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

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Agenda

Research background

Motivation

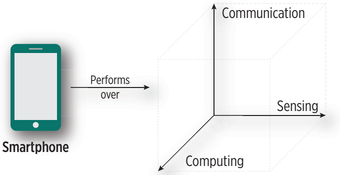


Figure: The advances in the communication, computing and sensing dimensions of mobile devices contribute to their acceptance by society [1].

Motivation

- The sensing dimension enables *context-awareness* in mobile devices, such as the smartphone.
- Battery advances are slower than those of other smartphone components [2], growing 5-10% yearly [3, 4], a critical issue for the **mobile sensing applications**.
- 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 Mobility Based Services (MBSs).

Research background

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 $\langle lat, lon, t \rangle$.

Research background

Problem statement

Sensors sampling adaptation

- Given a set of coarse and fine-grain mobility patterns $\mathcal{P} = \{p_{S_1}, p_{S_2}, \ldots, p_{S_n}\}$, and accuracy requirements of mobile app $req_{accuracy}$, implement a sampling policy for the adaptive duty cycling of sensors while reducing energy consumption:

$$\textbf{PolicyGeneration}(\mathcal{P}, req_{accuracy}) \longrightarrow \mathcal{S}_{conf}$$

where $\mathcal{S}_{conf} \rightarrow s, \mathcal{T}_{real}$ represents the sampling $\mathcal{T}_{real}$ that must be implemented for sensor s. The $req_{accuracy}$ refers to the granularity of GPS sampling.

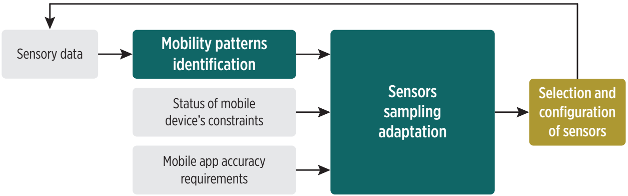


Figure: Interaction between problems.

Research background

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.

Research background

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.
- 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.

Research background

Methodology

Methodology

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.

State of the art

Taxonomy of solutions

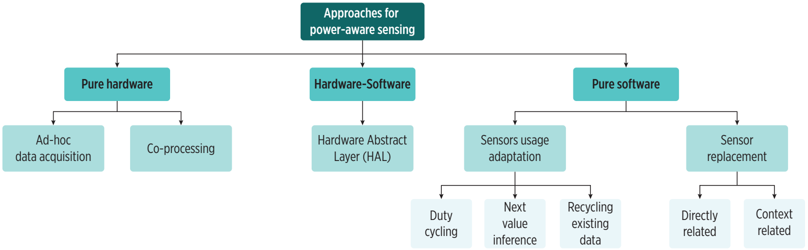


Figure: Taxonomy of solutions for power-aware sensing in mobility sensing systems.

State of the art
Remarks

Remarks

- The exploitation of coarse and fine-grain mobility information for modeling and characterizing user mobility has been barely explored.
- Although some of the proposed solutions employ a duty cycling strategy, it is fixed and obeys to instant mobility information, neglecting the temporal evolution of user mobility.
- A spatial-time accurate and energy efficient adaptive sampling could be produced by a cognitive approach that understands long-term mobility from fine and coarse-grain mobility events.
- The cognitive approach goes beyond typical pattern recognition and classic control strategies that follow a static configuration, as it evolves (in the learning and action tasks) across time.
- The smartphone itself could augment not only its location but also its mobility awareness (per-user basis).

Theoretical framework

Stay points, Event Driven Systems (EDSs)

Stay point

- A stay point refers to a geographical zone (of size $\delta_{distance}$) where the user remains for an amount of time (δ_{time}).
- It is a virtual location defined by latitude (*lat*), longitude (*lon*), arrival time (*at*) and departure time (*dt*).

