Positioning in Indoor Environments using WLAN Received Signal Strength Fingerprints

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2. Location Estimation Using RBF Networks

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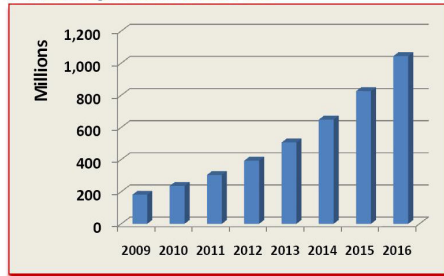
Why Indoor Positioning?

- People spend most of their time indoors, e.g. shopping malls, libraries, airports, university campuses

- Massive availability of mobile devices with wireless connectivity

- Satellite-based geolocation, e.g. GPS, is infeasible indoors

- Interest in indoor location-aware applications, e.g. in-building guidance, asset tracking, event detection

Time spent ...

indoor
outdoor

People spend 80-90% of their time indoors
70% of cellular calls and 80% of data connections originate from indoors.
(Source Strategy Analytics)

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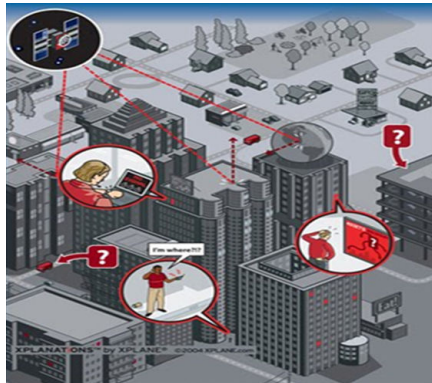
Global Smartphone Sales, 2009-2016

Source: Telecom Trends International, Inc.

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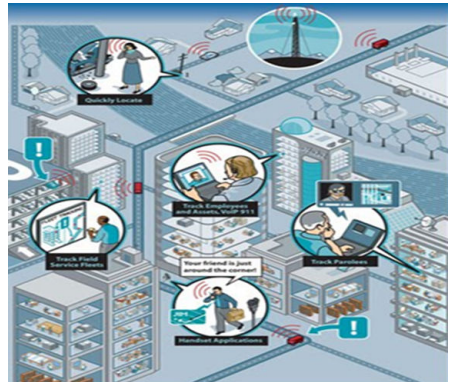Positioning with RSS fingerprints

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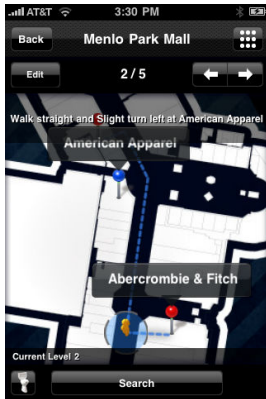
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Indoor Applications

Figure: FastMall

Figure: Aisle411

Figure: Micello

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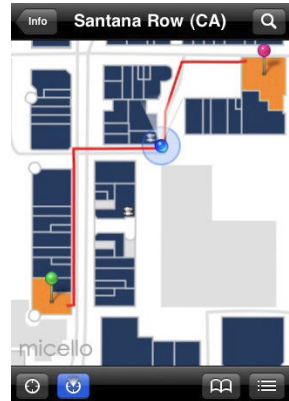
Indoor Applications

Figure: Point Inside (a mall)
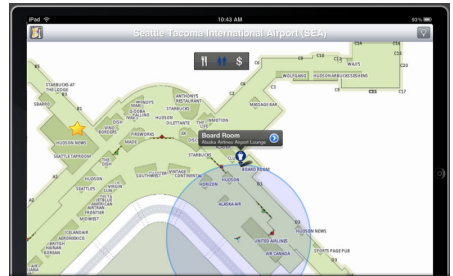
Figure: Point Inside (an airport)

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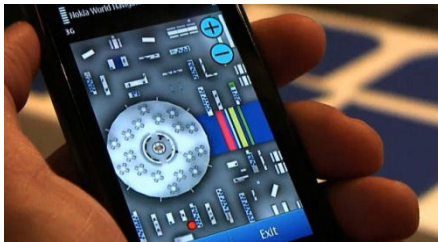
Figure: Nokia World Indoor Navigator

