Ubiquitous and Mobile Computing CS 403x: *Automatically Characterizing Places with Opportunistic CrowdSensing using Smartphones*

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Problem Statement

- Traditional location sensing systems only make use of WiFi and GPS
- The error in GPS-, GSM-, or WiFi-based location estimates often ranges between 10 and 400 meters
- 426 of the 1,241 place visits incorrectly reported based on the location estimate

Introducing CSP

- CSP - CrowdSense@Place
- Interpretation of a location from Location Sensor to user - as a place
- Framework that exploits sensors that most phone’s have
- Smartly capture images and audio clips from smartphones
- Goal is to link place visits to various place categories

Current Approach

- Place-discovery techniques these days:

- Exploit large-scale data collections, like point-of-interest databases (Google) to allocate place descriptors

Related Work

- Bing, Yelp
- Facebook, Twitter, FourSquare
- CenceMe - Similar application but doesn’t infer from images
- SenseCam - Goal to understand user’s environment
- VibN - Identifies points of interest in the city

How is CSP different?

- CrowdSense@Place - Place classification based on existing methods to perform place segmentation

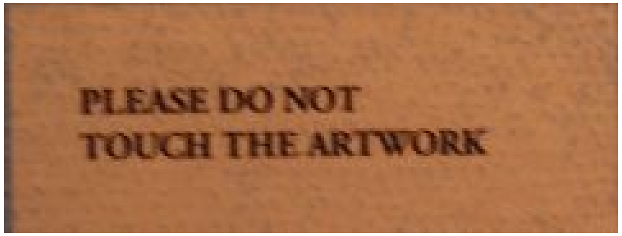
Overview

- Smartphone Application
  - Sensing and Data Collection
  - Privacy Settings
- Offline server-side processing
  - Processing and Location Detection

