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

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Introduction

- The popularity of mobile devices is a result of advances in their computation, **sensing**, and communication dimensions [8].
    - Smartphone's sensing facilities improve interaction with user, turning them into *omni-sensors* able to *know* about its surrounding environment.
    - Mobile devices have become *context-aware*, gaining understanding about user's activity and environment.
- However, battery is not evolving at the same pace than the advances in other smartphone's characteristics [11], growing only 5-10% each year [15, 7].
    - The energy constraint becomes more critical when continuous access to sensors is needed, which is the core requirement of **mobile sensing applications**.

Stages of mobile sensing applications

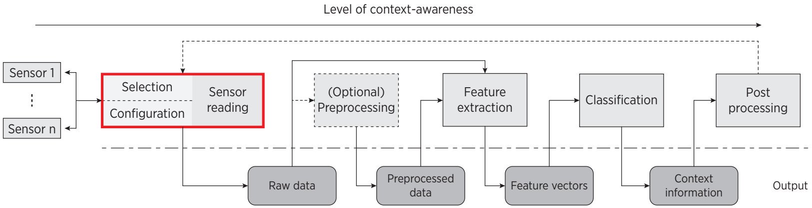

Figure: Stages of mobile sensing applications

There is a tradeoff between the accuracy of context information retrieved and the associated energy consumption [26, 25]. How to face it?

Hypothesis

Hypothesis

Intelligent policies produced through context information built from sensors data can be employed to reduce the energy consumption in a mobile device when performing continuous sensor readings.

- An intelligent policy is a special rule that defines how sensors should be selected and configured to reduce the energy consumption and achieve the requirements of a mobile sensing app. It is intelligent in terms of self-adaptness to changes detected in context information.
- 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 statement

Problem statement: Mobility pattern identification

Given a set $V = \{v_1, v_2, \ldots, v_n\}$ of data values read from sensor S in the time interval $T \in [t_1, t_2]$, identify the current mobility pattern p_S that represents the activity of user.

$$\text{PatternIdentifier}(V) \longrightarrow p_S \in \mathit{Patterns} \tag{1}$$

Where *Patterns* is a set of patterns that represent an interesting state in user mobility, specifically the set $\{no\_movement, walking, running, vehicle\_transportation\}$.

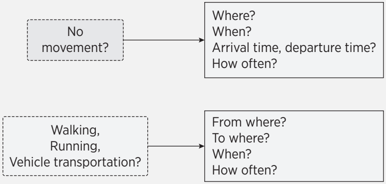

Figure: Context information related to mobility patterns

Problem statement

Problem statement: 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.

$$\text{PolicyGeneration}(\mathcal{P}, a, c) \longrightarrow \mathcal{S}_{new}, \mathcal{S}_{new_{conf}} \tag{2}$$

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

Interaction between problems

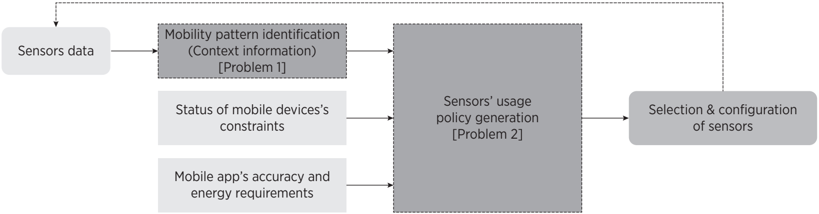

Figure: Interaction between the thesis work's problems

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.

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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, WPS).
- To generate policies for a self-adapting sensors' usage from identified mobility patterns, accuracy and energy requirements of mobile application, and status of mobile device's constraints.
- To ease the development of mobile sensing applications that require user location tracking, i.e., LBS, isolating the complexity of sensors' access and the associated efficient energy management.

