\textbf{FineGrainMobilityIdentifier}(\mathcal{V}) \rightarrow p_S \in \{\text{static, walking, biking, vehicle}\}$$

with each $v_{acc\ i} \in \mathcal{V}$ composed as $\langle acc_x, acc_y, acc_z, t \rangle$.

Coarse-grain mobility patterns identification

- They refer to motion at a large spatial scale related to user visiting stay points.
- Given a set of values $\mathcal{V} = \{v_{gps\ 1}, v_{gps\ 2}, \ldots, v_{gps\ n}\}$ obtained from GPS location provider in time interval $[t_1, t_2]$, identify coarse-grain mobility information:

$$\textbf{CoarseGrainMobilityIdentifier}(\mathcal{V}) \rightarrow p_S \in \{\text{new stay point, arrival, departure}\}$$

with each $v_{gps\ i} \in \mathcal{V}$ composed associated $\langle lat, lon, t \rangle$.

Hypothesis

Hypothesis

- The energy consumption of continuous and extended location tracking could be reduced by means of a cognitive dynamic system that learns an expanded spatial-time model from mobility events detected from sensors data and that employs such model in a cognitive controller for dynamically adapting GPS sampling rate through sampling policies tailored to current mobility state.

Objectives

Main objective

- To reduce the energy consumption of mobile sensing apps, which perform continuous sensor sampling, through self-adapting power-aware policies generated from context information obtained from sensors data.

Particular objectives

- To detect mobility patterns from context information obtained from an inertial sensor (accelerometer) and location provider (GPS).
- To generate an accurate representation of detected patterns for summarizing user mobility: a spatiotemporal model.
- To dynamically adapt GPS sampling rate by means of a cognitive controller that employs the learned mobility representation and accuracy requirements for implementing power-aware sampling policies.
- To ease the development of mobile sensing applications that require user location tracking, i.e., LBSs and MBSs, isolating the complexity of sensors access and the associated efficient energy management.

Contributions

Contributions pursued by this research work

- An on-device mobility patterns detector that works with streams of raw data collected by smartphone's sensors (GPS and accelerometer).
- An on-device mobility analyzer that incrementally builds a model of user mobility from the detected mobility patterns.
- A cognitive controller inspired on CDSs that, based on the mobility information learned, dynamically adapts GPS sampling rate through power-aware policies.
- A middleware with the previous modules embedded for easing the development of LBSs and MBSs for the Android mobile platform.

Methodology

Steps

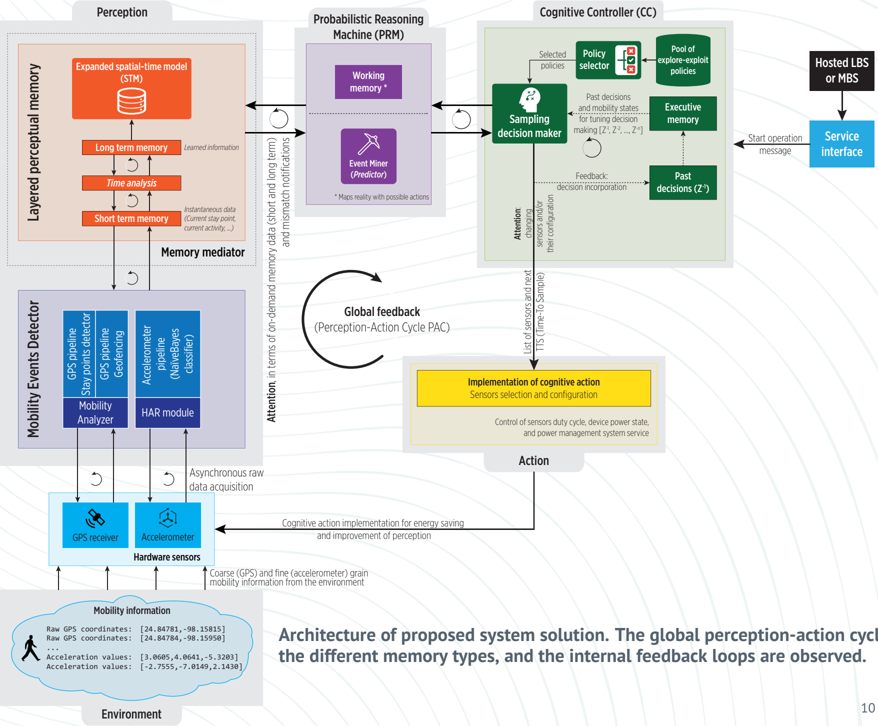
1. Revision of state of the art power-aware sensing techniques.
2. Formal definition and selection of mobility patterns to be identified.
3. Research on algorithms for detecting mobility patterns.
4. Design of the *Mobility Events Detector*.
5. Design of adaptive policies for energy efficient usage of sensors.
6. Design of the Cognitive Controller.
7. Development of a middleware involving the *Mobility Events Detector* and the Cognitive Controller for the Android platform.
8. Experimentation in terms of spatial-time accuracy and energy efficiency.

