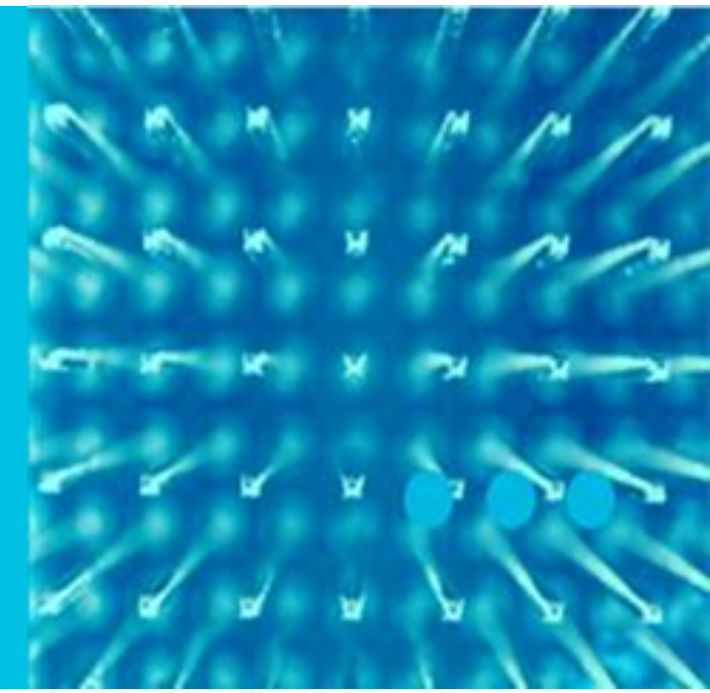
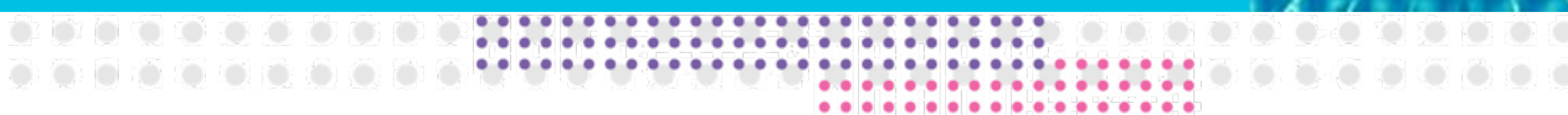
Bell Labs Alcatel·Lucent

Indoor Localization and Robotic Cartography



Piotr Mirowski



In collaboration with:
Tin Kam Ho, Phil Whiting, Ravi Palaniappan,
Harald Steck, Mike McDonald

October 11, 2012
DIMACS, Rutgers University

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

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

Goal: Indoor localization applications

Airports

Shopping Malls

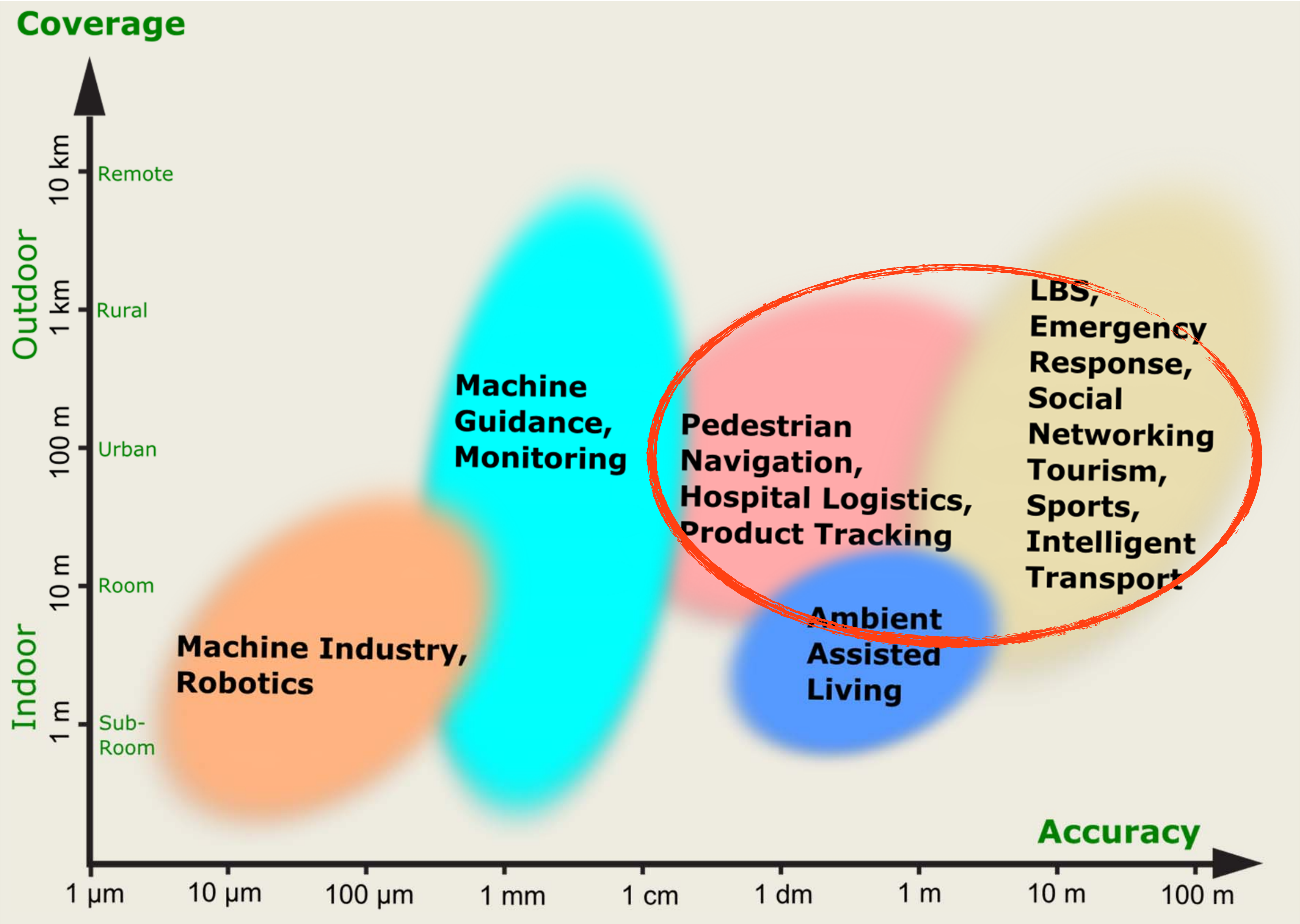
Trade shows

Hospitals

Museums

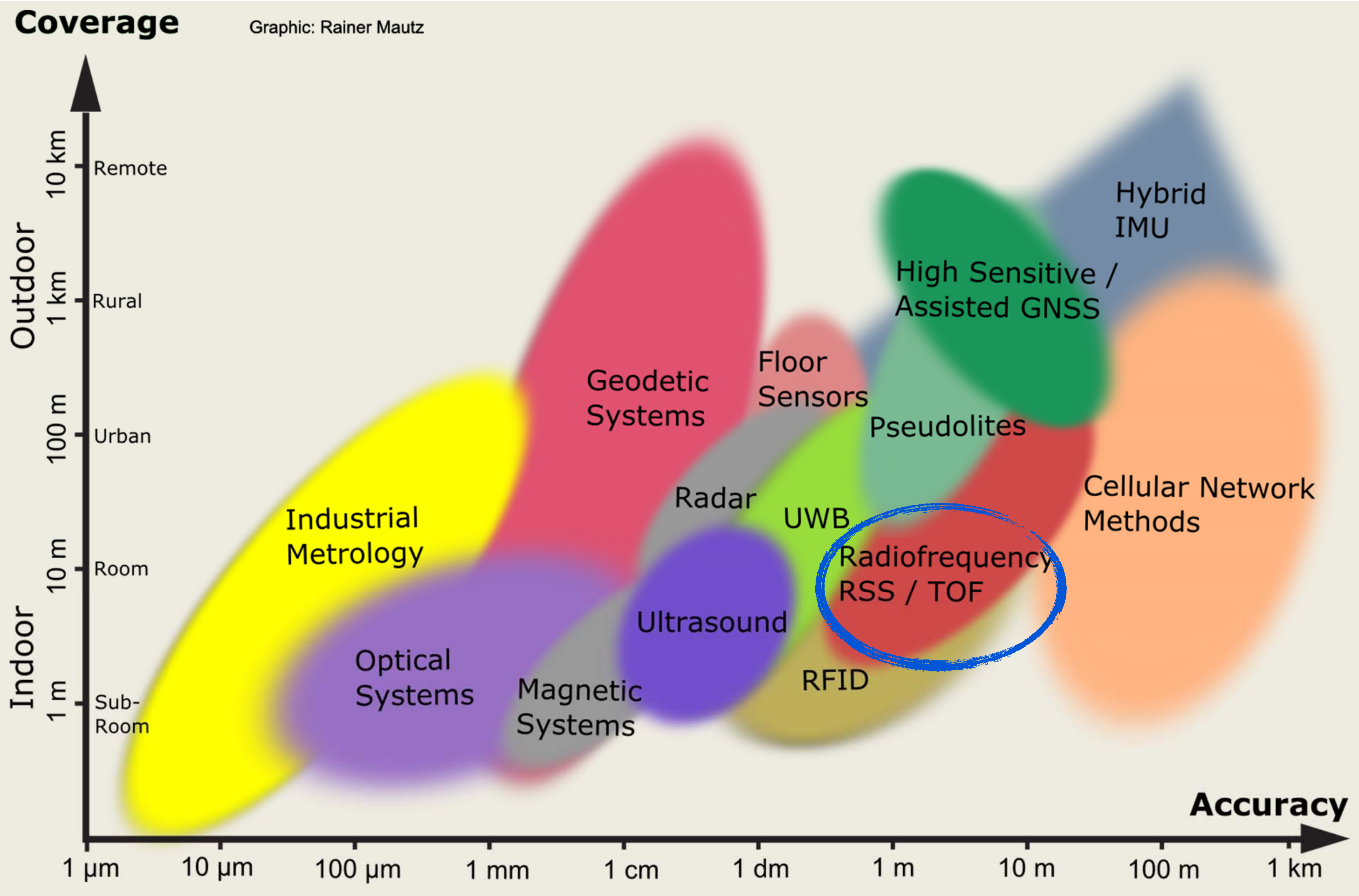
[http://www.flickr.com/photos/trixer/3795835074]

Goal: Indoor/outdoor localization applications



[Rainer Mautz, IPIN 2011]

Goal: Indoor/outdoor localization applications



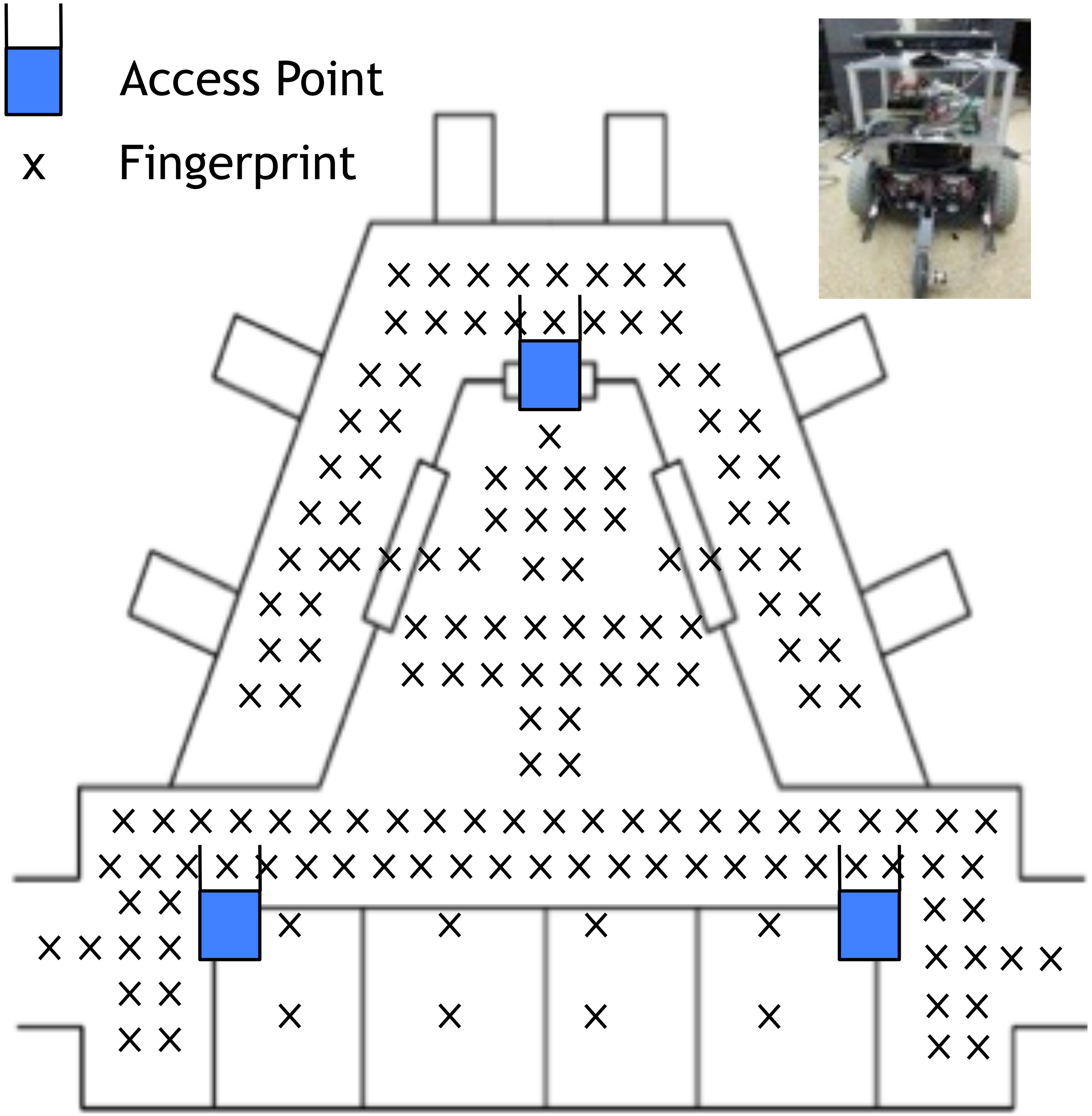
[Rainer Mautz, IPIN 2011]

