LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN

Praktikum Mobile und Verteilte Systeme

WLAN Positioning

Prof. Dr. Claudia Linnhoff-Popien
Philipp Marcus, Lorenz Schauer
http://www.mobile.ifi.lmu.de

Sommersemester 2015

WLAN Positioning

Today:

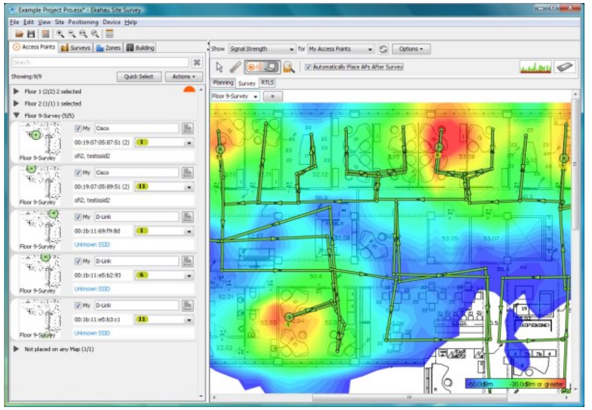
- Motivation
- Overview of different indoor positioning technologies/methods
- WLAN Positioning
- Sensor Fusion

Why Indoor Positioning?

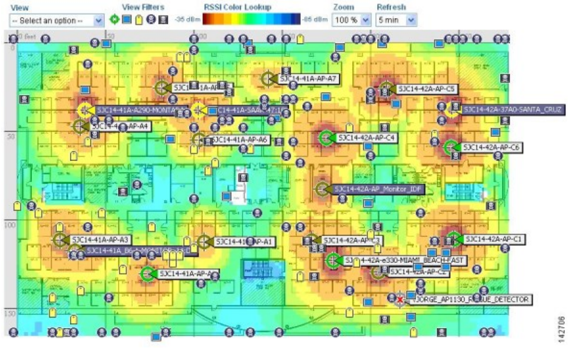
- Developement of Location-based Services
  Value-added services that consider the position of a mobile target
  - Navigation Systems
  - Information Systems
  - Emergency
  - Advertising
  - …
- Location-based Services require a positioning method
  - GPS / Galileo
  - GSM Cell-ID
  - Indoor?

Indoor Positioning Systems

- Application examples
  - Object & asset tracking
  - Workflow optimization & maintenance
  - Information services
  - Healthcare & ambient living
  - Security & safety



Ekahau (www.ekahau.com)



Cisco (www.cisco.com)





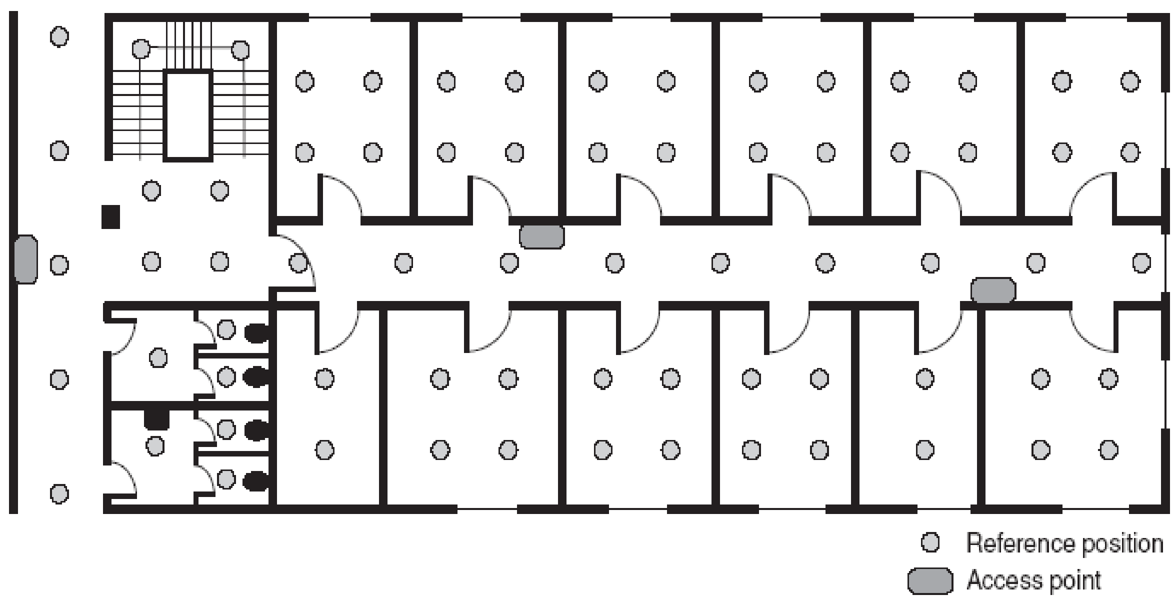
Positioning Fundamentals

- Positioning is determined by
  - one or several parameters observed by measurement methods
  - a positioning method for position calculation
  - a descriptive or spatial reference system
  - an infrastructure
  - protocols and messages for coordinating positioning

Positioning method	Observable	Measured by
Proximity sensing	Cell-ID, coordinates	Sensing for pilot signals
Lateration	Range or Range difference	Traveling time of pilot signals Path loss of pilot signals Traveling time difference of pilot signals Path loss difference of pilot signals
Angulation	Angle	Antenna arrays
Dead reckoning	Position and Direction of motion and Velocity and Distance	Any other positioning method Gyroscope Accelerometer Odometer
Pattern matching	Visual images or Fingerprint	Camera Received signal strength