Proposed solution

Solution's fundamentals

The underlying fundamentals of proposed solution

- Stay points [5].
- Event-driven systems [6].
- Cognitive Dynamic Systems [7, 8, 9].



Architecture of proposed system solution. The global perception-action cycle, the different memory types, and the internal feedback loops are observed.

Updated schedule

		2017					2018							
#	Activity	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
	I Integration of components													
1	Incorporation of the HAR module in the CC	●	●											
2	Incorporation of the accuracy requirement in the CC		●	○										
	II On-device implementation													
3	Implementation of sigmoid-driven sampling				○									
4	Watchdog mechanisms for Geofencing and Sampling Decision Maker modules				○									
5	Refinement of the list of candidate stay points employed by the Geofencing module				○	○								
	III Experimentation													
6	Experiments with larger and heterogeneous mobility						○	○	○					
7	Completion of evaluation framework					○	○	○						
8	Comparison with other solutions									○	○			
	IV Research work activities													
9	Thesis writing-review								○	○	○	○	○	
10	Thesis defense													○

Table: Schedule of research work pending activities for the last year of the doctoral program.

Thank you for your attention!

> Consider again that dot [Earth]. That's here. That's home. That's us.
>
> *Carl Sagan*

Cinvestav
Unidad
Tamaulipas

Detailed schedule

	Work: ● Done, ● In progress, ○ To be done	2014	2015			2016		
		3rd	1st	2nd	3rd	1st	2nd	3rd
	Step I							
1	State-of-art reading	●	●					
2	State-of-art works categorization		●	●				
3	Documentation of information found (committee request)			●				
	Step II							
4	Development of a mobile app for accelerometer and location data collection			●	●			
5	Analysis of data				●			
6	Formal definition of mobility pattern				●			
7	Selection of mobility patterns				●	●		
	Step III							
8	Research on classification algorithms for mobility patterns				●	●		
9	Definition of metrics for evaluating algorithms					●		
10	Implementation of algorithms in mobile platform					●	●	
11	Selection of best algorithms according to metrics						●	
	Step IV							
12	Definition and modeling of parameters needed by the *Mobility Events Detector*				●	●	●	●
13	Development of the *Mobility Events Detector*.				●	●	●	●

Table: Schedule of activities (each column represents a four months period)

Detailed schedule

		2016			2017			2018
	Work: ● Done, ● In progress, ○ To be done	1st	2nd	3rd	1st	2nd	3rd	1st
	Step V							
14	Formal definition of policy			●				
15	Research and evaluation of techniques for generation and adaption of policies			●	●			
16	Design and execution of experiments applied to use cases			●	●			
17	Selection of policies				●			
	Step VI							
18	Definition and modeling of Cognitive Controller parameters					●		
19	Development of the Cognitive controller					●		
	Step VII							
20	Analysis of components into software abstractions					●		
21	Research on Android API for specialized components					●		
22	Development of middleware					●		
	Step VIII							
23	Definition of experiments aimed at accuracy and energy consumption metrics						●	
24	Development of experimental sample mobile apps						●	
25	Experiments execution						●	○
26	Final results analysis							○

Table: Schedule of activities (each column represents a four months period)

Detailed schedule

		2014	2015			2016			2017			2018	
Work: ● Done, ● In progress, ○ To be done		3rd	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd	1st	2nd
	Required tasks												
A	Related courses	●	●	●									
B	Research articles submission				●		●					● (in progress)	
C	Predoctoral exam preparation									●			
D	Thesis writing	●			●			●			● (in progress)	○	○