Event Driven Systems (EDSs)

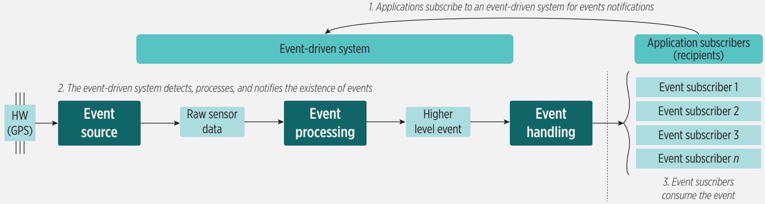


Figure: The architecture of an EDS.

Theoretical framework

Cognitive Dynamic Systems (CDSs)

Features

- Perception-action cycle
- Memory
- Attention
- Intelligence

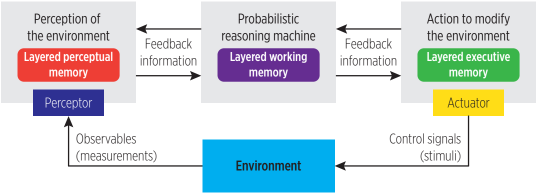
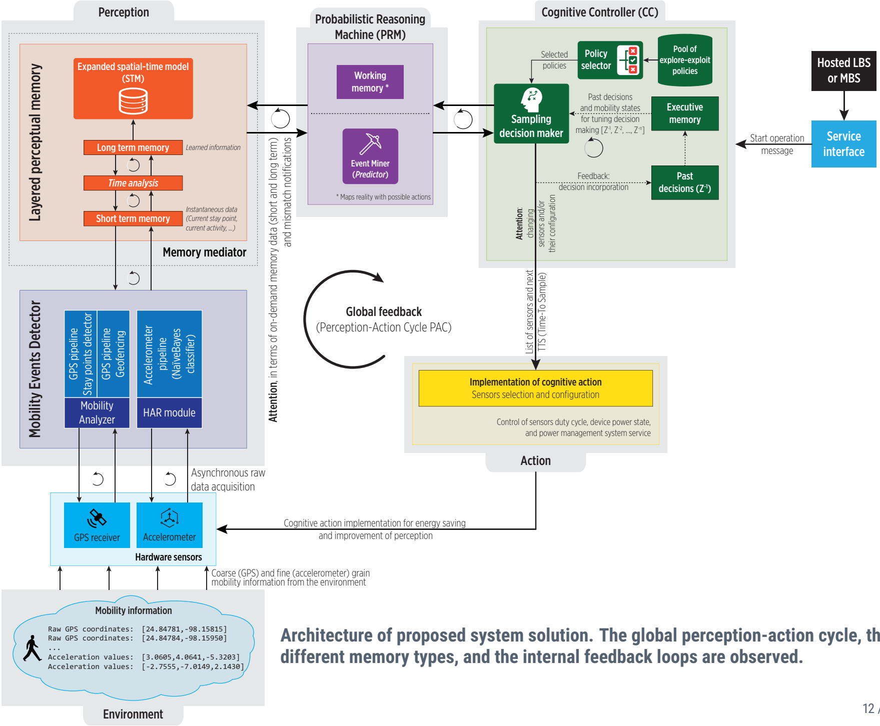


Figure: The generic architecture of a CDS.



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

Perception components

Mobility Events Detector

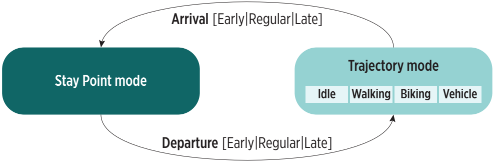


Figure: Individual's mobility as a sequence of high level states and associated events detected from raw sensor data [7, 8].

Mobility Events Detector

Aimed at identifying:

- Coarse-grain mobility events.
- Fine-grain mobility events.

Perception components

Mobility Events Detector: *Stay Points Detector* module

Stay Points Detector module

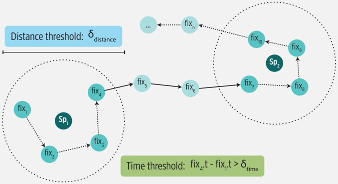
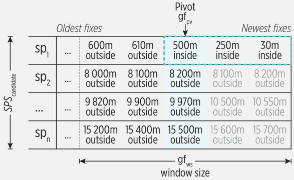


Figure: A conceptual representation of the stay points detection algorithm behavior.

