
Using Area-based Presentations and Metrics for Localization Systems in Wireless LANs

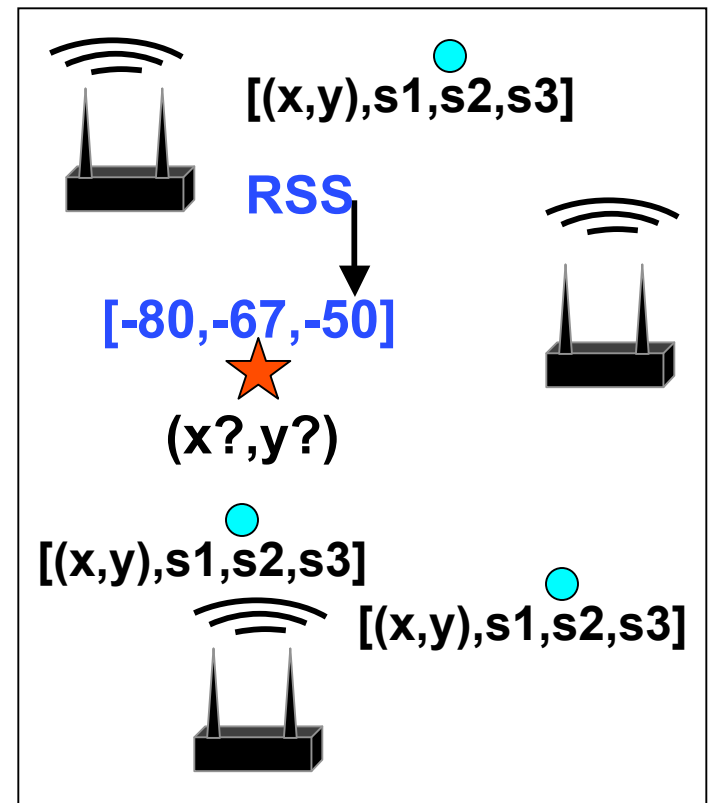
E. Elnahrawy, X. Li, and R. Martin
Rutgers U.

WLAN-Based Localization

- Localization in indoor environments using 802.11 and Fingerprinting
- Numerous useful applications
- Dual use infrastructure: a huge advantage

Background: Fingerprinting Localization

- Classifiers/matching/learning approaches
- Offline phase:
 - Collect training data (fingerprints)
 - Fingerprint vectors: $[(x,y),SS]$
- Online phase:
 - Match RSS to existing fingerprints probabilistically or using a distance metric

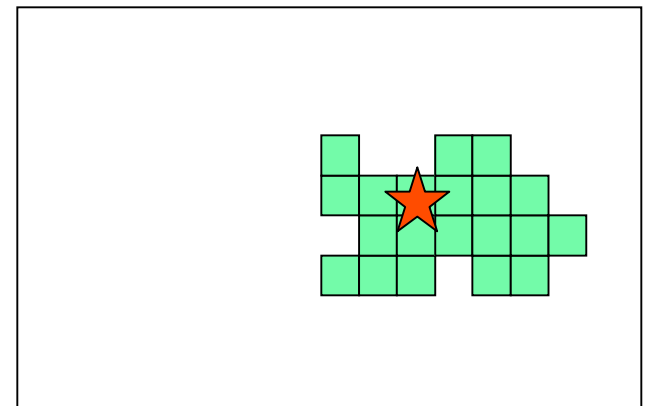


Background (cont)

- Output:
 - A single location: the closest/best match
 - We call such approaches “Point-based Localization”
 - Examples:
 - RADAR
 - Probabilistic approaches
- [Bahl00, Ladd02, Roos02, Smailagic02, Youssef03, Krishnan04]

Contributions: Area-based Localization

- Returned answer is area/volume likely to contain the localized object
- Area is described by a set of tiles
- Ability to describe uncertainty
 - Set of highly possible locations



