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

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Doctoral seminar, 2017

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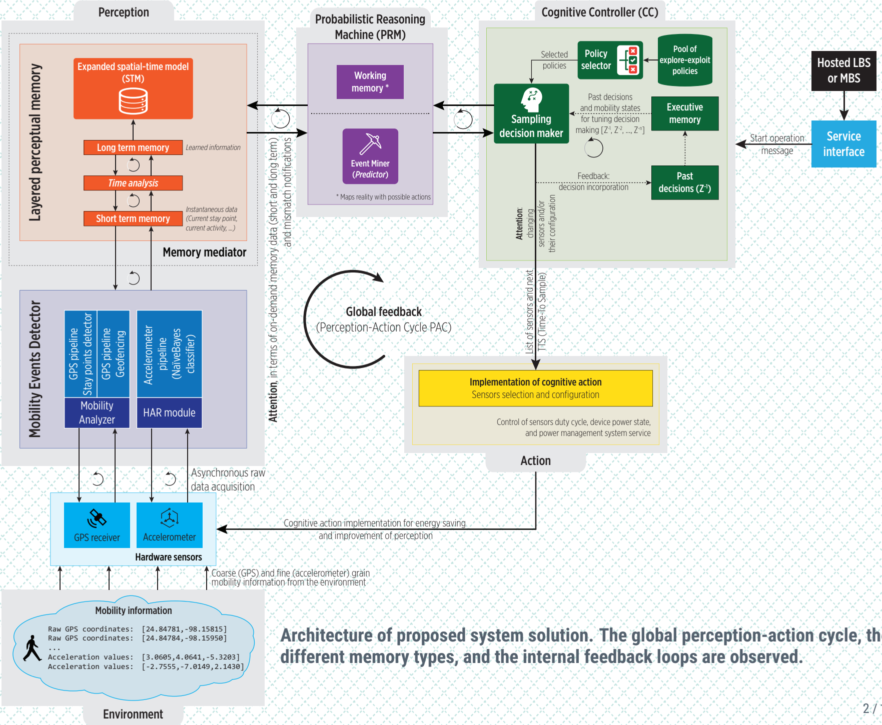
Agenda

Solution



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

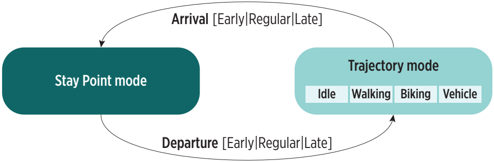


Figure: Individual's mobility as a sequence of high level states and associated events detected from raw sensor data [7, 8].

Mobility Events Detector

Aime at identifying:

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

Perception components

Mobility Events Detector: *Stay Points Detector* module

Stay Points Detector module

- Focused on detecting stay points in user mobility.
- Event driven design, it incrementally processes each low-level mobility event (raw GPS data).

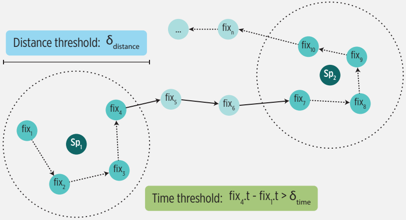


Figure: A conceptual representation of the stay points detection algorithm behavior.

Geofencing module

- Window-based approach with voting system.
- Requires an $SPS_{candidate}$ list of stay points.
- Incrementally analyzes GPS fixes for detecting coarse-grain mobility events under a $gf_{distance}$ threshold:

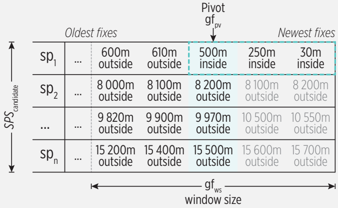


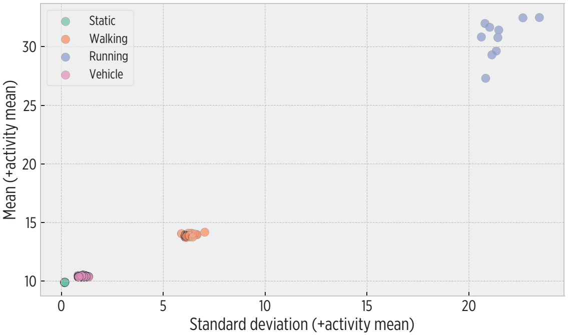
Figure: A conceptual representation of the window-based geofencing operation.

Perception components

Mobility Events Detector: *HAR* module

HAR module

- Window-based approach.
- Detects transportation mode from accelerometer data.
- Underlying NaïveBayes classifier.



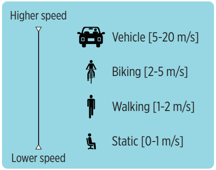


Figure: Distribution of mean and standard deviation features employed by the NaïveBayes classifier of the HAR module.

Layered perceptual memory

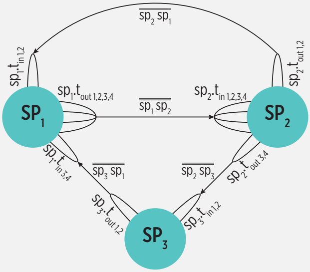
Short and long-term memory information

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*.

