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

Doctoral seminar 2016

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Agenda

Background
Motivation

- The popularity of mobile devices is a result of advances in their computation, **sensing**, and communication dimensions [1].
  - The sensing facilities improve interaction with user, turning them into *omni-sensors* able to *know* about its surrounding environment.
  - Smartphones have become *context-aware* devices, gaining understanding about user's activity and environment.
  - **Context** is the set of environmental states and settings that either determines an application's behavior or in which an application event occurs and is interesting to the user [2].
- However, battery is not evolving at the same pace of advances in other smartphone's characteristics [3], growing only 5-10% each year [4, 5].
  - The energy constraint becomes critical when continuous access to sensors is needed, which is a core requirement of **mobile sensing applications**.

Problem definition
Overall problem identification

Overall issue
Conceptually, the main problem pursued by this research work is to design a location provider aware of the energy limitations of the mobile device. Nonetheless, as the location is a reflection of the mobility patterns described by people, a set of more specific problems could be addressed.

Types of mobility patterns
There are two types of mobility patterns considered by this research:

- Fine grain mobility patterns.
- Coarse grain mobility patterns.

Problem definition
Problem statement

Problem 1: Mobility pattern identification

Given a set of values $\mathcal{V} = v_1, v_2, \ldots, v_n$ obtained from sensor $\mathcal{S}$ in time range $[t_1, t_2]$, identify coarse-grain or fine-grain mobility information:

$$\text{PatternIdentifier}(\mathcal{V}) \rightarrow p_S \in \text{Patterns}$$

where $\text{Patterns} = \{\text{static, walking, running, vehicle}\}$ for fine-grain location information, while for coarse-grain information refers to the arrival and departure to-from stay points described by user's mobility.
Additionally, the sensor $\mathcal{S}$ for fine-grain information is `accelerometer`, while sensor $\mathcal{S}$ for coarse-grain information is `GPS`.

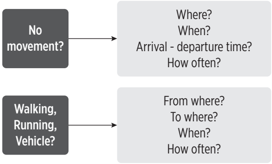


Figure: Context information related to mobility patterns

Problem definition
Problem statement

Problem 2: Policy generation

Given the set of detected mobility patterns $\mathcal{P} = \{p_{S_1}, p_{S_2}, \ldots, p_{S_n}\}$ in data from sensors $\mathcal{S} = \{S_1, S_2, \ldots, S_n\}$, accuracy required a, and physical constraints status c of a mobile device, find a policy that select the proper set of sensors $\mathcal{S}_{new}$ and its associated configuration $\mathcal{S}_{new_{conf}}$ while meeting application requirements.

$$\text{PolicyGeneration}(\mathcal{P}, a, c) \longrightarrow \mathcal{S}_{new}, \mathcal{S}_{new_{conf}} \quad (1)$$

The $\mathcal{S}_{new_{conf}}$ configuration is referred to as the *adaptive duty cycle* of associated sensors.

Problem definition

Interaction between problems

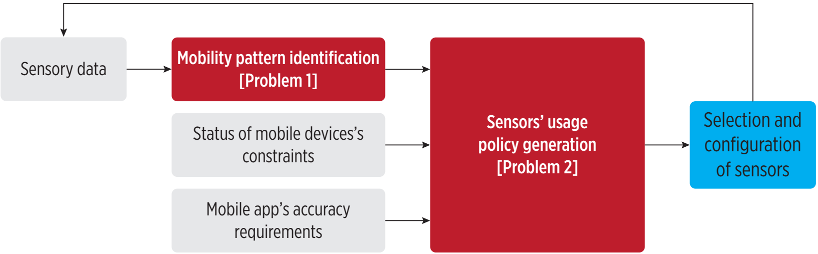


Figure: Interaction between problems

Problem definition

Hypothesis

Hypothesis

Dynamic policies driven by events detected in user mobility could reduce energy consumption of the mobile device when performing continuous location tracking. User mobility could be expressed by means of a spatial-time model learned from short and long time windows of context information extracted from GPS and accelerometer sensors data.