Figure: Indoor WiFi Tracker

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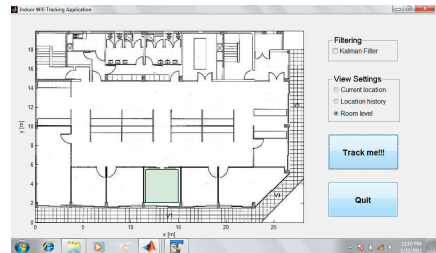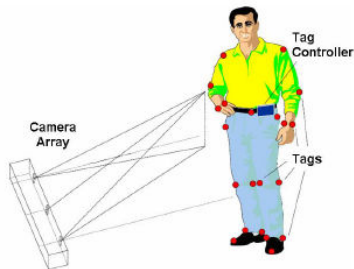**Overview of existing solutions**
Positioning with RSS fingerprints

Technologies for Indoor Positioning

- IR (e.g. Firefly)

- Ultrasound (e.g. Active Bat, Cricket)

- RFID (e.g. WhereNet)

- UWB (e.g. Ubisense)

- Cameras (e.g. Easy Living)

- WLAN (e.g. Ekahau)

Tag Controller

Camera Array

Tags

Why WLAN technology?

- Ubiquitous deployment of WLAN infrastructure (APs)

- Most mobile devices are equipped with WLAN adapters

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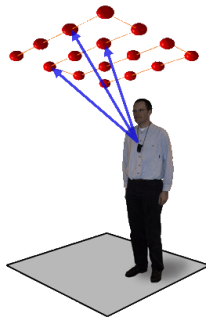- Cameras (e.g. Easy Living)

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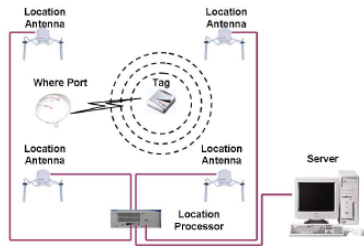- Cameras (e.g. Easy Living)

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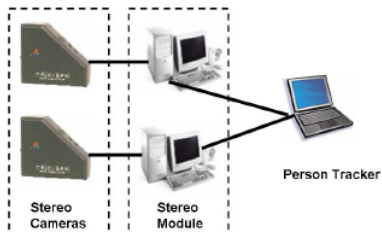- Cameras (e.g. Easy Living)

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Person Tracker

Stereo Cameras   Stereo Module

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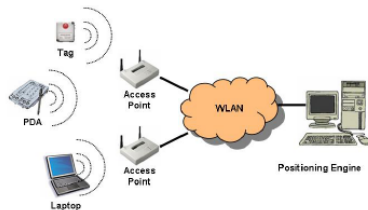- Cameras (e.g. Easy Living)

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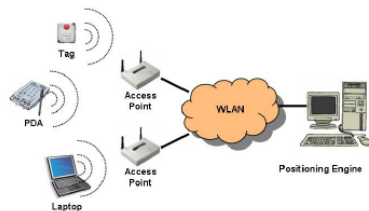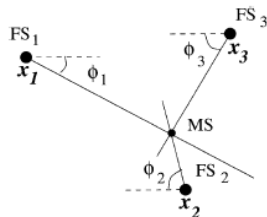- Cameras (e.g. Easy Living)

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Measurements and Algorithms

- Angle of Arrival (AOA)
- Time of Arrival (TOA)
  - $\tau_i = \frac{d_i}{c}$
- Time Difference of Arrival (TDOA)
  - $\rho_{i,j} = \frac{d_i - d_j}{c}$
- Received Signal Strength (RSS)
  - $rss_i = K - 10n \log d_i$ [dBm]

Why RSS measurements?

- AOA/TOA/TDOA measurements require additional hardware
- RSS values are constantly monitored and easily collected

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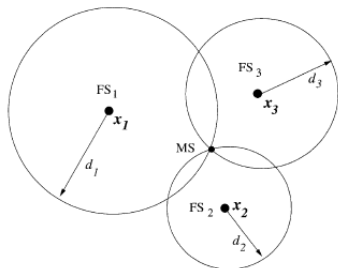
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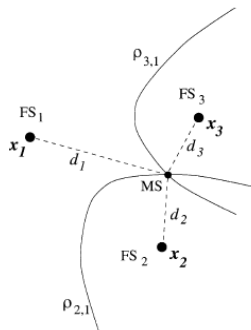 - $rss_i = K - 10n \log d_i$ [dBm]