Fingerprinting

- Position is derived by the comparision of location dependent online measurements with previously recoded data:



Positioning systems: some examples

Name	Signals	Observable	TB, NB, TA	Accuracy
Active Badge	Infrarot	CoO	NB	Cell (Room)
ActiveBat	Ultrasonic, Radio	TDoA	NB	10cm
AeroScout	RFID & WLAN	TDoA & RSS	NB	3 - 5m
Cisco WLA	WLAN	RSS	NB	~ 3m
Cricket	Ultrasonic, Radio	Proximity sensing	TB	few cm
EasyLiving (Microsoft Research)	misc.	misc.	NB	30cm
Ekahau	WLAN	RSS	NB	~2m
GPS	Satellite	ToA	TB	~2m
Horus (University of Maryland)	WLAN	RSS		1m
MagicMap	WLAN	RSS	TB, P2P	<10m
MetroGroup Future Store	RFID	TDoA & AoA	NB	30cm
PARCTAB (Xerox Research Center)	Infrarot	CoO	NB	Cell (Room)
PlaceLab	WLAN, Bluetooth, GSM	RSS	TB	~10m
PinPoint (Universität Maryland)	RFID	TDoA		1 - 3m
RADAR	WLAN	RSS	TA NB	2 - 3m
Rosum: TV-GPS	GPS & TV-Signale	RSS	TA	?
Rover (Universität Maryland)	WLAN & Bluetooth	RSS		2m
SmartFloor (Georgia Inst. of Techn.)		Footprint profile		90%
SpotOn (Predecessor of PlaceLab)	Radio	RSS	NB	3m
Tadlys: Topaz	Bluetooth	CoO	TA	2 - 3m
UbiSense	Ultra Wide Band	TDoA & AoA	NB	30cm
WhereNet	WLAN	TDoA	NB	2 - 3m
WIPS	Infrarot, WLAN	CoO	TA NB	Cell (Room)

(without engagement)

AoA = angle of arrival
CoO = cell of origin
RSS = received signal strength
TDoA = time difference of arrival

TB = terminal based
TA = terminal assisted
NB = network based

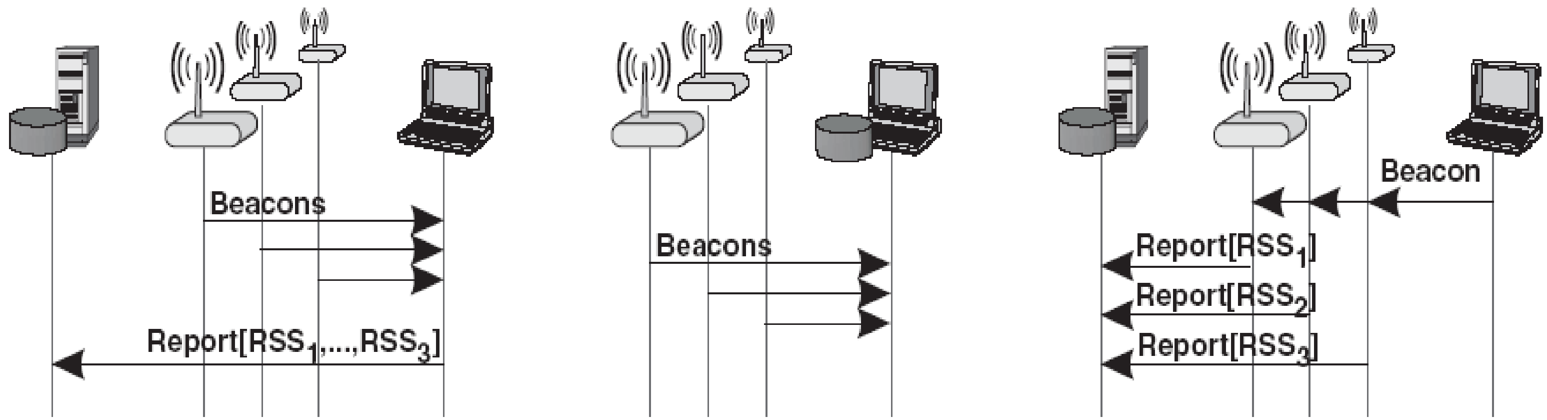
WLAN Positioning

Why use IEEE 802.11 components for indoor positioning?

- Widely deployed infrastructure
- Available on many mobile platforms
- 2,4 GHz → signal penetrates walls → no line-of-sight necessary
- A standard WLAN access point deployment is often already sufficient to achieve room-level accuracy

- **Active Scan:**
  - Sequentially iterate all WLAN bands. Probe Request -> Probe Response
- **Passive Scan:**
  - Passive listening for beacons or probe responses
  - Beacon: Small package with SSID name, transmission modes, encryption mode

WLAN Positioning – TA, TB, NB



(a) Terminal-assisted mode (b) Terminal-based mode (c) Network-based mode

Terminal assisted (TA)

- Measurements are made at the terminal
- Position calculation happens at the server

Terminal based (TB)

- Measurements and position calculation are made at the terminal

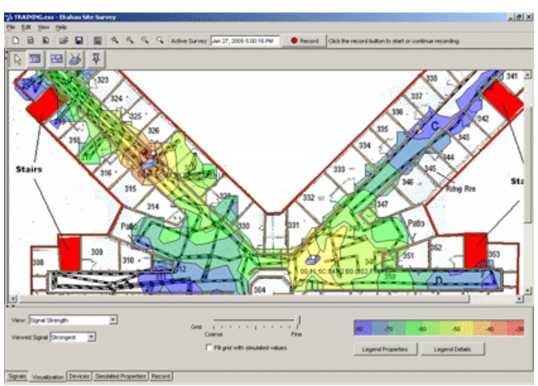
Network based (NB)

