Indoor Localization
and Robotic Cartography

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Outline

Introduction
- Indoor localization
- Multimodal signals
- Prior art in localization

Localization Algorithm
- Kullback-Leibler Divergence...
- ... Kernel Regression...
- Sampling RSSI during motion (tracking)

Tracking Results
- Tracking in office spaces with dense fingerprints
- Fingerprinting on the fly
- Open-space localization
- Fingerprinting and tracking in complex, busy public places

Automated Fingerprinting
- Robot Mapping Indoor Environments
- Autonomous navigation
- Simultaneous localization and mapping
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Goal: Indoor localization applications

- Airports
- Shopping Malls
- Trade shows
- Hospitals
- Museums

[http://www.flickr.com/photos/trixer/3795835074]
Goal: Indoor/outdoor localization applications

[Image of a diagram showing different coverage and accuracy levels for various applications such as Machine Industry, Robotics, Machine Guidance, Monitoring, Pedestrian Navigation, Hospital Logistics, Product Tracking, Ambient Assisted Living, LBS, Emergency Response, Social Networking, Tourism, Sports, Intelligent Transport.]
Goal: Indoor/outdoor localization applications

Graphic: Rainer Mautz
**Goal:** Indoor localization using RF (WiFi) fingerprints

**Fingerprinting**

Access Point

Fingerprint

**Tracking**

Access Point

Fingerprint
**Problem:** Non-Gaussian distribution of WiFi RSSI values

**Experiment:**
Acquire 30min of WiFi RSSI (Received Signal Strength Indicator) data along a corridor, at 15 locations distant by 1m.

Measured RSSI oscillates considerably.

Bin the RSSI into histograms: bimodal or multimodal distributions of RSSI values.
Introduction: Prior art in WiFi based localization

Common approach

- Step 1) (training phase) 
  **Fingerprinting** the RSSI and location

- Step 2) (test phase) 
  **Tracking** location based on RSSI

Need to be able to compare multimodal distributions of RSSI

Algorithms

- Nearest neighbor matching  
  [Bahl & Padnamabhan, 2000]

- Kalman filtering

- Particle filtering  
  [Evennou et al, 2005]

- Model-free smoothing  
  [Chen et al, 2007]

- KL-divergence on Gaussians  
  [Millorís et al, 2010]

- Naïve Bayes  
  [Castro et al, 2001; Roos et al, 2002]

- KL-divergence + statistical test  
  [Bargh & de Groote, 2008]

Major limitations

- **Ignore** the multimodal signal model in recorded RSSI values

- or lack an algorithm for regressing the location based on RSSI

- Need frequent retraining / recalibration  
  **Can resort to automated fingerprinting, e.g., using an autonomous robot that records RSSI and associated location, every few nights**  
  [Palaniappan et al, IPIN 2011]
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Methods: Kullback-Leibler divergence

Two distributions of RSSI values $S$

- **Fingerprint** distribution $q(S)$
- **Tracking** distribution $p(S)$

We assume that RSSI are discrete values

- If $p$ or $q$ are unknown, then $KL(p \mid \mid q) = \infty$ (we set $KL(p \mid \mid q) = \text{large value}$)
- Smooth the histogram of $p$ and $q$ using small value $\varepsilon$ to avoid taking $\log(0)$ or divide by 0

$$KL(p \mid \mid q) = \sum_s p(S = s) \log \left( \frac{p(S = s)}{q(S = s)} \right)$$

[Kullback & Leibler, 1951]

[Mirowski et al, IPIN 2011]
Methods: Kullback-Leibler divergence

Two distributions of RSSI values $S$

- **Fingerprint** distribution $q(S)$
- **Tracking** distribution $p(S)$

We assume that RSSI are discrete values

- Values expressed in dBm, e.g., values from -90dBm to 0dBm
- Alternatively, SNR (Signal-to-Noise Ratio), e.g., values from 0dB to 90dB (may need rescaling at tracking time)
- Bins of size 1dB, 2dB, 5dB?

\[
KL(p|q) = \sum_s p(S = s) \log \left( \frac{p(S = s)}{q(S = s)} \right)
\]

Symmetrized version of Kullback-Leibler divergence:

\[
D(p, q) = KL(p|q) + KL(q|p)
\]

[Kullback & Leibler, 1951]

[Mirowski et al, IPIN 2011]
Methods: Kullback-Leibler divergence, multiple APs

Two distributions of RSSI values $S$

- **Fingerprint** distribution $q(S)$
- **Tracking** distribution $p(S)$

Multivariate signal $S$

- $J$ different Access Points (APs)
- Conditional independence assumption between APs given the location $l$
- Sweep under the rug signal interference

\[
p(S|\{x, y\}) = \prod_{j=1}^{J} p(S_j|\{x, y\})
\]