Table: Schedule of required activities

Layered perceptual memory

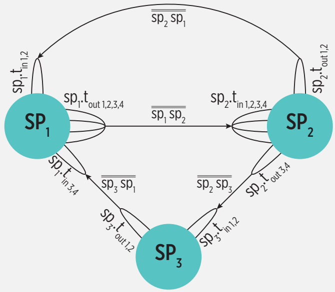
Short and long-term memory information

Layered perceptual memory

- Short-term memory information: current (observed) mobility status.
- Long-term memory information: the Expanded Spatial-Time model (STM).

Expanded Spatial-Time model

- The highest level of mobility information held by the system.



$\overline{sp_1\,sp_2}$ A summarized trajectory between sp_1 and sp_2

$\overline{sp_2\,sp_1}$ A summarized trajectory between sp_2 and sp_1

$\overline{sp_2\,sp_3}$ A summarized trajectory between sp_2 and sp_3

$\overline{sp_3\,sp_1}$ A summarized trajectory between sp_3 and sp_1

Figure: A conceptual representation of the STM's structure.

Layered perceptual memory

Expanded Spatial-Time model (STM)

Generation of the STM

- Incrementally built with the coarse-grain mobility events detected by the *Mobility Events Detector*.

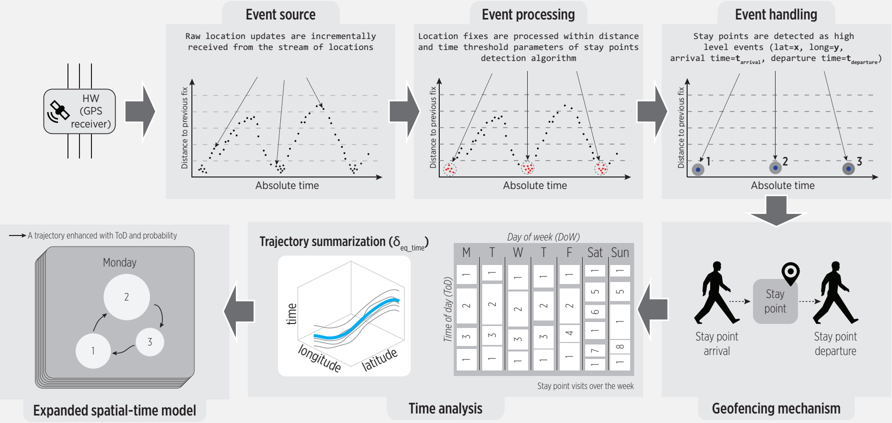


Figure: A conceptual representation of the steps for generating the STM from raw sensors data.

Cognitive controller (CC)

Description

Goals

- To reduce the energy consumption of location tracking by relying on PRM's estimations.
- To reduce the system uncertainty about current user mobility.

Possible cognitive actions

- **Exploitation policies**: When system uncertainty is low for saving energy purposes.
- **Exploration policies**: When system uncertainty is high for recovering for accuracy loss.

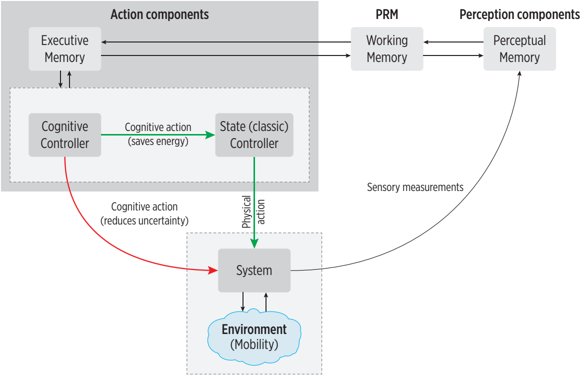


Figure: A generic cognitive controller architecture

Cognitive controller

Policies tailored for user mobility

Stay point mode

- A sampling based on the sigmoid function $sig(x) = \frac{1}{1+e^{-\alpha x}}$ as a model for the mobility phase transitions.
- Higher sampling rate on arrival and departure, when the user is more likely to move, and slower at the middle of a visit.