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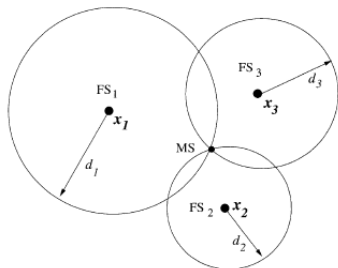 - $rss_i = K - 10n \log d_i$ [dBm]

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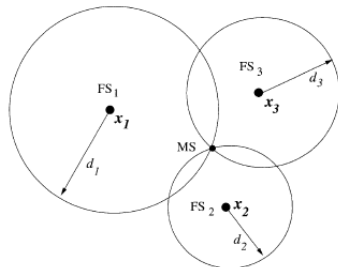 - $rss_i = K - 10n \log d_i$ [dBm]

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Attenuation Models vs Fingerprints

- Attenuation models are insufficient indoors
  - Complex propagation conditions (multipath, shadowing) due to walls and ceilings
  - RSS value fluctuates over time at a given location
  - Variable # of detected APs
  - Unpredictable factors (people moving, doors, humidity)

- Fingerprints
  - Capture the RSS-location dependency
  - More robust to signal variations

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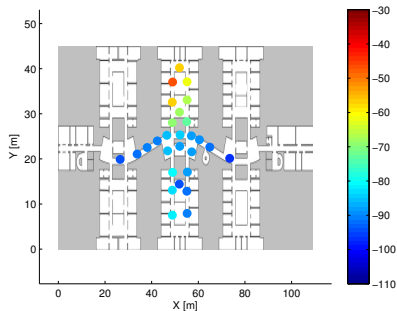**Positioning with RSS fingerprints**

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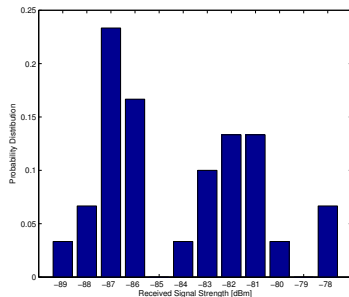**Positioning with RSS fingerprints**

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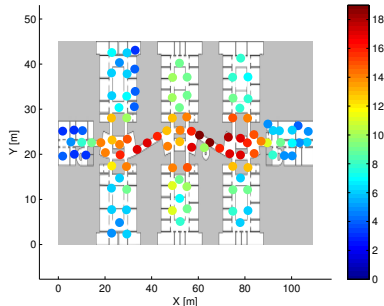Positioning with RSS fingerprints

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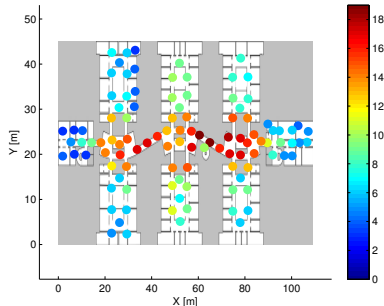**Positioning with RSS fingerprints**

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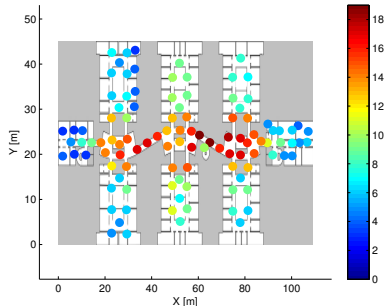Positioning with RSS fingerprints

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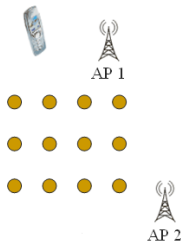   - More robust to signal variations

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Fingerprint-based Positioning

- **Offline phase:** Build RSS radio map
  - n APs deployed in the area
  - Fingerprints $r_i = [r_{i1}, \ldots, r_{in}]^T$
  - Series $r_i(t)$, $t = 1, \ldots, T$
  - Training set contains $N = I \cdot T$ fingerprints r^k, $k = 1, \ldots, N$
  - Averaging $\overline{r}_i = \frac{1}{T} \sum_{t=1}^{T} r_i(t)$

- **Online phase:** Positioning
  - Fingerprint $s = [s_1, \ldots, s_n]^T$ is observed
  - Obtain an estimate $\widehat{\ell}$ using the radio map

