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.
- *Context* refers to a four-dimensional space composed of *computing context*, *physical context*, *time context*, and *user context* [3].
- However, battery is not evolving at the same pace than the advances in other smartphone's characteristics [11], growing only 5% each year [15].
- The energy constraint becomes more critical when continuous access to sensors is needed, which is the core requirement of **mobile sensing applications**.

Problem antecedents: Stages of mobile sensing applications

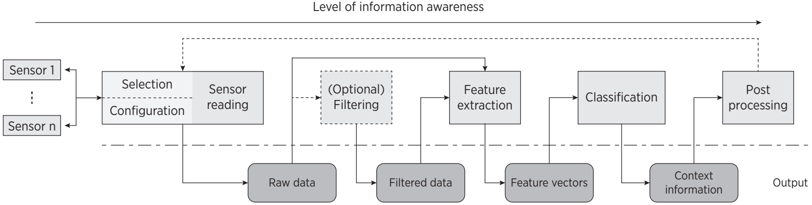

Figure: Stages of mobile sensing applications

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 accessed in order to reduce the energy consumption and achieve the requirements of a mobile 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 $\{\mathit{no\_movement}, \mathit{walking}, \mathit{running}, \mathit{vehicle\_transportation}\}$.

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 $\mathcal{S} = \{S_1, S_2, \ldots, S_n\}$, parameters for assigning weight to energy e and accuracy 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.