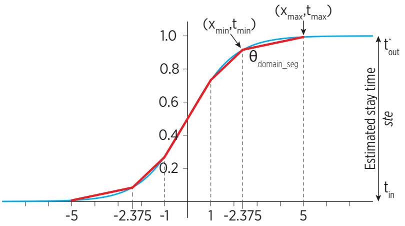


Figure: Approximation of the sigmoid through straight segments.

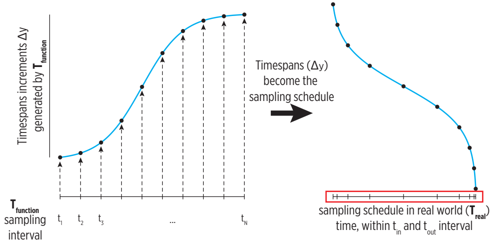


Figure: A snapshot of the process for producing a sigmoid sampling.

Preliminary experimentation

Stay Points Detector module spatial-time accuracy

Description

- This experiment evaluates the spatial-time accuracy of the *Stay Points Detector* module under different GPS sampling rates in terms of centroid distances and latencies.

Stay Points Detector	**Time threshold** (δ_{time}):	45 *min*
	Distance threshold ($\delta_{distance}$):	500 *m*
Sampling periods:	30, 60, 90, 120, 150, 180 seconds.	
Trajectories:	All ground truth trajectories.	

Table: Input parameters for the spatial-time accuracy of stay points experiment.

Results

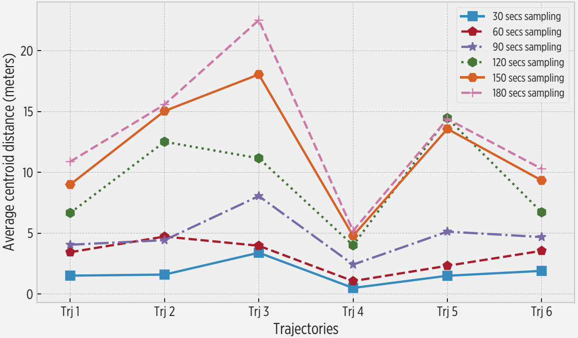


Figure: The impact of different sampling periods on the centroid distance of identified stay points in each trajectory. A maximum centroid distance of $22.52\ m$ is identified when employing the 180 seconds sampling period.

Preliminary experimentation

Geofencing module spatial-time accuracy: Results

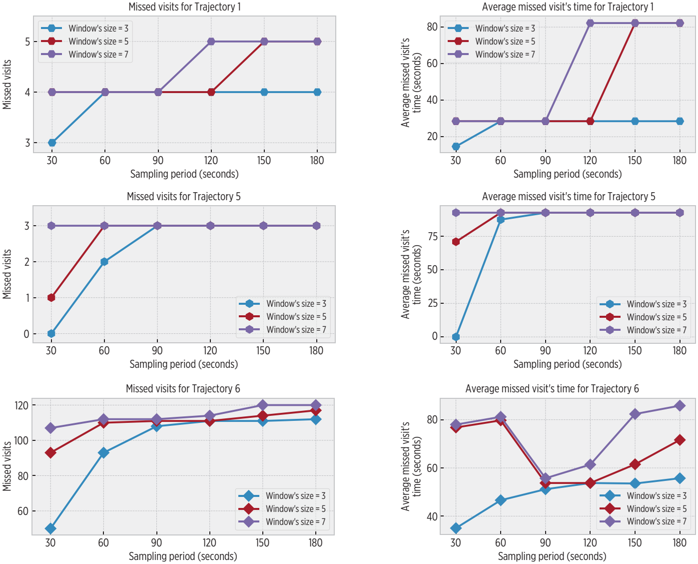


Figure: Visits missed by the *Geofencing* module for each combination of sampling period and window size values. The largest amount is obtained for the *Trajectory 6*, given its length (more than 30 days). Nevertheless, they do not account for a considerable time in overall trajectories.