Goal: Indoor localization using RF (WiFi) fingerprints

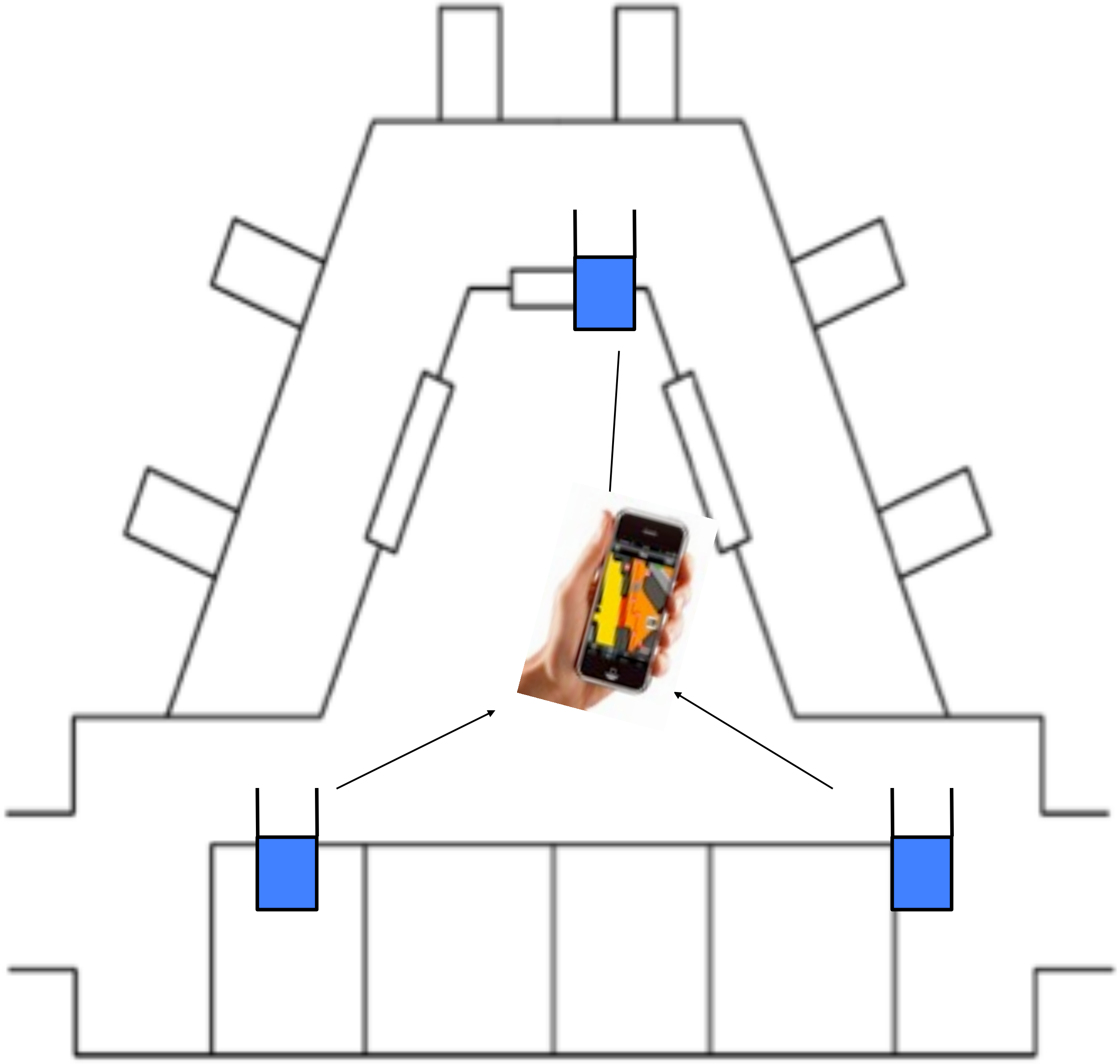
Fingerprinting

Access Point

x Fingerprint



Tracking

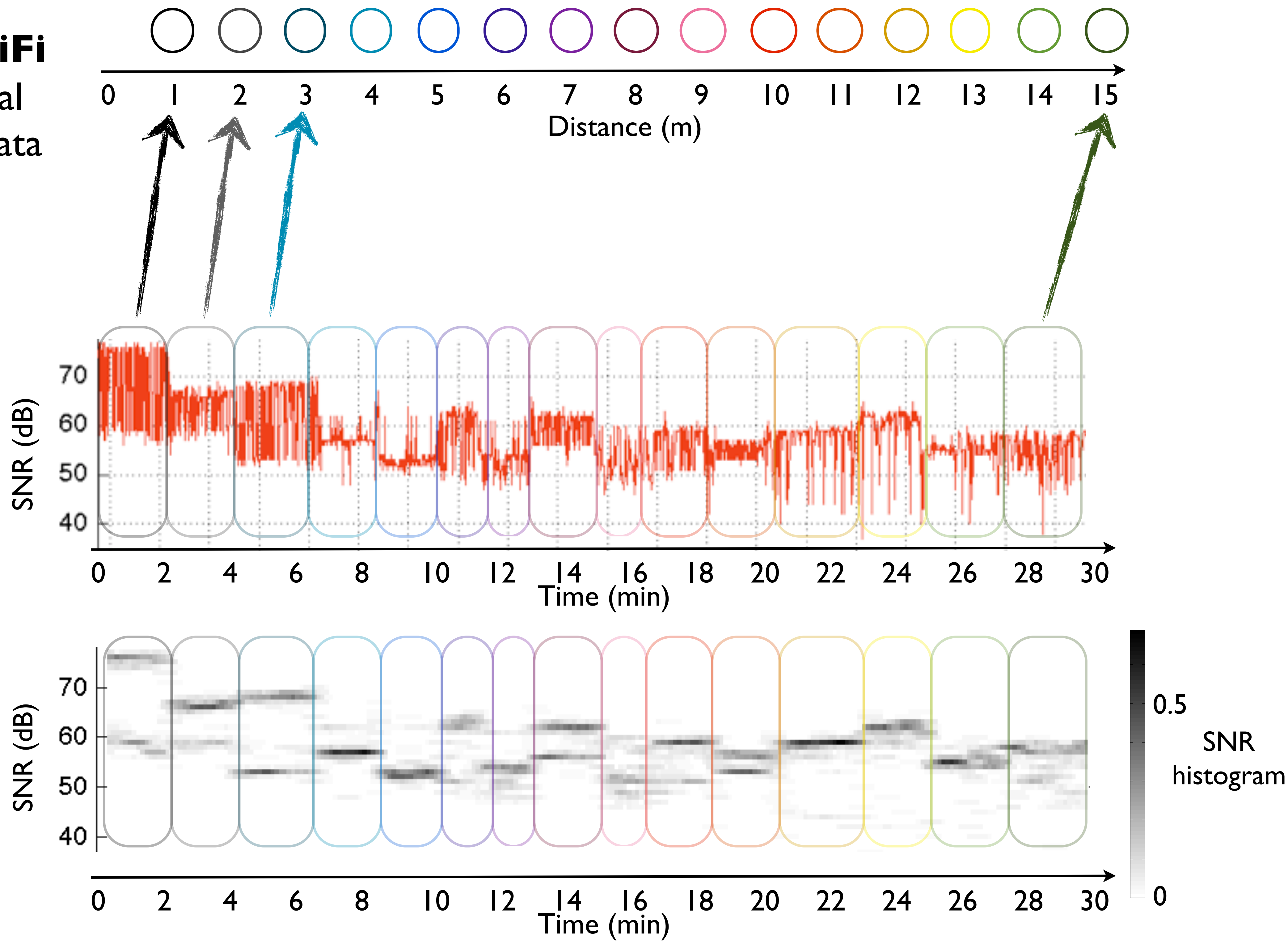


Problem: Non-Gaussian distribution of WiFi RSSI values

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
  [Milioris 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]

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

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($p||q$) = infinite
  (we set KL($p||q$) = large value)
- Smooth the histogram of p and q
  using small value ε
  to avoid taking log(0) or divide by 0

$$KL(p||q) = \sum_s p(S = s) \log \left(p(S = s)/q(S = s)\right)$$

[Kullback & Leibler, 1951]

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?

$$KL(p||q) = \sum_s p(S=s) \log \left(p(S=s) / q(S=s) \right)$$

Symmetrized version of Kullback-Leibler divergence:

$$D(p,q) = KL(p||q) + KL(q||p)$$

[Kullback & Leibler, 1951]

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

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

For a location *l* of coordinates {*x*$_l$, *y*$_l$}

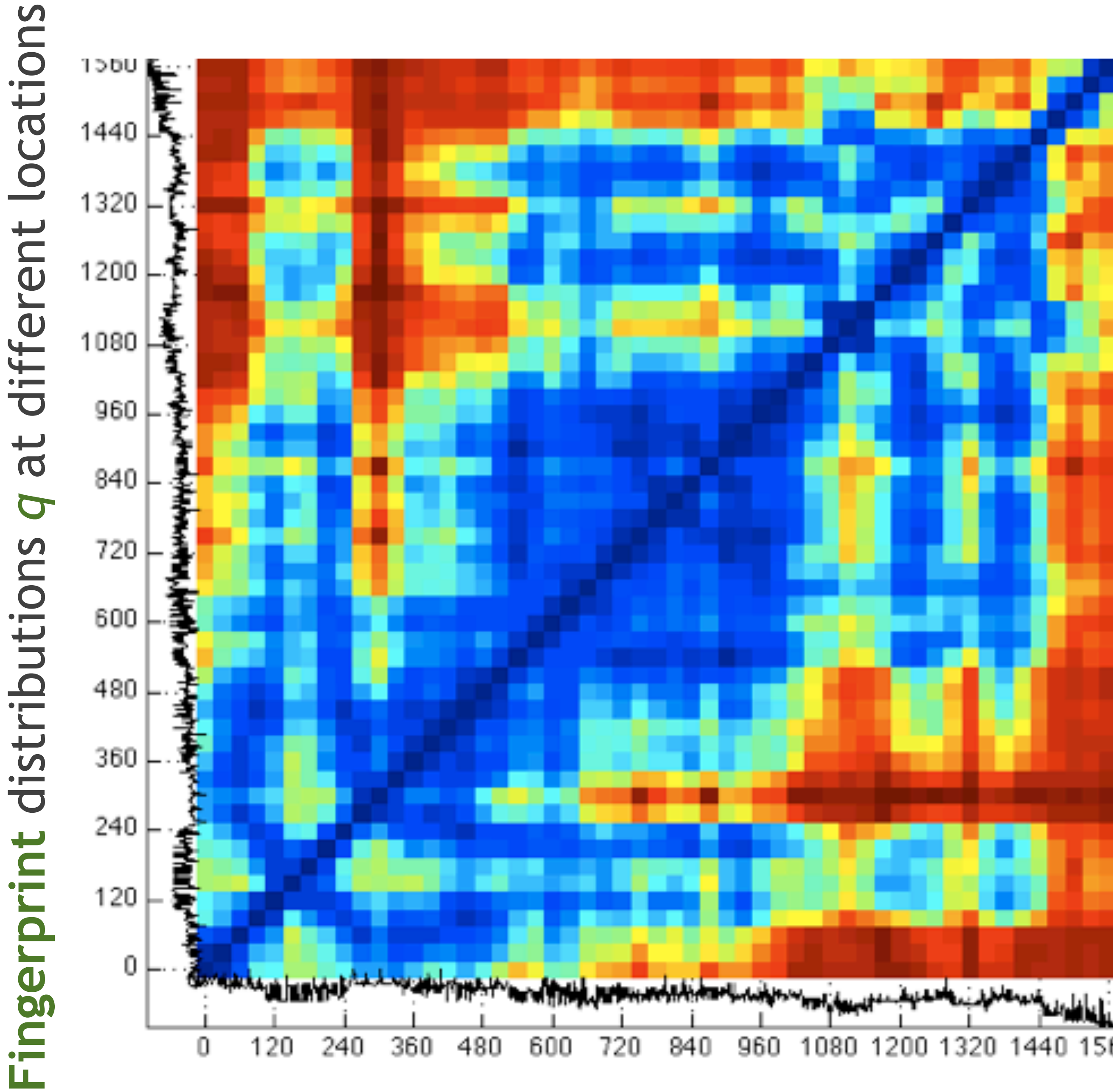
$$D\left(p, q_\ell\right) = \sum_{j=1}^{J} D\left(p(S_j|\{x,y\}), q(S_j|\{x_\ell, y_\ell\})\right)$$

[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

[Mirowski et al, IPIN 2011]

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]

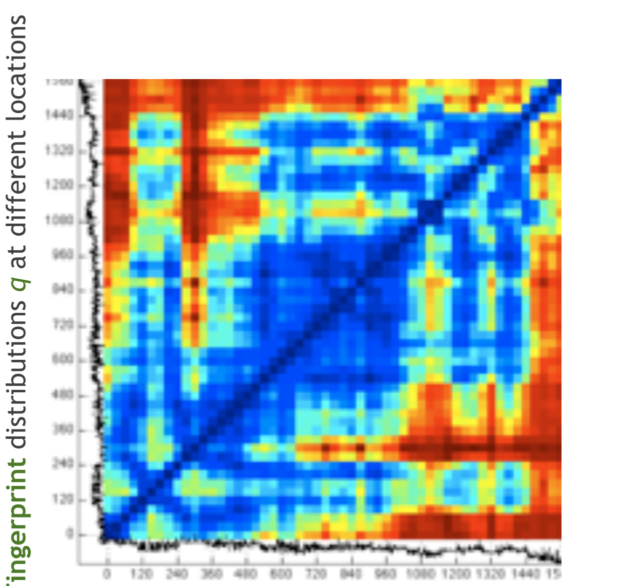
Kernel function

- 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

***J* conditionally independent access points**

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

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



Fingerprint distributions q at different locations

[Mirowski et al, IPIN 2011]

Methods: KL-divergence kernel regression

Two distributions of RSSI values S

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

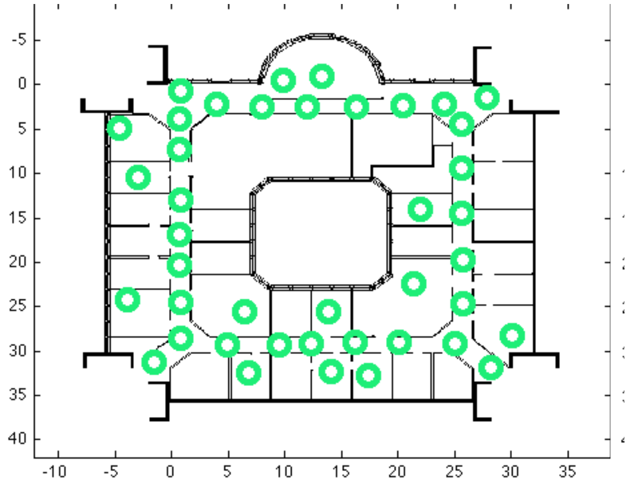
To cross-validate
(e.g., leave-one-out)
on training data

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]

