Automatically Characterizing Places with Opportunistic CrowdSensing using Smartphones

David Muchene

Computer Science Dept.

Worcester Polytechnic Institute (WPI)

Introduction

- Smart phones have a variety of new sensors
- Location is still the most widely used contextual information in most applications
- Need to abstract out the notion of “place” from location data

Contributions

- CrowdSense@place (CSP)
  - A framework that characterizes places using opportunistically acquired images and audio
  - Basic idea is that Images contain hints and CSP can extract these hints and use them in the classification
  - Classify into more categories than current approaches
- A novel modeling approach that combines image, audio, and traditional location sensors

Existing Approaches

- Discover places by mining user’s trajectory
- Label discovered places (e.g. mall, drug store)
  - Either User input, or by leveraging databases like Bing, Yelp or FourSquare
- Problem is that GPS/WiFi location estimates could have large margins of error
  - GPS is especially terrible indoors

System Overview

- Smart phone App and a offline server to process collected data
- App runs as a daemon and continually fingerprints WiFi Access points to detect places
- Opportunistically sample image and audio sensor
  - For example when a user receives a phone call
- Bootstrap the image and audio classifications using user input.

System Overview

- Indoor Scene Classification
- Object recognition
- OCR
- Speech Recognition
- Place modeling

System Overview

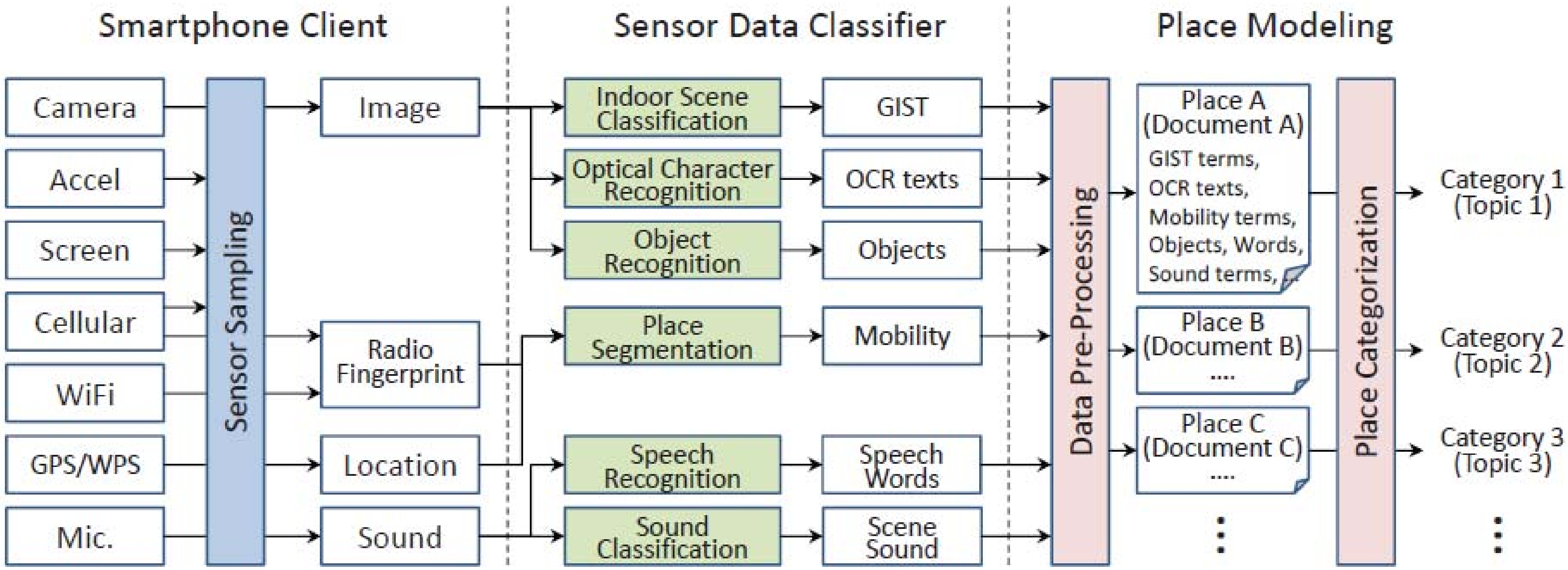


Figure 2. CrowdSense@Place processing stages.

Evaluation

- Recruited 36 users living in 5 locations
- Measured accuracy of place categorizations
- Used GPS data and Mobility
  - GPS data is fed into FourSquare
  - Mobility uses trajectory to do place classification
- Client was implemented using Android SDK 1.5
- Backend on Microsoft Azure

Results

Figure 4. Mobility pattern of several categories

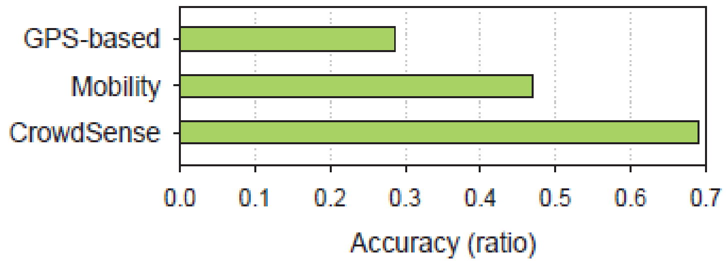
Mobility-based Method

Label \ Result	Col.	Work	Ent.	Shops	Food	Home	Oth.
College	0.44	0.30	0.01	0.04	0.04	0.04	0.12
Work	0.33	0.52	0.01	0.03	0.07	0.01	0.03
Ent.	0.07	0.07	0.19	0.15	0.11	0.19	0.22
Shops	0.00	0.06	0.13	0.38	0.06	0.06	0.31
Food	0.10	0.04	0.02	0.08	0.49	0.05	0.20
Home	0.00	0.00	0.00	0.09	0.00	0.80	0.11
Others	0.06	0.14	0.17	0.14	0.04	0.16	0.30

CrowdSense@Place

Label \ Result	Col.	Work	Ent.	Shops	Food	Home	Oth.
College	0.80	0.10	0.01	0.01	0.03	0.00	0.04
Work	0.05	0.71	0.03	0.01	0.02	0.01	0.03
Ent.	0.04	0.04	0.41	0.04	0.33	0.00	0.15
Shops	0.00	0.03	0.00	0.59	0.28	0.00	0.09
Food	0.02	0.11	0.05	0.09	0.66	0.00	0.06
Home	0.00	0.00	0.04	0.02	0.00	0.93	0.00
Others	0.05	0.09	0.09	0.20	0.12	0.10	0.36

Table 3. Confusion matrices of place categories for *Mobility* and CrowdSense@Place.



Future Work and Conclusions

- Finer place classification
  - Better use of the object and speech recognition
- Privacy
  - Perform more local computation to avoid leaking private information
- Applications
  - Better Local search, recommendations, targeted advertising, etc.
  - Understand large scale behavior patterns to gain insights about cities

References

- ***Automatically characterizing places with opportunistic crowdsensing using smartphones.*** *Yohan Chon, Nicholas D. Lane, Fan Li, Hojung Cha, and Feng Zhao*