For a location $l$ of coordinates $\{x_l, y_l\}$

\[
D(p, q_l) = \sum_{j=1}^{J} D(p(S_j|\{x, y\}), q(S_j|\{x_l, y_l\}))
\]

[Mirowski et al, IPIN 2011]
Methods: Kullback-Leibler divergence kernels

Two distributions of RSSI values $S$

- **Fingerprint** distribution $q(S)$
- **Tracking** distribution $p(S)$

![Fingerprint distributions $q$ at different locations](image)
**Methods: Kullback-Leibler divergence kernels**

Two distributions of RSSI values $S$

- **Fingerprint** distribution $q(S)$
- **Tracking** distribution $p(S)$

Probabilistic kernel

- KL-divergence kernels
  [Moreno et al, 2002]
- Alternative: Bhattacharyya kernel
  [Jebara et al, 2004]

Kernel function

- Symmetric function $k(p, q)$ measuring the similarity of $p$ and $q$
- $k(p, q) = 1$ when $p = q$
- $k(p, q)$ decays to 0 rapidly as $p$ becomes distinct from $q$
- Positive symmetric definite

$$k(p, q) = e^{-\alpha \sum_{j=1}^{J} D(p(S_j | \{x, y\}), q(S_j | \{x_l, y_l\}))}$$

$J$ conditionally independent access points

To cross-validate (e.g., leave-one-out) on training data

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[Mirowski et al, IPIN 2011]
**Methods: KL-divergence kernel regression**

Two distributions of RSSI values $S$
- **Fingerprint** distribution $q(S)$
- **Tracking** distribution $p(S)$

To cross-validate (e.g., leave-one-out) on training data

Fingerprint database
- **Fingerprint** distribution $q(S)$
- **Fingerprint** location $\{x_l, y_l\}$

**Weighted Kernel Regression (WKR)**
[Nadaraya, 1964]
- Simplest non-parametric regression
- Can define a neighborhood of size $N$, based on kernel similarity
- Alternative: Support Vector Regression
[Smola & Scholkopf, 2004]

\[
(\bar{x}, \bar{y}) = \frac{\sum_{\ell} (x_\ell, y_\ell) k(p, q_\ell)}{\sum_{\ell} k(p, q_\ell)}
\]
Methods: Access Point connection histograms

Two distributions of Access Point connections $S$ for $J$ APs i.e., how many times we could connect to each of the access point $j$ during sampling window of length $\tau$

- **Fingerprint** distribution $q(S)$
- **Tracking** distribution $p(S)$
- Ignore the RSSI values [Roski et al, 2010]

$$KL(p \| q) = \sum_s p(S = s) \log \left( \frac{p(S = s)}{q(S = s)} \right)$$

[Mirowski et al, IPIN 2011]
Methods: Sampling RSSI during motion (tracking)

Trade-off when collecting RSSI during tracking:

- More samples (longer sampling window $\tau$)
- Finer spatial resolution of fingerprints due to local signal variations (shorter sampling window $\tau$)

Assume “linear” variation of RSSI distribution $q(S)$

- In small neighborhoods
- Local similarity of physical phenomena behind variations in RSSI

Cross-validated or chosen ad-hoc, (based on motion model prior)

$$q(S|\lambda\{x_a, y_a\} + (1 - \lambda)\{x_b, y_b\}) \approx \lambda q_a + (1 - \lambda)q_b$$

[Mirowski et al, IPIN 2011; Mirowski et al, submitted]
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... Sampling RSSI during motion (tracking)

... Kernel Regression...

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... Tracking in office spaces

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Fingerprinting with dense fingerprints

... Tracking in office spaces

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Automated Fingerprinting
Results: 2D office space with dense fingerprinting

Results with 4 APs set-up for the experiment

Data from France Telecom
[Evennou et al, 2005]

Model free tracking [Chen et al, 2007]

<table>
<thead>
<tr>
<th>Technique</th>
<th>median</th>
<th>@90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kalman filter [Evennou et al, 2005]</td>
<td>2.0m</td>
<td>-</td>
</tr>
<tr>
<td>Voronoi particle filter [Evennou et al, 2005]</td>
<td>1.6m</td>
<td>-</td>
</tr>
<tr>
<td>Model-free tracking [Chen et al, 2007]</td>
<td>1.3m</td>
<td>2.5m</td>
</tr>
<tr>
<td>KL-divergence, 1 NN</td>
<td>1.25m</td>
<td>3.18m</td>
</tr>
<tr>
<td>KL-divergence, 3 NN WKR</td>
<td>1.06m</td>
<td>2.34m</td>
</tr>
</tbody>
</table>

KL divergence kernel regression using 3 nearest-neighbors

no smoothing!
no motion model!
Results: 2D office space with dense fingerprinting