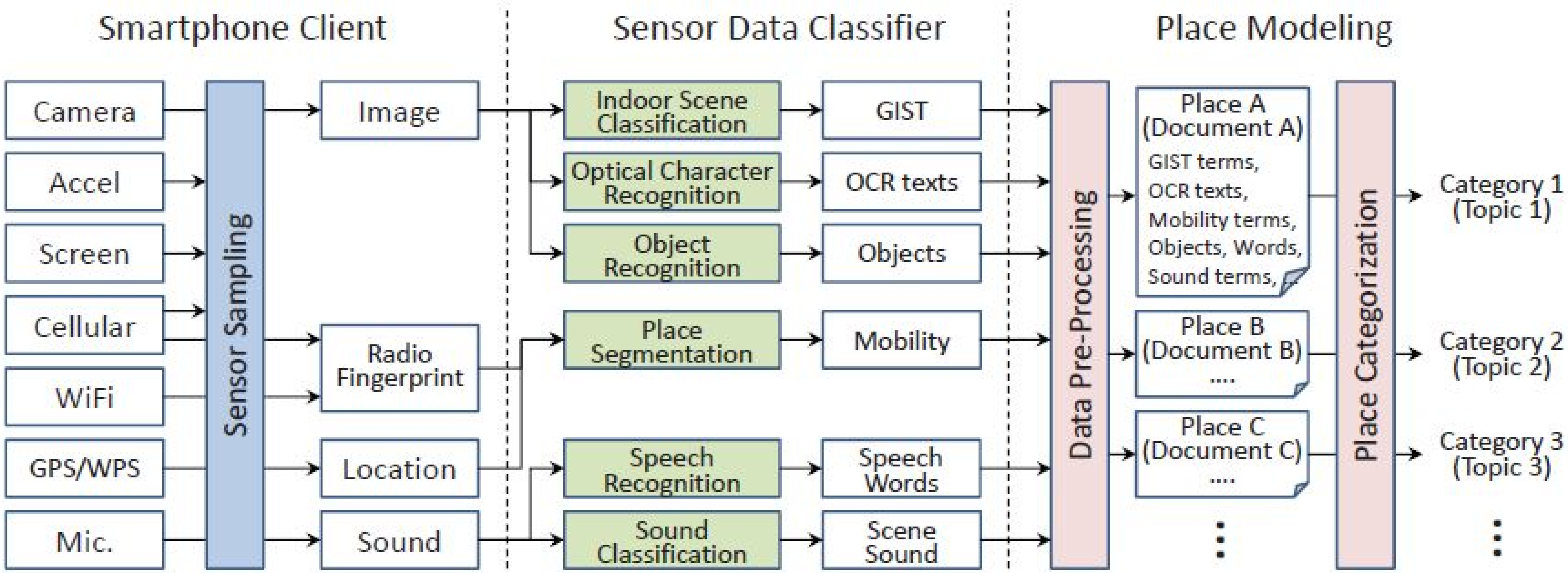
Data Collection

- Audio detection
  - "Do you have a Large size of these pants?"
- Pictures of objects