- An intelligent policy is a special rule that defines how sensors should be selected and configured to reduce energy consumption and achieve the mobile sensing app's requirements. It is intelligent in terms of self-adaptness to changes detected in context information across time.
- This research work is aimed at employing GPS and inertial sensors data (accelerometer) for inferring context information in terms of mobility patterns. This context information will then be exploited to adapt sensors' operation and produce power savings.

Problem definition
Objectives

Main objective

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

Particular objectives

- To identify mobility patterns from context information obtained from an inertial sensor (accelerometer) and location providers (GPS).
- To generate an accurate representation of mobility patterns, which in conjunction with accuracy mobile app requirements and mobile device constraints, allows to create power-aware GPS sensing policies.
- To reduce energy consumption in location-based mobile sensing apps through a middleware that implements policies fed with mobility patterns learned from sensors data. The middleware also eases the development of LBS, isolating the complexity of energy efficient sensors management.

Problem definition

Expected contributions

- A mechanism for detecting mobility patterns from the data read by sensors of mobile devices (GPS and accelerometer).
- A mechanism for generating policies for accessing sensors. The produced policies will allow to perform an intelligent usage of smartphone's sensing facilities in continuous sensor sampling, reducing the energy consumption.
- A middleware implementing the previous power-aware mechanisms for easing the development of location based services.

Methodology
Methodology steps

1. **Familiarization with state-of-art power-aware sensing related techniques**
2. **Formal definition and selection of mobility patterns to be identified**
3. **Research on pattern recognition algorithms focused on mobility patterns identification**
4. **Design of the Pattern Identification Element (PIE)**
5. **Research on (and proposition of) adaptive policies for energy efficient usage of sensors**
6. **Design of the Policy Generation Element (PGE)**
7. Development of a middleware involving the PIE and PGE for the Android platform
8. Experimentation in terms of accuracy and energy efficiency

Related work
Previous work

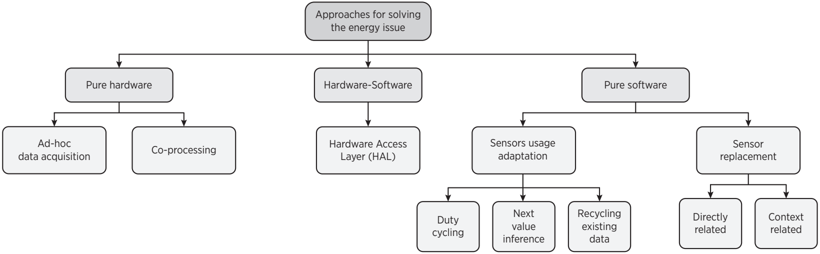


Figure: Taxonomy of related work solutions

Pure hardware approach

- The fundamental idea is the selection of power-aware hardware elements for providing physical data to upper layers, as well as the definition of mechanisms to adapt the hardware input parameters, like DVFS[1].
- Such mechanisms define control points for manipulating hardware (also known as power modes [6, 7, 8]).
- The hardware components obey a static behavior defined by power modes, whose control points are exported to upper layers of the mobile platform.

Variants

- Ad-hoc data acquisition
- Co-processing

[1] DVFS, Dynamic Voltage and Frequency Scaling

Related work
Hardware-software approach

Hardware-software approach

- It is aimed at defining system-wide policies for deciding when to turn sensors on and off, or when to switch hardware components to a different power mode.
- It abstracts fine-grain operation parameters into a coarse-grain set, easing the hardware usage for upper platform layers.
- It is also able to detect changes in the workload of hardware components.
- Because of the coupled interaction with hardware, solutions are produced as HAL's, or low-level hardware middlewares.

Related work
Pure software approach

Pure software approach

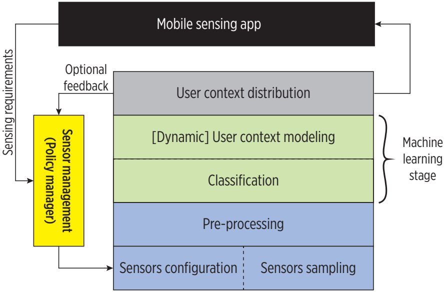
- *Spending power to save power* [6].
- It employs context information obtained from sensor data, for achieving activity awareness and making informed decisions towards dynamic power-aware sensors management.
- The lower layers know how to turn circuits on and off, but are unable to define when; whereas higher software layers can dynamically adapt to changes in user context, delegating how to do it to the lower layers.
- Typically, pure software approach solutions are implemented through a layered middleware with the classification and machine learning modules embedded on it.