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

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

Interaction between problems

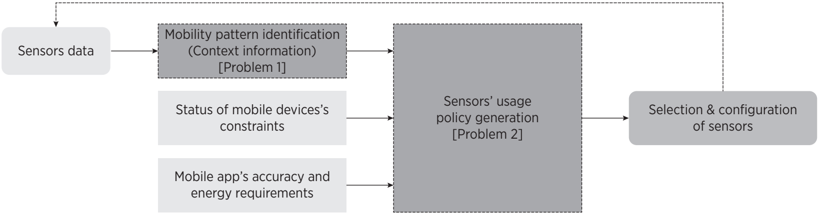

Figure: Interaction between the thesis work's problems

Problem's scenario

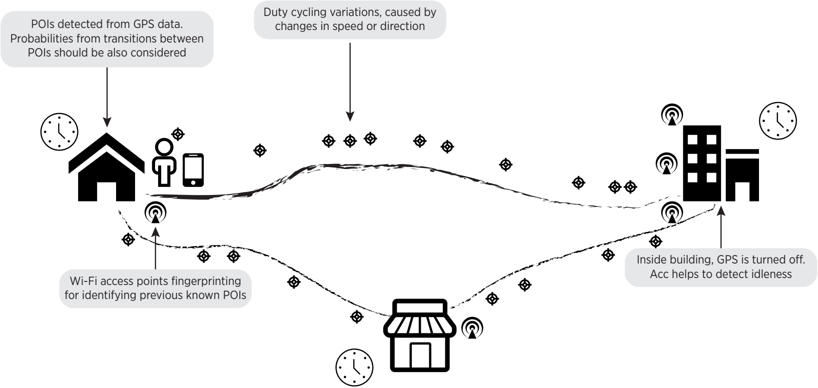

Figure: Basic problem's scenario

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

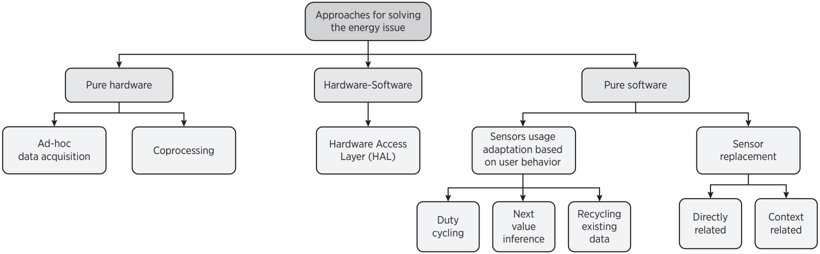

Figure: Taxonomy of solutions, seen from the sensors adaptation's perspective

Distribution of approaches

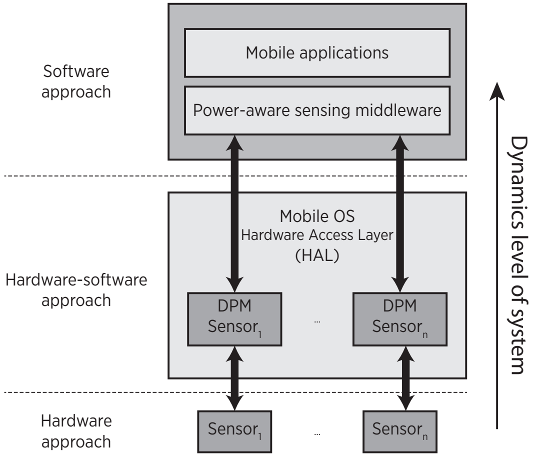

Figure: Distribution of approaches across mobile platform's layers

Characteristics of pure software approach solutions

Distinctive characteristics of pure software solutions

- Optimization oriented (OO)
- Online learning (OL)
- User state oriented (US)

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 [6]	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 [5]	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 [7]	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 [4]	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)

Framework for analyzing pure software solutions

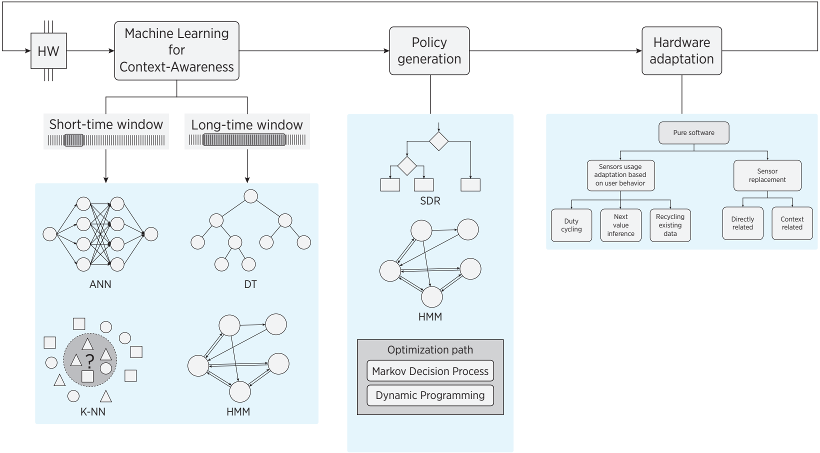

Figure: Decomposition of solutions

Characteristics of pure software approach solutions

Framework for analyzing solutions

Granularity of context information

- Input data type
- Classifier or machine learning technique
- Length of time window