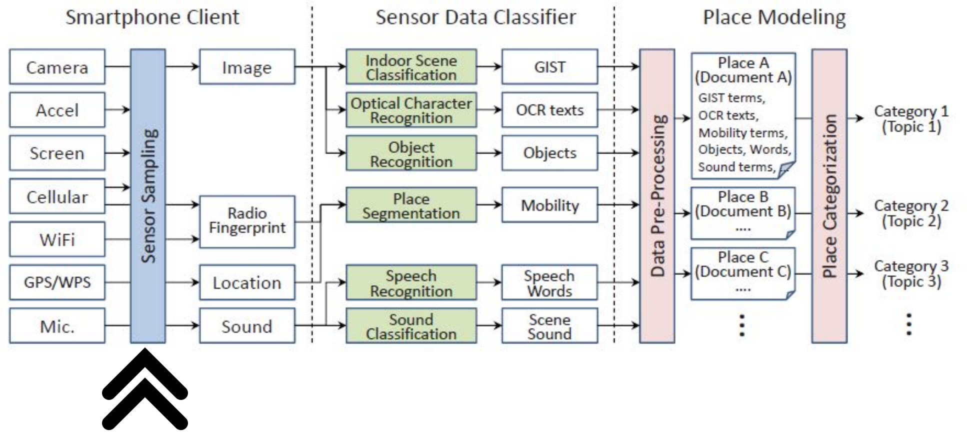
- Written Texts



Methodology

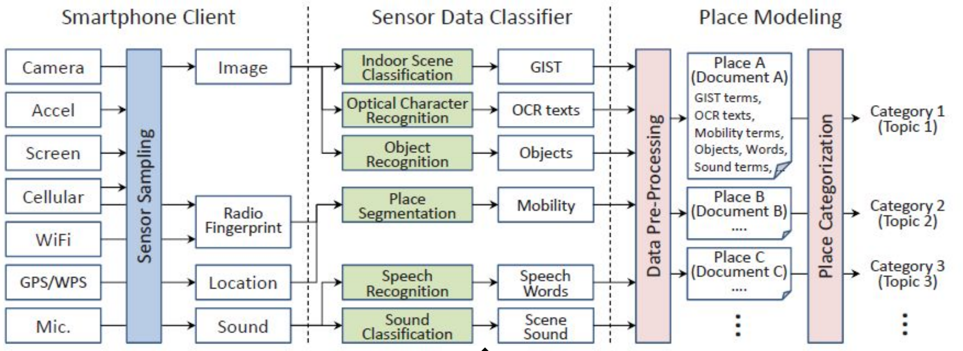


Smartphone Client



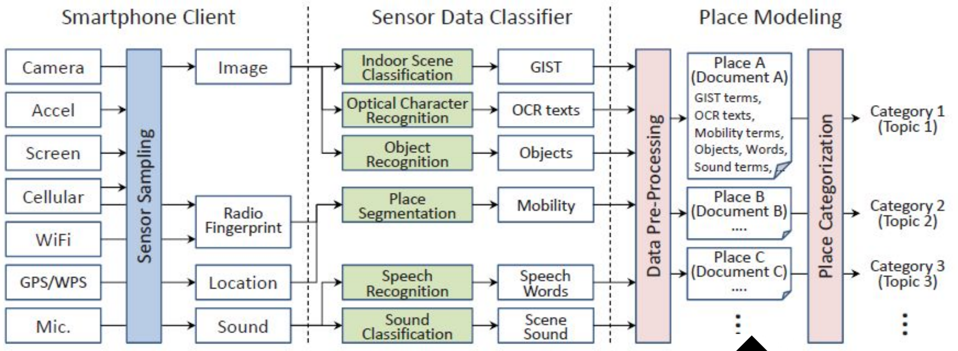
- Place Segmentation - WiFi fingerprinting and GPS to discover places
- Sensor Sampling - Simple heuristic to improve quality of data collected
- Privacy - Data resides on device for 24 hours

Sensor Data Classifiers



- Optical Character Recognition (OCR)
- Indoor Scene Classification
- Objects Recognition
- Speech Recognition
- Sound Classification

Place Modeling



- Data preprocessing
    - Classifier Terms
    - Mobility Terms
- Place Categorization

Results - Classifiers

- Indoor scene classification (GIST features) has the largest impact
- OCR does not have a strong overall effect
- Object detection, speech recognition, and sound classification had major effects

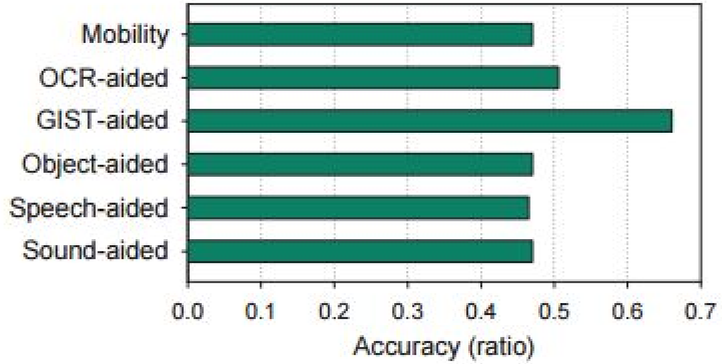
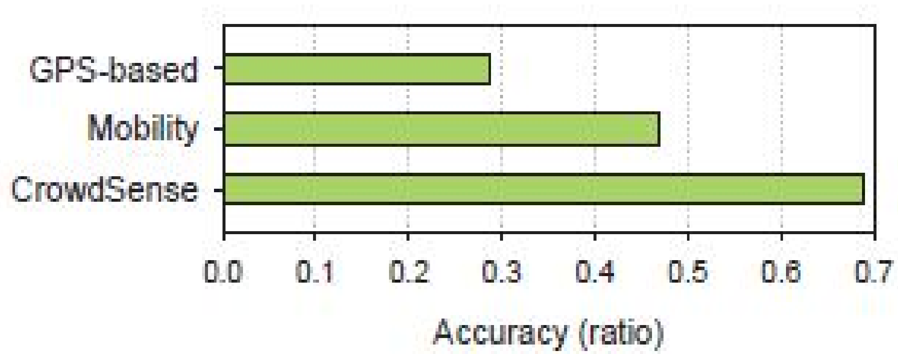


Figure 6. Accuracy of different classifiers used by isolation.

Results - Location Accuracy

- 69% Accuracy
- CSP outperforms GPS and Mobility by around 22% to 40%
- Mobility has 44% accuracy for workplace and 52% for college while CSP has 80% and 71% respectively



Applications of CSP

- Enhanced Local Search & Recommendations
-  Rich Crowdsourced Point-of-Interest Category Maps
- Understanding City-scale Behavior Patterns

Limitations and Future Work

- Finer Place Categorization
- Privacy
- Activity vs. Place Category
- Energy Issues

Conclusions

- 36 person study
- Seven-weeks total
- 1241 places on 5 locations
- Average accuracy of 69%

What we liked/disliked about the paper?

Likes:

- Graphs and tabulated data findings
- The intensive study conducted
- Limitations and issues considered

Dislikes:

- Doesn’t address privacy concerns appropriately

Questions

References

- http://www.fengzhao.com/pubs/ubicomp12_cps.pdf