Fingerprint database

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

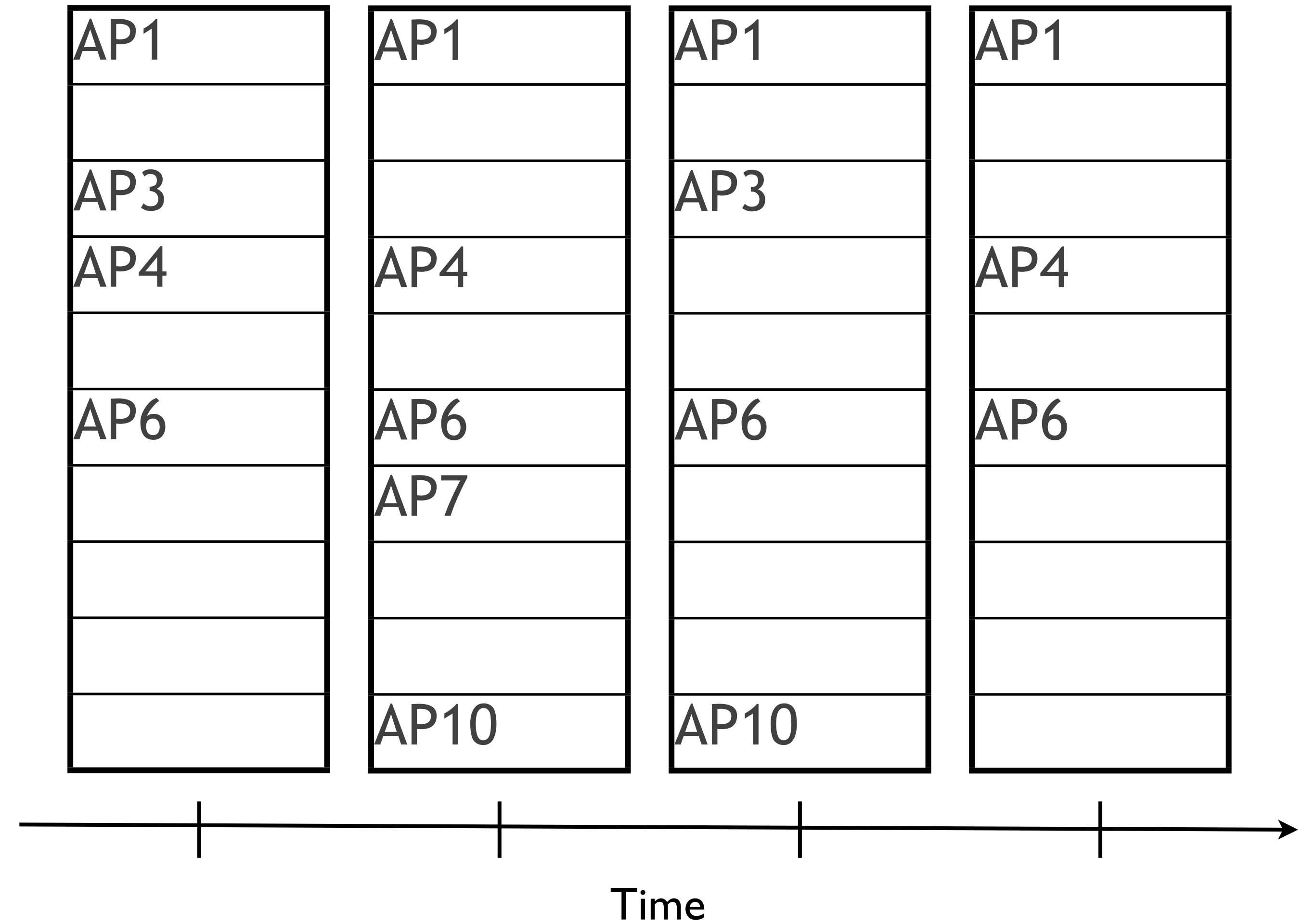


$$(\bar{x}, \bar{y}) = \frac{\sum_\ell (x_\ell, y_\ell) k(p, q_\ell)}{\sum_\ell k(p, q_\ell)}$$

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 τ

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



$$KL(p||q) = \sum_s p(S=s) \log \left(p(S=s) / q(S=s) \right)$$

[Mirowski et al, IPIN 2011]

Methods: Sampling RSSI during motion (tracking)

Trade-off when collecting RSSI during tracking:

- More samples (**longer** sampling window τ)
- Finer spatial resolution of fingerprints due to local signal variations (**shorter** sampling window τ)

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)

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

[Mirowski et al, IPIN 2011; Mirowski et al, submitted]

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

difficulty

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

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

difficulty

Automated Fingerprinting

- Robot Mapping Indoor Environments
- Autonomous navigation
- Simultaneous localization and mapping

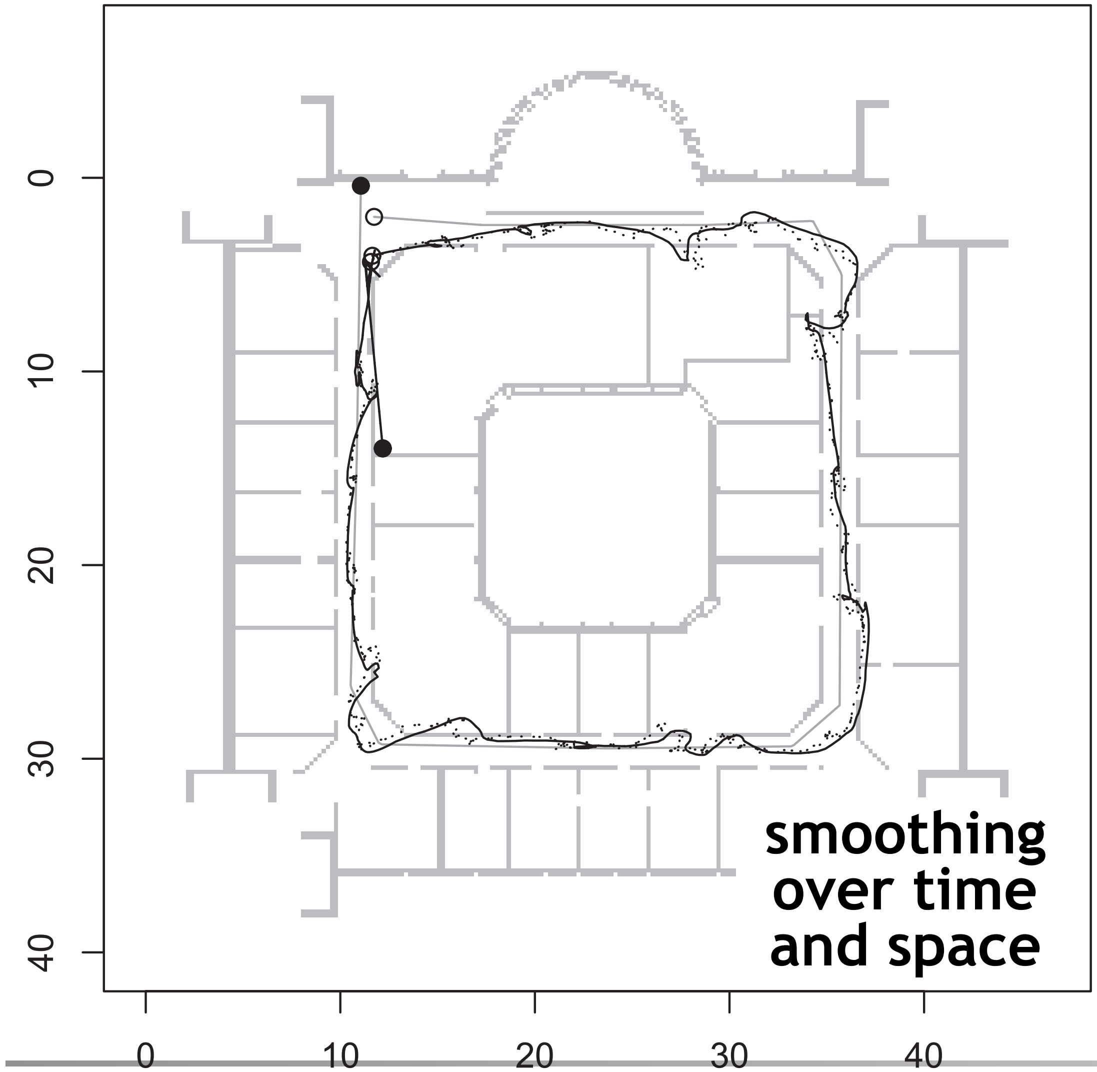
Results: 2D office space with dense fingerprinting

Results with 4 APs
set-up for the experiment

Data from France Telecom
[Evennou et al, 2005]

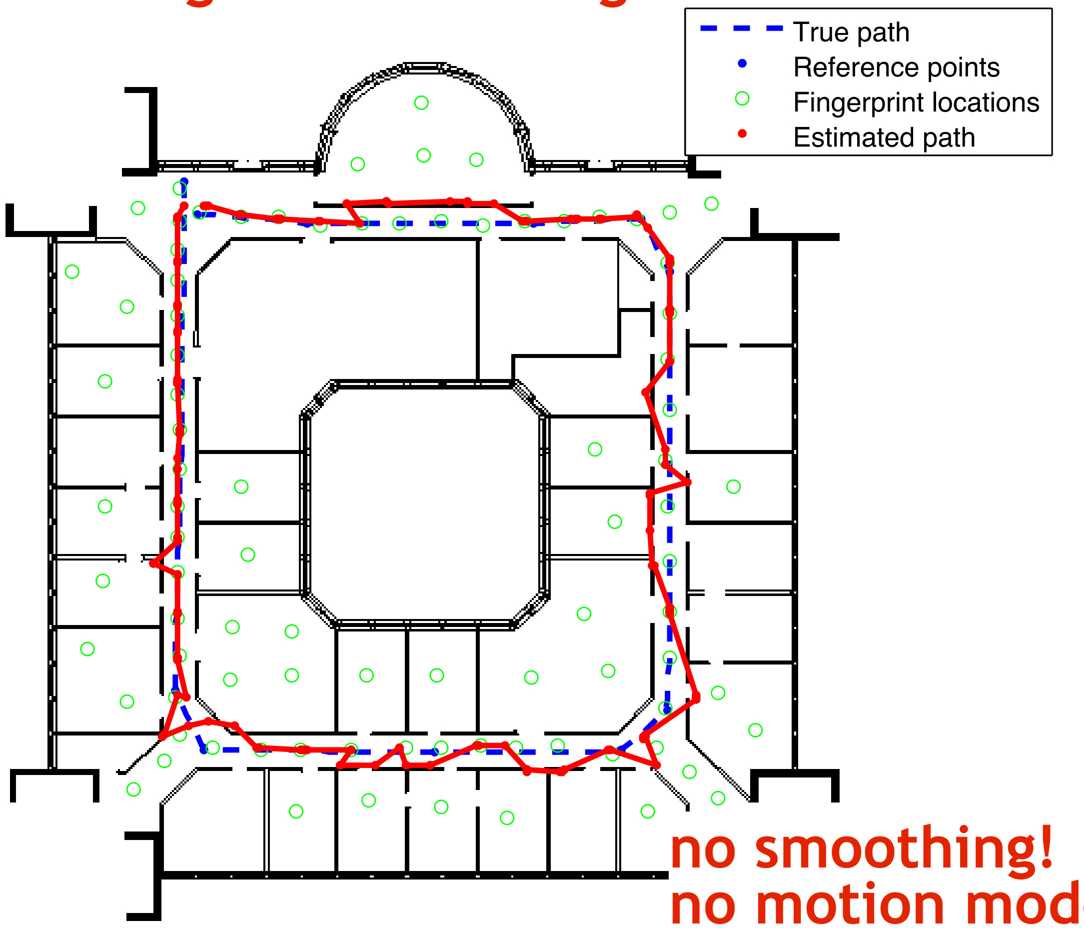
Technique	median	@90%
Kalman filter [Evennou et al, 2005]	2.0m	-
Voronoi particle filter [Evennou et al, 2005]	1.6m	-
Model-free tracking [Chen et al, 2007]	1.3m	2.5m
KL-divergence, 1 NN	1.25m	3.18m
KL-divergence, 3 NN WKR	**1.06m**	**2.34m**

Model free tracking [Chen et al, 2007]



smoothing over time and space

KL divergence kernel regression using 3 nearest-neighbors



no smoothing!
no motion model!

[Mirowski et al, IPIN 2011]

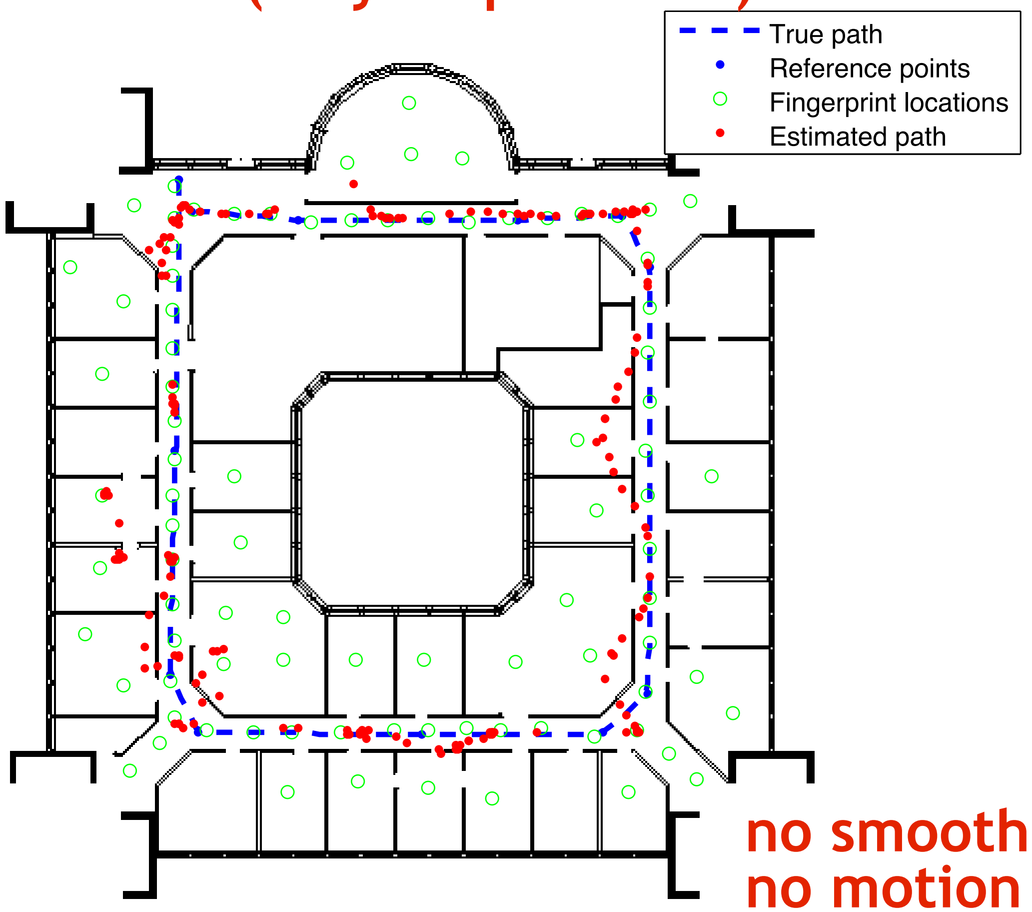
Results: 2D office space with dense fingerprinting

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

Data from France Telecom
[Evennou et al, 2005]

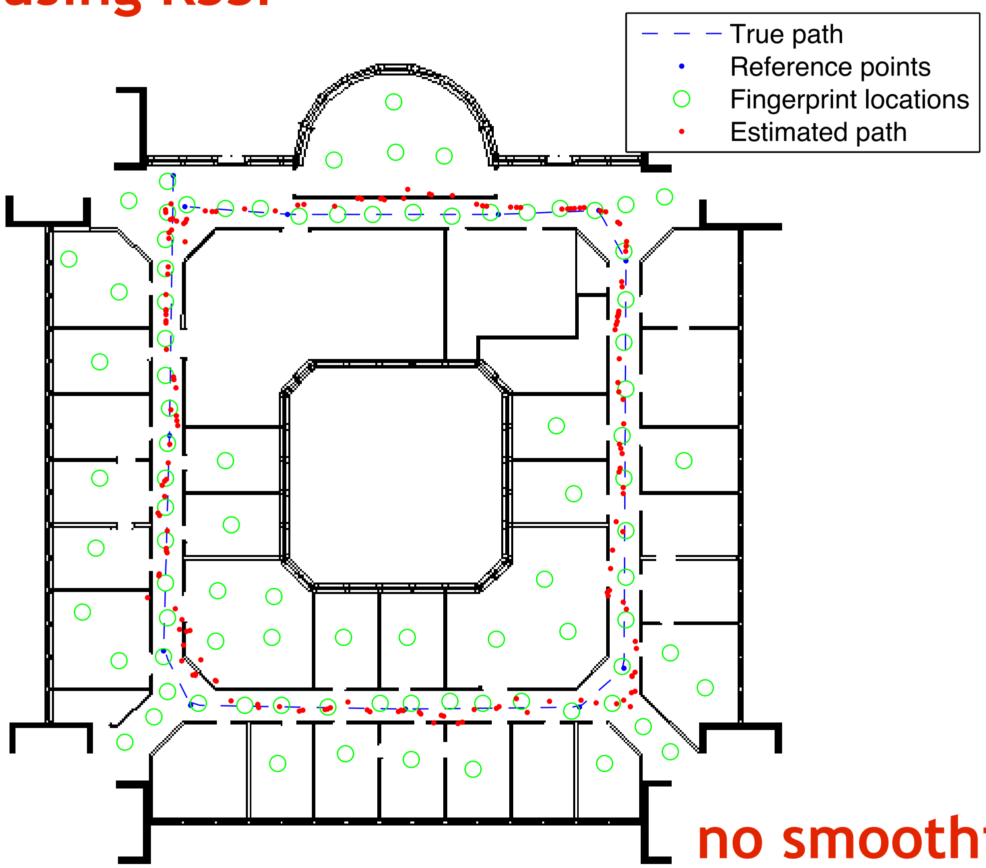
Technique	median	@90%
KL-divergence, with RSSI, 1 NN	1.16m	2.84m
KL-divergence, with RSSI, 6 NN WKR	**0.96m**	**1.88m**
KL-divergence, no RSSI, 1NN	1.94m	4.95m
KL-divergence, no RSSI, 27 NN WKR	1.90m	4.31m

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



no smoothing!
no motion model!