Related work
Pure software approach

Variants

- Sensors usage adaptation
  - Duty cycling
  - Next value inference
  - Recycling existing data
- Sensors replacement
  - Directly related
  - Context related

Generic pure software approach middleware



Related work

Characteristics of pure software approach solutions

Distinctive characteristics of pure software approach solutions

- **Optimization oriented (OO)**: Optimization orientation focused on minimizing energy consumption and/or the error in activity tracking.
- **Online learning (OL)**: Online learning from context information, enabling predictive features thanks to observance over long-time windows of sensory data.
- **User state oriented (US)**: Modeling of an enriched version of the context information, user state (US), for achieving full activity-awareness and ease the adaptation over the sensing dimension.

Proposed solution

Problem's scenario

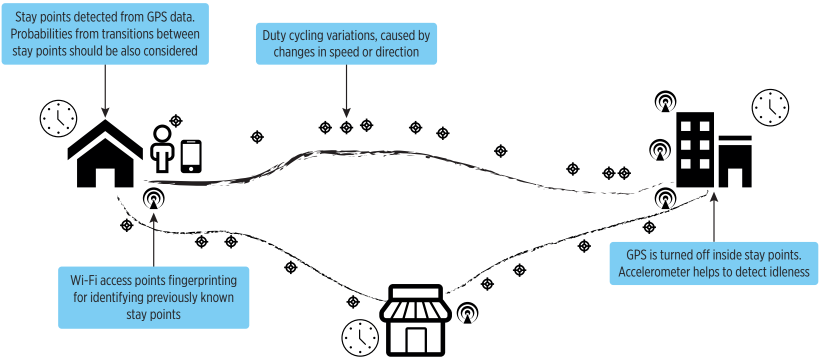


Figure: Basic problem's scenario

Proposed solution
Characteristics

- Pure software approach, implementing all of its variations.
- Online learning and user state oriented.
- Event-driven oriented, completely on device.
  - Top level mobility states-events: `on trajectory`, `on stay point`.
  - Low level mobility states-events: `transportation mode changed`, `arriving to stay point`, `leaving stay point`.
- Inspired on Cognitive Dynamic Systems [9], including
  - Perception-action cycle.
  - Memory.
  - Attention.
  - Intelligence.

Proposed solution
Overview

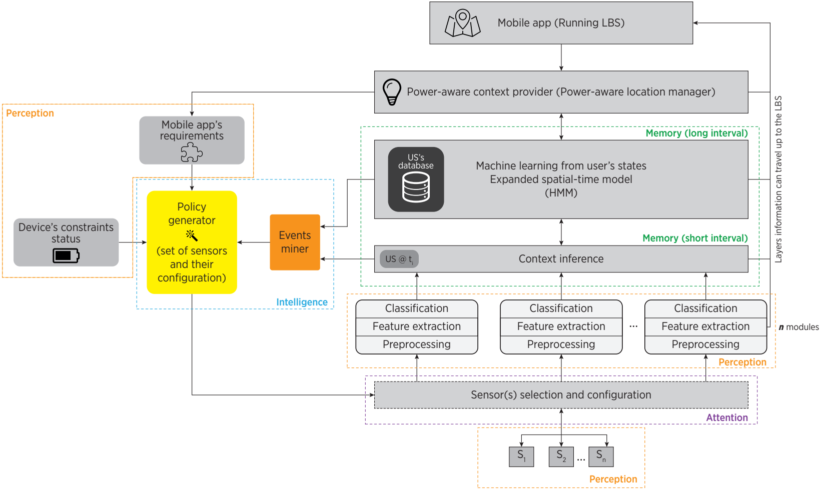


Figure: The layers of proposed solution

Proposed solution
Operation

- Overall problem divided in:
  - Detection and learning of stay points (The anchor points that user visits frequently).
  - Tracking of user commuting between stay points (Transition probability).