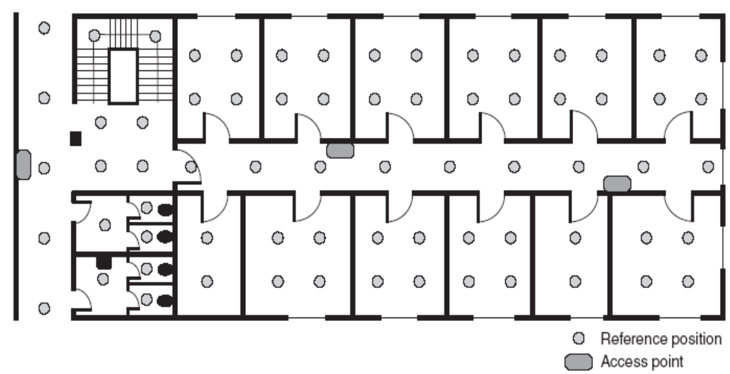
- Beacons are emitted by terminal
- Measurements and calculation are done at the server

WLAN Fingerprinting – Idea

WLAN Fingerprinting

- Derive position from **patterns of signals** received from/at several WLAN access points
- Observable: **received signal strength** (RSS)
- **Offline phase**
  - Record well-defined RSS patterns for well-defined reference positions and store them in a radio map
  - Due to line-of-sight conditions on the spot, it might be necessary to observe RSS patterns from several directions for each position
- **Online phase**
  - RSS patterns related to the target are recorded and compared with the RSS fields of the entries stored in the radio map
  - Position of the target is extracted from the reference position with the closest match





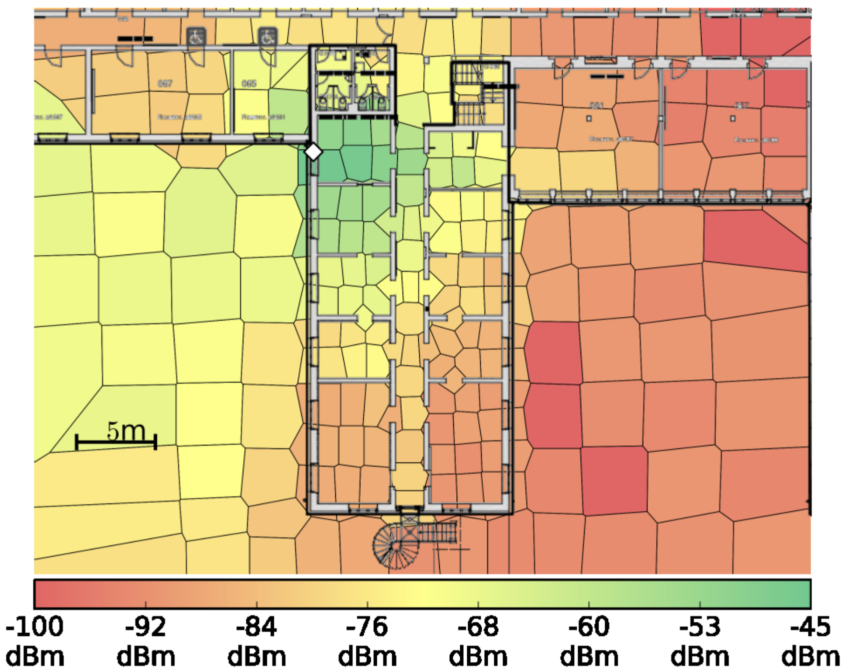
WLAN Fingerprinting – Example of a Radio Map

The results of collecting the fingerprints in the offline-phase could be the following table, for example:

Position	Direction	RSS / [dBm] from 00:02:2D:51:BD:1F	RSS / [dBm] from 00:02:2D:51:BC:78	RSS / [dBm] from 00:02:2D:65:96:92
Pos. 1	0°	-59	-75	-71
	90°	-54	-73	-67
	180°	-49	-72	-69
	270°	-55	-73	-65
Pos. 2	0°	-35	-64	-50
	90°	-27	-64	-43
	180°	-40	-65	-52
	270°	-30	-60	-64
Pos. 3	0°	-69	-66	-73
	90°	-65	-60	-68
	180°	-63	-66	-70
	270°	-68	-62	-76

Data Representation of radio maps

Visualization using polygon method based on Voronoi cells:




```
fingerprint: 1 599 902 0 6 344
measure: 1 98:fc:11:6b:d6:fc -81.0 1
measure: 2 68:ef:bd:fc:c6:cf -61.0 1
measure: 3 c4:7d:4f:88:b7:47 -61.0 1
measure: 4 68:ef:bd:fc:c9:e1 -66.0 1
measure: 5 c4:7d:4f:88:b5:0f -74.0 1
measure: 6 98:fc:11:6b:d6:fc -81.0 1
measure: 7 68:ef:bd:fc:c6:cf -61.0 1
measure: 8 c4:7d:4f:88:b7:47 -61.0 1
measure: 9 68:ef:bd:fc:c9:e1 -66.0 1
measure: 10 c4:7d:4f:88:b5:0f -74.0 1
measure: 11 98:fc:11:6b:d6:fc -80.0 1
measure: 12 00:03:52:ab:82:c4 -92.0 1
measure: 13 00:03:52:ab:82:c5 -92.0 1
measure: 14 c4:7d:4f:88:b7:47 -60.0 1
```

