Ubiquitous and Mobile Computing CS 403x: CrowdSense@Place

Yo Karita
Steven Ireland
Johnny Hernandez

Computer Science Dept.
Worcester Polytechnic Institute (WPI)

Motivation

- Location sensors: Most successful and widely used sensor in mobile computing
  - Local Search
  - Point-Of-Interest services
  - Navigation
  - Geo-tagging
- Location data and “Place”
  - Giving context to location
  - Link locations with categories or actions
- Location and Context based apps
- Activity recognition

CrowdSense@Place

- Framework for categorizing locations
- Uses opportunistically collected data
  - Phone calls, check email, browse the web, etc
- Analyze image and audio data to infer hints
  - Image data: Written text, objects
  - Audio data: Spoken words
- Places are categorized using most dominant topic

CrowdSense@Place

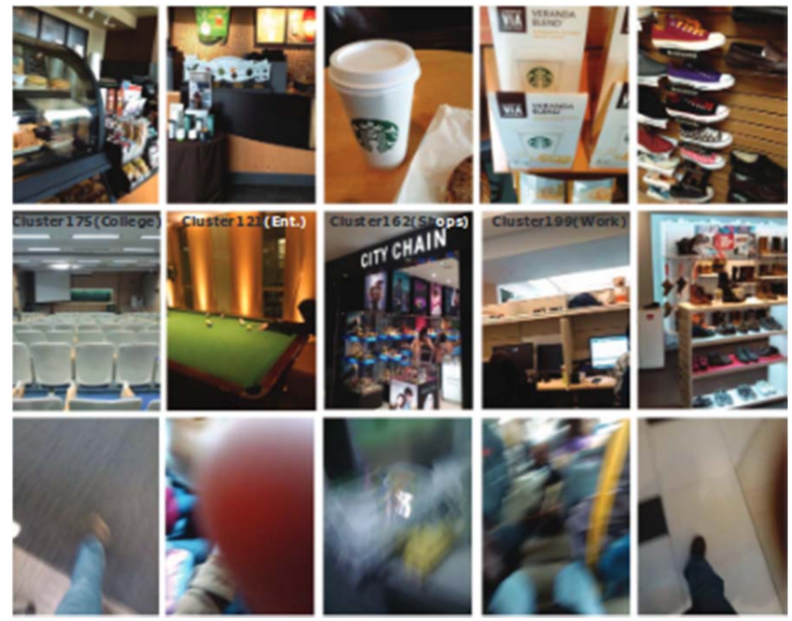
- Existing Approaches
  - Point-Of-Interest databases
  - Location based community-generated content
- Problems
  - GPS Inaccuracy
- Solve this by relying on other sensors

Related App

- Application improves point-of-interest search recommendation
- Both use audio data from microphone
- VibN requires users to analyze audio clips
- Techniques in CSP could be applied in VibN’s manual stages

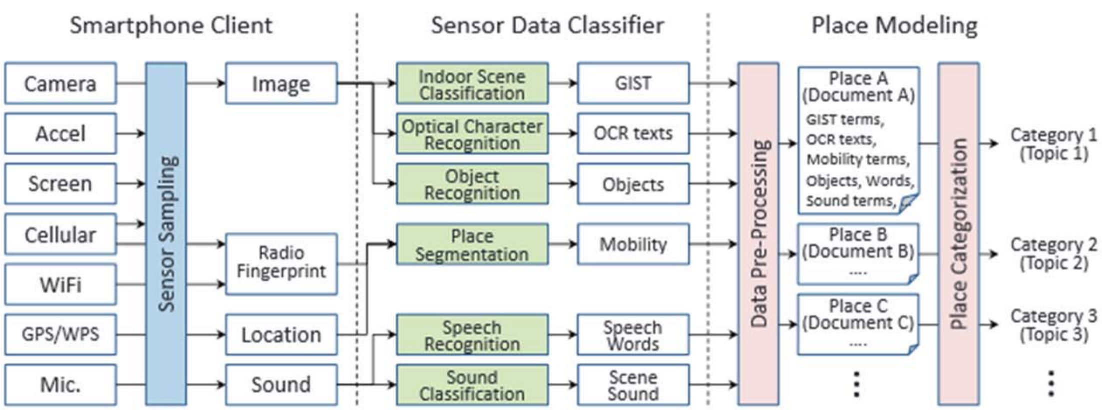
Sensors Used

- Opportunistic Sensing
  - Camera
    - Takes pictures of the area
  - Microphone
    - Records conversations/sounds in the area
- Identifying "Places"
  - WiFi
    - Uses radio fingerprinting of nearby access points
  - GPS
    - Location tied when encountering a place for the first time



Methodology

- Smartphone Client
  - Background process
  - Privacy configuration
- Server Side Classification
  - Object recognition
  - Indoor scene classifier
  - OCR
  - Speech recognition
  - Sound event classifier