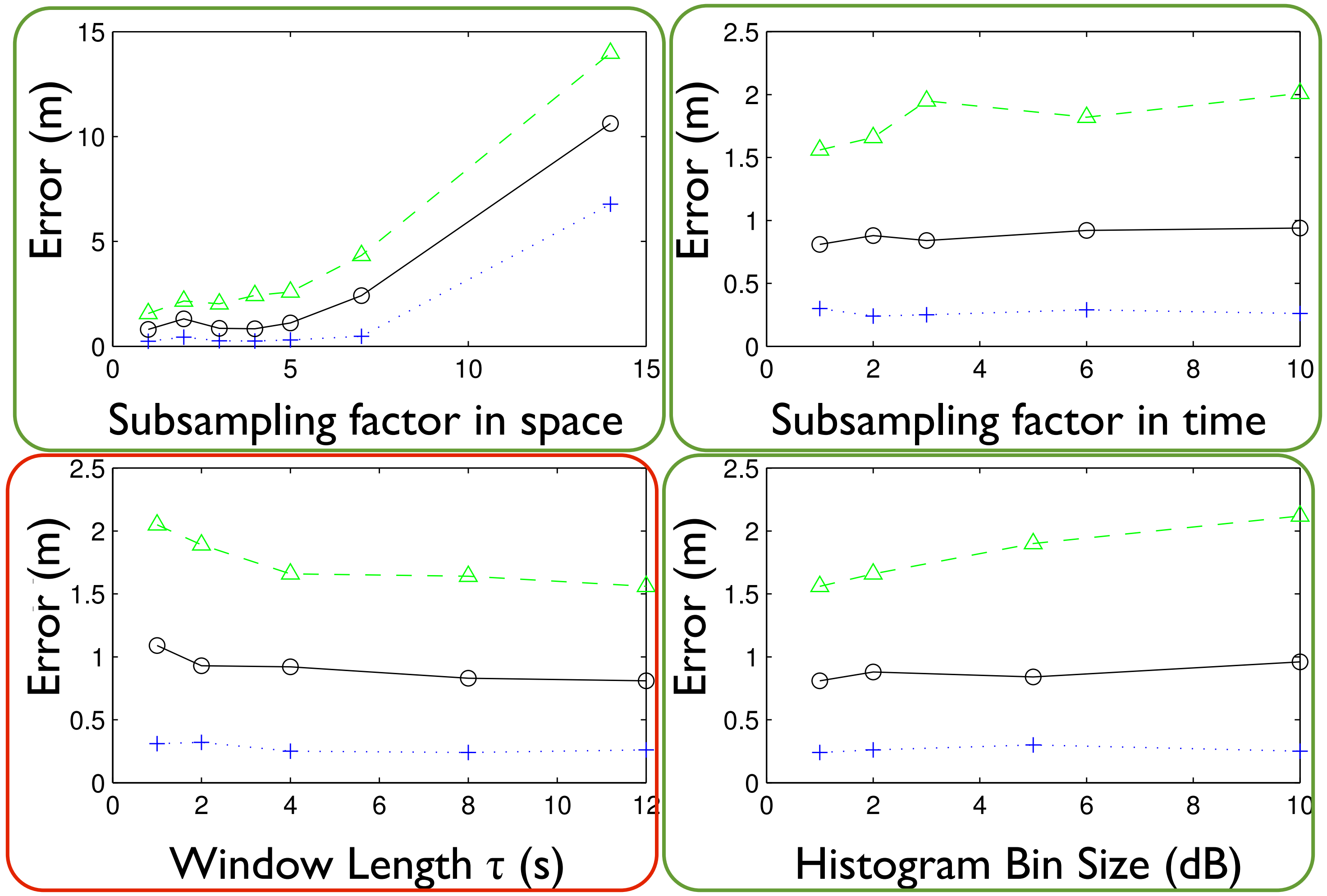
KL divergence kernel regression
using 6 nearest-neighbors,
using RSSI



no smoothing!
no motion model!

[Mirowski et al, IPIN 2011]

Results: Effects of fingerprint and tracking parameters



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 *τ*)**

[Mirowski et al, IPIN 2011; Mirowski et al, submitted]

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

difficulty

Automated Fingerprinting

- Robot Mapping Indoor Environments
- Autonomous navigation
- Simultaneous localization and mapping

Results: Fingerprinting "on the fly" while walking

Walk along 300m corridor

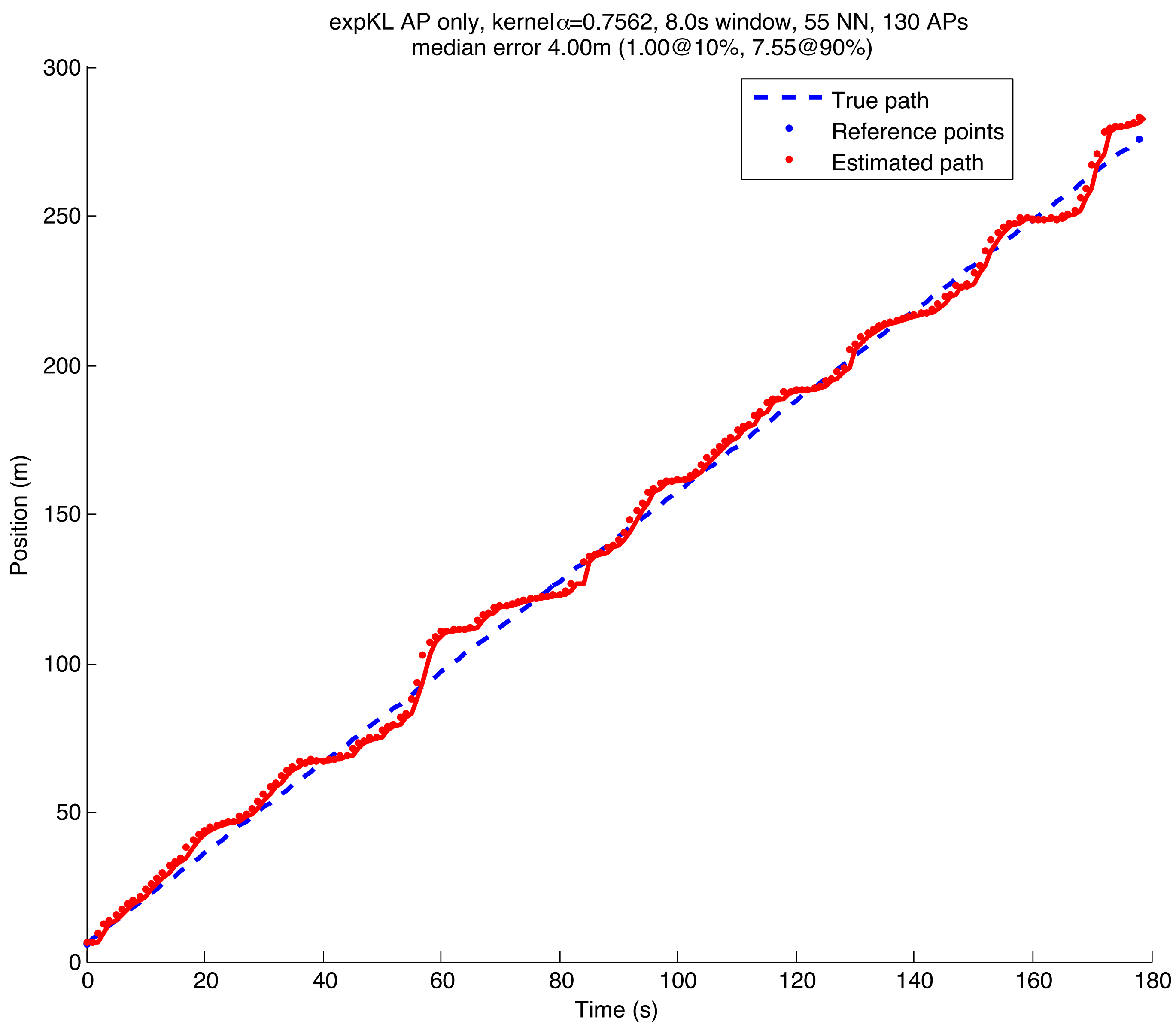
Observed 130 ad-hoc APs

Defined 55 fingerprints

Used only AP presence
(no RSSI)

Tracking results
(one week later)

median: 4m
error at 90%: 7.6m



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

difficulty

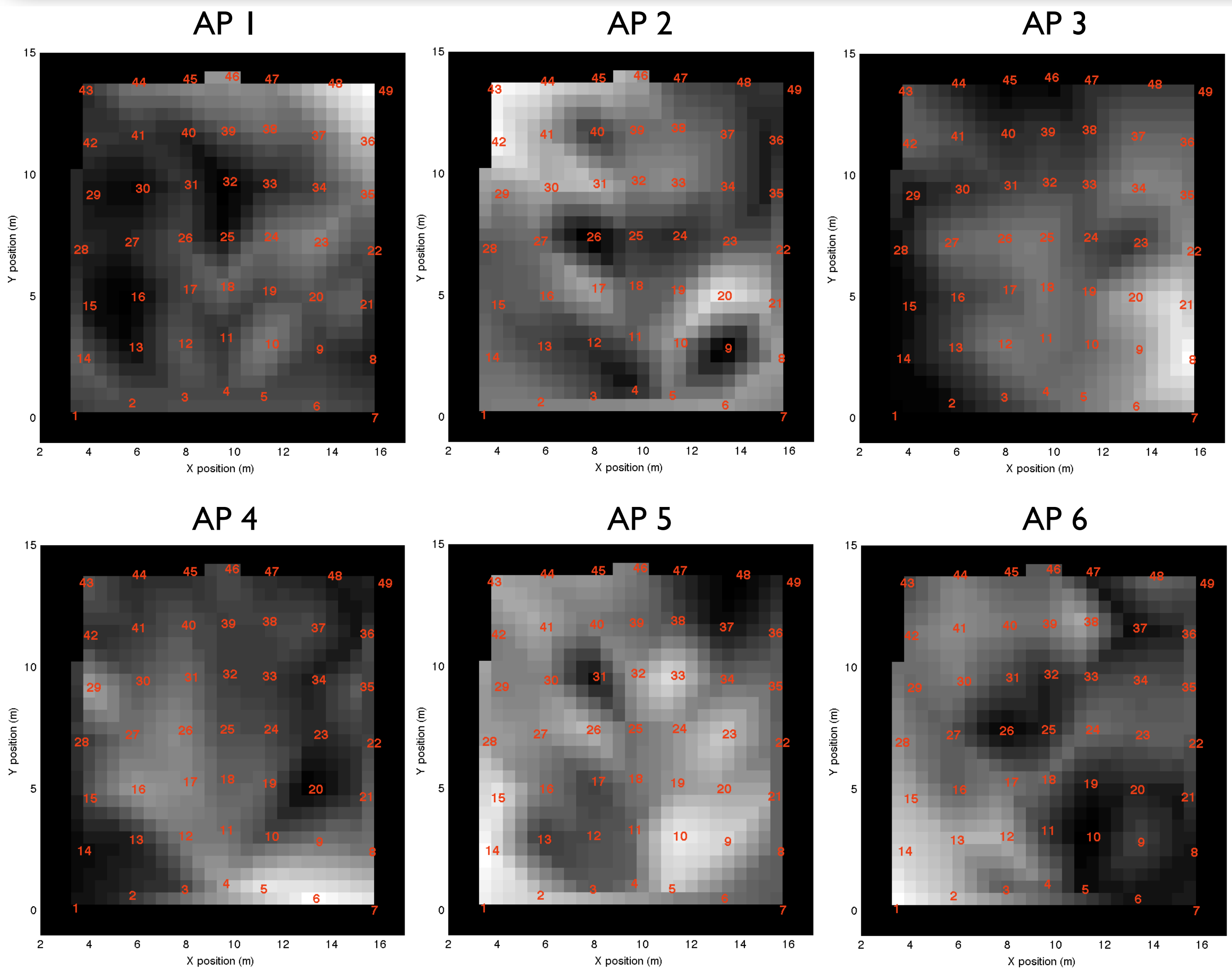
Automated Fingerprinting

- Robot Mapping Indoor Environments
- Autonomous navigation
- Simultaneous localization and mapping

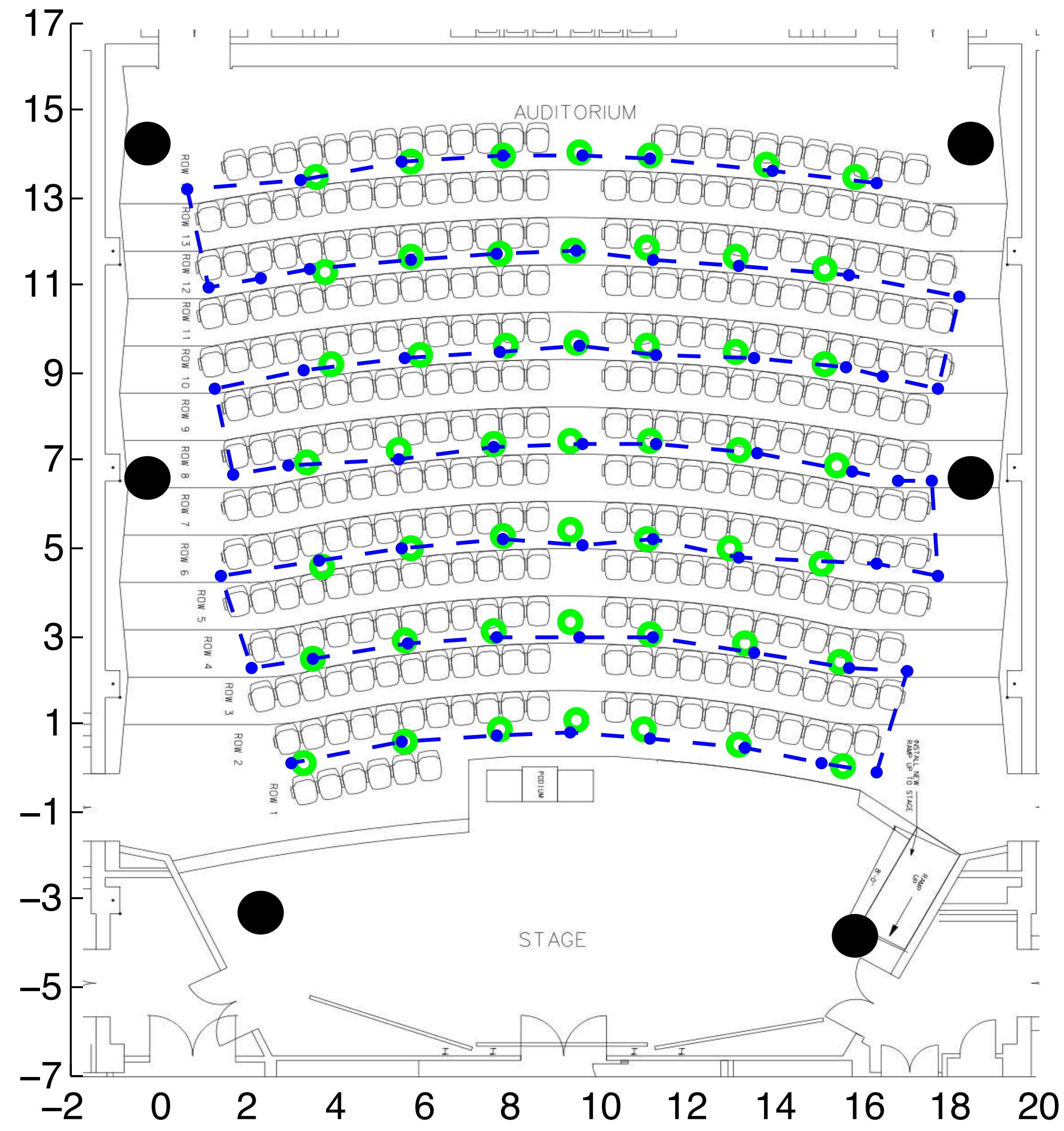
Results: Open-space localization in an auditorium