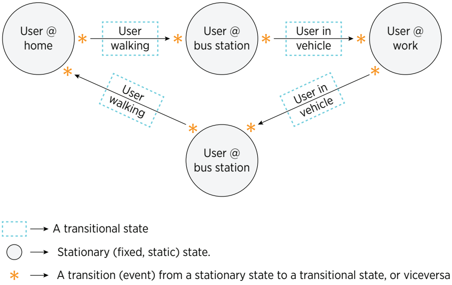


Figure: Information modeled by the expanded spatial-time model

Proposed solution
Event-driven implementation

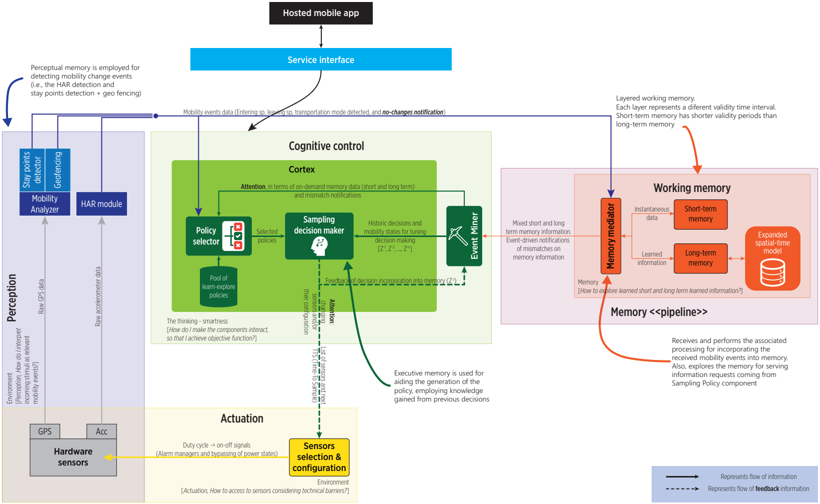


Figure: Cognitive components of platform and their interaction

Preliminary results

Feasibility of on-device mobility analysis

- Several experiments were carried out for exploring the feasibility of performing on-device mobility analysis.
- Feasibility is understood as the ability for executing the middleware in the mobile device [2] under different stress levels without a premature finalization caused by CPU and memory consumption usage issues.

Table: Summary of results of first experiment (SP = stay point).

Sampling period (seconds)	Event-driven algorithm	Obtained GPS fixes	Average GPS fixes per SP	Running time (minutes)
30 seconds	Buffered	3,876	218.3	6,752
	Sigma	5,199	244.4	8,243
60 seconds	Buffered	5,307	155.6	14,877
	Sigma	3,054	126.3	8,428
90 seconds	Buffered	2,573	115.2	7,694
	Sigma	2,447	108.1	7,522
120 seconds	Buffered	1,708	77.4	8,460
	Sigma	1,993	82.2	10,214
150 seconds	Buffered	1,417	53.8	10,433
	Sigma	1,651	51.1	10,349

[2] Google Nexus 6, 2.7 GHz quad-core processor, 3 GB RAM, 3220 mAh battery, Android 6.

Preliminary results

Energy performance (solution vs MCC oriented approach)

- Purpose of comparing the energy consumption of the proposed middleware with respect to an MCC oriented solution that offloads location data processing.
- The MCC oriented solution subscribed for location updates to the middleware, but translated each location update into a string representation (116 bytes, in average) sent to an application server using cellular data network.

Sampling period (seconds)	Processing strategy	Obtained GPS fixes	GPS-on time (minutes)	Average acquisition time per fix (seconds)	Running time (minutes)	Data sent (bytes)	Data received (bytes)
30	On-device	12,341	1,614	7.84	7,790	-	-
	MCC oriented	9,324	770	4.98	5,402	1,084,901	18,796
60	On-device	10,816	1,219	6.76	12,028	-	-
	MCC oriented	7,205	764	6.45	7,907	838,640	14,696
90	On-device	7,868	1,178	8.91	13,075	-	-
	MCC oriented	5,624	546	5.84	8,946	653,833	12,223
120	On-device	5,189	809	9.26	11,289	-	-
	MCC oriented	4,332	387	5.43	8,931	504,012	8,838
150	On-device	5,576	933	9.94	14,998	-	-
	MCC oriented	4,564	452	6.06	11,619	530,764	10,309

Table: Summary of results of second experiment.