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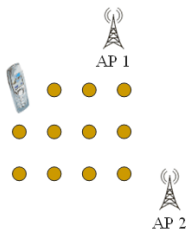
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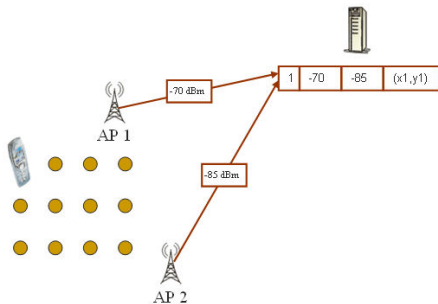**Positioning with RSS fingerprints**

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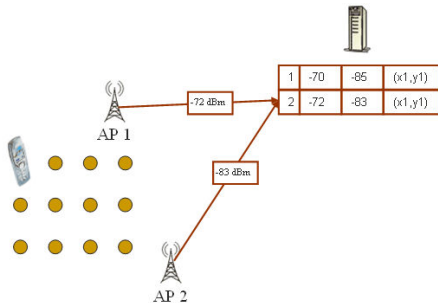- **Offline phase:** Build RSS radio map
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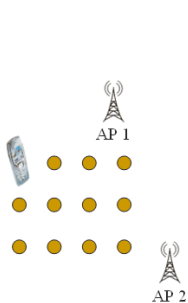

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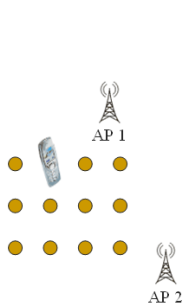

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  - Fingerprint $s = [s_1, \ldots, s_n]^T$ is observed
  - Obtain an estimate $\widehat{\ell}$ using the radio map

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Fingerprint-based Positioning
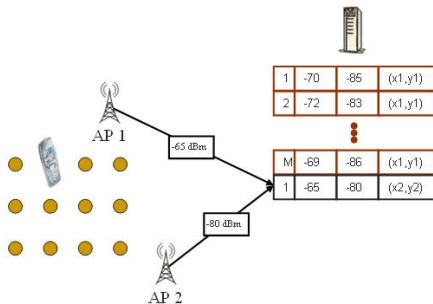

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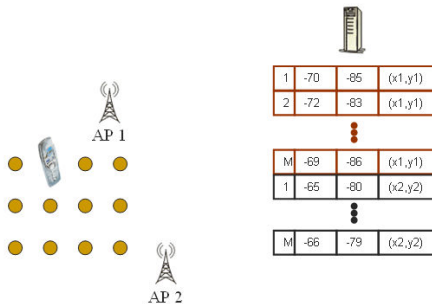

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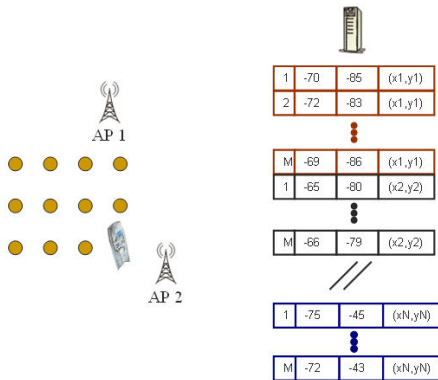

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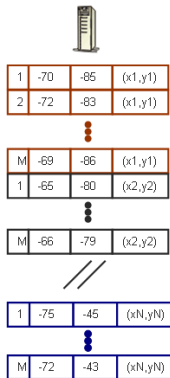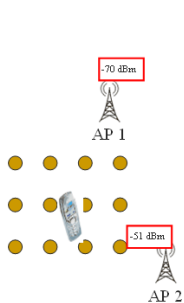

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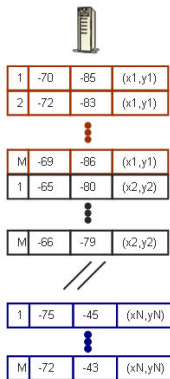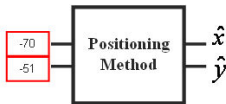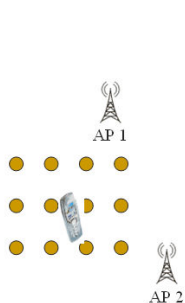 - Fingerprints $r_i = [r_{i1}, \ldots, r_{in}]^T$
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Deterministic Approach

Deterministic positioning methods

Location is estimated as a convex combination of the reference locations ℓ_i by using the K locations with the shortest distances between $\overline{r}_i$ and s.

$$\widehat{\ell} = \sum_{i=1}^{K} \frac{w_i}{\sum_{j=1}^{K} w_j} \ell_i' \tag{1}$$

where $\{\ell_1', \ldots, \ell_l'\}$ denotes the ordering of reference locations with respect to increasing distance $\|\overline{r}_i - s\|$.