Open space (auditorium)	median	@90%
KL-divergence, with RSSI, 4 NN WKR	4.7m	10.2m
KL-div. on Gaussians, with RSSI, 4 NN WKR	4.9m	8.2m
Random prediction	9m	15m

Narrow corridor	median	@90%
KL-divergence, with RSSI, 3 NN WKR	**1m**	**2m**



Set 6 APs in an auditorium



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

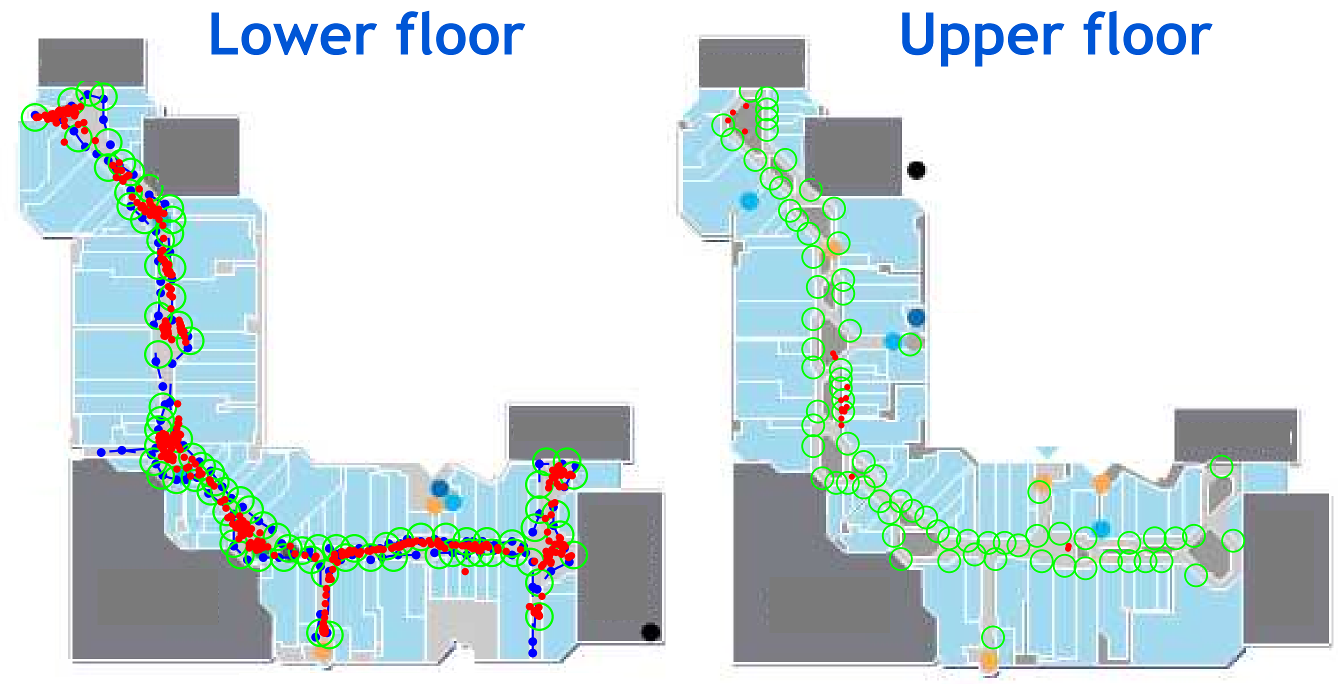
difficulty

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

Results: Sparse fingerprints in a complex public space

Tracking signal recorded on lower floor (3 days later)

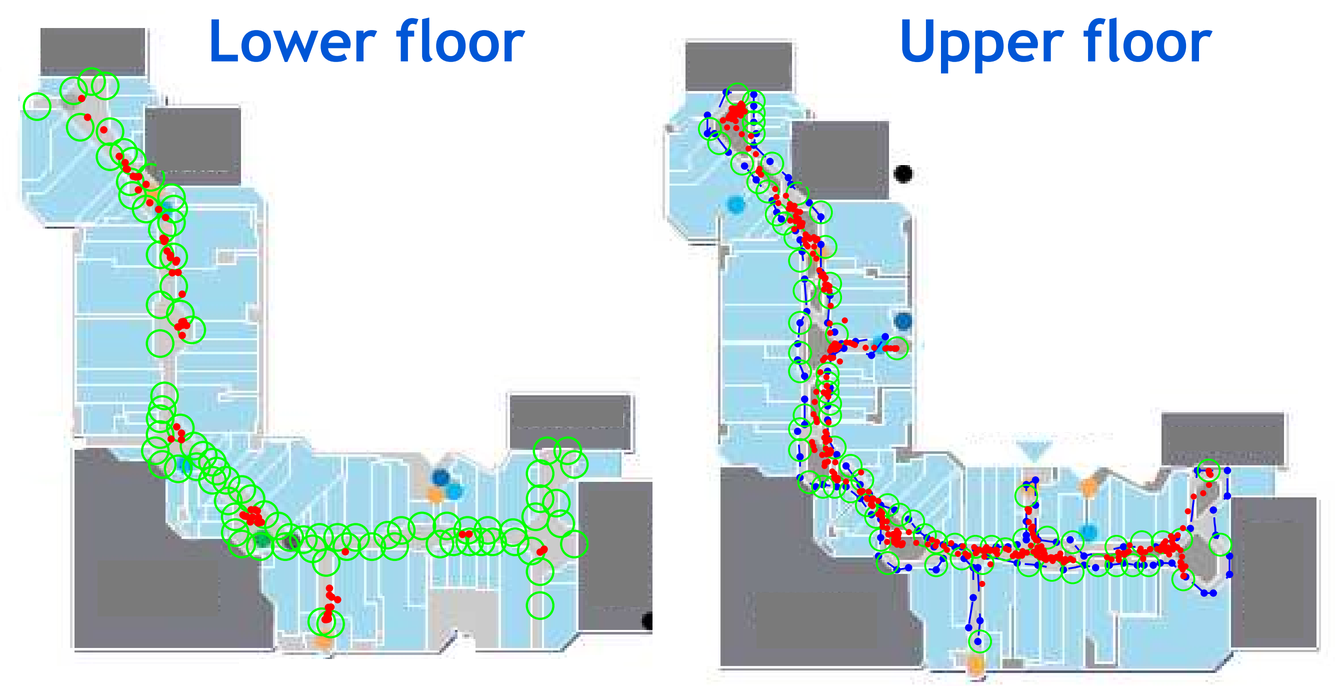
Predictions on the lower floor	median	@90%	floor
KL-div., no RSSI, 31 NN WKR	10.3m	24.3m	89%
KL-div., RSSI, 8 NN WKR	8.2m	16.9m	96.2%
KL-div. Gauss, RSSI, 8 NN WKR	**6.7m**	**14.8m**	**96%**



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

Tracking signal recorded on upper floor (3 days later)

Predictions on the lower floor	median	@90%	floor
KL-div., no RSSI, 31 NN WKR	9.1m	17m	92.6%
KL-div., RSSI, 8 NN WKR	9m	17.1m	83.8%
KL-div. Gauss, RSSI, 8 NN WKR	**8m**	**13.4m**	**84.4%**



[Mirowski et al, IPIN 2011; Mirowski et al, submitted]

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

Automated fingerprinting: Motivation for a robot

Indoor mapping robot capabilities

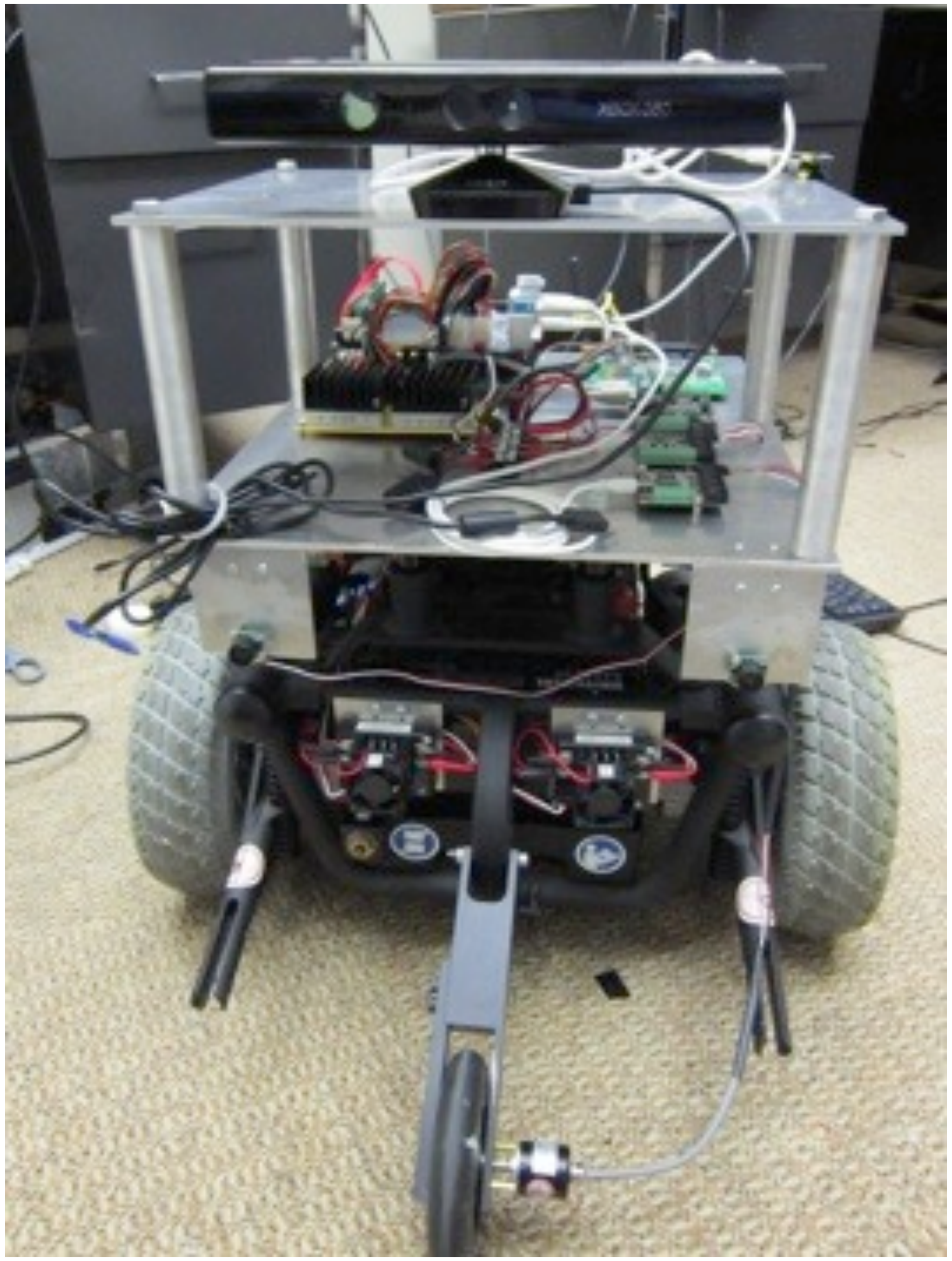
- Automated **collection** of RF signal
- Autonomous **navigation** through narrow corridors and open spaces
- Equipped with multitude of **sensors**