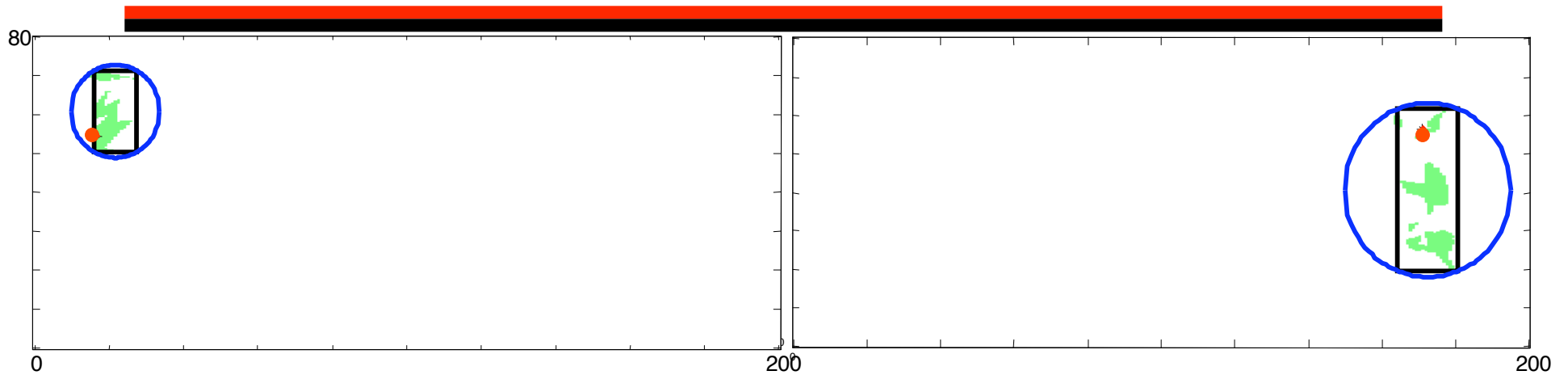
Contributions: Area-based Localization

- Show that it has critical advantages over point-based localization
- Introduce new performance metrics
- Present two novel algorithms: SPM and ABP-c
- Evaluate our algorithms and compare them against traditional point-based approaches
- Related Work: different technologies/algorithms [Want92, Priyantha00, Doherty01, Niculescue01, Savvides01, Shang03, He03, Hazas03, Lorincz04]

Why Area-based?

- Noise and systematic errors introduce position uncertainty
- Areas improve system's ability to give meaningful alternatives
 - A tool for understanding the confidence
 - Ability to trade Precision (area size) for Accuracy (distance the localized object is from the area)
 - Direct users in their search
 - Yields higher overall accuracy
- Previous approaches that attempted to use areas only use them as intermediate result → output still a single location

Area-based vs. Single-Location



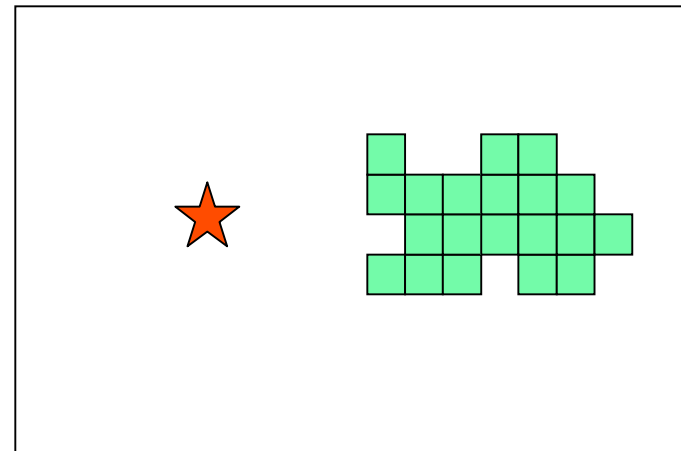
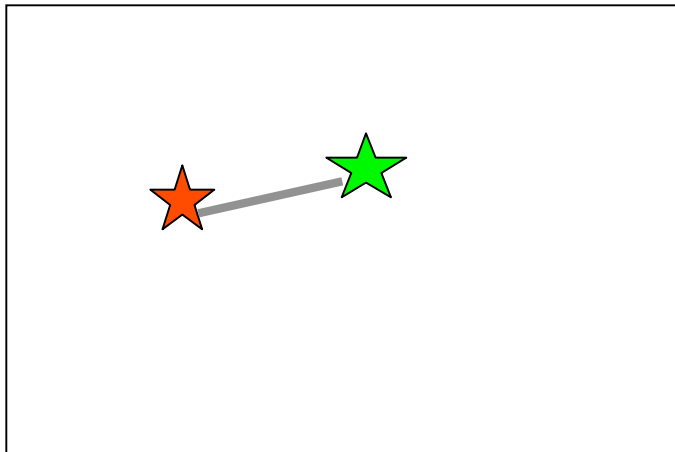
- Object can be in a single room or multiple rooms
- Point-based to areas
 - Enclosing circles -- much larger
 - Rectangle? no longer point-based!