Geofencing module



sp_1	...	600m outside	610m outside	500m inside	250m inside	30m inside
sp_2	...	8 000m outside	8 100m outside	8 200m outside	8 100m outside	8 200m outside
...	...	9 820m outside	9 900m outside	9 970m outside	10 500m outside	10 550m outside
sp_n	...	15 200m outside	15 400m outside	15 500m outside	15 600m outside	15 700m outside

Figure: A conceptual representation of the window-based geofencing operation.

HAR module

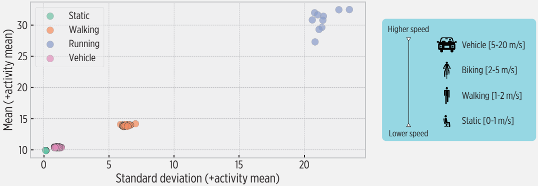


Figure: Distribution of mean and standard deviation features employed by the NaïveBayes classifier of the HAR module.

Layered perceptual memory

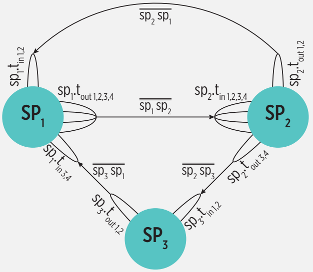
Short and long-term memory information

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*.

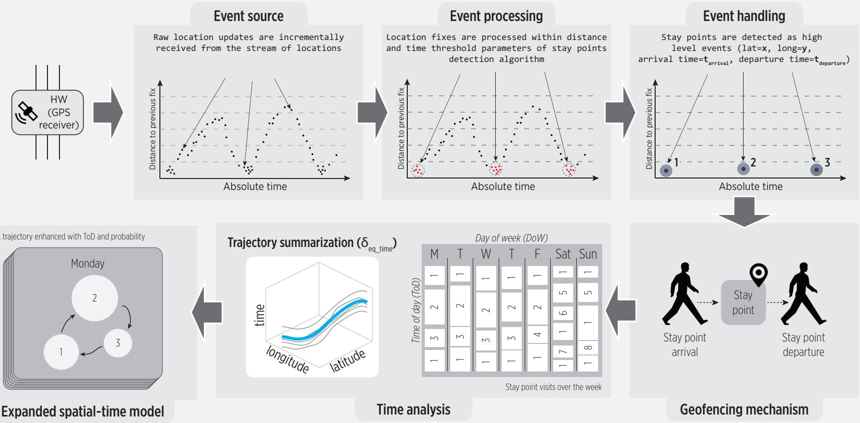


Figure: A conceptual representation of the steps for generating the STM from raw sensors data.

Working memory

Probabilistic Reasoning Machine (PRM)

PRM features

- It gives a meaning to the observed mobility information with respect of the STM information.
- It produces an estimation of future mobility state that links perceptual and working memory.

Interpretation

- The *Event Miner* traverses the STM for identifying whether learned information is:
  - Consistent, or
  - Inconsistent (mismatch)

  with respect of observed mobility information.

Estimation

- The *Event Miner* looks in the STM for a link (if any) with learned mobility information for generating spatial-time estimations:
  - Get next departure time.
  - Get next arrival time.

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.

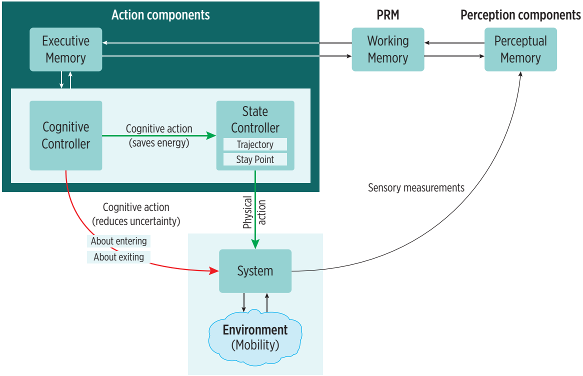


Figure: A cognitive controller generic architecture.

