

Mining Data from Mobile Devices 1



MINING DATA FROM MOBILE DEVICES

Algorithms: Sensing

Spiros Papadimitriou, Tina Eliassi-Rad



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Overview

- **Indoor localization**
- Low-level activity detection
 - High-level: in next part (context)

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Indoor localization

Overview

- GPS not available indoors
- Cell tower triangulation is far too coarse
- Use other signals instead to infer location or proximity

RSSI
(Received Signal Strength Indicator)

Localization

(x,y,z)
location label
"raw" RSSI

Accelerometer
(dead-reckoning)

Proximity

Audio
(ambient noise)

Mapping

⋮

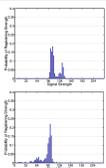
?

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WiFi-based localization

[Ladd et al., IROS 2002]

- Signal propagation and attenuation models work reasonably outdoors
- Indoors, signal strength is determined by building geometry, which may change (doors open/close, movements, etc) – very hard to model



Actual RSSI distributions

- *Supervised* learning approach:
 - Bayesian localization framework
 - Sensor fusion using HMM (people walk slow enough)
- Accuracy of up to 1m

Andrew M. Ladd, Kostas E. Bekris, Guillaume Marceau, Algis Rudys, Dan S. Wallach, Lydia E. Kavvaki: Using wireless Ethernet for localization. IROS 2002: 402-408.

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WiFi SLAM (GP-LVM)

[Ferris et al., IJCAI 2007]

- SLAM: Simultaneous Localization and Mapping (robotics)
- Gaussian Process (GP):

$$Y_i = f(X_i) + \epsilon$$

RSSI position
- Latent Variable Model (LVM): position is unobserved
- Assumptions:
 - Similar locations have similar RSSI – squared exponential kernel
 - Instead of odometry data, assume "office building" constraints on:
 - Distance between successive positions
 - Change in orientation between successive positions
 - Alignment of parallel line segments

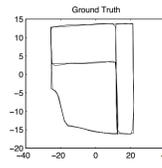
Brian Ferris, Dieter Fox, Neil D. Lawrence: WiFi-SLAM Using Gaussian Process Latent Variable Models. IJCAI 2007: 2480-2485

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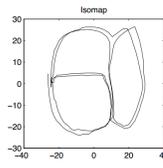
WiFi SLAM (GP-LVM)

[Ferris et al., IJCAI 2007]

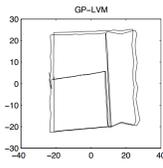
Ground Truth



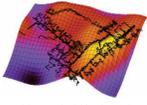
Isomap



GP-LVM



- Initialization: Isomap
- Localization error ~ 4 ± 0.6m



GP model for RSSI of one AP

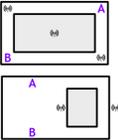
Brian Ferris, Dieter Fox, Neil D. Lawrence: WiFi-SLAM Using Gaussian Process Latent Variable Models. IJCAI 2007: 2480-2485

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WiFi GraphSLAM

[Huang et al., ICRA 2011]

- Assumption that similar RSSI corresponds to similar locations is not true in signal-sparse environments
- Additionally, can use phone sensors for basic odometry

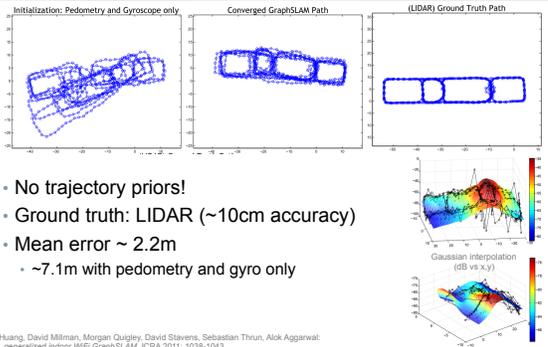


Joseph Huang, David Milman, Morgan Quigley, David Stevens, Sebastian Thrun, Arak Aggarwal. Efficient, generalized indoor WiFi GraphSLAM. ICRA 2011: 1038-1043

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WiFi GraphSLAM

[Huang et al., ICRA 2011]



- No trajectory priors!
- Ground truth: LIDAR (~10cm accuracy)
- Mean error ~ 2.2m
 - ~7.1m with pedometry and gyro only

Joseph Huang, David Milman, Morgan Quigley, David Stevens, Sebastian Thrun, Arak Aggarwal. Efficient, generalized indoor WiFi GraphSLAM. ICRA 2011: 1038-1043

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RSS-space tasks

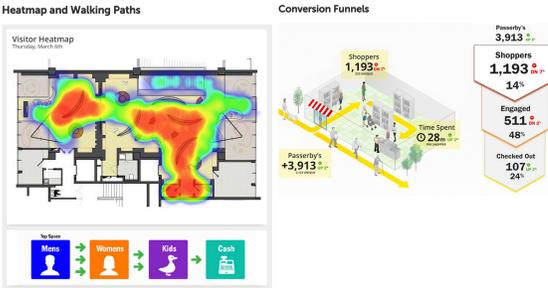
- May not need mapping to (Euclidean) spatial coordinates
 - Proximity detection
 - Geo-fencing
- Substantially simplifies processing
- Still need some way to filter noise, esp. if a large number of APs and/or measurements are not available

[e.g.] Christos Laoudias, George Constantinou, Marios Constantinides, Sitouanos Nicolaou, Demetrios Zeinalipour-Yazdi, Christos G. Pansyiotou. The Airplace Indoor Positioning Platform for Android Smartphones. MDM 2012.