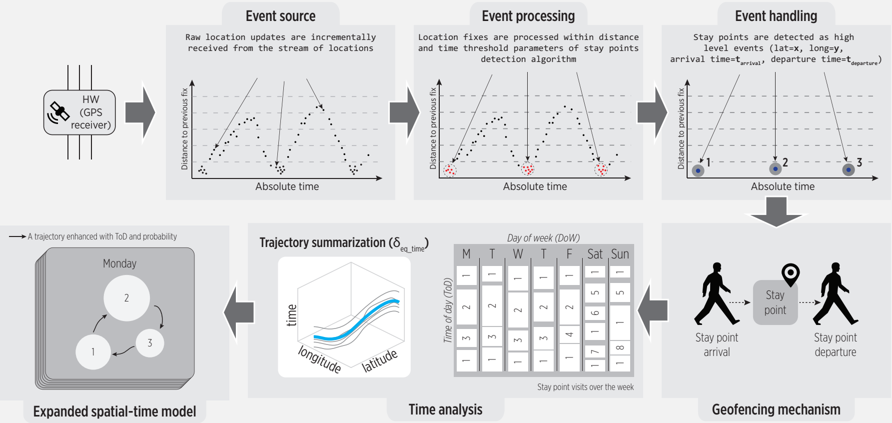


Figure: A conceptual representation of the steps for generating the STM from raw sensors data.

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.

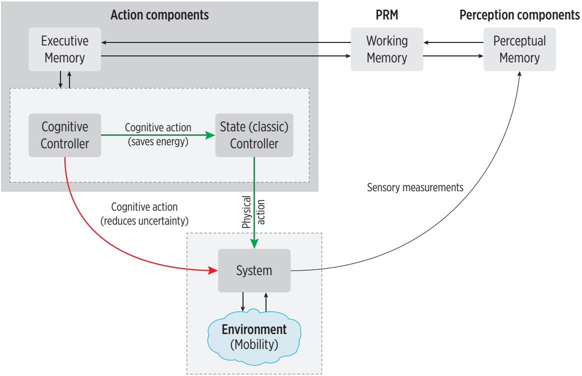


Figure: A cognitive controller generic architecture

Cognitive controller

Policies tailored for user mobility

Stay point mode

- A sampling based on the sigmoid function $sig(x) = \frac{1}{1+e^{-\alpha x}}$ as a model for the mobility phase transitions.
- Higher sampling rate on arrival and departure, when the user is more likely to move, and slower at the middle of a visit.
- Central part is assisted by motion detection from the *HAR* module.

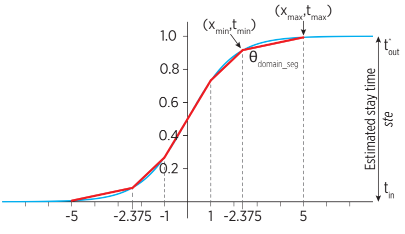


Figure: Approximation of the sigmoid through straight segments.

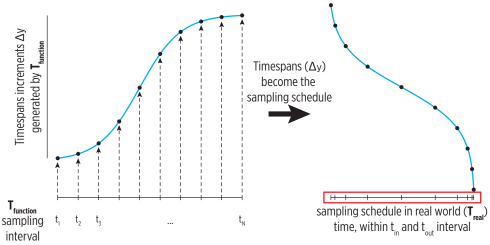


Figure: A snapshot of the process for producing a sigmoid sampling.

Cognitive controller

Policies tailored for user mobility

Trajectory mode

- The spatiotemporal characterization of people's motion during trajectory is complex: it is hard to produce a single spatiotemporal model for summarizing how all people move.
- No special modeling of motion during a trajectory is performed other than the user moves within a speed range.
- A hint of such speed is provided by the HAR module from the detected transportation mode.
- The speed tendency over a window of identified transportation modes is employed for adjusting GPS sampling.

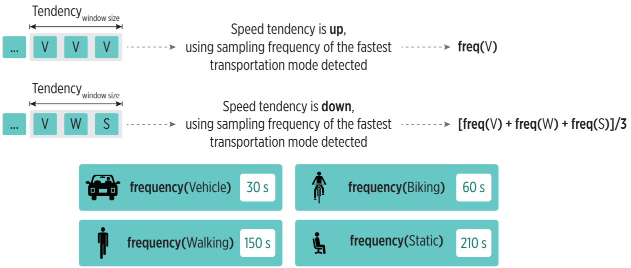


Figure: GPS sampling adaptation based on the speed tendency of detected transportation modes.

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 implements one policy, employing the spatial-time estimation provided by the PRM.
- It updates its *Executive Memory* with the selected cognitive action for feedback in further executions.

Reaction for mobility events

- Reaction for arrival event:
  - The sampling rate is reduced by following a sigmoid-based sampling.
- Reaction for departure event:
  - The sampling rate is increased by implementing a target sampling T_{target}.

Cognitive controller

Mobility mismatches

Mismatches

- A mismatch represents a discrepancy between observed and learned mobility information.
- In general, the system increases the sampling rate for recovering the accuracy lost.

Reaction for mobility mismatches

- Reaction for early arrival:
  - The sampling rate is reduced by following a sigmoid-based sampling.
- Reaction for early departure:
  - The fastest sampling rate is selected for recovering accuracy and improving system perception.
- Reaction for late arrival:
  - The fast sampling rate must be maintained as long as the user is still in trajectory.
- Reaction for late departure:
  - A *conservative sampling* rate is implemented for detecting the eventual departure.

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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