Format:

fingerprint: <fid> <level> <x> <y> <level> <measured-orientation> <real-orientation>

measure <number> <mac> <RSSI> <level> <fid>

WLAN Fingerprinting – Empirical vs. Modeling Approach

Empirical approach

- Create radio maps from measurements
- Disadvantages
  - Time consuming
  - Measurements must be repeated whenever the configuration of access points changes

Modeling approach

- Create radio maps from a mathematical model
  - Calculate the radio propagation conditions taking into account the positions of access points, transmitted signal strengths, free-space path loss, obstacles reflecting or scattering signals, …
- Disadvantages
  - Complexity and accuracy of mathematical models

WLAN Fingerprinting – Overview Systems

System	Observable	Accuracy	Mode			Radio Map		Matching	
			ta	tb	nb	Emp.	Mod.	Det.	Prob.
RADAR	RSS	2.1m / 50%			X	X		X	
Ekahau	RSS	3.1-4.6m / 90%	X			X			X
Horus	RSS	2.1m / 90%		X		X			X
Nibble	SNR	10m /80%	X			X			X
WhereMaps	RSS	1.5m / 50% 6.0m / 95%		X			X		X
Cisco WLA	RSS	-			X	X	X		X

WLAN Fingerprinting – Deterministic vs. Probabilistic Approach

Deterministic Approach

- Record several RSS samples for each reference position and direction
- Create radio map from mean values of these samples
- Online phase: match observed and recorded sample according to Euclidian distance and adopt the reference position with the smallest distance as the current position of the terminal

Probabilistic Approach

- Describe variations of signal strengths experienced during the offline phase by probability distribution
- Probability distributions of various access points are applied to the observed RSS pattern to find the most probable position
- Accuracy can be significantly refined compared to the deterministic approach

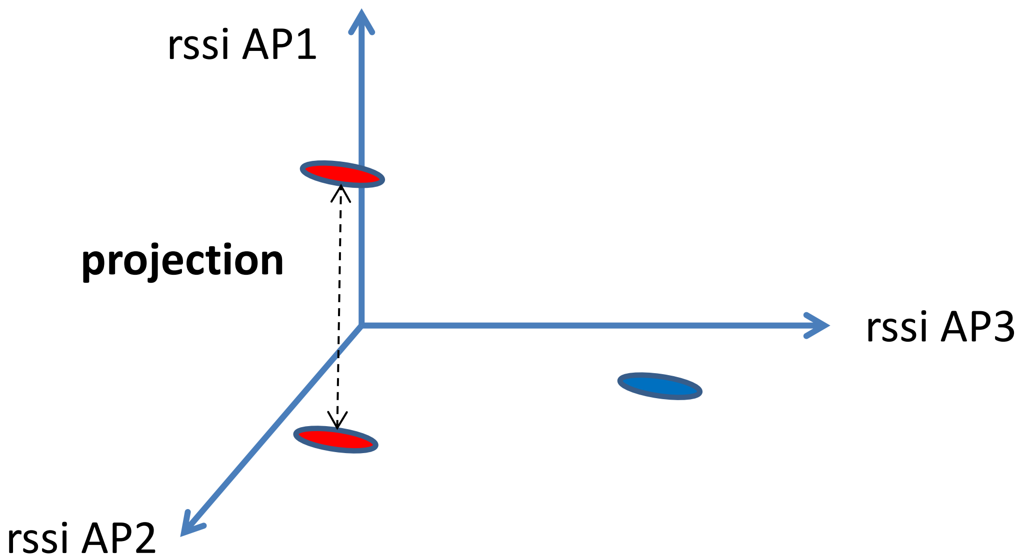
WLAN Fingerprinting – Deterministic Positioning

- Position estimates are computed for terminal-based approaches as follows:
  1. Perform a measurement of signal strengths on a given point
  2. Search for the k-nearest-neighbors – the k recorded fingerprints with the minimal distance
     - k is a system parameter – often derived empirically for a given scenario
     - We will use a value of k=1
  3. For each kNN-fingerprint lookup the location where it has been recorded
  4. Compute the position estimate as the center of mass of these locations (coincides with the first fingerprint for 1NN)

WLAN Fingerprinting – Selecting the kNN (1)

- When comparing the measurement with the fingerprints, both vectors need to contain signal strengths for the same access points

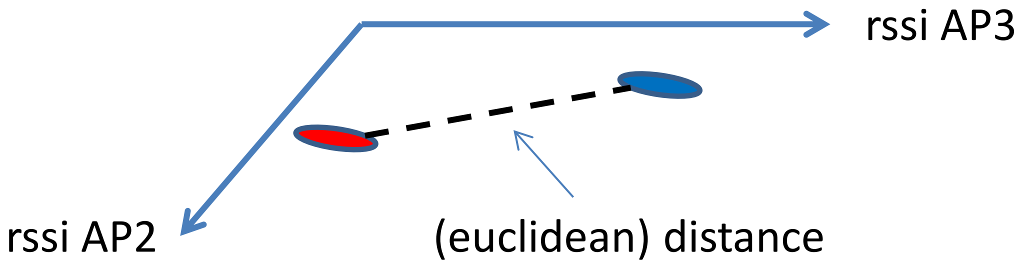
  → Compute a distance by looking at the common access points in a measurement and a fingerprint (**projection** to a common vector subspace)



WLAN Fingerprinting – Selecting the kNN (2)