K-Nearest Neighbor (KNN) variants

- NN: $K = 1$
- KNN: $K \neq 1$, $w_i = \frac{1}{K}$
- Weighted KNN: $K \neq 1$, $w_i = \frac{1}{\|\overline{r}_i - s\|}$

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Probabilistic Approach

Probabilistic positioning methods

Location ℓ is treated as a random vector that can be estimated by calculating the conditional probabilities $p(\ell_i|s)$ (*posterior*) given s.

$$p(\ell_i|s) = \frac{p(s|\ell_i)p(\ell_i)}{p(s)} = \frac{p(s|\ell_i)p(\ell_i)}{\sum_{i=1}^{I} p(s|\ell_i)p(\ell_i)} \quad (2)$$

$$p(s|\ell_i) = \prod_{j=1}^{n} p(s_j|\ell_i) \quad (3)$$

where $p(s|\ell_i)$ is the *likelihood*, $p(\ell_i)$ is the *prior* and $p(s)$ is a constant.
Positioning variants

- Maximum Likelihood (ML): $\widehat{\ell} = \arg\max_{\ell_i} p(s|\ell_i)$

- Maximum A Posteriori (MAP): $\widehat{\ell} = \arg\max_{\ell_i} p(s|\ell_i)p(\ell_i)$

- Minimum Mean Square Error (MMSE): $\widehat{\ell} = \mathbf{E}[\ell|s] = \sum_{i=1}^{I} \ell_i p(\ell_i|s)$

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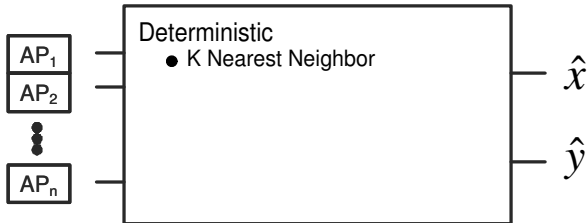Experimental Results
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RBF-based Positioning Method I

Data Regression

$$\ell(s) = \sum_{i=1}^{C} w_i u(s, c_i)$$

where $u(s, c_i) = \frac{\varphi(\|s-c_i\|)}{\sum_{j=1}^{C} \varphi(\|s-c_j\|)}$

- C: number of centers
- c_i: n-dimensional center
- $\varphi(\|s - c\|) = \exp\left(-\frac{1}{2}\|s - c\|^2\right)$
- w_i: 2-dimensional weights

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RBF-based Positioning Method
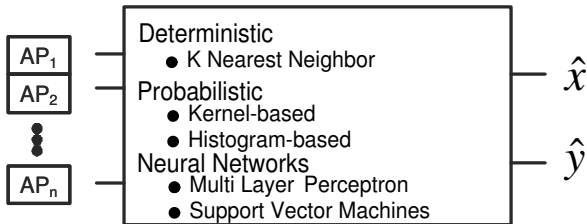Properties of the cRBF Positioning Method
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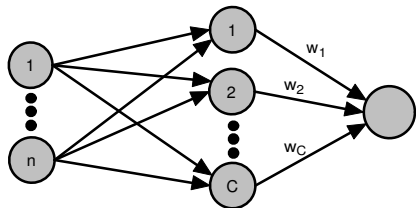
RBF-based Positioning Method II

Training (offline)

System of linear equations using the $N = I \cdot T$ reference fingerprints

$$\ell_i = \sum_{j=1}^{C} w_j u\big(r_i(t), c_j\big), \ i = 1, \ldots, I, \ t = 1, \ldots, T \tag{4}$$

Matrix form $\mathbf{Uw} = \mathbf{d}$

- $\mathbf{U} \in R^{N \times C}$: each row contains the responses to a particular fingerprint
- $\mathbf{w} \in R^{C \times 2}$: unknown weights
- $\mathbf{d} \in R^{N \times 2}$: outputs that represent the location coordinates

The weights can be easily determined through linear algebra.