Results with 4 (set-up) + 18 (ad-hoc) APs visible during the experiment

Data from France Telecom
[Evenou et al, 2005]

<table>
<thead>
<tr>
<th>Technique</th>
<th>median @90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>KL-divergence, with RSSI, 1 NN</td>
<td>1.16m 2.84m</td>
</tr>
<tr>
<td>KL-divergence, with RSSI, 6 NN WKR</td>
<td>0.96m 1.88m</td>
</tr>
<tr>
<td>KL-divergence, no RSSI, 1NN</td>
<td>1.94m 4.95m</td>
</tr>
<tr>
<td>KL-divergence, no RSSI, 27 NN WKR</td>
<td>1.90m 4.31m</td>
</tr>
</tbody>
</table>

KL divergence kernel regression using 27 nearest-neighbors, no RSSI (only AP presence)

KL divergence kernel regression using 6 nearest-neighbors, using RSSI

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FT1: expKL RSSI, kernel = 0.0141707, 8.0s window, 1dB bins, 6 NN, 22 APs
median error 0.95m (0.35@10%, 1.87@90%)

Student Version of MATLAB
no smoothing!
no motion model!

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[Mirowski et al, IPIN 2011]
**Results: Effects of fingerprint and tracking parameters**

![Graphs showing error vs subsampling factor in space, time, and window length](image)

**Most important factors:**

- **Spatial density of fingerprints**
- **Number of fingerprint samples** $N$ (but no improvement beyond 20)
- **Number of tracking samples** $n$ (or sampling window duration $\tau$)

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[Mirowski et al, IPIN 2011; Mirowski et al, submitted]
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Results: Fingerprinting “on the fly” while walking

Walk along 300m corridor
Observed 130 ad-hoc APs
Defined 55 fingerprints
Used only AP presence (no RSSI)

Tracking results (one week later)
median: 4m
error at 90%: 7.6m
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- **Fingerprinting on the fly**
- **Open-space localization**
- **Fingerprinting and tracking in complex, busy public places**

Results

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Results: Open-space localization in an auditorium

<table>
<thead>
<tr>
<th>Open space (auditorium)</th>
<th>median</th>
<th>@90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>KL-divergence, with RSSI, 4 NN WKR</td>
<td>4.7m</td>
<td>10.2m</td>
</tr>
<tr>
<td>KL-div. on Gaussians, with RSSI, 4 NN WKR</td>
<td>4.9m</td>
<td>8.2m</td>
</tr>
<tr>
<td>Random prediction</td>
<td>9m</td>
<td>15m</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Narrow corridor</th>
<th>median</th>
<th>@90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>KL-divergence, with RSSI, 3 NN WKR</td>
<td>1m</td>
<td>2m</td>
</tr>
</tbody>
</table>

Set 6 APs in an auditorium

![Plot of AP locations in an auditorium](image)
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Results: Sparse fingerprints in a complex public space

Tracking signal recorded on lower floor (3 days later)

<table>
<thead>
<tr>
<th>Predictions on the lower floor</th>
<th>median</th>
<th>@90%</th>
<th>floor</th>
</tr>
</thead>
<tbody>
<tr>
<td>KL-div., no RSSI, 31 NN WKR</td>
<td>10.3m</td>
<td>24.3m</td>
<td>89%</td>
</tr>
<tr>
<td>KL-div., RSSI, 8 NN WKR</td>
<td>8.2m</td>
<td>16.9m</td>
<td>96.2%</td>
</tr>
<tr>
<td>KL-div. Gauss, RSSI, 8 NN WKR</td>
<td>6.7m</td>
<td>14.8m</td>
<td>96%</td>
</tr>
</tbody>
</table>

We fingerprinted 500+ different MAC addresses (“APs”) that were available

Tracking signal recorded on upper floor (3 days later)

<table>
<thead>
<tr>
<th>Predictions on the lower floor</th>
<th>median</th>
<th>@90%</th>
<th>floor</th>
</tr>
</thead>
<tbody>
<tr>
<td>KL-div., no RSSI, 31 NN WKR</td>
<td>9.1m</td>
<td>17m</td>
<td>92.6%</td>
</tr>
<tr>
<td>KL-div., RSSI, 8 NN WKR</td>
<td>9m</td>
<td>17.1m</td>
<td>83.8%</td>
</tr>
<tr>
<td>KL-div. Gauss, RSSI, 8 NN WKR</td>
<td>8m</td>
<td>13.4m</td>
<td>84.4%</td>
</tr>
</tbody>
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We fingerprinted 500+ different MAC addresses (“APs”) that were available
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Automated fingerprinting: Motivation for a robot

Indoor mapping robot capabilities
- Automated collection of RF signal
- Autonomous navigation through narrow corridors and open spaces
- Equipped with multitude of sensors