Cognitive controller

Policies tailored for user mobility

Stay point mode

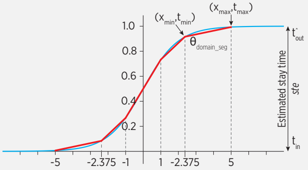


Figure: Approximation of the sigmoid through straight segments.

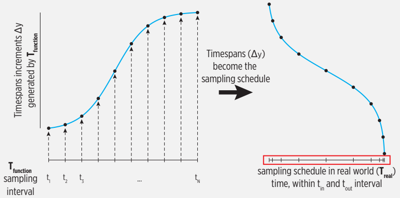


Figure: A snapshot of the process for producing a sigmoid sampling.

Trajectory mode

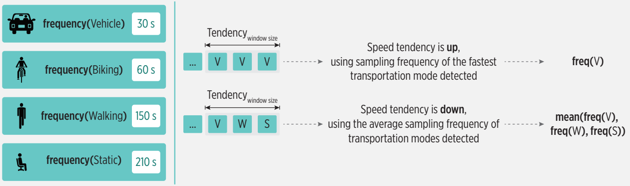


Figure: GPS sampling adaptation based on the speed tendency of detected transportation modes.

Cognitive controller

Sampling Decision Maker module

Sampling Decision Maker module

- It filters from the *pool of exploration-exploitation policies* those apt for the mobility state detected by PRM.
- It updates its *Executive Memory* with the selected cognitive action for feedback in further executions.

Implementation of cognitive action

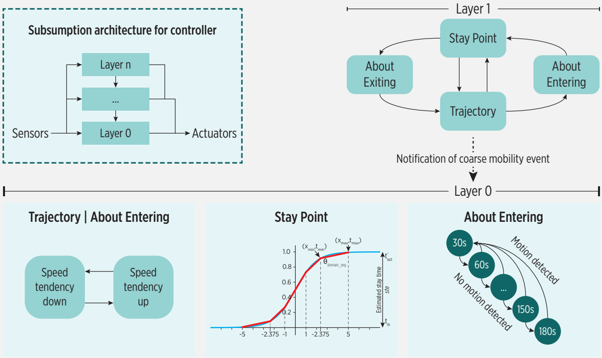


Figure: The subsumption architecture of the controller and the reactions to different coarse grain mobility events.

Implementation

Android device implementation

Smartphone device

The Google Nexus 6 smartphone with Android 7 was employed.

- Quad-core 2.7 GHz Krait 450 mobile processor (Qualcomm Snapdragon 805 chipset).
- 3 GB RAM.
- Qualcomm Snapdragon 805 chipset.
- 3220 mAh battery.

Technical barriers

1. Asynchronous access to sensors, affected by sensing infrastructure (GPS satellite signal intermittency).
2. Out-of-the-box energy saving mechanisms:
   - Application specific: **App StandBy**.
   - System wide: **Doze mode**.

Workarounds

1. Grace periods for sampling (`Timer` + `TimerTasks`).
2. `Alarms`, `WakeLocks`, foreground services.

Experimentation

Materials and methods

Attributes evaluated

- Spatial-time accuracy.
- Energy consumption.

Desktop version

- It features different modules of the proposed system (except from HAR module).
- It allows the quick evaluation of system performance through different parameter combinations.
- It includes a logic *trajectory file* reader that simulates user motion.

On-device trials

- Two Nexus 6 smartphone units.
- The smartphones were always carried together with the GPS logger device by a campus student.
- No mobile apps other than the developed middleware were executed by the smartphones.
- The smartphones were not employed for communication tasks (texting, calls).

Experimentation

Materials and methods

Ground-truth mobility information

- High frequency (1 Hz) location data collected employing a Qstarz BT-Q1000eX GPS logger.
- 6 trajectories collected by the same user, mostly using a vehicle as transportation mode.

Stay Points Detector	**Time threshold** (δ_{time}):	45 min
	Distance threshold ($\delta_{distance}$):	500 m
Geofencing	**Radio distance** ($gf_{distance}$):	250 m
	Window size (gf_{ws}):	3
Sampling period:	1 second	

Table: Input parameters for the discovery of ground truth mobility information.