Preliminary experimentation

Holistic evaluation: Results

Sigmoid configurations

- segs: [-5,-2.375,-1,1,2.375,5], max-time-seps: [90, 150, 180, 150, 90]
- segs: [-5,-2.375,-1,1,2.375,5], max-time-seps: [60, 120, 180, 120, 60]
- segs: [-4,-2.375,-1,1,2.375,5], max-time-seps: [60, 150, 180, 150, 60]
- segs: [-5,-2.375,-1,1,2.375,5], max-time-seps: [90, 120, 180, 120, 90]
- segs: [-4,-2.375,-1,1,2.375,5], max-time-seps: [90, 150, 180, 150, 90]
- segs: [-4,-2.375,-1,1,2.375,5], max-time-seps: [60, 120, 180, 120, 60]
- segs: [-5,-2.375,-1,1,2.375,5], max-time-seps: [60, 150, 180, 150, 60]
- segs: [-4,-2.375,-1,1,2.375,5], max-time-seps: [90, 120, 180, 120, 90]
- 30 secs fixed sampling

Arrival latency

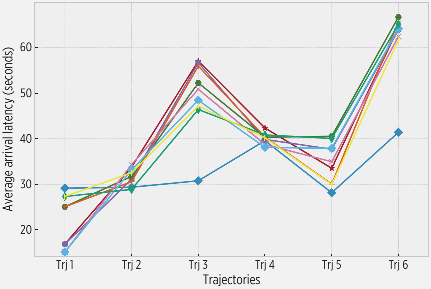


Figure: Arrival latency observed by the platform in experimental trials. The largest average value is below 65 seconds, explained by the fact that 2 location updates must be collected by the *Geofencing* module before identifying an arrival event.

Departure latency

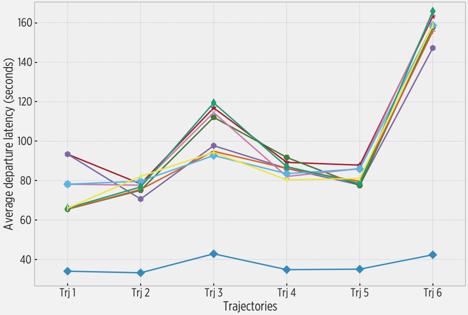
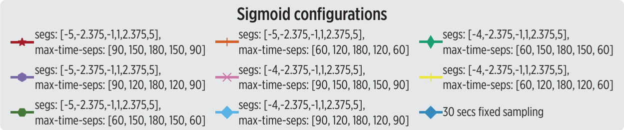


Figure: Departure latency observed by the platform across performed experimental trials. The latencies are within 65 and 165 seconds, which is aligned with the different values specified to the CC for its sigmoid-driven sampling.

Preliminary experimentation

Holistic evaluation: Results



Trajectory distance difference

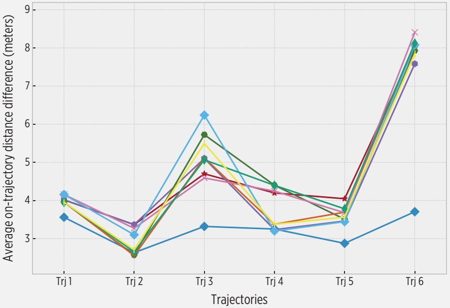


Figure: The average distance of equivalent trajectory segments during experimental trials. The values are enclosed within 2.5 *m* and 8.5 *m*, with the 30 seconds sampling obtaining the lowest values in each trial.

Overall reduction of location update requests

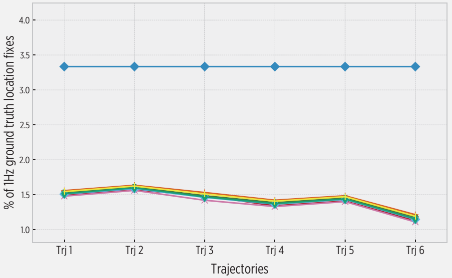


Figure: The proportion of location update requests employed by each experimental trial with respect to the corresponding 1 *Hz* ground truth trajectory. All of the parameter combinations outperform the 30 seconds sampling period, which provides a rough estimation of the energy savings that the system could achieve in on-device implementations.

Preliminary experimentation

Energy saving expectations of on-device stay points detection

Description

- This experiment explored whether a smartphone could detect stay points by itself, and the energy savings of such implementation with respect of typical Mobile Cloud Computing (MCC) based solutions.

