Experiences with Performance Tradeoffs in Practical, Continuous Indoor Localization

Azeem Khan, Vikash Ranjan, Trung-Tuan Luong, Rajesh Balan and Archan Misra
Singapore Management University

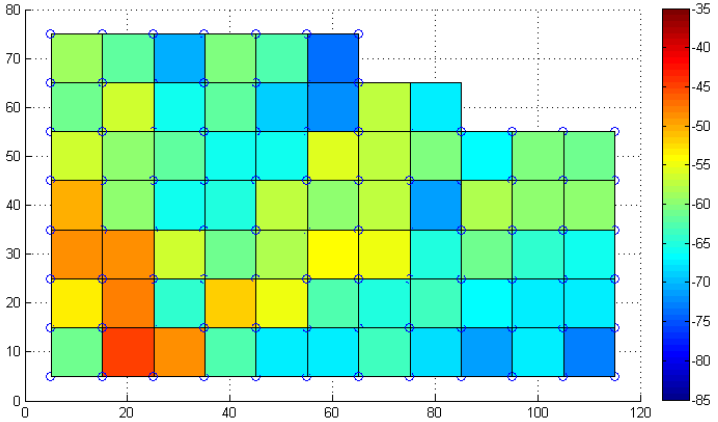
Presenter: Shervin Amini

Motivation

- Indoor localization of consumer mobile devices
- Previous works focuses on accuracy of the localization
- Less work on scalability and energy consumption
- Challenge: accuracy and energy consumption

Concepts

- Indoor localization is based on Wi-Fi-based positioning system
- Wi-Fi positioning uses access points (AP)
- Any localization technique measures the intensity of the signals (received signal strength)
- RSSI from different APs form radio map for a given area (probability of RSSI values for a location/ fingerprinting)
- Comparing new RSSI values against fingerprint and estimate the location



Fingerprint map of a playground wrt. a particular landmark

System setup

- Using two dominant smart phone OS
  - Android on Samsung Galaxy S3 phone
  - iOS on iPhone 4 (does not have open API to scan Wi-Fi data)
- Public indoor locations
  - Mall (high visitor load on evenings and weekends)
  - SIS(campus building), high load during class times

	Mall	SMU
Number of Floors	7	5
Indoor/Outdoor	Fully-Indoor	Mixed Indoor+ Outdoor (Floor 1&2)
Avg. Floor Area (sq.m)	5000[1]	3000
Avg. Store/ Room Width (m)	8	3
No. of Wi-Fi APs/floor	12	24
No. of Fingerprint Landmarks	26 (floor 1) 27 (floor 2)	67 (floor 2) 76 (floor 4)

Contributions

- Localization strategy for Android and iOS
  - Combining Wi-Fi fingerprinting and motion estimation with Viterbi algorithm
  - Finding temporal sequence of locations
- Building characteristics (density, building structure) affects the accuracy