Trajectory	Duration (days)	Inside SP time (minutes)	In traj. time (minutes)	Total SPs	Total visits	Individual SP weight	
Trajectory 1	5.38	7,442.10 (96.06%)	305.07 (3.94%)	4	13	Home: 72.25% Bob's place: 0.94%	Civestav: 26.03% Store: 0.78%
Trajectory 2	6.05	8,348.42 (95.80%)	365.73 (4.20%)	6	21	Home: 69.67% Bob's place: 1.20% Store: 0.82%	Cinvestav: 26.51% Park: 0.99% Stadium: 0.82%
Trajectory 3	6.15	8,542.12 (96.53%)	307.45 (3.47%)	6	31	Home: 67.94% Park: 2.94% Fast food: 1.15%	Cinvestav: 24.50% Bob's place: 2.58% City center: 0.89%
Trajectory 4	7.22	10,024.63 (96.42%)	371.98 (3.58%)	2	16	Home: 66.50%	Cinvestav: 33.50%
Trajectory 5	7.35	10,026.22 (94.74%)	556.20 (5.26%)	4	19	Home: 67.29% Cinema: 2.41%	Cinvestav: 29.33% City center: 0.97%
Trajectory 6	34.31	47,599.62 (96.34%)	1,807.52 (3.66%)	11	146	Home: 65.31% Home 2: 2.81% Bob's place: 0.37% Store: 0.35% Workshop: 0.20% Workshop 2: 0.11%	Cinvestav: 29.36% Fast food: 0.71% Restaurant: 0.36% City center: 0.30% Store 2: 0.12%

Table: Mobility information of collected ground truth trajectories (SP=stay point).

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

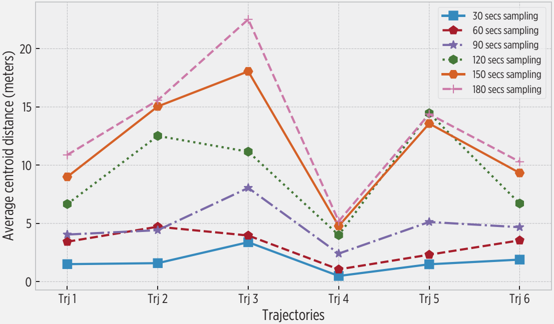


Figure: The impact of different sampling periods on the centroid distance of identified stay points in each trajectory. A maximum centroid distance of 22.52 *m* is identified when employing the 180 seconds sampling period.

Experimentation

Geofencing module spatial-time accuracy: Description

Description

- This experiment evaluates the spatial-time accuracy of the *Geofencing* module under different GPS sampling rates, in terms of missed visits, and arrival and departure latency.

Geofencing	**Radio distance** ($gf_{distance}$):	250 m
	Window size (gf_{ws}):	3, 5, 7
Sampling periods:	30, 60, 90, 120, 150, 180 seconds.	
Trajectories:	All ground truth trajectories.	
STM	Preloaded with corresponding ground truth stay points.	

Table: Input parameters for the spatial-time accuracy of Geofencing module experiment.

Results

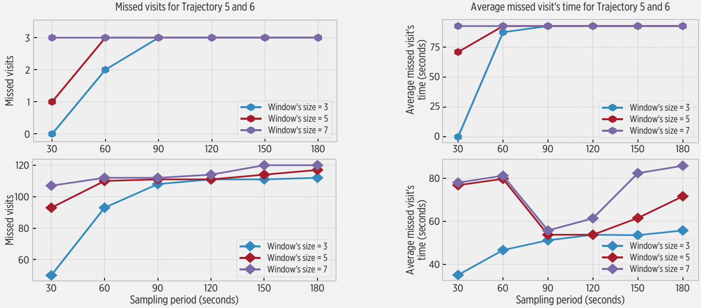


Figure: Visits missed by the *Geofencing* module for each combination of sampling period and window size values. The largest amount is obtained for the *Trajectory 6*, given its length (more than 30 days). Nevertheless, they do not account for a considerable time in overall trajectories.

Experimentation

Reaction to STM mobility mismatches: Description

Description

- This experiment was focused on evaluating the ability of the system for reacting to mismatches in mobility information, with a particular emphasis on mismatch departure events.
- For some trials the information of the STM was intentionally modified by giving it longer stay times than those in the actual visits.
- The missed visits, the delay for detecting the temporal mismatches, and the departure latency were evaluated.