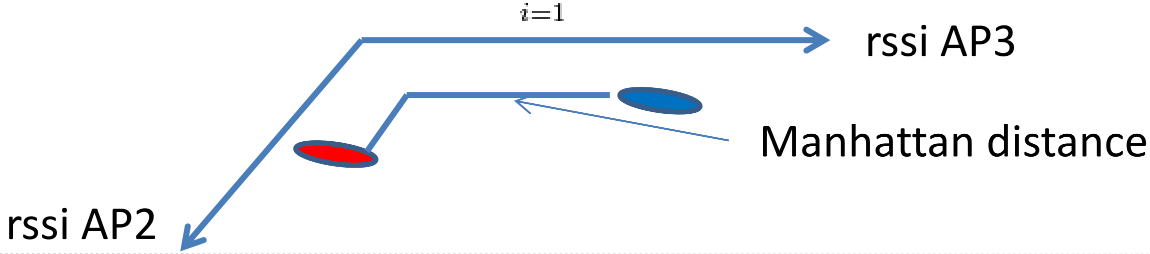
- The selection of the kNN in Step 2. can be done in several ways
  1. Euclidean distance in the largest common signal strength vector subspace:

$$\mathrm{d}(\mathbf{p},\mathbf{q}) = \mathrm{d}(\mathbf{q},\mathbf{p}) = \sqrt{(q_1-p_1)^2 + (q_2-p_2)^2 + \cdots + (q_n-p_n)^2} = \sqrt{\sum_{i=1}^{n}(q_i-p_i)^2}.$$



  2. Manhattan distance in the largest common signal strength vector subspace:

$$d_1(\mathbf{p},\mathbf{q}) = \|\mathbf{p}-\mathbf{q}\|_1 = \sum_{i=1}^{n}|p_i-q_i|,$$ mit $\mathbf{p}=(p_1,p_2,\dots,p_n)$ und $\mathbf{q}=(q_1,q_2,\dots,q_n)$



WLAN Fingerprinting – Computing the Position

- The position estimate can be computed from the set of kNN in different ways

1. Take the selected fingerprint if using 1NN
2. Compute the **center of mass** of kNN fingerprints:
   In this example, we have a vector r of fingerprints and each has a weight of m_i=1:

   $$\mathbf{R} = \frac{1}{M} \sum_{i=1}^{n} m_i \mathbf{r}_i,$$

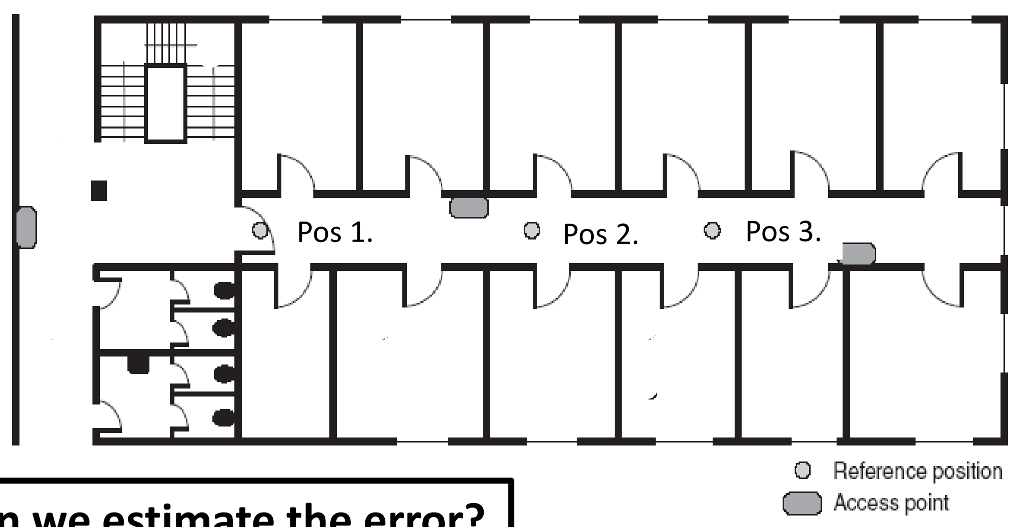
3. Compute a **weighted center of mass**:
   The weights m_i can be depend on the distance to the underlying measurement (penalty for very unsimilar fingerprints):

   $m_i = 1/d_i$

   $M = \sum m_i$

WLAN Fingerprinting – Example

- Imagine the following example
  - We collected a measurement $m = \begin{pmatrix} -65 \\ -57 \\ -71 \end{pmatrix}$
  - We work on the radio map presented before
  - The closest match is **Pos. 3** with an orientation of **90°**
  - Simplified example for the given radio map:



How can we estimate the error?

Estimating Positioning Errors

- Two categories of error estimations do exist:
  - Prediction of expected errors in advance
    a) Fingerprint Clustering
    b) Leave Out Fingerprint
  - Infer the expected position error from live measurements in the online phase
    c) Best Candidate Set
    d) Signal Strength Variance

Estimating Positioning Errors: Fingerprint Clustering (1)

Idea: As within given areas the fingerprints are nearly equal, a positioning system can‘t make an excact positioning assumption.