Advantages

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

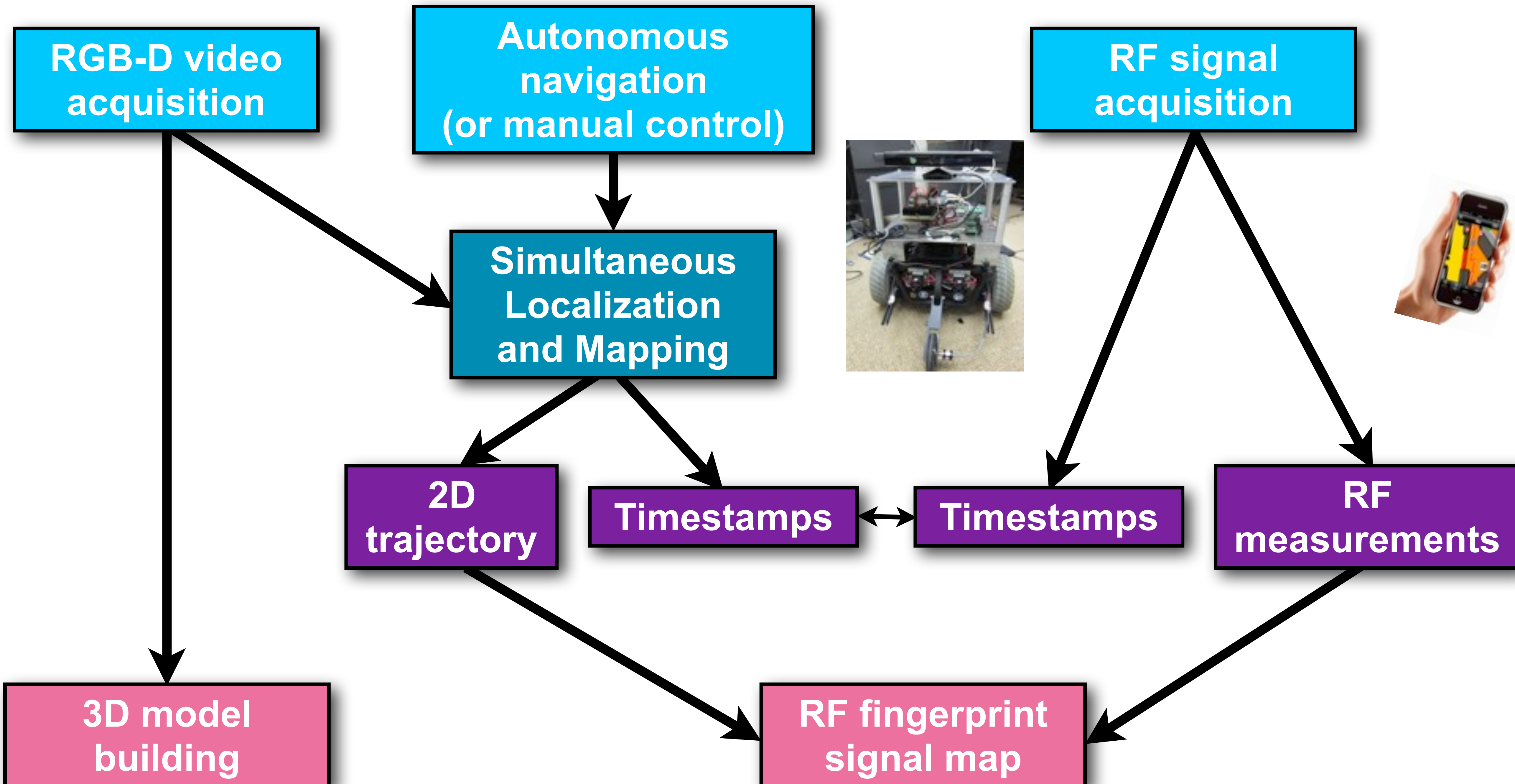
Applications

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



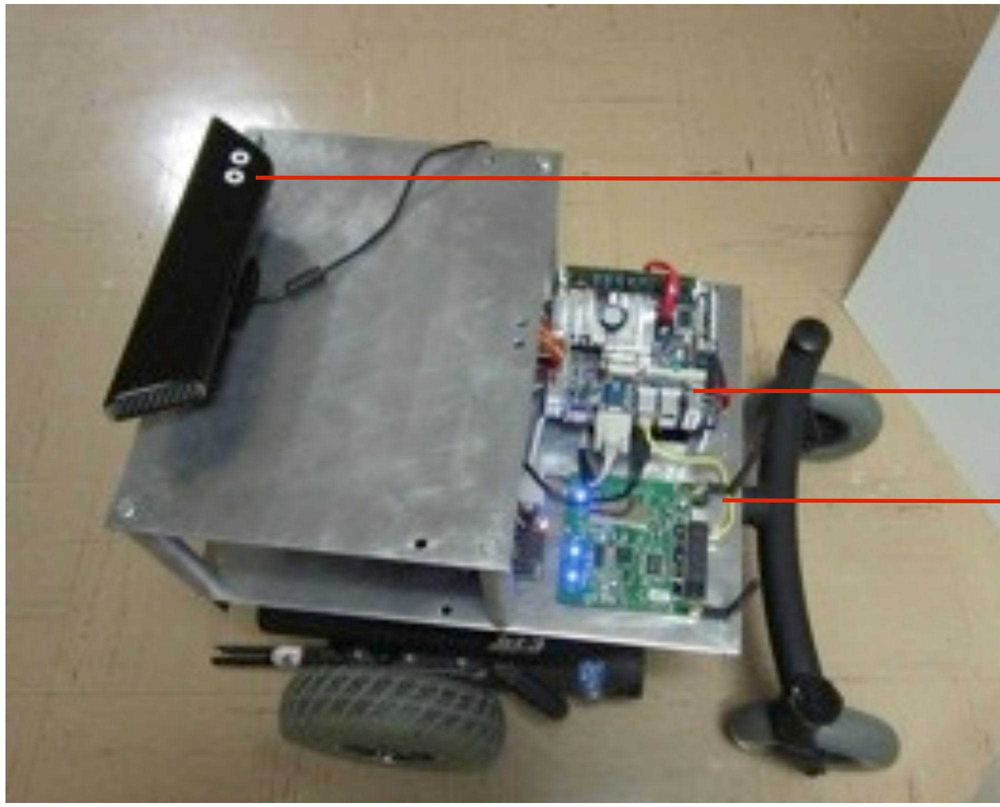
[Palaniappan, Mirowski et al, IPIN 2011]

Automated fingerprinting: Process flow



[Palaniappan, Mirowski et al, IPIN 2011]

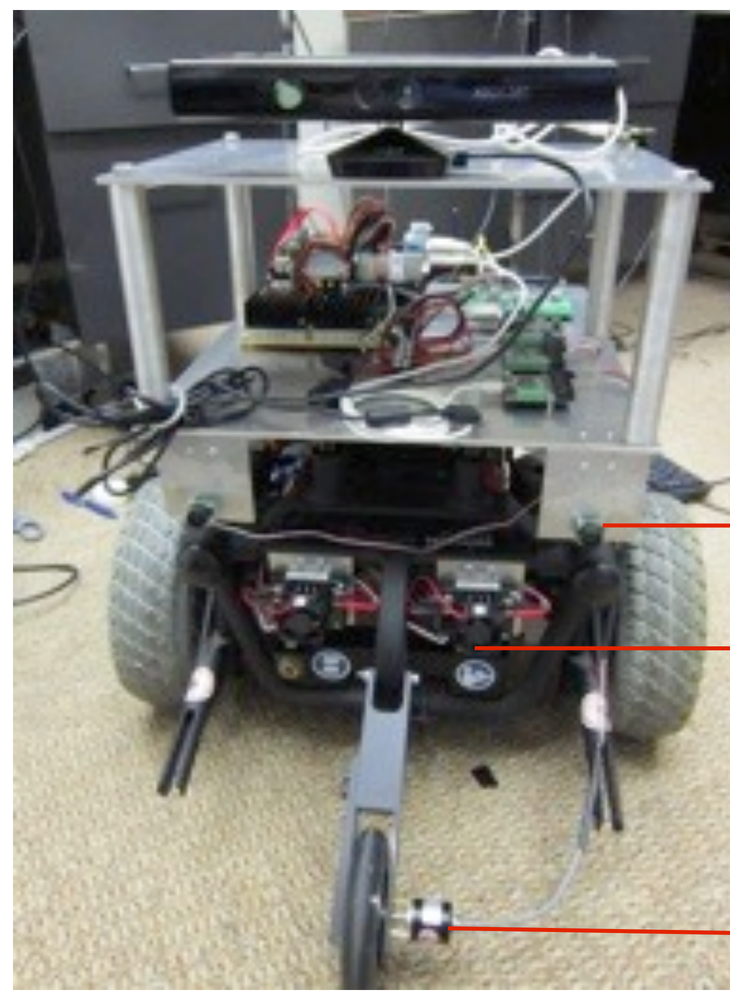
Automated fingerprinting: Using a mapping robot



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

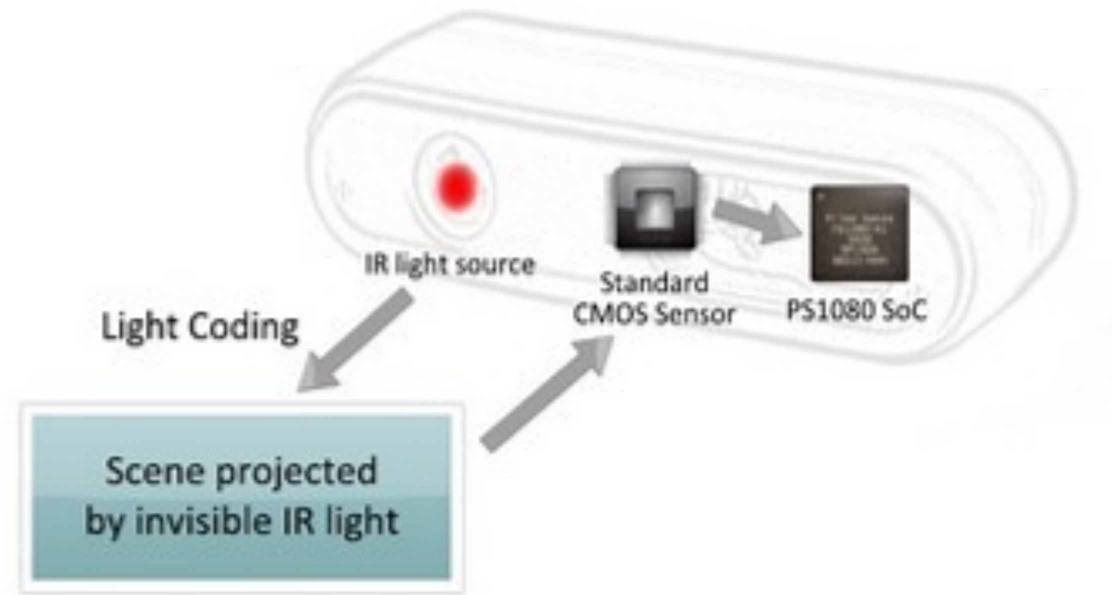
- Debian Linux O/S
- C, C++ for control and navigation

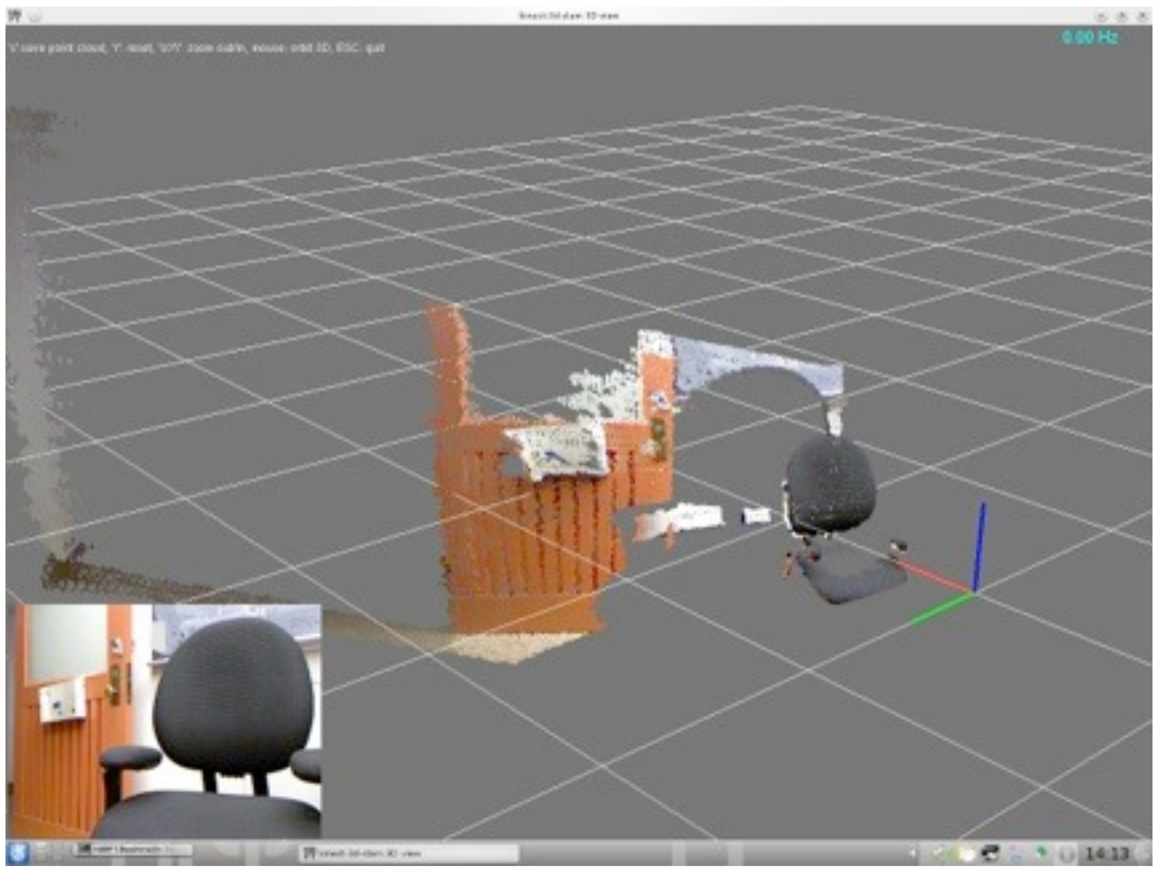
Specs

- 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





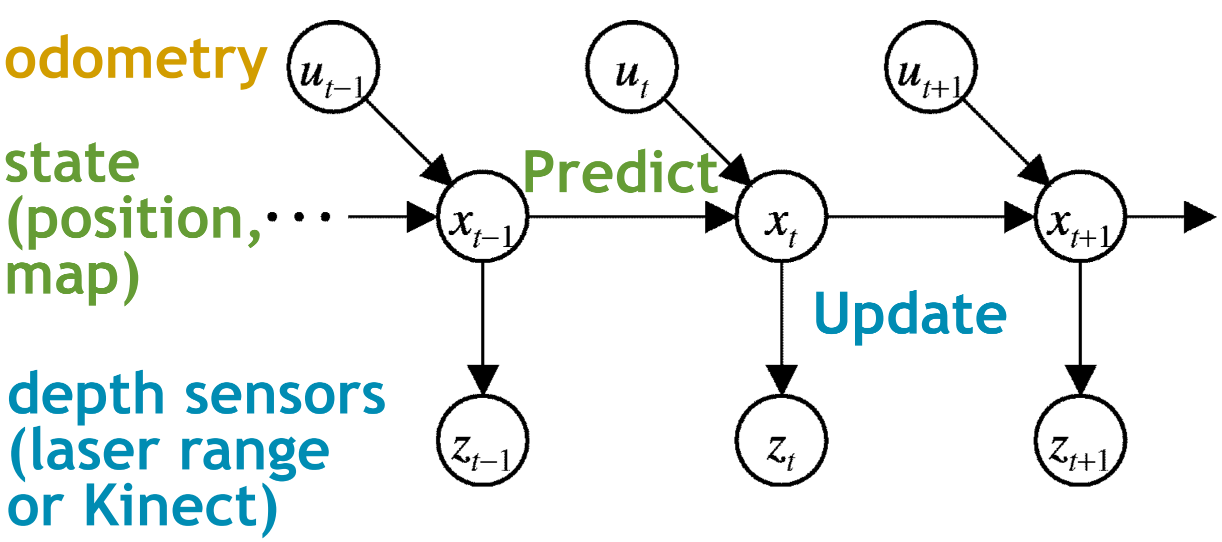
[Palaniappan, Mirowski et al, IPIN 2011]

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]

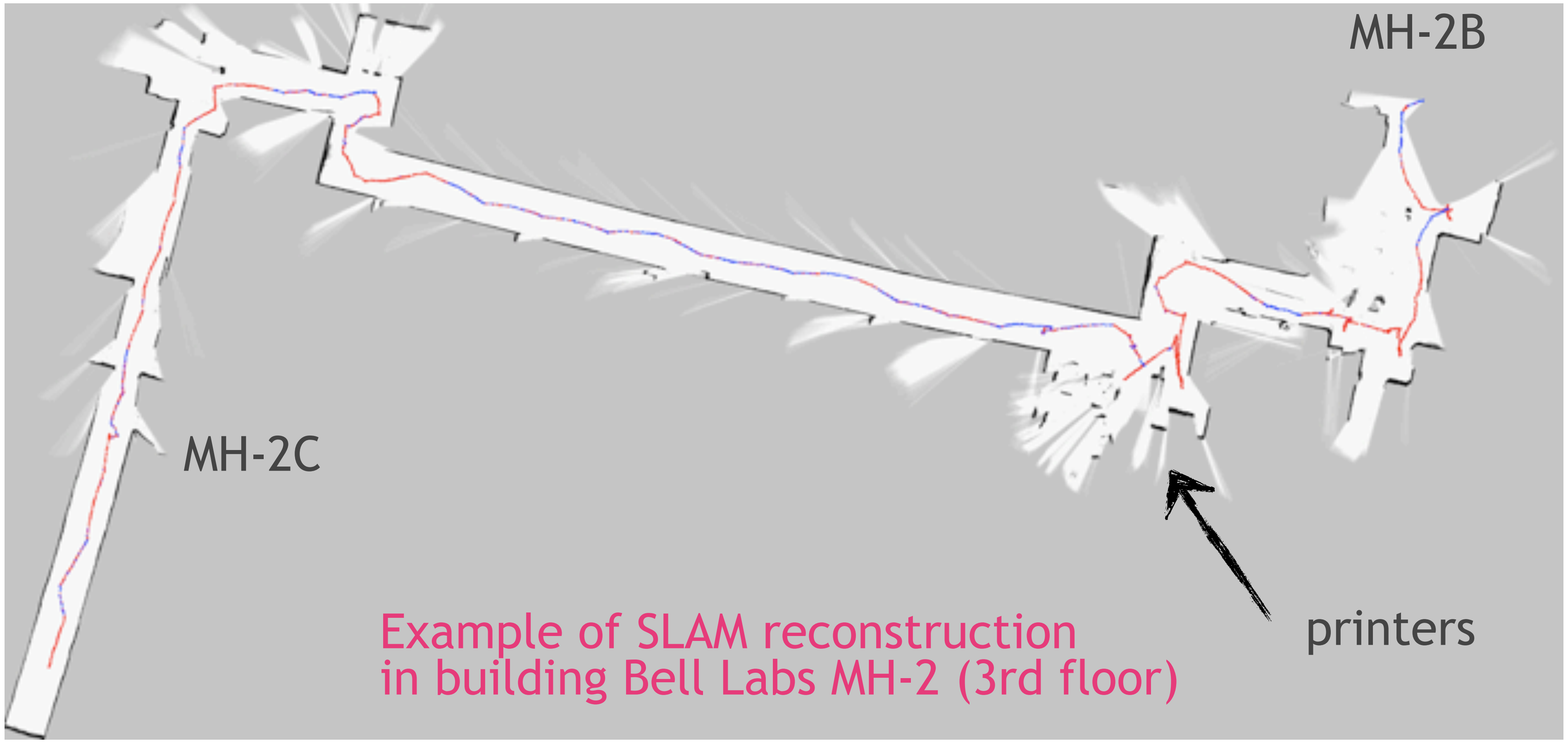
- Not probabilistic, approximate but fast
- Inputs:
  - Wheel encoder odometry
  - Rotation guess (from controls)
  - 2D “laser range” from Kinect
- We use it to compute the rotation angles

