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

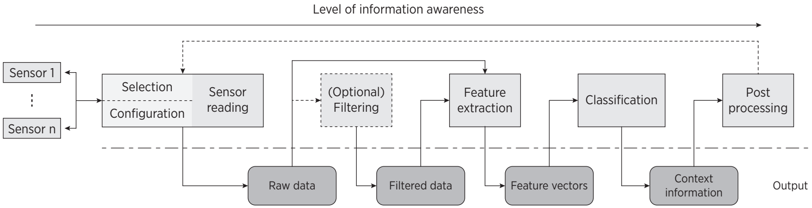

Figure: Stages of mobile sensing applications

There is a tradeoff between the accuracy of context information retrieved and the associated energy consumption [25, 24]. 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.

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

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

Interaction between problems

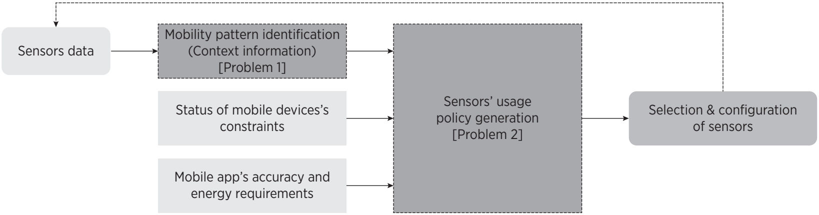

Figure: Interaction between the thesis work's problems

Problem's scenario

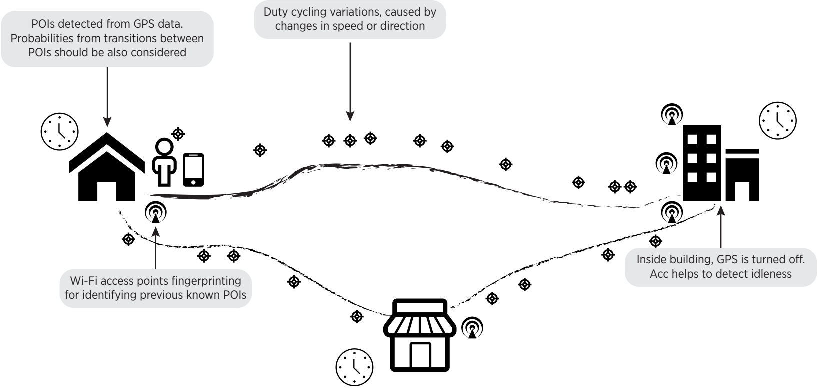

Figure: Basic problem's scenario

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

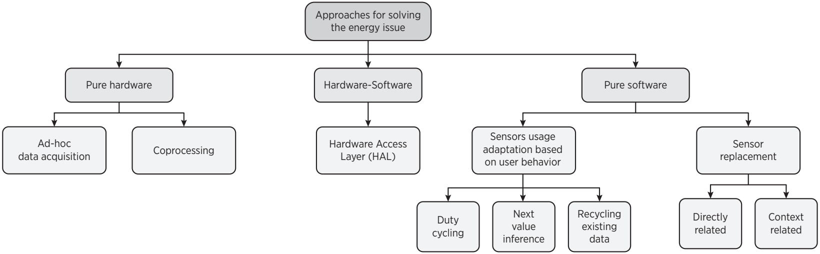

Figure: Taxonomy of solutions, seen from the sensors adaptation's perspective

Distribution of approaches

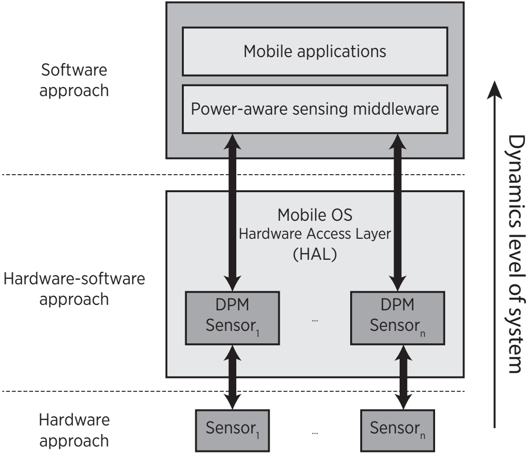

Figure: Distribution of approaches across mobile platform's layers

Solutions characteristics

Distinctive characteristics of works

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

En general, podemos describirlos de forma más o menos organizada a través de...

Granularity of context information (input data type + classifier + time window length)

- Basic context information powered policies.
- Medium context information powered policies.
- High level context information policies NO ES CIERTO! NO EXISTE ESTO! ES SIMPLEMENTE UNA EVALUACIÓN INCREMENTAL. EN TODO CASO HAY QUE PONER AQUI LO QUES ESTA ENTRE PARENTESIS (CLASS+TIMEWINDOWS...)