Problem's scenario

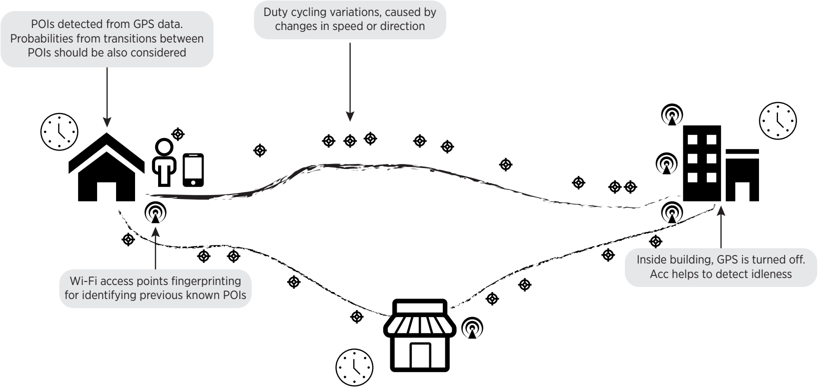

Figure: Basic problem's scenario

Methodology

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

Taxonomy of state of art solutions

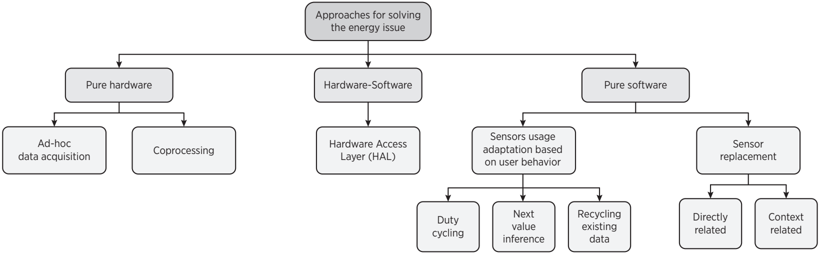

Figure: Taxonomy of solutions, seen from the sensors adaptation's perspective

Distribution of approaches

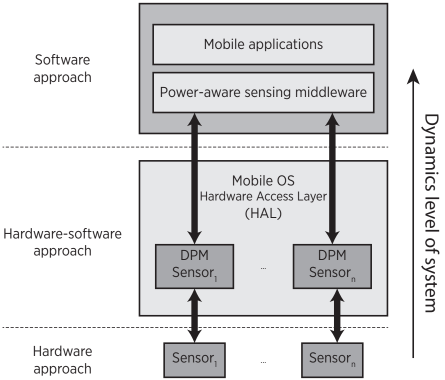

Figure: Distribution of approaches across mobile platform's layers

Characteristics of pure software approach solutions

Distinctive characteristics of pure software solutions

- **Optimization oriented (OO)**: Works can follow an optimization orientation focused on minimizing energy consumption and/or the error in activity tracking.
- **Online learning (OL)**: Solutions can incorporate mechanisms for online learning (OL) from context information, enabling predictive features thanks to observance over long-time windows of sensory data.
- **User state oriented (US)**: Solutions can employ an enriched version of the context information, known as user state (US) for allowing the device to become fully activity-aware and ease its adaptation over the sensing dimension.