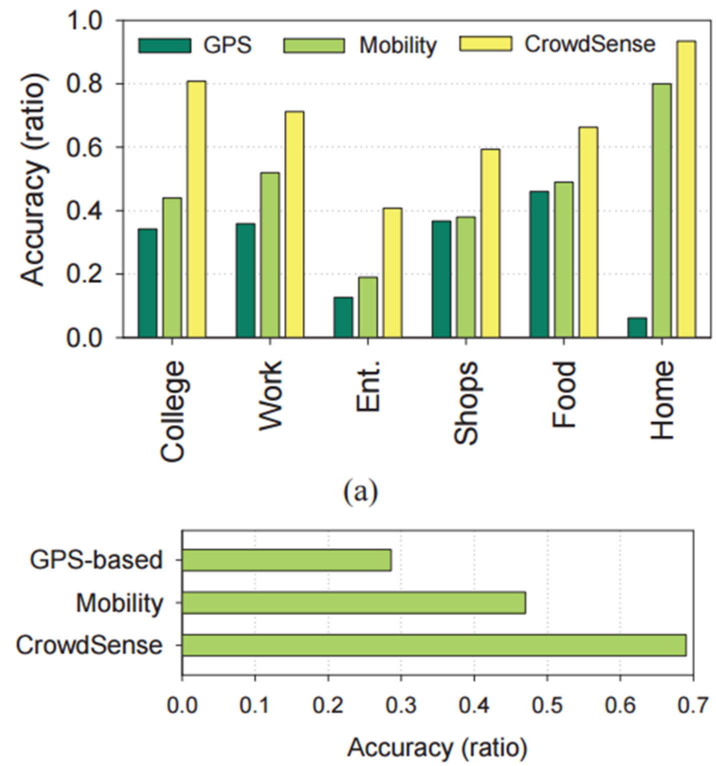


Privacy

- Users have rights to control sensitivities
- All data stays in the smartphone for 24 hours
- Remove all data collected for previous 1, 6, or 24 hours
- Pause data collecting
  - For upcoming time interval
  - Location based

Results

- Outperforms GPS and Mobility by 40% and 22%
- 69% Overall Accuracy
- Better at distinguishing college and workplace than Mobility alone
- Food and Shopping locations have good OCR detection



Accuracy

- Hard time differentiating between entertainment and food
- Some locations have more than one category

Figure 4. Mobility pattern of several categories

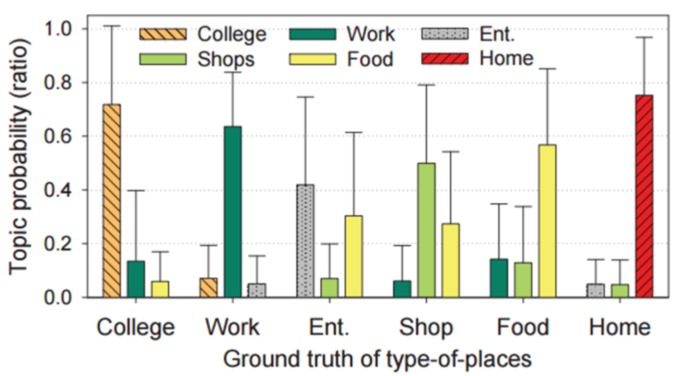
Mobility-based Method

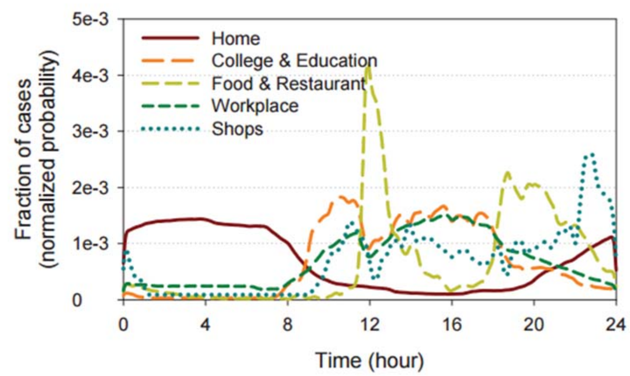
Label \ Result	Col.	Work	Ent.	Shops	Food	Home	Oth.
College	0.44	0.30	0.01	0.04	0.04	0.04	0.12
Work	0.33	0.52	0.01	0.03	0.07	0.01	0.03
Ent.	0.07	0.07	0.19	0.15	0.11	0.19	0.22
Shops	0.00	0.06	0.13	0.38	0.06	0.06	0.31
Food	0.10	0.04	0.02	0.08	0.49	0.05	0.20
Home	0.00	0.00	0.00	0.09	0.00	0.80	0.11
Others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





Classifier Effectiveness

- GIST and OCR had the strongest discriminative value
- Object detection only effective outside
- Speech recognition and sound classification have weak discriminative power

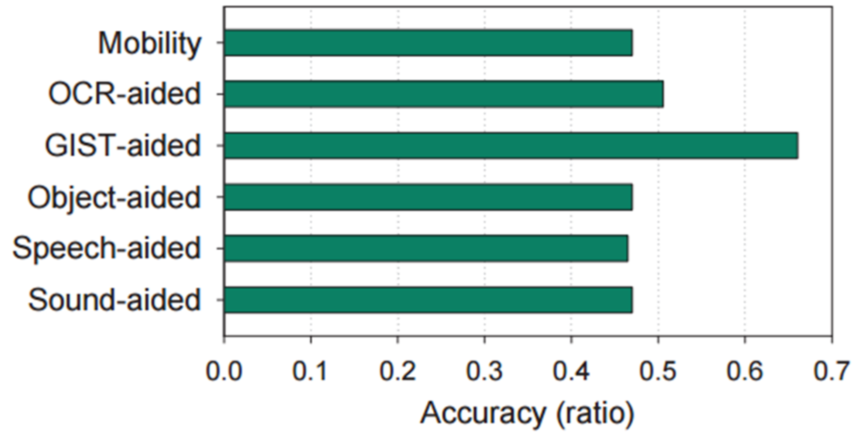


Figure 6. Accuracy of different classifiers used by isolation.

Limitations and Future Work

- Finer grain categorization can occur with specific place hints
- Better privacy protection
- Better suited to incrementally learning information over long time scales

Potential Uses

- Enhanced recommendation services
- Crowdsourced point category maps
- Category to category behavior patterns

Questions?