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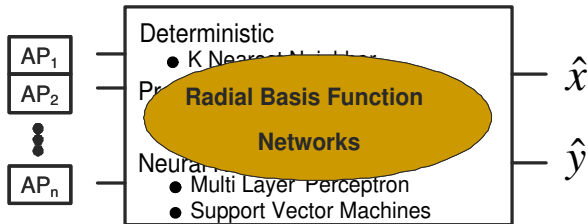Properties of the cRBF Positioning Method
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RBF-based Positioning Method III

Positioning (online)

$$\widehat{\ell}(s) = \sum_{j=1}^{C} w_j u(s, c_j) \tag{5}$$

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Center Selection

standard RBF (sRBF)

- $C = N$, i.e. $c_i = r^i, \; i = 1, \ldots, N$

- $w = U^{-1}d$

  - High memory requirements
  - Computational complexity (weight calculation and positioning)
  - Prone to overfitting

clustered RBF (cRBF)

- $C = l$, i.e. $c_i = \bar{r}_i, \; i = 1, \ldots, l$

- $w = U^{+}d, \; U^{+} = (U^{T}U)^{-1}U^{T}$

  - Better than selecting $C < N$ centers randomly or experimentally or by using a center selection algorithm (e.g. OLS)
  - Computationally efficient due to the compact size
  - Better generalization

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Distance Calculation

Set of basis functions

$$\varphi(\|s - c_j\|) = \exp\left(-\frac{1}{2}(s - c_j)^T \Sigma^{-1}(s - c_j)\right), \ j = 1, \ldots, C.$$

- $\Sigma = \sigma^2 I$, where σ^2 is a common variance (width) for all n APs
  - Select σ^2 experimentally and fine-tune with validation data
  - Use a heuristic so that $\sigma^2 \propto d_{max}$, where
    $d_{max} = \max \|c_i - c_j\|$ for $i, j = 1, \ldots, C$

- $\Sigma = diag(\sigma_1^2, \ \sigma_2^2, \ \ldots, \ \sigma_n^2)$
  - σ_k^2 is the sample variance of the k-th AP
  - Can be used to build an AP selection methodology for dimensionality reduction

- A non-diagonal covariance matrix Σ does not work well in practice, because the RSS values from neighboring APs are independent

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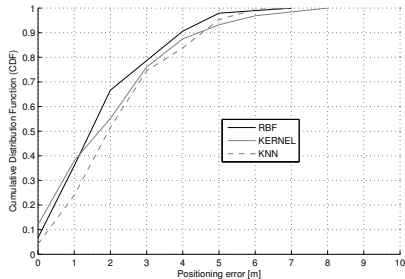Experimental Results
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Properties of the cRBF Positioning Method

- Reduced network size
  - Unknown weights are fast and easy to compute
  - Low memory requirements for storing few centers and weights
  - Low computational complexity during positioning

- Practicality & Scalability
  - Retraining time for new data is reduced with appropriate matrix operations (e.g. MLP has to be trained from scratch)
  - Network size is decided in a principled manner (e.g. MLP size is selected experimentally)
  - Easily scaled to other setups with different number of APs, reference locations or fingerprints

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Indoor Positioning System

- **Offline phase**
    1. Collect and store reference fingerprints
    2. Train RBF to determine network weights

- Online phase
    1. Transmit a small set of parameters
    2. Use the observed fingerprint to self-locate

- Properties
    1. Reduced start-up time
    2. Low communication overhead
    3. Privacy and Security

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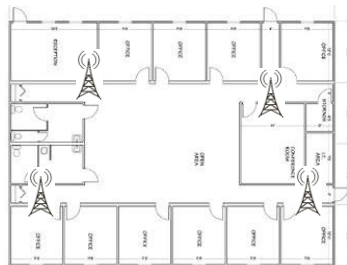
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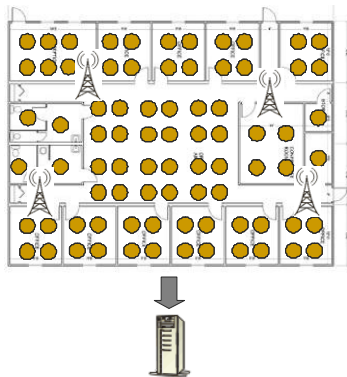
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RBF weights

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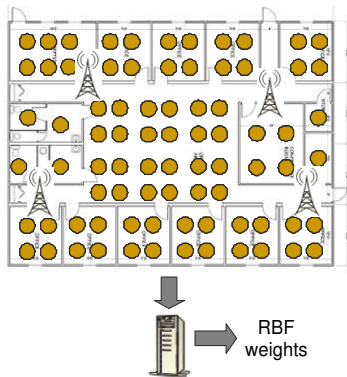- **Offline phase**
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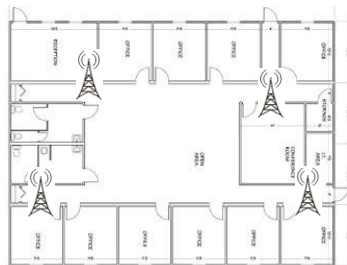# Indoor Positioning System