Framework for analyzing pure software solutions

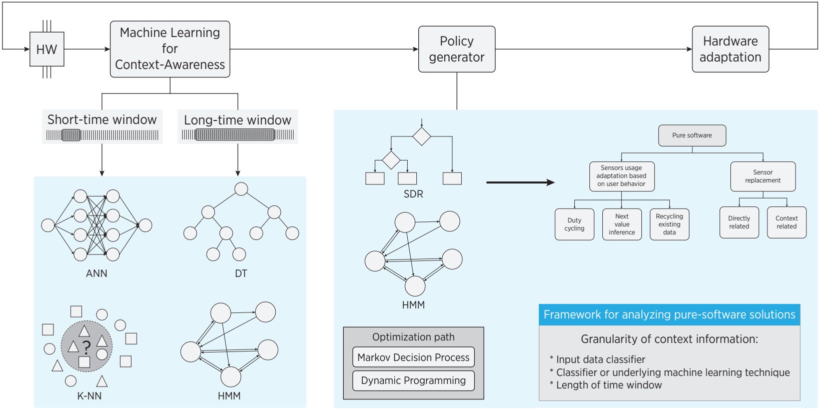

Figure: Decomposition of solutions

Proposed solution

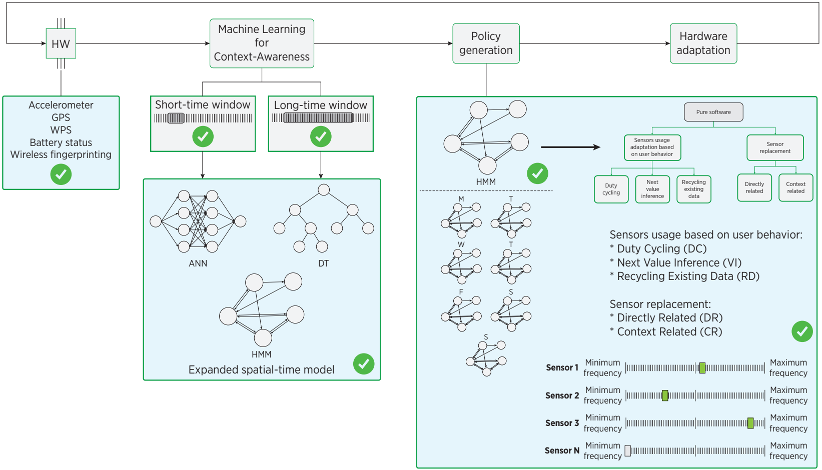

Figure: Decomposition of our solution

Proposed solution

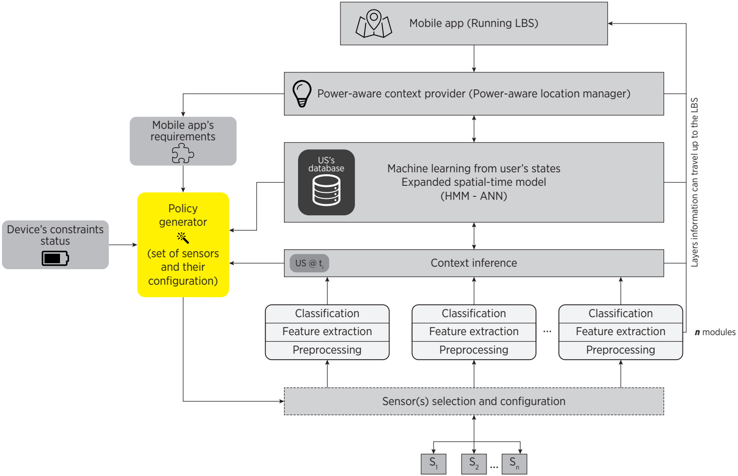

Figure: Overview of current solution

The model of information learned in proposed solution

- The overall problem can be splitted into learning and detection of stay points, and the trajectory tracking.
- This information can be abstracted and learned into an expanded-spatial time model.

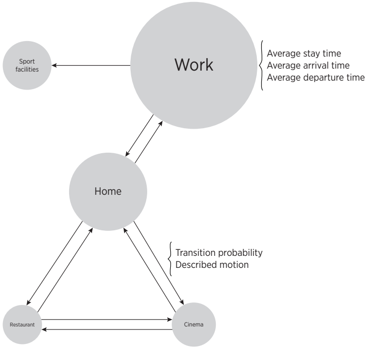

Figure: Basic unit of information learned in the expanded spatial-time model (User state)

The model of information learned in proposed solution

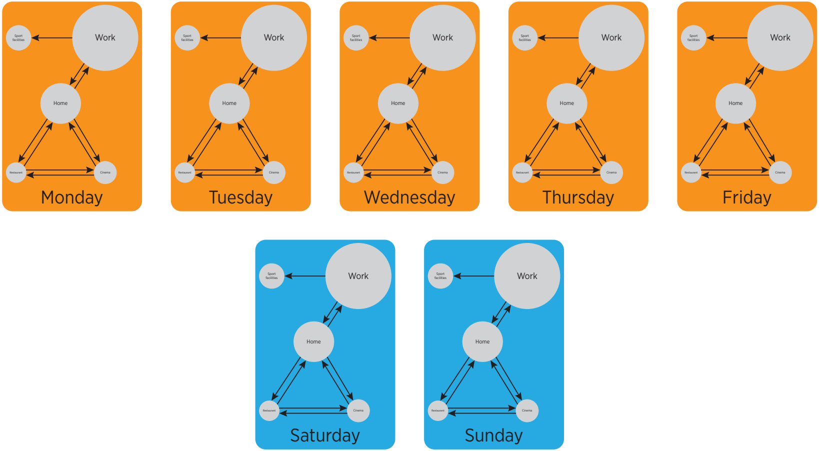

Figure: Mobility patterns learned over longer time windows

First steps towards expanded spatial-time model: a proof of concept

- A first step towards the acquisition of the expanded spatial-time model, locally at the mobile device, has been performed.
- This involved a proof-of-concept experimentation aimed at calculating stay points completely on-device.
- For this purpose, an event-oriented methodology was followed, which is a trend for **proactive** long-term applications focused on learning patterns from user activity.
- Such methodology involved adapting classic stay points algorithms [19, 31] for *online* operation while reducing memory footprint.
- In this way, the learning of context information that can be employed for adapting sensory operations has been shown possible.