Wi-Fi Data Collections

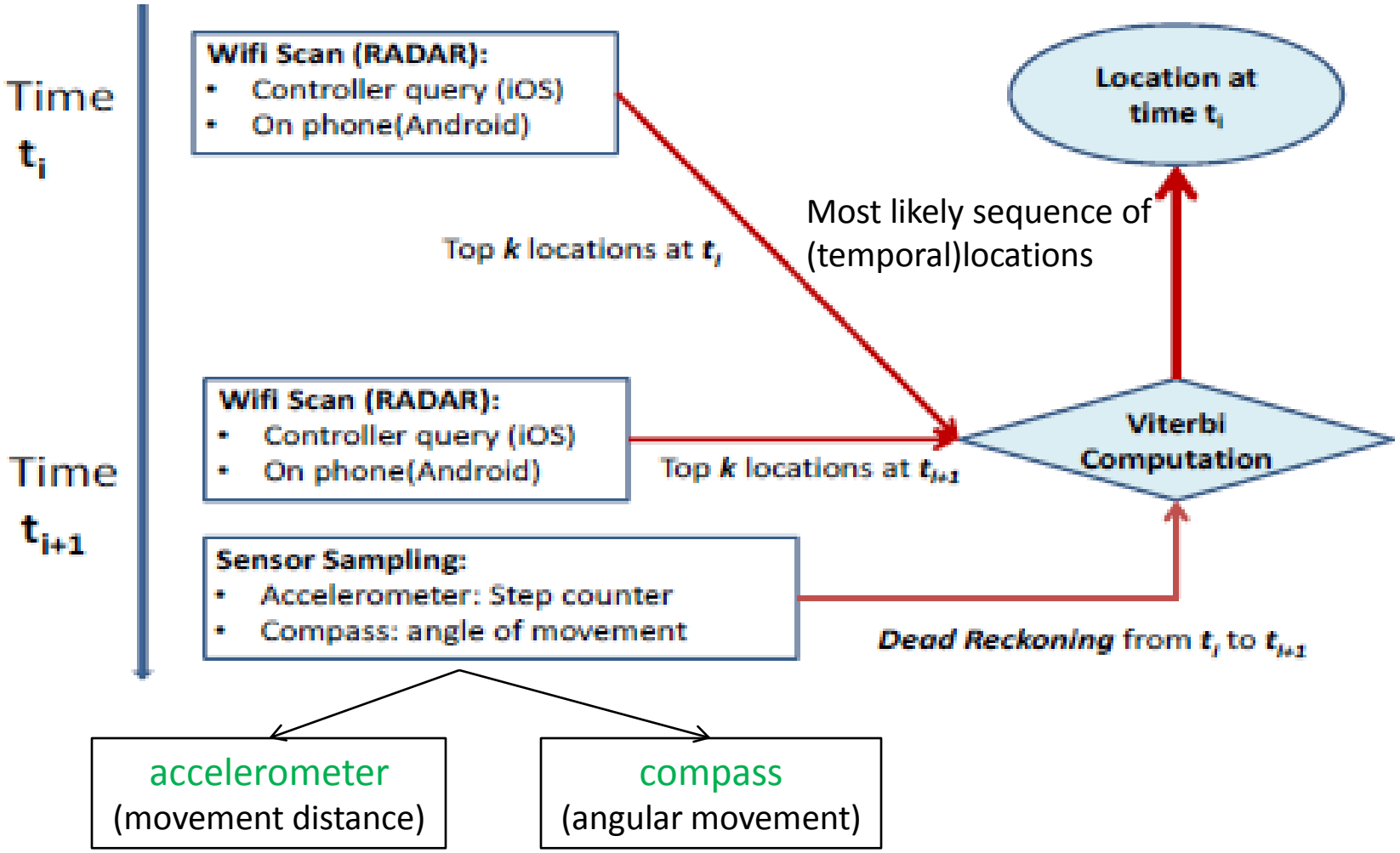
- Offline collection of RF at known landmaks

  (AP_i, signature AP_i)
- Generating fingerprint maps
  - Android: using custom application for scanning Wi-Fi access points.

    <timeStamp, RSSI, AP ID>
  - iOS: reverse fingerprinting

    A server(controller) is responsible for measuring the signal to noise ratio (SNR) sent form iPhone

Localization Process



Fingerprinting on Android

landmark

AP

AP

Fingerprint(iOS)

$$L_i, [AP_i, SNR_{AP_i}]$$

$$L_{i+1}, [AP_{i+1}, SNR_{AP_{i+1}}]$$

Fingerprint (offline phase)