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Commercial applications

Example: AisleLabs



Integration of data from radio-based localization systems (e.g., iBeacon, BLE-based) for providing analytics dashboards

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Overview

- Indoor localization
- Low-level activity detection**

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Activity detection

- Active area of research (esp. in networking / ubi-comp)
 - Could probably do an entire tutorial on just this ☺
- Becoming mainstream: Android APIs

Low-level (this part):

- Am I standing/falling, walking/driving, etc?
- How is my mood?
- ...

High-level / "context" (later):

- Out with friends, looking for a restaurant
- Commuting to work, drive or take public transit?
- ...

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Fall detection

[Sposaro, Tyson, EMBS 2009]

- Use accelerometer data to detect fall
- Relatively simple threshold approach:
 - Acceleration exceeds a threshold
 - Followed by a "still" period
 - In a 90° changed orientation
- Challenges: false positives
- A lot of work in this area

Public dataset (Reyes-Ortiz et al., donated 2012) <http://archive.ics.uci.edu/ml/dataset/human+Activity+Recognition+Using+Smartphones>

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Classification for activity detection

- How about detecting more than a single type of event? E.g.,
 - Standing vs. sitting
 - Walking vs. cycling vs. driving
- Challenges:
 - Phone data can be very noisy (loose phone, many factors)
 - Efficiency of on-phone classification
 - Population variances (one size does not fit all)
 - Sampling frequency (power draw)
 - ...

Background] Anguita, D., Ghio, A., Pichiorra, S., Ridaelli, S.: A Hardware-Friendly Support Vector Machine for Embedded Automotive Applications, UICNN 2007.

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Population-based activity detection

- Collecting data requires substantial effort
- What if we could also use data from other "similar" people?
- "Community Similarity Networks" – 3 similarity measures:
 - Physical similarity (age, height, weight, well-being measures)
 - Lifestyle similarity (mobility patterns, activity distributions)
 - Sensor data similarity ("set": duplicate elimination)
- Performs better than out-of-the box semi-supervised methods

Nicholas D. Lane, Ye Xu, Hong Lu, Shaohan Hu, Tanzeem Choudhury, Andrew T. Campbell, Feng Zhao, Enabling Large-scale Human Activity Inference on Smartphones using Community Similarity Networks (CSN), Ubicomp 2011

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Mood detection

[LiKamWa et al. 2013]

- Can cellphone usage patterns reveal user's mood?
 - Communication patterns
 - App usage patterns
- Accuracy 66%, improved up to 93% over time
 - Vs. self-reported, 32 users

Data Type	Histogram by:	Dimensions
Email contacts	# Messages	10
SMS contacts	# Characters	10
Phone call contacts	# Calls	10
Website domains	# Visits	10
Location Clusters	# Visits	10
Apps	# App launches	10
Categories of Apps	App Duration	12
Previous 2 Pleasure and Activeness Averages	N/A	4

Multi-linear regression + (greedy) feature selection

Robert LiKamWa, Yunxin Liu, Nic Lane, and Lin Zhong, MoodScope: Building a Mood Sensor from Smartphone Usage Patterns, MobiSys 2013

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Android activity recognition API

- Classifier [?] now available in Android APIs
- Apps can request one-shot estimates or event stream

```

public class ActivityRecognitionIntentService extends IntentService {
    ...
    @Override
    protected void onHandleIntent(Intent intent) {
        ...
        if (ActivityRecognitionResult.hasResult(intent)) {
            ActivityRecognitionResult result =
                ActivityRecognitionResult.extractResult(intent);
            DetectedActivity mostProbableActivity =
                result.getMostProbableActivity();
            int confidence = mostProbableActivity.getConfidence();
            int activityType = mostProbableActivity.getType();
            // IN_VEHICLE, ON_BICYCLE, ON_FOOT, STILL, UNKNOWN, TILTING, ...
            ...
        }
    }
}

```

<http://developer.android.com/training/location/activity-recognition.html>

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Recap

- Indoor localization (focus: WiFi RSS-based)
- Low-level activity detection

Other:

- Localization using other modalities (e.g., ambient noise: Color app)
- Face detection and recognition (e.g., screen unlock)
- Power consumption logging and mining
- ...

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OF NEW JERSEY

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