Geofencing	**Radio distance** ($gf_{distance}$):	250 m
	Window size (gf_{ws}):	3
Cognitive Controller	**Sigmoid segments** (Θ_{domain_segs}):	$(-5, -2.375), (-2.375, -1), (-1, 1), (1, 2.375), (2.375, 5)$ $(-4, -2.375), (-2.375, -1), (-1, 1), (1, 2.375), (2.375, 5)$
	Time separations (Θ_{time_sep}):	$[90, 150, 180, 150, 90]$ seconds $[90, 120, 180, 120, 90]$ seconds $[60, 150, 180, 150, 60]$ seconds $[60, 120, 180, 120, 60]$ seconds
Trajectories	All ground truth trajectories.	
STM	Preloaded with ground truth stay points, with increased time (injured) in the proportions $[5, 10, 15, \ldots, 90, 95, 100]$ %	

Table: Input parameters for the reaction to mobility mismatches experiment.

Experimentation

Reaction to STM mobility mismatches: Results

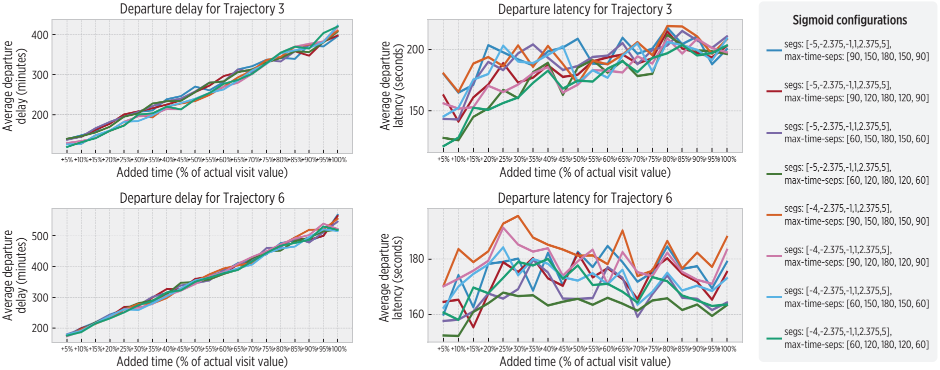


Figure: On the left, the evolution of the timespan between the expected and actual departures detected by the system when the STM is injured with additional time. Similar tendencies are observed, highlighting that the sigmoid sampling allows to identify that user is leaving the stay points before expected.
On the right, the variation of the latency values of departures detection. The observed values are under the theoretical 360 seconds maximum peak

Experimentation

Holistic evaluation: Description

Description

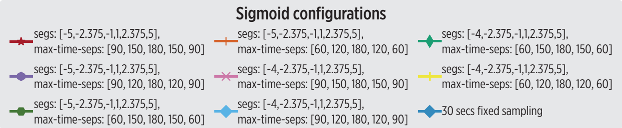
- This experiment was aimed at evaluating the overall spatial-time accuracy performance of the system with all of its component enabled, including:
  - The continuous learning of stay points in the STM for adapting GPS sampling rate.
  - The handling of mobility mismatches.

Geofencing	**Radio distance** ($gf_{distance}$):	250 m
	Window size (gf_{ws}):	3
Cognitive Controller	**Sigmoid segments** (Θ_{domain_segs}):	$(-5, -2.375), (-2.375, -1), (-1, 1), (1, 2.375), (2.375, 5)$ $(-4, -2.375), (-2.375, -1), (-1, 1), (1, 2.375), (2.375, 5)$
	Time separations (Θ_{time_sep}):	$[90, 150, 180, 150, 90]$ seconds $[90, 120, 180, 120, 90]$ seconds $[60, 150, 180, 150, 60]$ seconds $[60, 120, 180, 120, 60]$ seconds
	On trajectory sampling:	30 seconds
	Conservative sampling:	60 seconds
Trajectories	All ground truth trajectories.	
STM	Empty	

Table: Input parameters for the holistic evaluation experiment. The *conservative* sampling refers to the late departure mismatch reaction.