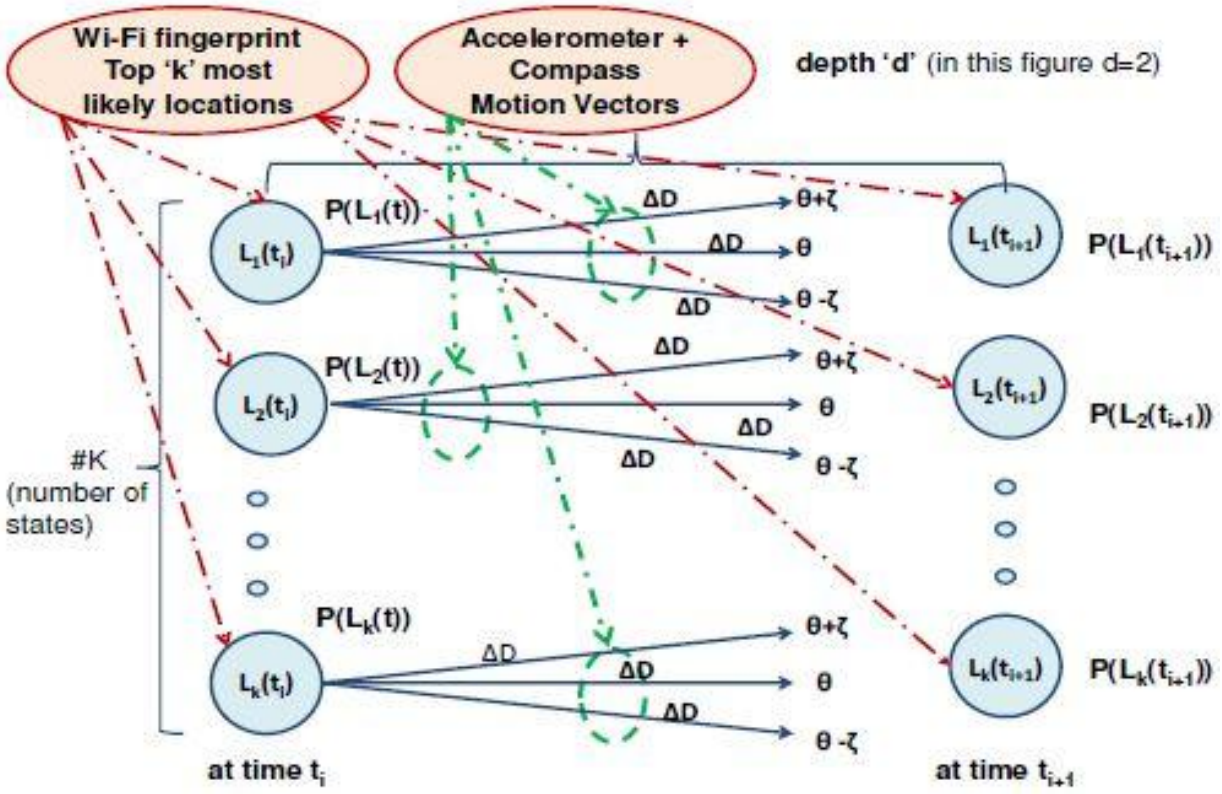
$$\begin{pmatrix} \dots & \\ L_i, & [\overline{RSSI^i_{AP_1}}, \dots, \overline{RSSI^i_{AP_L}}] \\ L_{i+1}, & [\overline{RSSI^{i+1}_{AP_1}}, \dots, \overline{RSSI^{i+1}_{AP_L}}] \\ \dots & \end{pmatrix}$$