On-device stay points detection platform

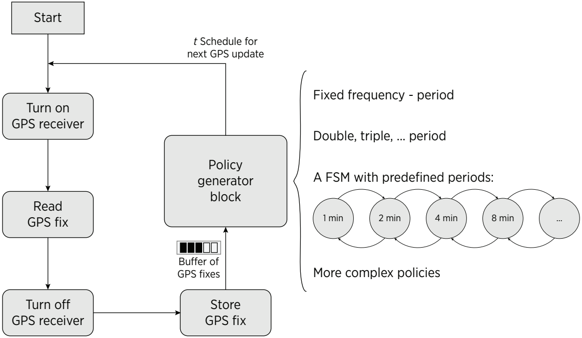

Figure: Logical workflow of the platform for on-device stay points detection

Results of early experimentation

- The first experiment is aimed at ensuring the calculation of stay points locally at the smartphone (Samsung Galaxy Note II, Quadcore 1.6 GHz processor, 16 GB RAM, 3,100 mAh battery).
- Both versions of the algorithm for stay points detection, original (buffered) and sigma, have been employed.
- Policies implemented:
  - Periodic GPS sampling: 1, 3, and 5 minutes.
  - FSM doubling policy. (Doubling if no movement detected within a 50m range).
  - FSM linear policy.
- The parameters for running the stay point detection algorithms for all tests were set at 10 minutes for θ_{tmin}, 1 hour for θ_{tmax} and 150 m for θ_d.

GPS reading period	Algorithm	Stay points detected	Average fixes	Maximum fixes	GPS accesses	Running time (hours)
1 minute	Sigma Montoliou	27	70	652	2251	43.68
1 minute	Buffered Montoliou	26	79	685	2334	43.92
3 minutes	Sigma Montoliou	47	27	248	1361	71.84
3 minutes	Buffered Montoliou	28	41	248	1241	64.96
5 minutes	Sigma Montoliou	43	25	154	1119	95.88
5 minutes	Buffered Montoliou	45	21	154	1021	87.78
Doubling 1-2-4-8-16	Sigma Montoliou	59	17	80	1223	189.69
Linear 1-3-5-9-12-15	Sigma Montoliou	35	21	84	888	144.85

Table: Results of the first experiment

Scientific products

- As a product of the study and analysis of related solutions, we have prepared a survey[1] covering:
  - The characteristics of smartphone-based sensing.
  - The power-awareness in smartphone-based sensing and related areas.
  - A taxonomy of the different solutions aimed at energy efficiency in smartphone-based sensing.
  - A framework for dissecting and studying the characteristics of these solutions.
  - The different tendencies and open challenges of the field.

[1] *Power management techniques in smartphone-based mobile sensing: a survey*, first review round, Pervasive and mobile computing (Elsevier)

Future work

		2014 3rd	2015 1st	2015 2nd	2015 3rd	2016 1st	2016 2nd	2016 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 the Android platform that collects accelerometer and location data							
5	Analysis of data delivered by the mobile app							
6	Creation of the formal definition of mobility pattern							
7	Selection of the mobility patterns to be recognizable by the system							
	Step III							
8	Research on classification algorithms adequate to work with mobility patterns							
9	Definition of metrics for evaluating algorithms when executing on a mobile platform							
10	Implementation of algorithms (including proper adaptions towards running on a mobile platform) for evaluation							
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)

Schedule

		2016			2017		
		1st	2nd	3rd	1st	2nd	3rd
	Step V						
14	Creation of the formal definition of policy						
15	Research and evaluation of techniques for generation and adaption of policies						
16	Design and execution of experiments with techniques applied to use cases						
17	Selection of best techniques						
	Step VI						
18	Definition and modeling of parameters needed by the PGE						
19	Building of the PGE						
	Step VII						
20	Analysis of elements involved into software abstractions						
21	Research on Android API for specialized components						
22	Development of the middleware						

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

Schedule

		2017			2018	
		1st	2nd	3rd	1st	2nd
	Step VIII					
23	Definition of experiments targeting accuracy and energy consumption axes					
24	Development of needed sample mobile apps for running experimentation					
25	Execution of experimentation					
26	Results analysis					

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

Schedule

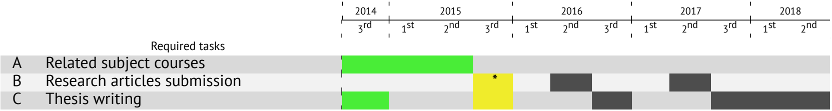

Table: Schedule of required activities

* Survey was out of original schedule, however, it brings added value to our work and also act as a scientific booster for improving and achieving our solution.

Conclusions

In this talk the latest advances in our thesis work have been presented. Specifically:

- We have presented a brief analysis of the problem aimed to be solved by this thesis work.
- We have covered a summary of related state of art solutions, as suggested by commitee. For this particular point, we have presented:
  - A taxonomy for categorization of the solutions, seen from the perspective of sensors adaptation.
  - A new framework for decomposing and studying different internal aspects of solutions.
- We have introduced the general approach of our solution, which is based on a expanded spatial-time model of user mobility for identifying and learning mobility patterns (OL, US).
- The policies considered by this solution:
  - Are context-aware oriented.
  - Identify and learn mobility patterns.
  - Adapt sensory operations with fine granularity through the different variants of the pure software approach.
- We have also presented an experimental step that ensures the on-device identification of such expanded models and the implementation of basic policies for accessing to sensors.