Proposed solution

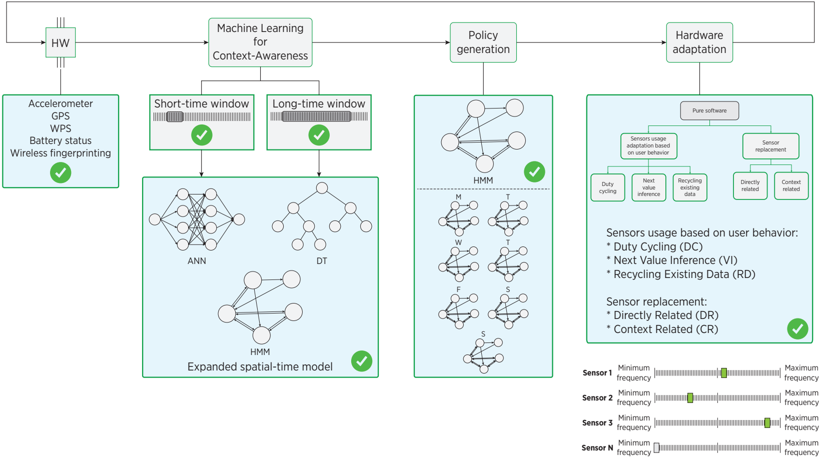

Figure: Decomposition of our solution

Proposed solution

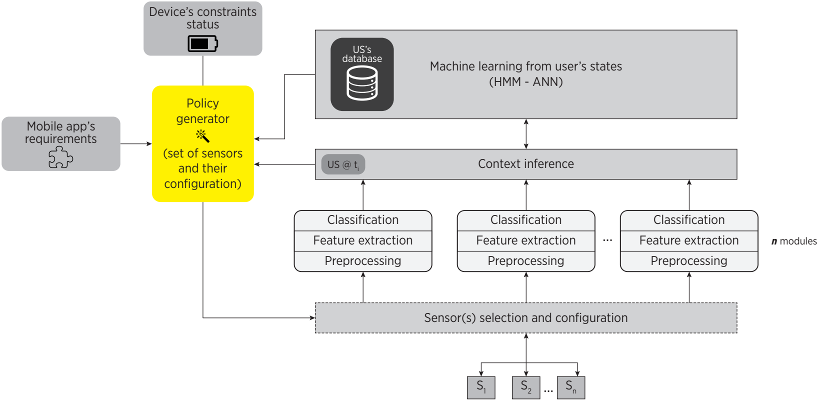

Figure: Overview of current solution

Results

- The feasibility of on-device detection of stay points has been partially prooved through experimentation.
- These experiments ensure proper calculations of stay points, even under mobile device constraints.
- A slight adaptation of classic algorithms for stay points detection has been implemented.
- Such variant (sigma) obeys an event-oriented paradigm, which is a trend for **proactive** long-term applications focused on learning patterns from user activity.

On-device stay points detection platform

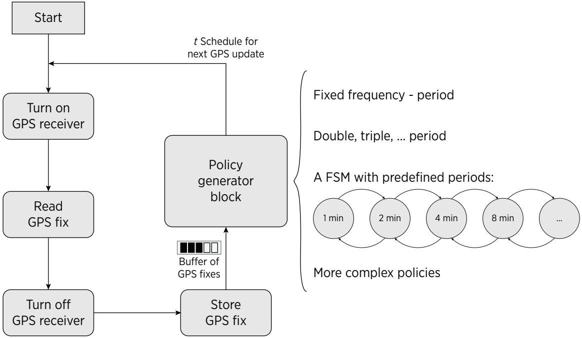

Figure: Logical workflow of the platform for on-device stay points detection

Results

- The first experiment is aimed at ensuring te calculation of stay points locally at the smartphone (Samsung Galaxy Note II more details here).
- 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. Starting with 1 minute reading period, doubling if no movement within a threshold of 50 meters was detected (Upper limit 16 minutes).
  - FSM linear policy. Possible fixed states at 1, 3, 6, 9, and 12 minutes.
- 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
1 minute	Buffered	20	200	456	1744	36 hrs
1 minute	Zigma	21	198	400	1750	37 hrs

Table: Results of the first experiment

Scientific products

- As a product of the study and analysis of related solutions, we have prepared a survey 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.
- The previously mentioned experimentation is also under expansion and improvement for preparing an article focused on:
  - On-device learning of mobility information following an event-oriented perspective.
  - The employment of such information for adapting the sensing dimension of smartphone looking for energy efficiency.
  - Setting the base for further modules and strategies for boosting the learning of mobility patterns.
  - All of these targetted at building the main blocks of our solution.

Future work

Adequate the calendar-schedule explaining the apparent delay produced by the survey, but remarking its added value as a metric and as a scientific booster for improving the work.

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. 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 solution intended for building intelligent sensing policies aimed at *continuous* user location tracking.
- This solution identifies and learns enhanced 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.

Thank You
for your attention!

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

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