Decomposition of related solutions

De forma general, el framework para evaluar queda como:

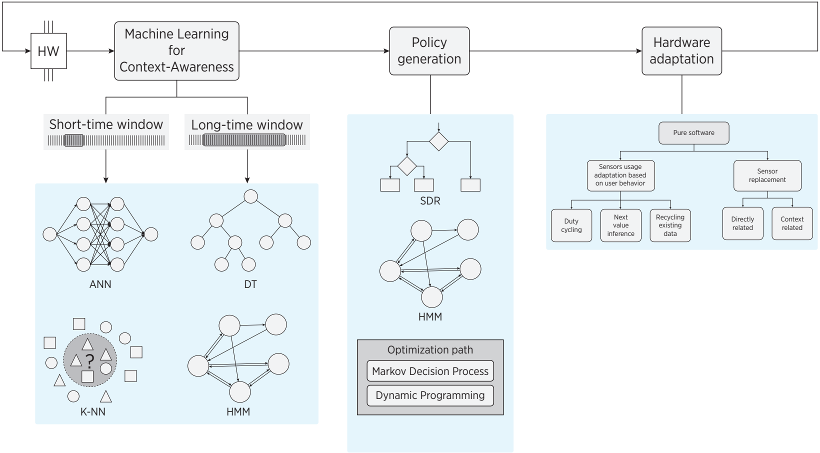

Figure: Decomposition of solutions

State-of-art solutions

Name	Variants	Machine learning technique	Sensors involved	Complex-ity	OL	OO	US
G-Sense [22]	User behavior learning (DC)	SDR	GPS	low			
Not given [23]	User behavior learning (DC)	SDR	GPS	low			
SenseLess [1]	User behavior learning (DC), Sensor replacement (CR, DR)	SDR	WPS, GPS, ACC	low			
SensTrack [29]	User behavior learning (DC), Sensor replacement (CR, DR)	SDR	ACC, orientation sensor, GPS, WPS	low			
Not given [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
Not given [2, 19]	–	Ameva algorithm	ACC	medium			
Not given [18]	Sensor replacement (CR)	DT	Temperature, humidity, pressure	medium			
Not given [26]	User behavior learning (DC)	DT	ACC	medium			
Not given [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 [21]	User behavior learning (DC, RD), Sensor replacement (CR)	SDR	GPS, cellular ID	medium	✓		
RAPS [20]	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		✓	✓
Not given [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 [27]	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	✓		✓
Not given [28]	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)

Proposed solution

How are we going to be different?. At the end we can describe that:

- In the ML block, we are going to produce an enhanced-expanded spatial-time model by:
  - Classifying accelerometer data in user activity.
  - Obtaining context information from other sources:
    - Fingerprinting, battery status.
  - Obtaining speed from GPS
  - Obtaining location from GPS and WPS
- In the policy block, we will try to adapt the sensing dimension spliting the problem into:
  - Learning and detection of stay points (Already covered)
  - Learning and detection (tracking) of trajectories.
- In the HW adaptation bloc, we will use several variants of the PS approach. For instance, we will do:
  - Sensor replacement, Context related (battery) and Direct related (WPS).
  - Adapt accordingly to what is learned from user through Duty Cycling (DC) and Recycling existing Data (RD). Maybe we will use Next Value Inference (VI) in the policy, when we adapt under uncertainty. For instance, we are 80% sure that user is running, we will proceed with caution adapting duty cycle with fine granularity, this is negotiable.
- At the end, we are trying to maintain sensors within a range that allows to perform the tracking but considering the trade-off.

Proposed solution

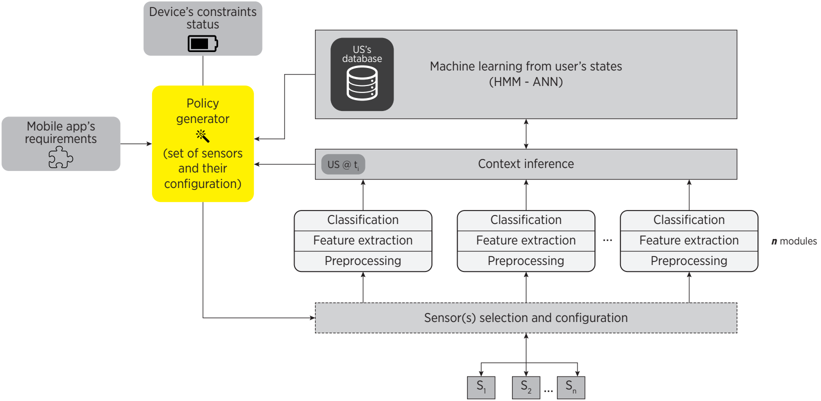

Figure: Overview of current solution

Results

Here, we can mentioned that we have partially prooved the possibility of performing user location tracking and stay points detection using only the smartphone. This empowers us to keep building the blocks that will complement our solution.

Scientific products

I think we can menton the survey. We need to find out whether we can describe the article related to the on-device detection of stay points, highlighting its 'event-oriented' perspective, which represent the most natural way on which smartphone-based systems for LBS should work, being proactive.

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:

- An introduction to the energy consumption issue in mobile sensing apps and its relevance has been presented.
- A description of the important components of our thesis work has been also given.
- An overview of the proposed methodology for solving the energy consumption issue has been provided.

Thank You
for your attention!

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