→ The real positition is expected to be anywhere in the area with a similar signal strength characteristic

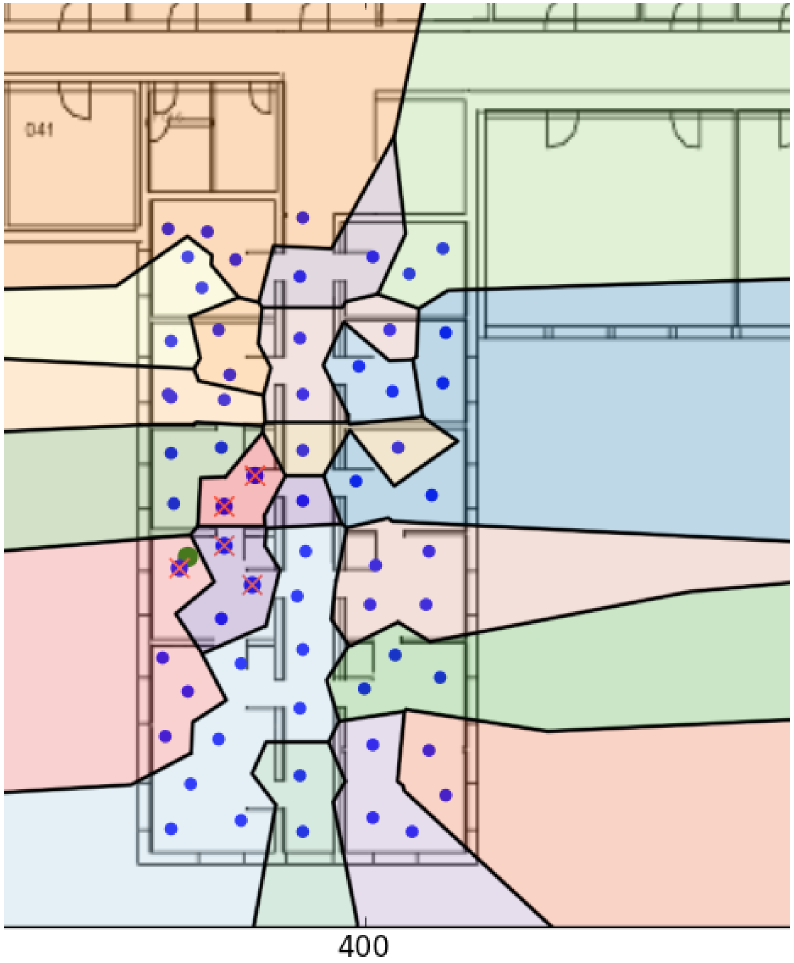
Steps of the algorithm:

1. Compute Voronoi-Cells for the offline fingerprint database. Each fingerprint is now embedded in a Voronoi-Cell. Each collected fingerprint is represented by a collection of measured samples.
2. Randomly select a cluster and merge it with a random neighboring cluster iff the similarity is greater than a given threshold.
3. Repeat this step until no pair of neighboring clusters suffices the threshold.
4. Merge single-cell clusters with their most similar neighboring cluster.
5. The error is deduced from the size of the area the cluster covers

Estimating Positioning Errors: Fingerprint Clustering (2)

A cluster map computed for the G-floor:

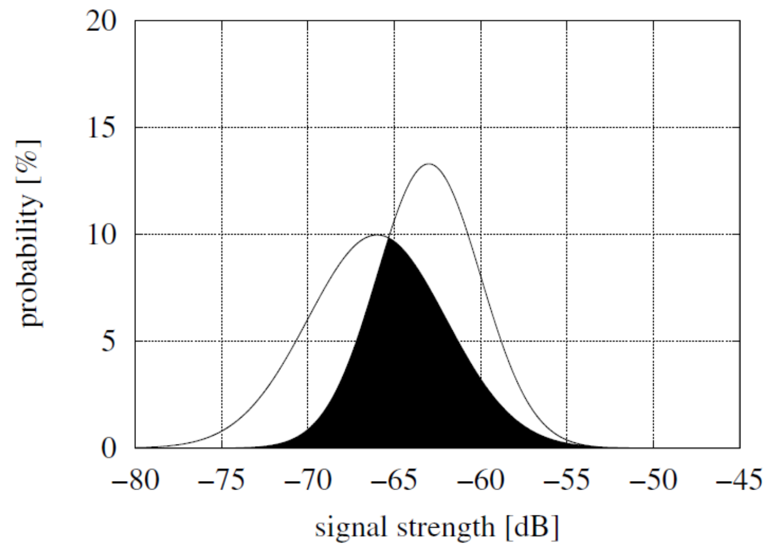
- Computed clusters are not deterministic
- and strongly related to the chosen threshold
- Here:
  - Initially 61 Fingerprints (Voronoi-Cells) have been reduced to 20 cells
  - The merge threshold was 0.4
  - Only one multi-cell cluster merge as the inter-fingerprint similarity is too high

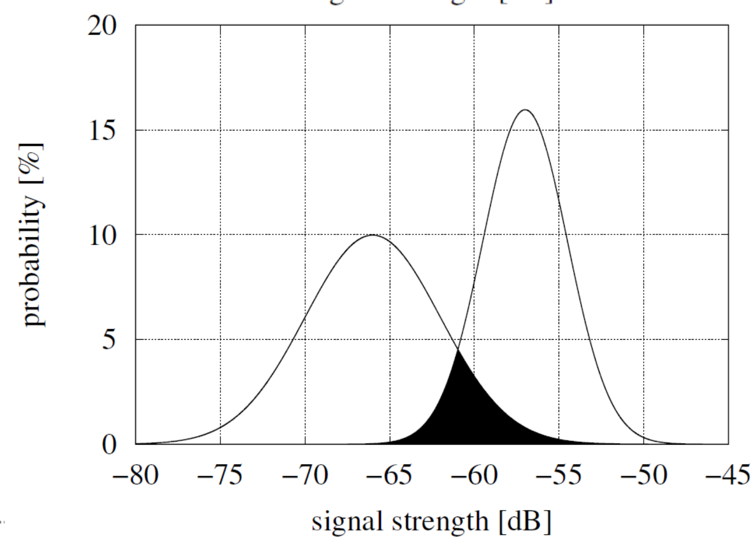


Estimating Positioning Errors: Fingerprint Clustering (3)