Advantages
- Commercial-off-the-shelf hardware and free source software for easy replication
- Very long run-time
- Supports sensing payload up to 100 kg

Applications
- Empirical test bed for novel methodologies
- Systematic evaluation of in-building mobile communication networks
- Surveillance applications

[Palaniappan, Mirowski et al, IPIN 2011]
Automated fingerprinting: Process flow

- **RGB-D video acquisition**
- **Autonomous navigation (or manual control)**
- **Simultaneous Localization and Mapping**
  - 2D trajectory
  - Timestamps
  - RF fingerprint signal map
- **RF signal acquisition**
  - Timestamps
  - RF measurements
- **3D model building**

[Palaniappan, Mirowski et al, IPIN 2011]
Automated fingerprinting: Using a mapping robot

- Kinect RGBD sensor
- Motherboard
- Wireless router
- Sonar
- Motor controller
- Optical encoder

[Palaniappan, Mirowski et al, IPIN 2011]
Robot: WiFi-mapping Robot

Hardware
- Electric Wheel Chair base
- Microsoft Kinect for building 3D database
- VIA Mini-ITX motherboard 1.66 GHz and 4 GB RAM
- Linksys WiFi Router
- Sonar and Kinect for obstacle avoidance
- Microcontrollers
- Optical encoder for dead reckoning
- DC-DC convertors

Software
- Debian Linux O/S
- C, C++ for control and navigation

Specs
- Two 12V 32 Ah rechargeable batteries for 4 hours runtime
- Platform supports up to 100 kg of test and measurement equipment
- Multiple USB, RS232, RS422 ports for additional sensors and hardware
- 50 GB HDD for data storage
Robot: Using the Kinect sensor for 3D vision

- Full VGA resolution depth map acquired via infrared structured light
- Overlapping RGB video (needs calibration and rectification)
- OpenKinect/OpenNI software library

[Palaniappan, Mirowski et al, IPIN 2011]
**Robot: Simultaneous Localization and Mapping (SLAM)**

### General SLAM principles
[Thrun et al, Probabilistic Robotics 2003]
- Integrate:
  - Input from (wheel) **odometry**
  - Motion model
- **Predict** the position and map (**state**)
  - State vector contains position and map
- Observe **sensors** (e.g., laser range)
- **Update** the state using observations

### tinySLAM (real time)
[Steux & El Hamzaoui, ICARCV 2010]
- Not probabilistic, approximate but fast
- Inputs:
  - Wheel encoder odometry
  - Rotation guess (from controls)
  - 2D “laser range” from Kinect
  - We use it to compute the rotation angles

### DP-SLAM (offline)
[Eliazar & Parr, IJCAI 2003; Eliazar & Parr, ICRA 2004]
- Particle-filter based
- Inputs:
  - Wheel encoder odometry
  - Rotation angles from tinySLAM
  - 2D “laser range” from Kinect
Robot: Simultaneous Localization and Mapping (SLAM)


- Kinect sensor covers only 60 deg (laser ranges typically cover 180 deg)
- Kinect depth sensor works until 5.5m: problem in open spaces
- Slow processing speed of embedded hardware (e.g., no GPU-based computing abilities)
- Most SLAM processing needs to be done offline
- Research in progress on loop closures

Example of SLAM reconstruction in building Bell Labs MH-2 (3rd floor)
**Robot: Simultaneous Localization and Mapping (SLAM)**

- Trajectory from wheel odometry
- Trajectory from particle filtering SLAM [Eliazar & Parr, 2003, 2004]
- Optimized trajectory superimposed on building blue prints [Mirowski et al, TePRA 2012]
Automated fingerprinting: a corridor at Bell Labs

Cluster the path keypoints of the robot using K-Means algorithm with constraints on inter-fingerprint distance

- Fingerprints collected on the fly as the robot moves
- Robot speed: 0.23m/s
- Each fingerprint spans 2m of spatial extent
- 22 distinct MAC addresses (~ APs) at unknown locations
Automated fingerprinting: a corridor at Bell Labs

The signal recorded along a simple (linear) trajectory is extremely noisy

Tracking accuracy:
median: 3 m
error at 90%: 6 m

[Mirowski et al, TePRA 2012]
Automated RF Mapping: Using a self-localizing robot

Simultaneous Localization and Mapping (SLAM) for map building from start (without blueprints), trajectory registration using self-describing QR codes

Real-time Monte Carlo Localization on an existing blueprint map, along with path planning and collision avoidance

Real-time (30Hz) precise RGB-D image (color + depth) up to 5.5m distance, using the Kinect sensor

Automated building of RF signal maps

[Palaniappan, Mirowski et al, IPIN 2011; Mirowski et al, TePRA 2012]
Thank you!


• http://www.netstumbler.com/