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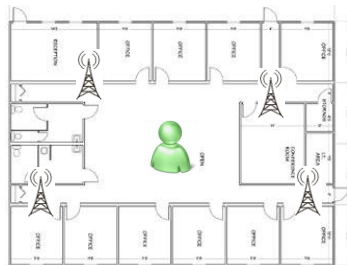- **Offline phase**
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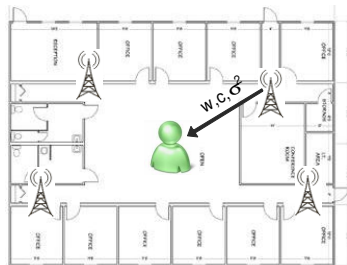- **Offline phase**
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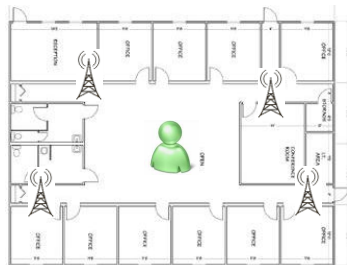# Indoor Positioning System

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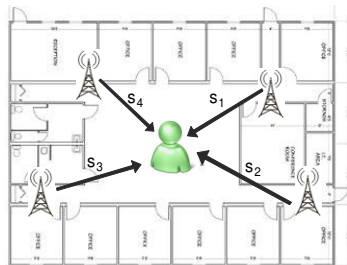- **Offline phase**
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SNAP Algorithm

Subtract on Negative Add on Positive (SNAP) algorithm

- Event detection in binary sensor networks
- Low computational complexity and fault tolerance

Objective

- Adapt the SNAP algorithm to the WLAN setup
- Enhance the performance in terms of **fault tolerance** and **accuracy**

Methodology

- Modify the original SNAP algorithm to use WLAN RSS fingerprints
- Examine the **fault tolerance** of SNAP using our fault models
- Improve the **accuracy** by exploiting the RSS levels in the fingerprints

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Positioning with Binary Data

SNAP Algorithm

1. *Region of Coverage (RoC)*
   $RoC_j \subseteq L, \ j = 1, \dots, n$

2. *Likelihood Matrix $\mathcal{L}$*

   $$\mathcal{L}(i,j) = \begin{cases} +1, & j \in S \text{ AND } \ell_i \in RoC_j \\ -1, & j \notin S \text{ AND } \ell_i \in RoC_j \\ 0, & \ell_i \notin RoC_j \end{cases}$$

   $$LV_i = \sum_{j=1}^{n} \mathcal{L}(i,j)$$

3. *Location Estimation*

   $$\widehat{\ell}(s) = \arg\max_{\ell_i \in L} LV_i$$

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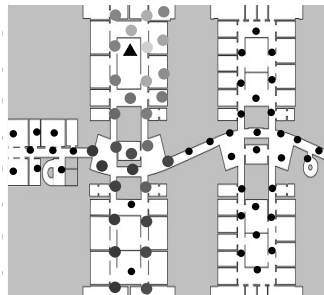 $RoC_j \subseteq L, \ j = 1, \ldots, n$

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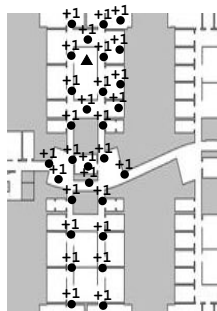 $RoC_j \subseteq L, \ j = 1, \ldots, n$

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SNAP Algorithm

1. *Region of Coverage (RoC)*
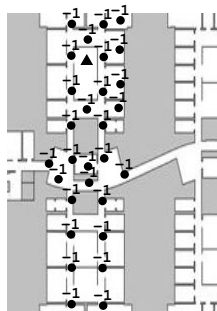 $RoC_j \subseteq L, \ j = 1, \ldots, n$

2. *Likelihood Matrix $\mathcal{L}$*

   $$\mathcal{L}(i,j) = \begin{cases} +1, & j \in S \text{ AND } \ell_i \in RoC_j \\ -1, & j \notin S \text{ AND } \ell_i \in RoC_j \\ 0, & \ell_i \notin RoC_j \end{cases}$$

   $$LV_i = \sum_{j=1}^{n} \mathcal{L}(i,j)$$

3. *Location Estimation*

   $$\widehat{\ell}(s) = \arg \max_{\ell_i \in L} LV_i$$

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SNAPz: Improving the Accuracy of SNAP I

Idea

If an AP is detected, then the user is more likely to reside in the locations inside the *RoC* that have similar RSS values to the observed RSS value.