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)

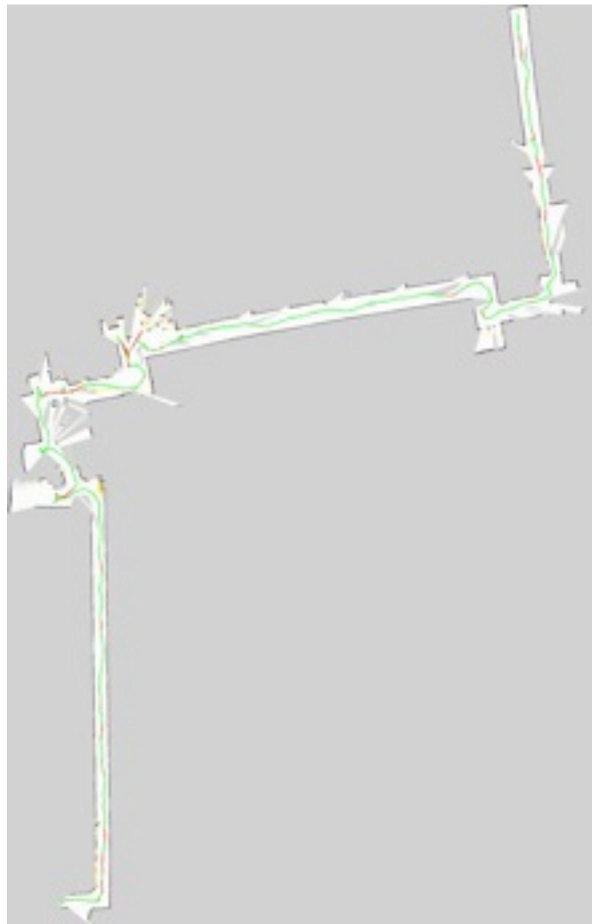


Current limitations of SLAM [Steux & El Hamzaoui, 2010; Eliazar & Parr, 2003, 2004]

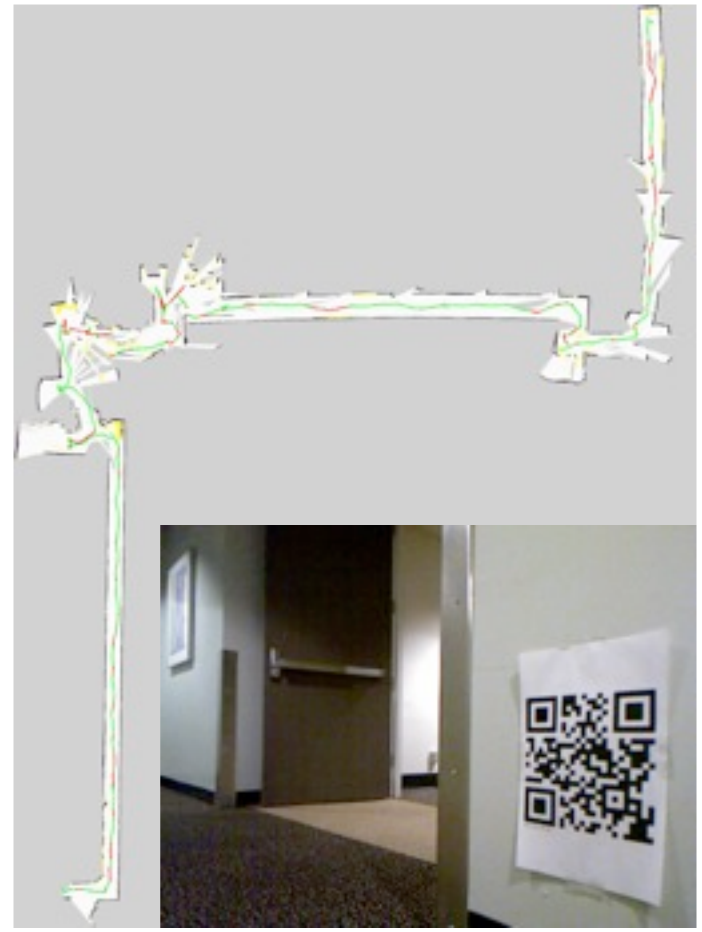
- Kinect sensor covers only 60 deg (laser ranges typically cover 180 deg)
- Kinect depth sensor works until 5.5m: problem in open spaces
- Slow processing speed of embedded hardware (e.g., no GPU-based computing abilities)
  - Most SLAM processing needs to be done offline
- Research in progress on loop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

Robot: Simultaneous Localization and Mapping (SLAM)

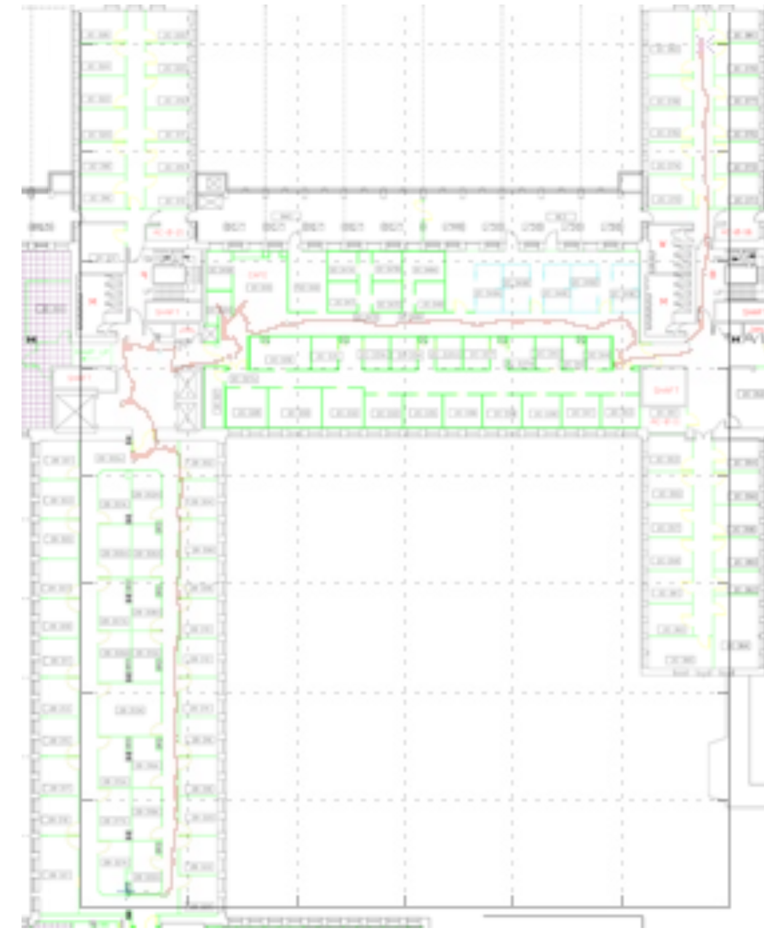
Trajectory from wheel odometry



Trajectory from particle filtering SLAM
[Eliazar & Parr, 2003, 2004]



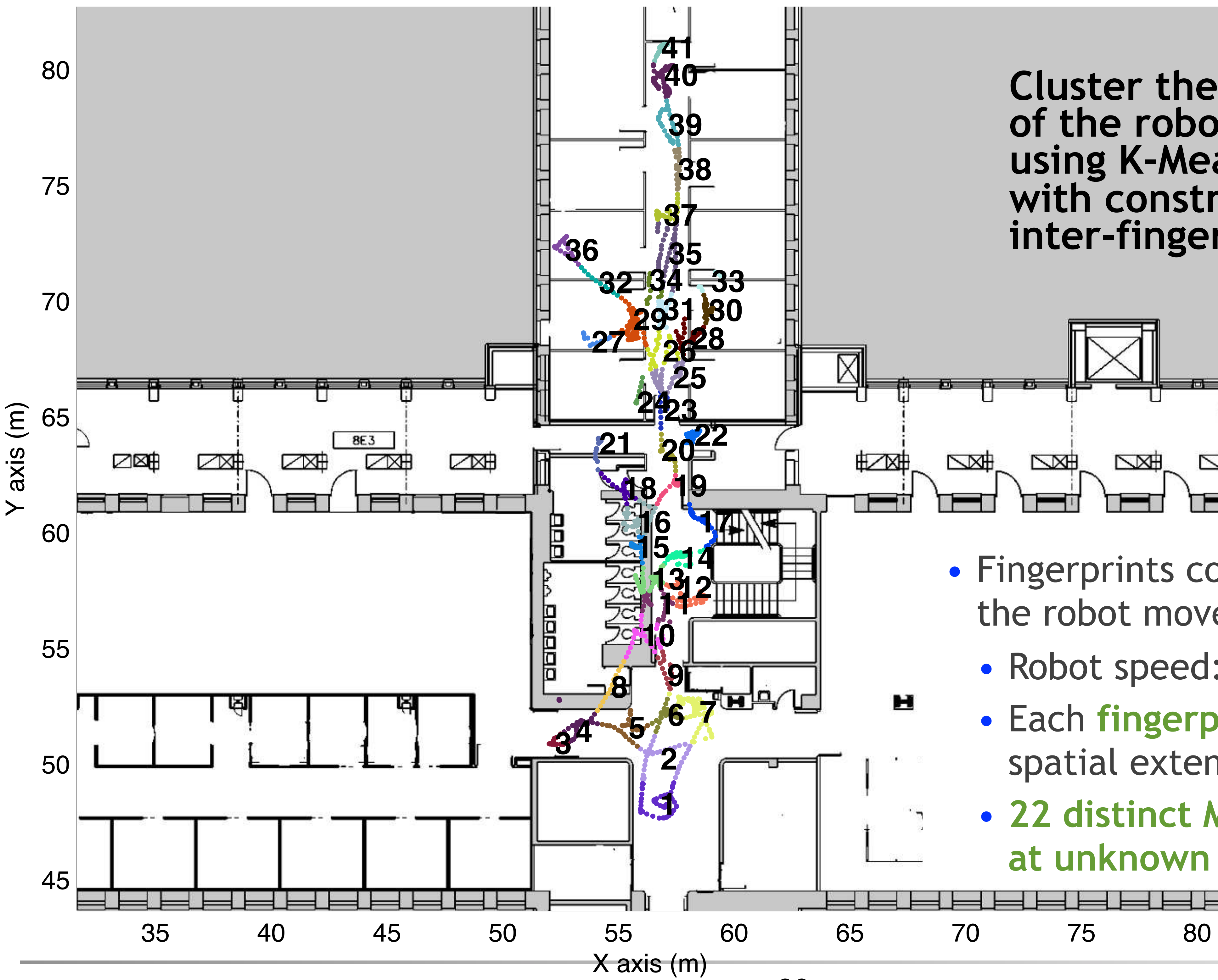
Trajectory optimized using absolute-position landmarks (self-describing QR codes)
[Grisetti et al, 2007, 2010]



Optimized trajectory superimposed on building blue prints

[Mirowski et al, TePRA 2012]

Automated fingerprinting: a corridor at Bell Labs

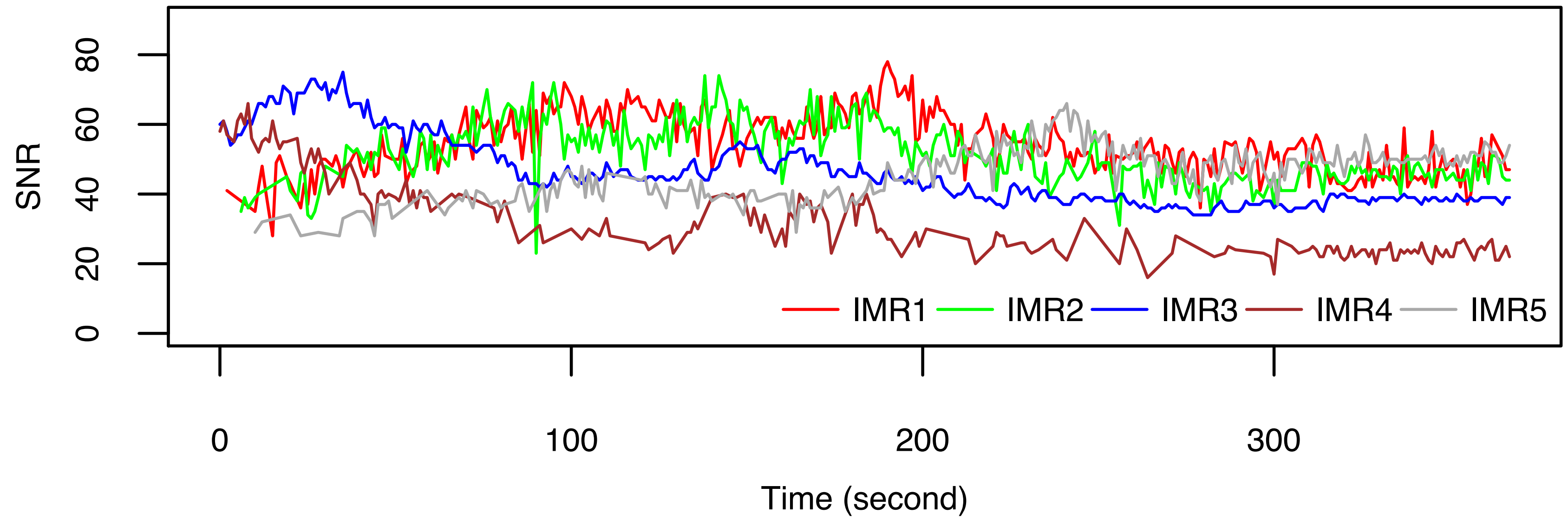


Cluster the path keypoints of the robot using K-Means algorithm with constraints on inter-fingerprint distance