Stay Points Detector	**Time threshold** (δ_{time}):	45 *min*
	Distance threshold ($\delta_{distance}$):	500 *m*
Sampling periods:	30, 60, 90, 120, 150 seconds	

Table: Input parameters for the energy saving expectations of on-device stay points detection experiment.

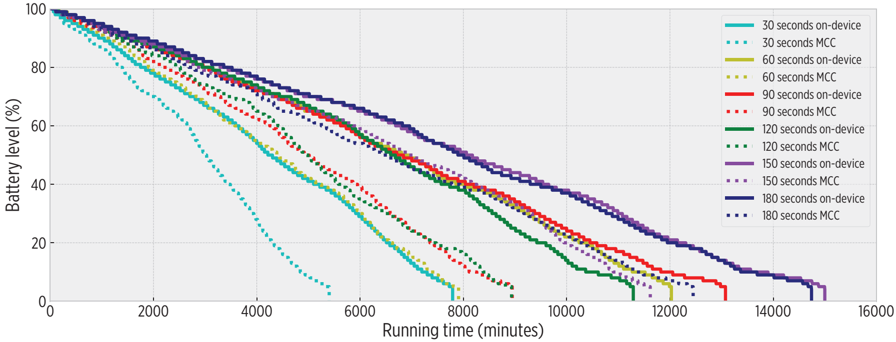


Figure: Energy performance comparison of on-device vs. MCC sample apps using different GPS sampling periods. Each of the on-device trials last longer than its corresponding remote implementation.

Preliminary experimentation

Energy consumption of fixed-sampling periods: Results

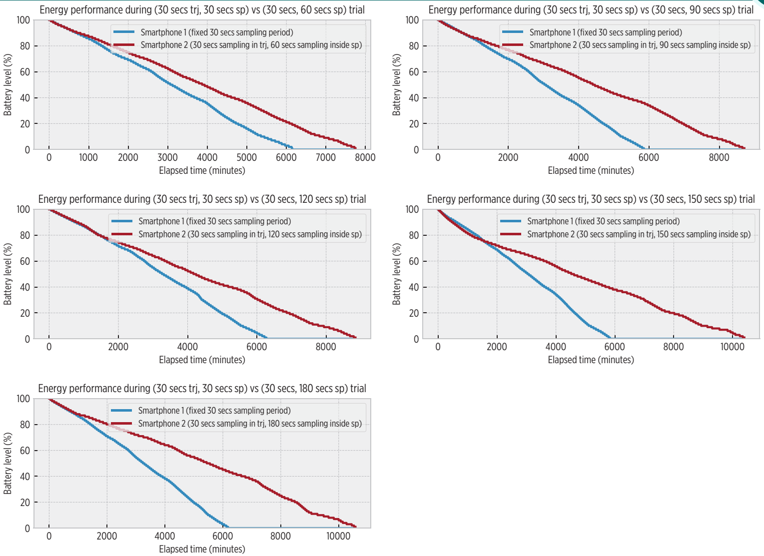


Figure: Energy performance of a fixed 30 seconds sampling versus a basic sampling adaptation consisting in a 30 seconds sampling in trajectory mode and a slower sampling rate during stay point mode. The separation between the lines in each plot starts after the system learns the stay points with the largest weight in user mobility (home and work places).