Zone of Coverage (ZoC)

$$Z_m = \left[min + (m-1)\frac{max - min}{M}, \ min + m\frac{max - min}{M}\right], \ m = 1, \ldots, M$$

- $ZoC_{mj} \subseteq RoC_j, \ m = 1, \ldots, M$ and $j = 1, \ldots, n$
- $\{ZoC_{mj} : \ell_i | \bar{r}_{ij} \in Z_m, \ i = 1, \ldots, l\}$
- $RoC_j = \bigcup_{m=1}^{M} ZoC_{mj}$

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SNAPz: Improving the Accuracy of SNAP II

SNAPz algorithm

$$\mathcal{L}(i,j) = \begin{cases} +1, & j \in S \text{ AND } \ell_i \in ZoC_{mj} \\ 0, & j \in S \text{ AND } \ell_i \in ZoC_{(m-1)j} \cup ZoC_{(m+1)j} \\ -1, & j \in S \text{ AND } \ell_i \in RoC_j - \bigcup_{k=m-1}^{m+1} ZoC_{kj} \\ -1, & j \notin S \text{ AND } \ell_i \in RoC_j \\ 0, & \ell_i \notin RoC_j \end{cases}$$

If an AP is detected with certain RSS value, then the user resides

- with high probability in the zone where the reference locations have similar RSS values

- with some probability in the neighboring zones

- with low probability in the remaining zones

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Experimental Results I
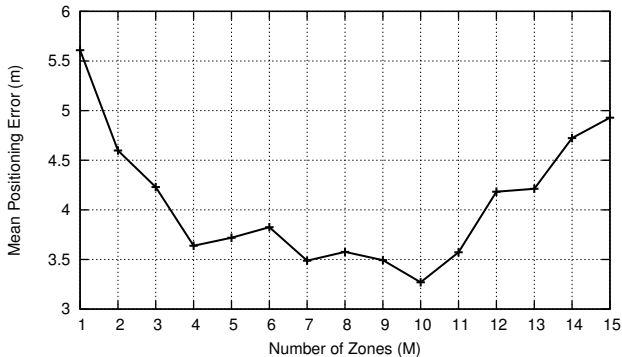
Figure: Performance of SNAPz for varying number of zones.

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Experimental Results II

Table: Positioning Error in meters

	Mean	Median	Std	Min	Max
KNN	2.70	2.39	1.61	0.16	8.78
MMSE	2.46	2.18	1.63	0.09	8.99
cRBF	2.38	2.07	1.51	0.08	7.87
SNAPz	3.64	3.37	2.41	0.06	13.21

Table: Computational Complexity

	additions	multiplications	exp	sorts	time (msec)
KNN	$(2n-1)l$	nl	0	l	1.25
MMSE	$(2n+3)l-3$	$(2n+4)l$	nl	0	2.18
cRBF	$(2n+2)l-3$	$(n+3)l$	l	0	1.73
SNAPz	$(n-1)l$	0	0	l	0.49

l: # of reference locations, n: # of APs, sorts: # of floats to be sorted

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Outline

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Concluding Remarks

- Introduction to indoor positioning and fingerprint methods
- Fingerprint positioning method based on RBF networks
  - High level of accuracy, scalable and applicable in different WLAN setups
  - Positioning system based on the proposed RBF method
- SNAP algorithm with WLAN RSS fingerprints
  - Trade-off between positioning accuracy and computational complexity
  - Investigate the actual power savings on mobile devices

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Open Research Issues

Main focus of fingerprint positioning methods so far has been on reducing the positioning error.

Computational Complexity

Time required to estimate location is important, because it affects the battery life of low power mobile devices.

Fault Tolerance

It is desirable to provide smooth performance degradation in the presence of faults, due to unpredicted failures or malicious attacks.

Heterogeneous Devices

Maintain an adequate level of accuracy for various types of devices (different WLAN adapters), without collecting device-specific fingerprints.

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Thank you for your attention