Outline

- Introduction, Motivations, and Related Work
- Area-based vs. Point-based localization
- Metrics
- Localization Algorithms
 - Simple Point Matching (SPM)
 - Area-based Probability (ABP-c)
 - Interpolated Map Grid (IMG)
- Experimental Evaluation
- Conclusion, Ongoing and Future Work

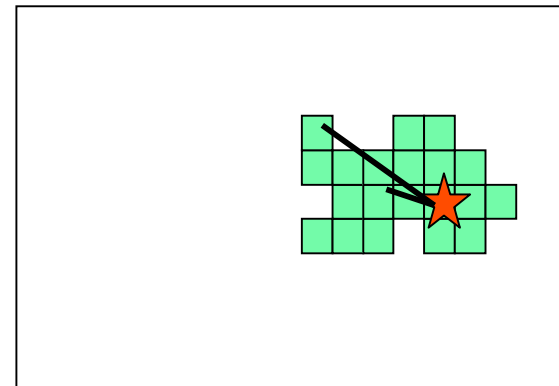
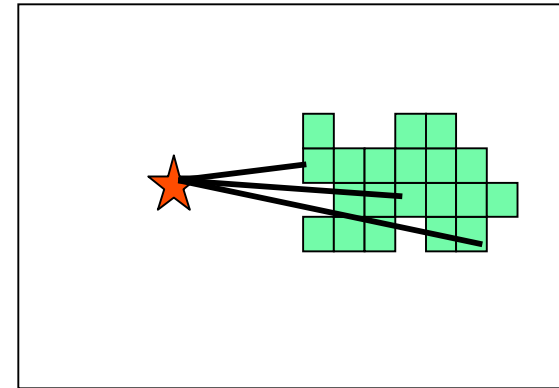
Performance Metrics

- Traditional: **Distance error between returned and true position**
 - Return avg, 95th percentile, or full CDF
 - Does not apply to area-based algorithms!
 - Does not show accuracy-precision tradeoffs!



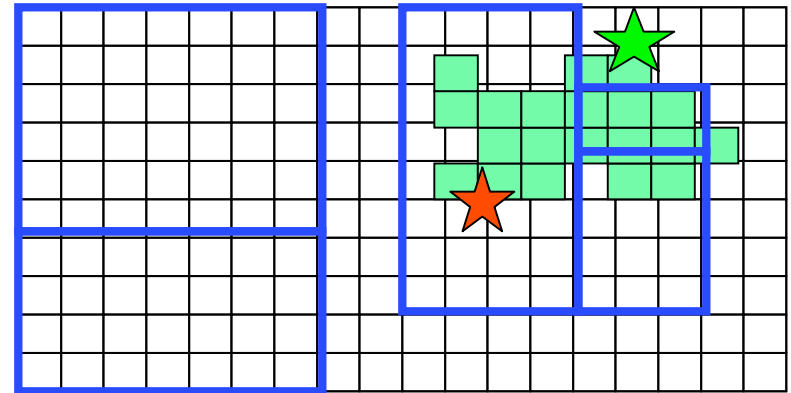
New Metrics: Accuracy Vs. Precision

- Tile Accuracy % true tile is returned
- Distance Accuracy distance between true tile and returned tiles (sort and use percentiles to capture distribution)
- Precision size of returned area (e.g., sq.ft.) or % floor size