Online measurement

$$m(t) = [\overline{RSSI^*_{AP_1}}, \dots, \overline{RSSI^*_{AP_L}}]$$

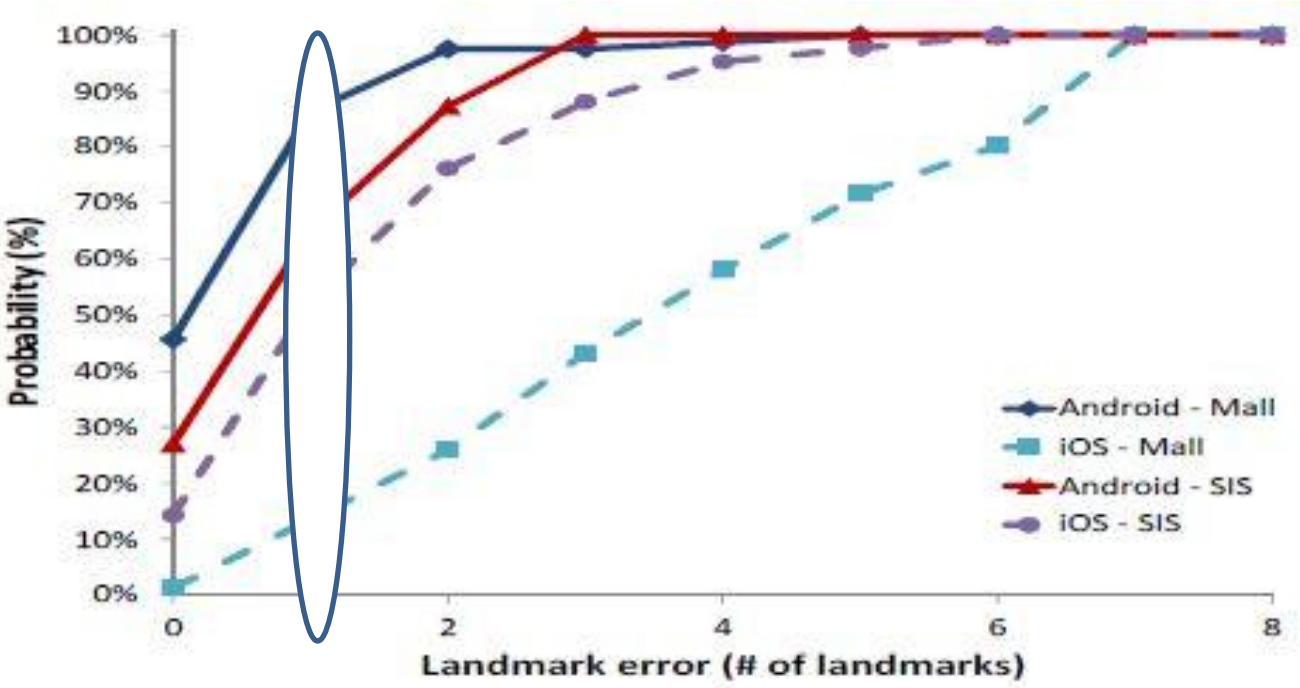
Euclidean distance of m(t) with fingerprint ⇨ Selecting top *K* nearest landmarks

Path Estimation (Viterbi)



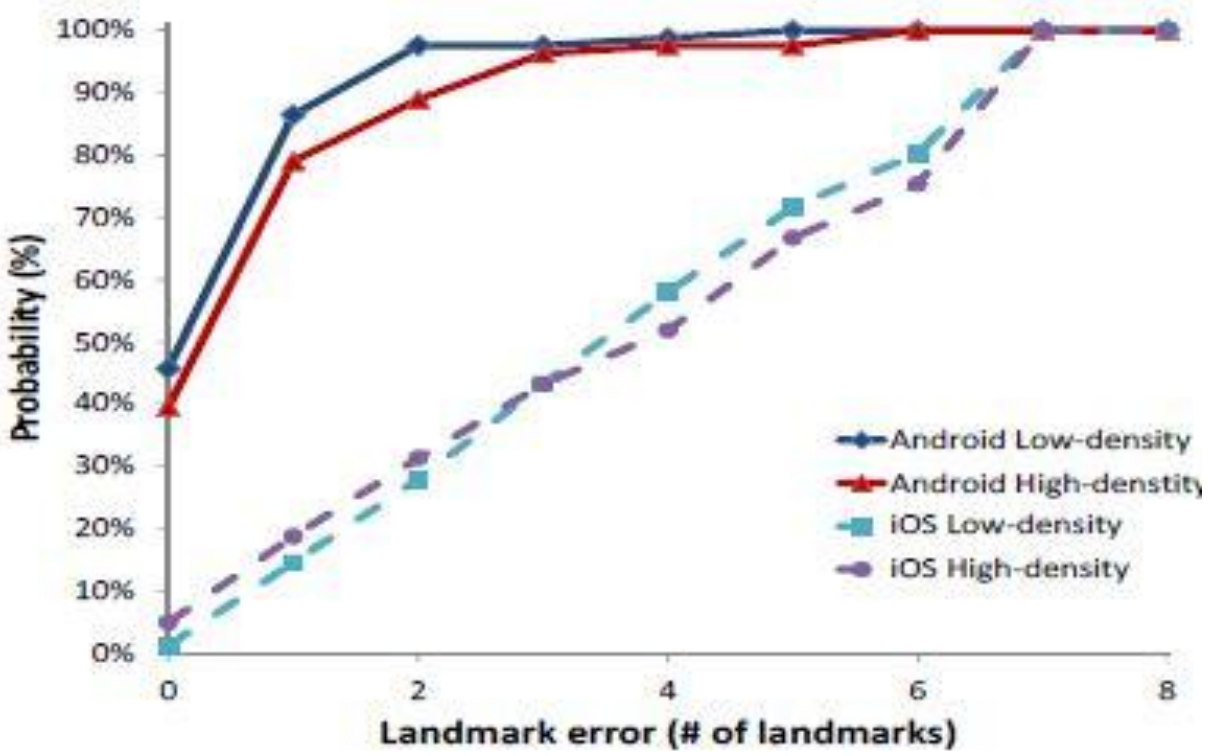
$$P(L_m(t_i) \rightarrow L_n(t_{i+1})) = P(L_m(t_i)) * P(L_n(t_{i+1}) \mid L_m(t_i)) * P(L_n(t_{i+1}))$$