The distance between two clusters c1 and c2 is computed in the following way:

1. Compute the set of common access points
2. For each common access point in c1:
   i. Compute a gaussian from the collected samples in c1
   ii. Compute a gaussian from the collected samples in c2
   iii. Compute the overlap coefficient as:
   $\int_{-\infty}^{\infty} min(\text{c1.pdf}(x), \text{c2,pdf}(x))\, \text{d}x$
3. Return the similarity as the average overlap coefficient





Estimating Positioning Errors: Leave Out Fingerprint

- Estimation of the error by performing an analysis on the radio map:

Assumption: For each given FP on a position p, the signal strength has been collected in m samples

1. Compute the distance in the signal strength vector space to all the (n-1) other fingerprints and select the nearest. Store the geographical distance.
2. The error is computed as the average of all the geographical distances + 2 times the standard deviation

Estimating Positioning Errors: Best Candidate Set

- Estimate the error by either computing:
  - Computing the average geographical distance between the nearest and the k-1 nearest neighbors
  - Computing the maximum geographical distance between the nearest neighbor and any of the remaining k-1 nearest neighbors
  - Compute the maximum distance between any of the k nearest neighbors
- The latter two tend to highly overestimate the error when k is chosen large

Estimating Positioning Errors: Signal Strength Variance

- Small scale fading, multipath propagation etc. can lead to large changes in the measured signal strengths even for small movements
- If the variance of all samples in a FP is high, the probability that a FP far away might be selected is high too

1. For each AP in the samples of a FP, find the largest measured signal strength value (in dB)
2. Subtract this value from all the measured signal strength for this AP in all collected samples
3. Calculate the signal strength variance for each AP in this FP
4. Compute the average signal strength variance from the variances computed for each AP.

Comparing the Error Estimates

- The performance is measured by:
  distance difference = estimated_error – real_error

- The performance of the algorithms depends on the setting:

	Aarhus Dataset		Mannheim Dataset	
Algorithm	Avg. Error [m]	Std. Dev. [m]	Avg. Error [m]	Std. Dev. [m]
Fingerprint Clustering	2.24	2.91	1.90	1.09
Leave Out Fingerprint	4.68	3.53	1.95	1.47
Best Candidates Set	3.06	2.61	1.45	1.26
Signal Strength Variance	3.92	5.08	2.69	2.45
Random	3.58	2.84	3.43	2.39

Sensor Fusion

Idea:

- Refine the WLAN positioning with additional measurements from other sensor sources
  - Accelerometer
  - Gyroskope
  - Compass

How to combine several sensors (Sensor Fusion):

- Probability distributions
  - Kalman Filter
  - Particle Filter

Sensor Fusion: WLAN Positionierung

Offline phase:

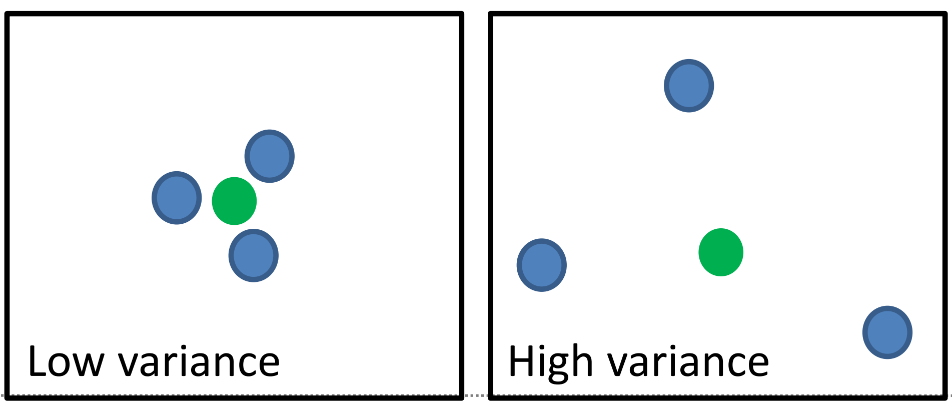
Recording of fingerprints (x, y, e, d, <MAC, RSSI>)

Online phase:

Distance computation between current signal strength measurment and fingerprints . One possibility:

Own position is estimated as the weighted average of k-Nearest-Neighbors (kNN) in signal space.

The reference positions of the neighbors allow for the etimation of variance:



Sensor Fusion: Step Detection

Recognition of steps with the help of the accelerometer.

Example: Recognition of a large drop in vertical acceleration.

Computation *(similar FootPath – IPIN 2011)***:**

- Ringbuffer with 5 entries (≈ 1 second by a sampling speed of 5Hz)
- Drop in vertical acceleration > $-2ms^{-2}$
  - step detected
  - empty buffer
- Else write current vertical acceleration to the buffer

Sensor Fusion: Particle Filter

„Recursive Bayesian filter for state etsimation of a dynamic system"

Assumptions:

- Current position is unknown but can be observed
- Observations are error-prone
- Position is modelled as probability distribution
- Discretisation of the distribution with a point cloud (particle)