Preliminary results

Energy performance (solution vs MCC oriented approach)

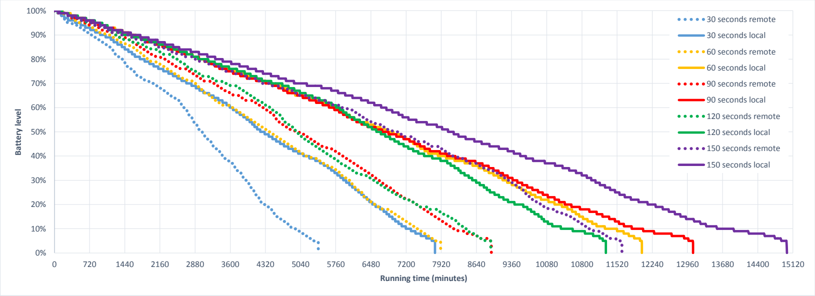


Figure: Energy performance comparison of on-device vs MCC oriented sample apps using different GPS sampling periods.

Preliminary results

Early adaptive sampling implementation

Recall the cognitive components are implementing and reacting to changes in mobility. Such changes are detected and learned by the platform. Although reaction is expressed as in simple policies, the platform now could implement something else.

Publications

Two journal articles have been published along the development of thesis work:

- Pérez-Torres, R., Torres-Huitzil, C., & Galeana-Zapién, H. (2016). Power management techniques in smartphone-based mobility sensing systems: A survey. *Pervasive and Mobile Computing*, 1-21. https://doi.org/10/bds7 [10]
- Pérez-Torres, R., Torres-Huitzil, C., & Galeana-Zapién, H. (2016). Full On-Device Stay Points Detection in Smartphones for Location-Based Mobile Applications. *Sensors*, 16(10), 1693. https://doi.org/10/brst [11]

Future work

Specific activities

Next are tasks to be performed in short-term towards defining policies to be implemented by the system solution.

- Preliminary integral experimentation for studying mobility information generated by cognitive components.
- Selection of mobility cases on which platform will be tested.
- Prepare and launch experiments using those scenarios, towards detecting anomalies not observed by the platform.
- Definition of policies - behaviors that allow platform to identify and react to such cases accordingly.
- Build a software library for exploring - interpreting the mobility information collected by platform.
- Evaluate, by experimentation, the policies defined for addressing the issues on mobility cases.
- Selection of policies with the best time-spatial accuracy metrics.

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 PIE				●	●	●	●
13	Building of the PIE				●	●	●	●

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

Detailed schedule

Work: ● Done, ● In progress, ○ To be done		2016 1st	2016 2nd	2016 3rd	2017 1st	2017 2nd	2017 3rd	2018 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 PGE parameters					●		
19	Building of the PGE					●		
	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				●		●					○	
C	Predoctoral exam preparation									○			
D	Thesis writing	●			●			●			○	○	○

Table: Schedule of required activities

Conclusions

As conclusions, the current talk has been provided:

- lualatex

Thank you for your attention!

We make our world significant by the courage of our questions and by the depth of our answers.

Carl Sagan

Cinvestav

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State-of-art solutions

Name	Variants	Machine learning technique	Sensors involved	Complex-ity	OL	OO	US
G-Sense [12]	User behavior learning (DC)	SDR	GPS	low			
Perez-Torres [13]	User behavior learning (DC)	SDR	GPS	low			
SenseLess [14]	User behavior learning (DC), Sensor replacement (CR, DR)	SDR	WPS, GPS, ACC	low			
SensTrack [15]	User behavior learning (DC), Sensor replacement (CR, DR)	SDR	ACC, orientation sensor, GPS, WPS	low			
Man and Ngai [16]	User behavior learning (DC, VI), Sensor replacement (CR)	SDR	ACC, magnetic field sensor, GPS	low			
EnLoc [17]	User behavior learning (DC, VI), Sensor replacement (DR)	SDR, Mobility Tree	WPS, GPS, cellular ID	medium		✓	
EnTracked [18]	User behavior learning (DC), Sensor replacement (CR)	SDR	ACC, GPS	medium		✓	