Indoor localization accuracy



- On Android: having more number of APs does NOT lead to better accuracy (redundant measurements)
- On iOS: Having more number of APs helps for better location estimation(SNR queries are sent every 3 to 4 minues)

Density(impact on localization accuracy)



Higher densities leads to less movement ⇨ Less accuracy

Energy versus Accuracy

	WI-FI	WI-FI + Viterbi
Power Consumption (mW)	14.538	251.842
Accuracy ± 1 landmark	77%	87 %

- Experiments done on Samsung SII phone (over 20 minutes)

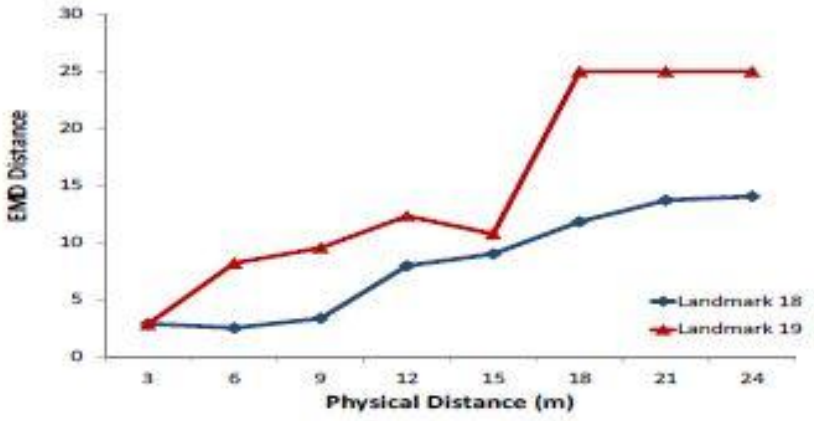
✓ Most of the energy is consumed by inertial sensors (237 mW)

My final project theme: improving the energy consumption while maintaining the accuracy/performance

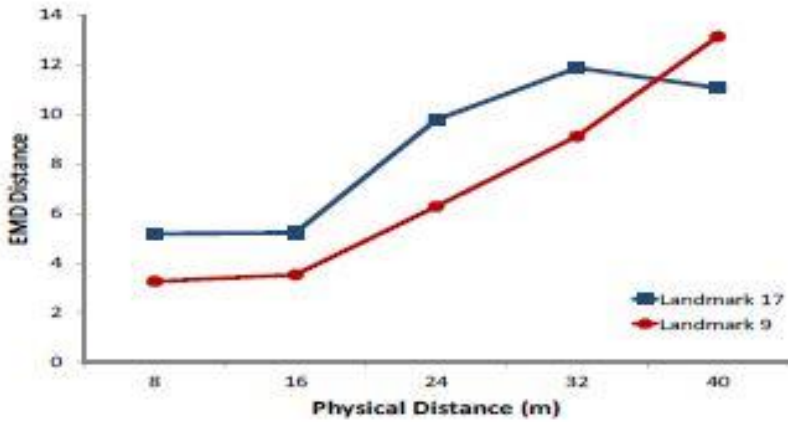
Critique

- Strength
  - Using state-of-the-art mobile technologies for tracking large number of mobile devices
- Challenges
  - Proposed localization technology is not universal for individual indoor space
  - Localization techniques do not support continuous location tracking

Choosing Landmarks(backup)



a. SIS



b. Mall