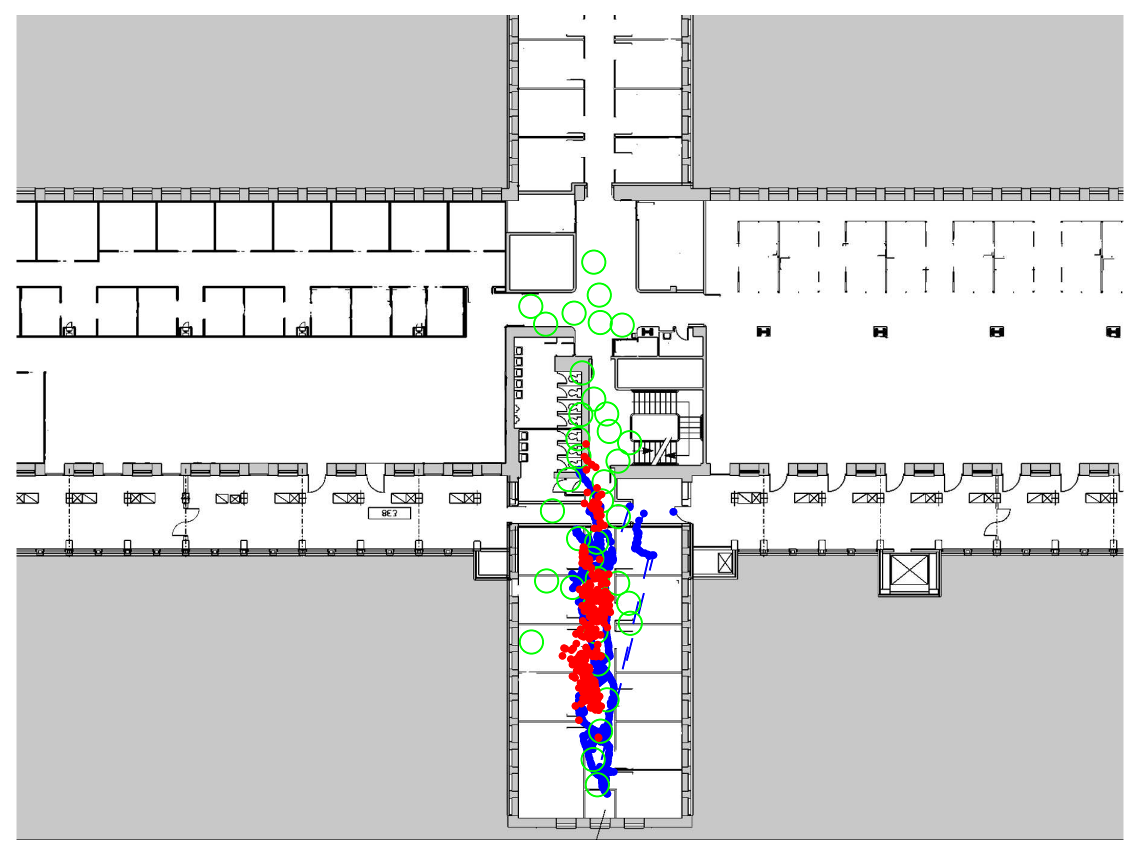
- Fingerprints collected on the fly as the robot moves
  - Robot speed: 0.23m/s
  - Each **fingerprint** spans 2m of spatial extent
  - **22 distinct MAC addresses (~ APs) at unknown locations**

Automated fingerprinting: a corridor at Bell Labs

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

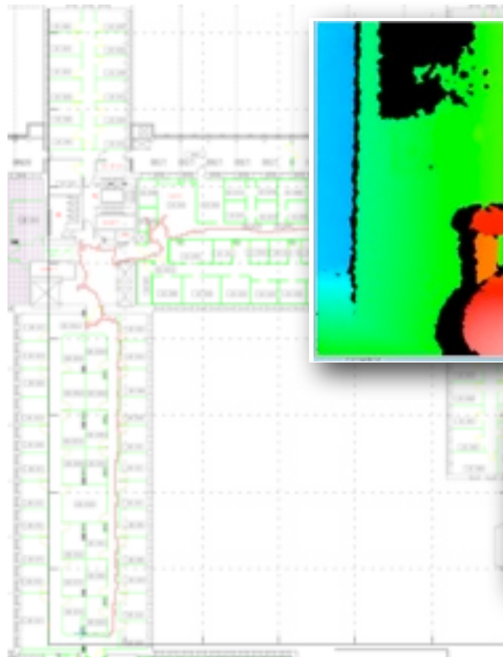


Tracking accuracy:
median: 3 m
error at 90%: 6 m

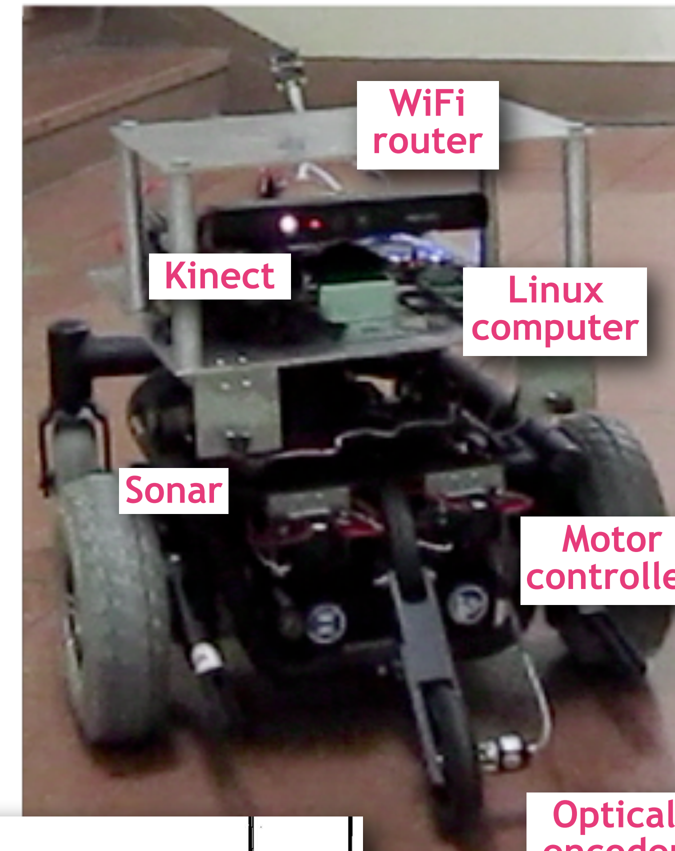


[Mirowski et al, TePRA 2012]

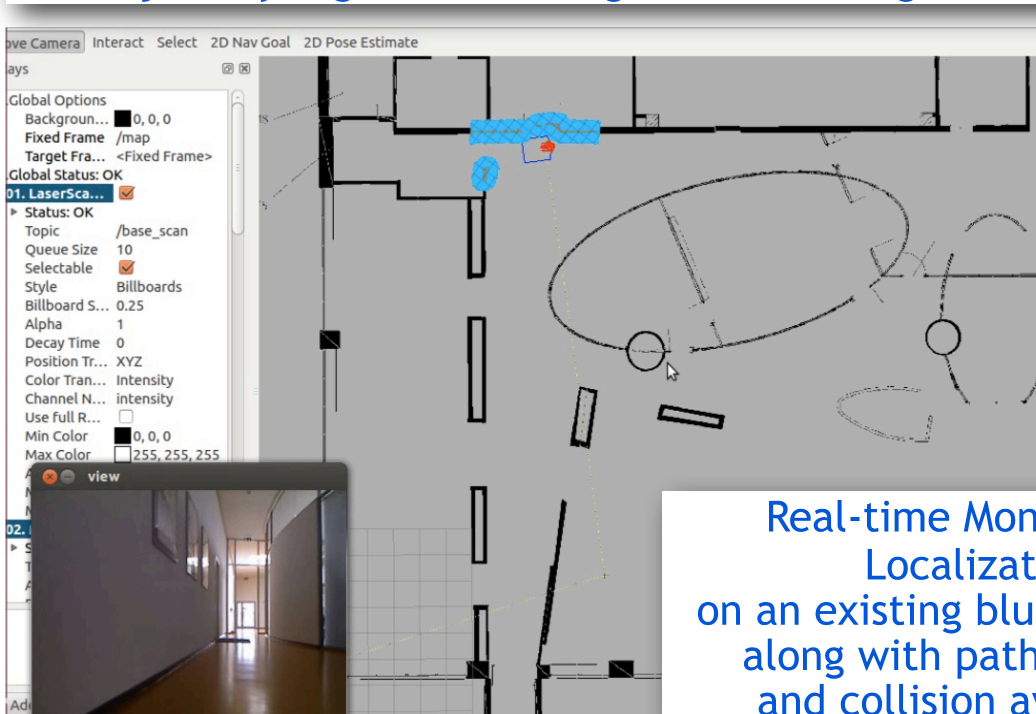
Automated RF Mapping: Using a self-localizing robot



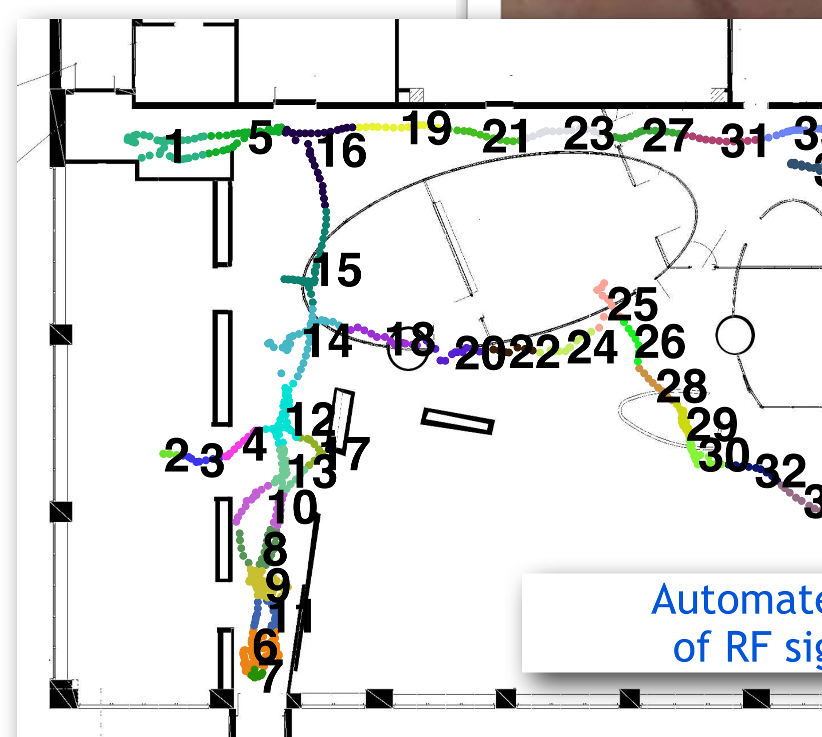
Real-time (30Hz) precise RGB-D image (color + depth) up to 5.5m distance, using the Kinect sensor



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



Automated building of RF signal maps

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

Thank you!

- P. Bahl and V.N. Padmanabhan, "An In-Building RF-based User Location and Tracking System", IEEE Infocom, 2000.
- M.S. Bargh and R. de Groote, "Indoor Localization Based on Response Rate of Bluetooth Inquiries", International Workshop on Mobile Entity Localization and Tracking in GPS-less Environments, 2008.
- P. Castro, P. Chiu, T. Kremenek and R. Muntz, "A Probabilistic Location Service for Wireless Network Environments", Ubiquitous Computing, September 2001.
- A. Chen, C. Harko, D. Lambert and P. Whiting, "An algorithm for fast, model-free tracking indoors", ACM SIGMOBILE Mobile Computing and Communications Review, 2007.
- F. Evennou, F. Marx and E. Novakov, "Map-aided indoor mobile positioning system using particle filter", IEEE Conference on Wireless Communications and Networking, 2005.
- T. Jebara, R. Kondor and A. Howard, "Probability Product Kernels", Journal of Machine Learning Research, 2004.
- S.Kullback and R.A.Leibler, "On Information and Sufficiency", Annals of Mathematical Statistics, 1951.
- D. Milioris, L. Kriara, A. Papakonstantinou and G. Tzagkarakis, "Empirical Evaluation of Signal-Strength Fingerprint Positioning in Wireless LANs", ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems, 2010.
- P.J. Moreno, P.P. Ho and N. Vasconcelos, "A Kullback-Leibler divergence based kernel for SVM classification in multimedia applications", Neural Information Processing Systems, 2002.
- E. Nadaraya, "On estimating regression", Theory of Probability and Applications, 1964.
- I.C. Paschalidis, K. Li and D. Guo, "Model-Free Probabilistic Localization of Wireless Sensor Network Nodes in Indoor Environments", Second International Workshop on Mobile Entity Localization and Tracking in GPS-less Environments, 2009.
- T. Roos, P. Myllymaki, H. Tirri, P. Misikangas and J. Sievanen,"A Probabilistic Approach to WLAN User Location Estimation", International Journal of Wireless Information Networks, 2002.
- T. Vauper, J. Seitz, F. Kiefer, S. Haimerl and J. Thielecke, "Wi-Fi Positioning: System Considerations and Device Calibration", International Conference on Indoor Positioning and Indoor Navigation (IPIN), 2010.

Thank you!

- M. Hedley, D. Humphrey and P. Ho, “System and algorithms for accurate indoor tracking using low-cost hardware”, IEEE Position, Location and Navigation Symposium 2008.
- R.M. Geiss, Visual Target Tracking, US Patent Application 20110058709 2011.
- http://www.netstumbler.com/
- T. Roos, P. Myllymaki, H. Tirri, P. Misikangas and J. Sievanen, “A Probabilistic Approach to WLAN User Location Estimation”, International Journal of Wireless Information Networks 2002.
- T. Gramegna, G. Cicirelli, G. Attolico and A. Distante, “Automatic construction of 2D and 3D models during robot inspection”, Industrial Robot 2006.
- P. Henry, M. Krainin, E. Herbst, X. Ren and D. Fox, “RGB-D Mapping: Using Depth Cameras for Dense 3D Modeling of Indoor Environments”, International Symposium on Experimental Robotics 2010.
- G. Grisetti, S. Grzonka, C. Stachniss, P. Pfaff and W. Burgard, “Efficient Estimation of Accurate Maximum Likelihood Maps in 3D”, International Conference on Intelligent Robots and Systems 2007.
- P. Mirowski and Y. LeCun, “Dynamic Factor Graphs for Time Series Modeling”, European Conference on Machine Learning 2009.
- A.I. Eliazar and R. Parr, “DP-SLAM 2.0”, International Conference on Robotics and Applications 2004.
- A.I. Eliazar and R. Parr, “DP-SLAM: Fast, Robust Simultaneous Localization and Mapping Without Predetermined Landmarks”, International Joint Conference on Artificial Intelligence 2003.
- B. Steux and O. El Hamzaoui, “tinySLAM: A SLAM algorithm in less than 200 lines C-language program”, ICARCV 2010.
- P. Mirowski, H. Steck, P. Whiting, R. Palaniappan, M. MacDonald and T. K. Ho, “KL-Divergence Kernel Regression for Non-Gaussian Localization”, Indoor Positioning and Indoor Navigation 2011.
- R. Palaniappan, P. Mirowski, H. Steck, T.K. Ho, P. Whiting and M. MacDonald, “Autonomous RF Surveying Robot for Indoor Localization and Tracking”, International Conference on Indoor Positioning and Indoor Navigation (IPIN), 2011.
- P. Mirowski, R. Palaniappan and T. K. Ho, “Depth Camera SLAM on a Low-cost WiFi Mapping Robot”, IEEE Conference on Technologies for Practical Robot Applications (TePRA) 2012.