Thank You
for your attention!

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Montoliou's algorithm for stay points detection [19]

Require: A GPS trajectory $T = \{p_1, p_2, \ldots, p_N\}$, a distance threshold θ_d, a minimum time threshold θ_{tmin}, and a maximum time threshold θ_{tmax}.
Ensure: A set of points of interest Π

$i \leftarrow 1$
$\Pi \leftarrow \emptyset$
while $i < N$ **do**
  $j = i + 1$
  while $j < N$ **do**
    $t \leftarrow$ **timeDifference**(p_j, p_{j-1})
    if $t > \theta_{tmax}$ **then**
      $i \leftarrow j$
      break
    end if
    $d \leftarrow distance(p_i, p_j)$
    if $d > \theta_d$ **then**
      $t \leftarrow$ **timeDifference**(p_i, p_{j-1})
      if $t > \theta_{tmin}$ **then**
        $\pi.\text{lat} = \sum_{k=i}^{j-1} \frac{p_k.\text{lat}}{|j-1-i|}$
        $\pi.\text{lon} = \sum_{k=i}^{j-1} \frac{p_k.\text{lon}}{|j-1-i|}$
        $\pi.\text{at} = p_i.\text{ts}$
        $\pi.\text{dt} = p_{j-1}.\text{ts}$
        $\Pi \leftarrow \Pi \cup \pi$
      end if
      $i \leftarrow j$
      break
    end if
    $j \leftarrow j + 1;$
  end while
end while

State-of-art solutions

Name	Variants	Machine learning technique	Sensors involved	Complex-ity	OL	OO	US
G-Sense [23]	User behavior learning (DC)	SDR	GPS	low			
Perez-Torres [24]	User behavior learning (DC)	SDR	GPS	low			
SenseLess [1]	User behavior learning (DC), Sensor replacement (CR, DR)	SDR	WPS, GPS, ACC	low			
SensTrack [30]	User behavior learning (DC), Sensor replacement (CR, DR)	SDR	ACC, orientation sensor, GPS, WPS	low			
Man and Ngai [17]	User behavior learning (DC, VI), Sensor replacement (CR)	SDR	ACC, magnetic field sensor, GPS	low			
EnLoc [5]	User behavior learning (DC, VI), Sensor replacement (DR)	SDR, Mobility Tree	WPS, GPS, cellular ID	medium		✓	
EnTracked [12]	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 [2, 20]	–	Ameva algorithm	ACC	medium			
Mazilu [18]	Sensor replacement (CR)	DT	Temperature, humidity, pressure	medium			
Srinivasan [27]	User behavior learning (DC)	DT	ACC	medium			
Khalifa [9]	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 [10]	User behavior learning (DC, RD), Sensor replacement (CR)	SDR	Wi-Fi fingerprinting, GPS, ACC	medium	✓		
CAPS [22]	User behavior learning (DC, RD), Sensor replacement (CR)	SDR	GPS, cellular ID	medium	✓		
RAPS [21]	User behavior learning (DC, RD), Sensor replacement (CR, DR)	SDR	WPS, GPS, ACC, Bluetooth, cellular ID	medium	✓		
A-Loc [13]	User behavior learning (DC, RD), Sensor replacement (CR, DR)	HMM, Bayesian estimation framework	GPS, WPS, Bluetooth, cellular ID	medium	✓	✓	
SmartDC [4]	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 [14]	User behavior learning (DC), Sensor replacement (CR)	Microphone: NB with Gaussian Mixture Model (GMM). ACC: DT. GPS: MDP.	ACC, Microphone, GPS	high		✓	✓
Donohoo [6]	User behavior learning (DC)	Several. KNN and NN selected as best.	ACC, GPS, WPS, cellular ID, light, device data, mobile app requirements	high			✓
EEMSS [28]	User behavior learning (DC), Sensor replacement (CR, DR)	GPS and ACC: SDR. Microphone: SSCH algorithm.	ACC, microphone, GPS	high			✓
iLoc [16]	User behavior learning (RD), Sensor replacement (CR)	HMM	Wi-Fi & GSM fingerprinting	high	✓		✓
Yurur [29]	User behavior learning (DC, RD)	HMM	ACC	high	✓		✓
FreeTrack [3]	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)