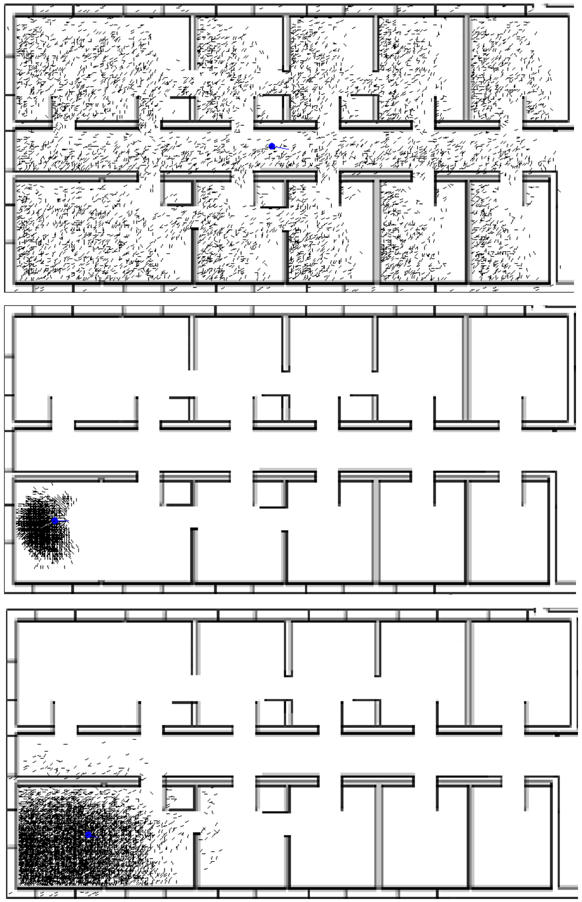
Three phases:

- Initialisation
  - creation of particles
- Prediction
  - propagation of particles
- Update
  - weighting of particles

Particle Filter: Initialisation

Different possibilities:

- Uniform distribution in building
- Point distribution at certain location
- Distribution according to initial measurement
  - for example WLAN fingerprinting
  - 2D Gaussian distribution
  - variance according to kNN

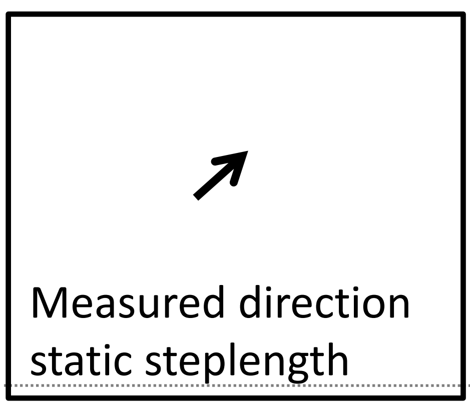


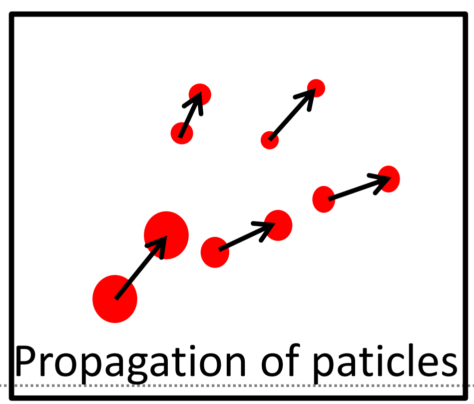
Particle Filter: Prediction

- Executed each time a step is detected
- Propagation of each particle x by a randomly disturbed steplength l in a randomly disturbed direction of the current compass readings d:

$$x_k^i = x_{k-1}^i + (l_{k-1} + \lambda_{k-1}^i)\begin{pmatrix}\cos(d_{k-1} + \theta_{k-1}^i)\\ \sin(d_{k-1} + \theta_{k-1}^i)\end{pmatrix}$$

- Gaussian distributed noise θ and λ
- Collision with walls let particles die (Map Matching)
- At certain occasions: creation of new particles





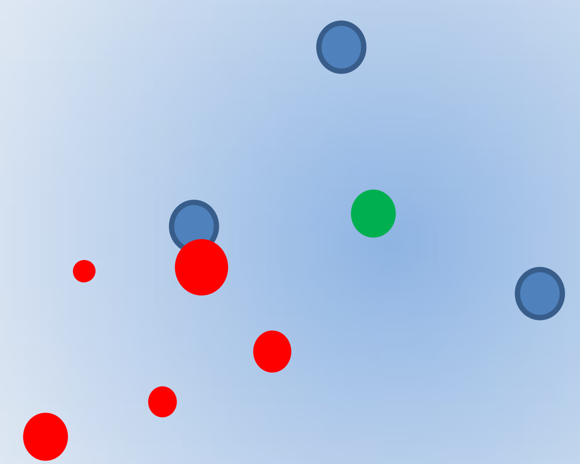
Particle Filter: Update

- Execution each time a WLAN scan was successful
- Calculate probability distribution based on WLAN positioning (e.g., Gaussian distibution $p(x_k^i \mid z_k) \sim \mathcal{N}_{\mu,\sigma}$)
- Update the weight w of each particle x accordingly:

$$w_k^i = p(x_k^i \mid z_k) \cdot w_{k-1}^i$$

- Finlally normalise the weight:

$$w_k^i = \frac{w_k^i}{\sum_i w_k^i}$$



Links & Videos

- **Multi-Sensor Pedestrian Indoor/Outdoor Navigation 2.5 D (DLR)**
  - http://www.youtube.com/watch?v=2NfSHNurOAc
- **Pedestrian Inertial Navigation and Map-Matching (DLR)**
  - http://www.youtube.com/watch?v=4ZdBtZdNEzg
- **Particle filters in action (University of Washington)**
  - http://www.cs.washington.edu/ai/Mobile_Robotics/mcl/

Practical Course

- A simple WLAN positioning system
  - Deterministic
  - Empirical
- Android classes
  - Broadcast Receiver
  - WifiManager (active scanning)
  - ScanResult