Experimentation

Holistic evaluation: Results



Arrival latency

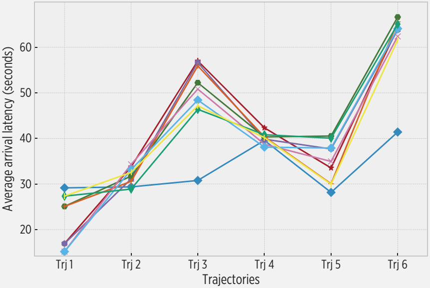


Figure: Arrival latency observed by the platform in experimental trials. The largest average value is below 65 seconds, explained by the fact that 2 location updates must be collected by the *Geofencing* module before identifying an arrival event.

Departure latency

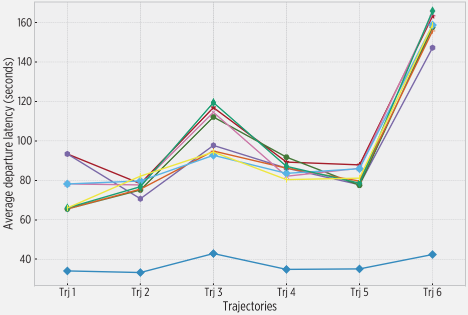


Figure: Departure latency observed by the platform across performed experimental trials. The latencies are within 65 and 165 seconds, which is aligned with the different values specified to the CC for its sigmoid-driven sampling.

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

Trajectory distance difference

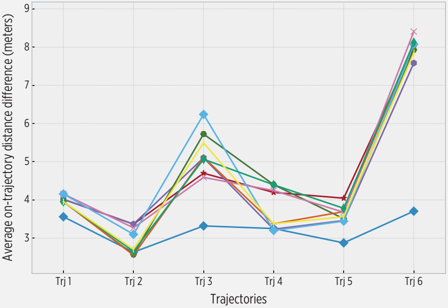


Figure: The average distance of equivalent trajectory segments during experimental trials. The values are enclosed within 2.5 m and 8.5 m, with the 30 seconds sampling obtaining the lowest values in each trial.

Overall reduction of location update requests

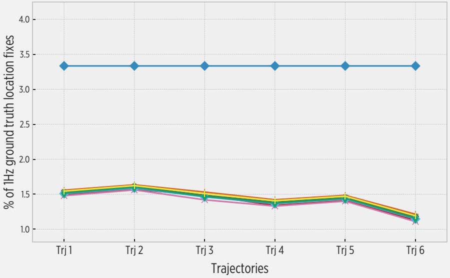


Figure: The proportion of location update requests employed by each experimental trial with respect to the corresponding 1 Hz ground truth trajectory. All of the parameter combinations outperform the 30 seconds sampling period, which provides a rough estimation of the energy savings that the system could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

Experimentation

Energy consumption of fixed-sampling periods: Description

Description

- This experiment evaluated the impact of sampling adaptations based on fixed sampling rates on the energy consumed by the proposed CDS.
- All system components were enabled, with the exception of the sigmoid sampling of the CC.
- The CC followed fixed sampling periods depending on the current mobility state recognized by the system.
- The experiment also demonstrated the mobility awareness that the system provides to the smartphone (STM).

Stay Points Detector	**Time threshold** (δ_{time}):	45 *min*
	Distance threshold ($\delta_{distance}$):	500 *m*
Geofencing	**Radio distance** ($gf_{distance}$):	250 *m*
	Window size (gf_{ws}):	3
HAR module	**Individual window length**:	5 seconds
	Meta-window size (HAR_{mws}):	5
Cognitive Controller	**Smartphone 1**:	On trajectory sampling periods: 30 seconds On stay point sampling period: 30 seconds
	Smartphone 2:	On trajectory sampling period: 30 seconds On stay point sampling period: one in the set $\{60, 90, 120, 150, 180\}$ seconds

Table: Input parameters for the energy consumption of fixed-sampling periods experiment.