Table: Pure software solutions. (OL: Online Learning from user data, OO: Optimization Oriented solution, US: User State context insight)

State-of-art solutions

Name	Variants	Machine learning technique	Sensors involved	Complex-ity	OL	OO	US
Alvarez, Morillo [19, 20]	–	Ameva algorithm	ACC	medium			
Mazilu [21]	Sensor replacement (CR)	DT	Temperature, humidity, pressure	medium			
Srinivasan [22]	User behavior learning (DC)	DT	ACC	medium			
Khalifa [23]	Sensor replacement (CR)	KNN	Model of ACC-based harvesting device	medium			

Table: Pure software solutions. (OL: Online Learning from user data, OO: Optimization Oriented solution, US: User State context insight)

State-of-art solutions

Name	Variants	Machine learning technique	Sensors involved	Complex-ity	OL	OO	US
SensLoc [24]	User behavior learning (DC, RD), Sensor replacement (CR)	SDR	Wi-Fi fingerprinting, GPS, ACC	medium	✓		
CAPS [25]	User behavior learning (DC, RD), Sensor replacement (CR)	SDR	GPS, cellular ID	medium	✓		
RAPS [26]	User behavior learning (DC, RD), Sensor replacement (CR, DR)	SDR	WPS, GPS, ACC, Bluetooth, cellular ID	medium	✓		
A-Loc [27]	User behavior learning (DC, RD), Sensor replacement (CR, DR)	HMM, Bayesian estimation framework	GPS, WPS, Bluetooth, cellular ID	medium	✓	✓	
SmartDC [28]	User behavior learning (DC, RD), Sensor replacement (CR, DR)	HMM and LZ predictor	GPS, WPS, Wi-Fi and cellular ID fingerprinting	medium	✓	✓	

Table: Pure software solutions. (OL: Online Learning from user data, OO: Optimization Oriented solution, US: User State context insight)

State-of-art solutions

Name	Variants	Machine learning technique	Sensors involved	Complex-ity	OL	OO	US
Jigsaw [29]	User behavior learning (DC), Sensor replacement (CR)	Microphone: NB with Gaussian Mixture Model (GMM). ACC: DT. GPS: MDP.	ACC, Microphone, GPS	high		✓	✓
Donohoo [30]	User behavior learning (DC)	Several. KNN and NN selected as best.	ACC, GPS, WPS, cellular ID, light, device data, mobile app requirements	high			✓
EEMSS [31]	User behavior learning (DC), Sensor replacement (CR, DR)	GPS and ACC: SDR. Microphone: SSCH algorithm.	ACC, microphone, GPS	high			✓
iLoc [32]	User behavior learning (RD), Sensor replacement (CR)	HMM	Wi-Fi & GSM fingerprinting	high	✓		✓
Yurur [33]	User behavior learning (DC, RD)	HMM	ACC	high	✓		✓
FreeTrack [34]	User behavior learning (DC, RD), Sensor replacement (CR, DR)	HMM	GPS, Wi-Fi, cellular ID, battery status	high	✓		✓

Table: Pure software solutions. (OL: Online Learning from user data, OO: Optimization Oriented solution, US: User State context insight)

Additional experiments results

Accuracy evaluation of detected stay points

Table: Spatial and time accuracy observed in results of first experiment (SP = stay point).

Sampling period (seconds)	Event-driven algorithm	Detected SP's	Average SP stay time difference (seconds)	Average SP distance difference (meters)
30	Buffered	16 (out of 19)†	64.13	13.35
	Sigma	19 (out of 19)	68.78	16.01
60	Buffered	29 (out of 29)	98.24	14.97
	Sigma	21 (out of 29)†	82.35	19.42
90	Buffered	20 (out of 20)	104.95	20.6
	Sigma	20 (out of 20)	211.68	20.68
120	Buffered	19 (out of 21)†	63.7	35.56
	Sigma	21 (out of 21)	59.7	34.05
150	Buffered	24 (out of 29)†	116.4	59.11
	Sigma	28 (out of 29)‡	115.6	50.81

† Due to battery depletion, ‡ Actual SP miss