Preliminary experimentation

Energy consumption of fixed-sampling periods: Results

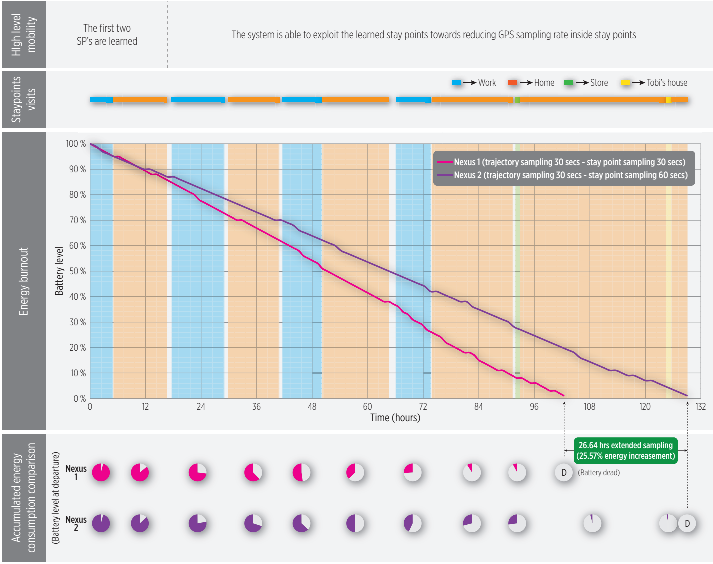


Figure: Energy performance obtained by the CDS along the mobility described by user (trial corresponding to the 30 seconds in trajectory and 60 seconds in stay point sampling).

Preliminary experimentation

Energy consumption of fixed-sampling periods: Results

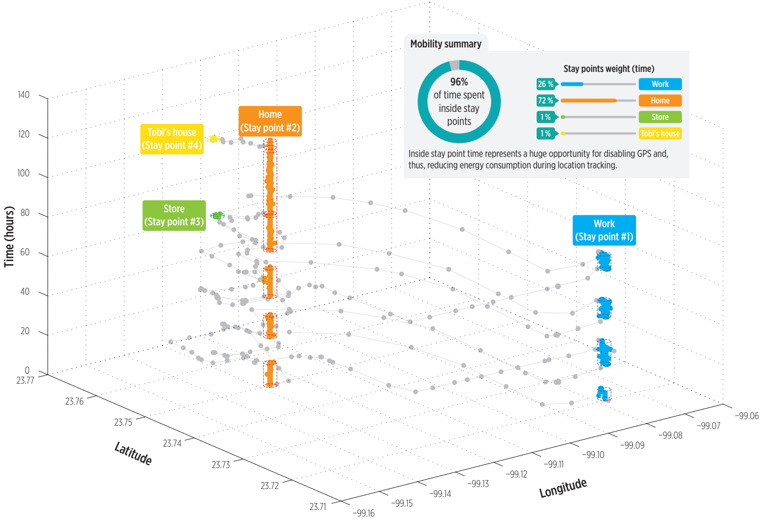


Figure: The stay points and visits identified by the system, as well as the mobility summary obtained from such information (trial corresponding to the 30 seconds in trajectory and 60 seconds in stay point sampling).

References I

[1] Mikkel Kjaergaard.
Location-based services on mobile phones: Minimizing power consumption.
IEEE Pervasive Computing, 11:67–73, 2012.

[2] Xiao Ma, Yong Cui, and Ivan Stojmenovic.
Energy efficiency on location based applications in mobile cloud computing: A survey.
In *Procedia Computer Science*, volume 10, pages 577–584, 2012.

[3] Eric C. Evarts.
Lithium batteries: To the limits of lithium.
Nature, 526(7575):S93–S95, oct 2015.

[4] Andrea Zanella, Nicola Bui, Angelo Castellani, Lorenzo Vangelista, and Michele Zorzi.
Internet of Things for Smart Cities.
IEEE Internet of Things Journal, 1(1):22–32, feb 2014.

[5] Quannan Li, Yu Zheng, Xing Xie, Yukun Chen, Wenyu Liu, and Wei-Ying Ma.
Mining user similarity based on location history.
In *Proceedings of the 16th ACM SIGSPATIAL international conference on Advances in geographic information systems - GIS '08*, number c, page 1, New York, New York, USA, 2008. ACM Press.

[6] Ted Faison.
Event-based programming: Taking events to the limit.
Apress, Berkely, CA, USA, 1st edition, 2006.

[7] Simon Haykin and Joaquin M. Fuster.
On Cognitive Dynamic Systems: Cognitive Neuroscience and Engineering Learning From Each Other.
Proceedings of the IEEE, 102(4):608–628, apr 2014.

[8] Simon Haykin, Mehdi Fatemi, Peyman Setoodeh, and Yanbo Xue.
Cognitive Control.
Proceedings of the IEEE, 100(12):3156–3169, dec 2012.

[9] Shuo Feng, Peyman Setoodeh, and Simon Haykin.
Smart Home : Cognitive Interactive People-Centric Internet of Things.
IEEE Communications Magazine, 55(February):34–39, feb 2017.