Experimentation

Energy consumption of fixed-sampling periods: Results

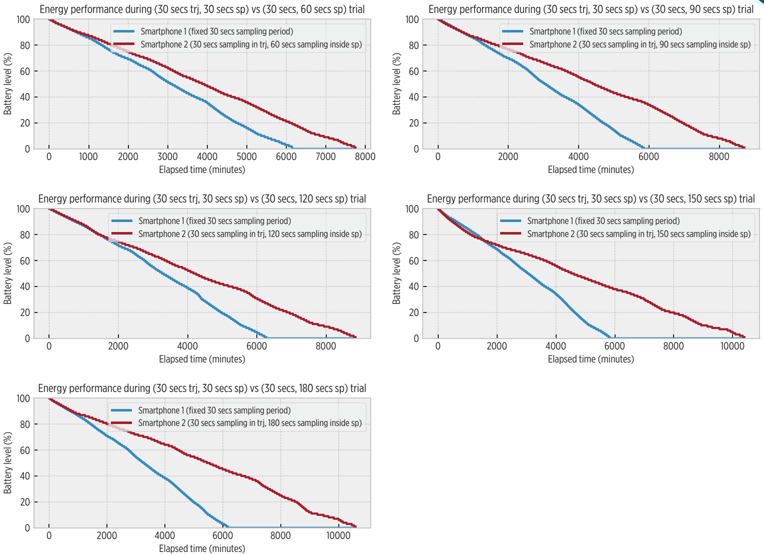


Figure: Energy performance of a fixed 30 seconds sampling versus a basic sampling adaptation consisting in a 30 seconds sampling in trajectory mode and a slower sampling rate during stay point mode. The separation between the lines in each plot starts after the system learns the stay points with the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

Experimentation

Energy consumption of fixed-sampling periods: Results

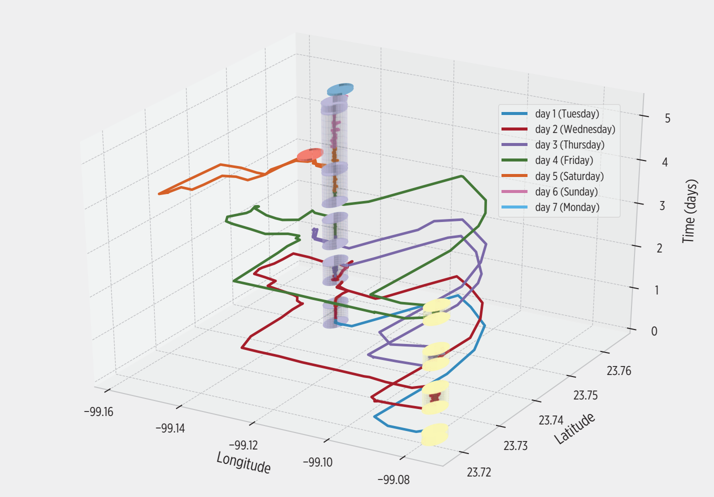


Figure: The information autonomously learned by the STM during the trial corresponding to the 30 seconds in trajectory and 60 seconds in stay point sampling scheme. The height of cylinders corresponds with the stay time during each stay point visit.

Experimentation

Energy overhead of cognitive system: Description

Description

- This experiment evaluated the energy overhead of the proposed cognitive system.
- A sample application was developed for collecting HAR + GPS data with a 30 seconds sampling rate.
- One smartphone unit instructed the sampling rate without using any cognitive feature.
- Another smartphone unit used the cognitive features with the exception of the cognitive controller.

Stay Points Detector	**Time threshold** (δ_{time}):	45 *min*
	Distance threshold ($\delta_{distance}$):	500 *m*
Geofencing	**Radio distance** ($gf_{distance}$):	250 *m*
	Window size (gf_{ws}):	3
HAR module	**Individual window length**:	5 seconds
	Meta-window size (HAR_{mws}):	5
Cognitive Controller	Disabled	

Table: Input parameters for the energy overhead measurement experiment (Geofencing and Stay Points Detector enabled only in one smartphone).

Experimentation

Energy overhead of cognitive system: Results

Results

Figure goes here

Thank you for your attention!

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

Cinvestav Tamaulipas

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