Room-Level Metrics

- Applications usually operate at the level of rooms
- Mapping: divide floor into rooms and map tiles
 - (Point -> Room): easy
 - (Area -> Room): tricky



Metrics: accuracy-precision

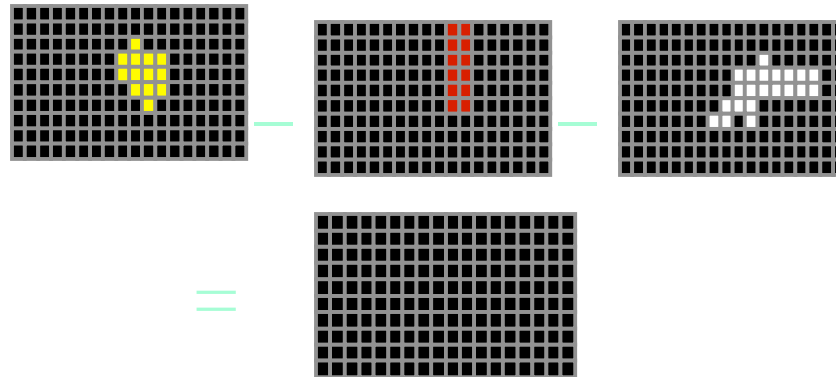
Room Accuracy % true room is the returned room

Top-n rooms Accuracy % true room is among the returned rooms

Room Precision avg number of returned rooms

1. Simple Point Matching (SPM)

- Build a regular grid of tiles, match expected fingerprints
- Find all tiles which fall within a “threshold” of RSS for each AP



- Eager: start from low threshold (s , $2s$, $3s$, ...)
- Threshold is picked based on the standard deviation of the received signal
- Similar to Maximum Likelihood Estimation

2. Area-Based Probability (ABP-c)

Build a regular grid of tiles, tile _ expected fingerprint

Using “Bayes’ rule” compute likelihood of an RSS matching the fingerprint for each tile

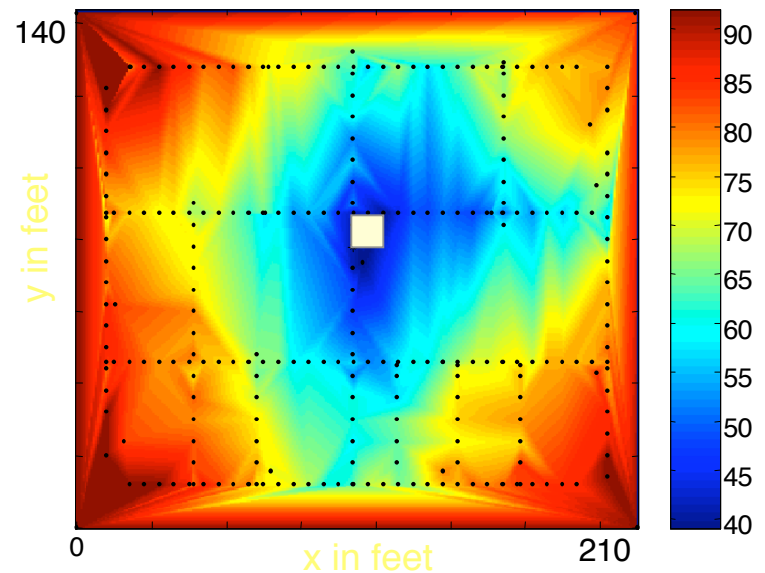
$$p(T_i|RSS) \propto p(RSS|T_i) \cdot p(T_i)$$

Return top tiles bounded by an overall probability that the object lies in the area (Confidence: user-defined)

Confidence _ _ Area size _

Measurement At Each Tile Is Expensive!

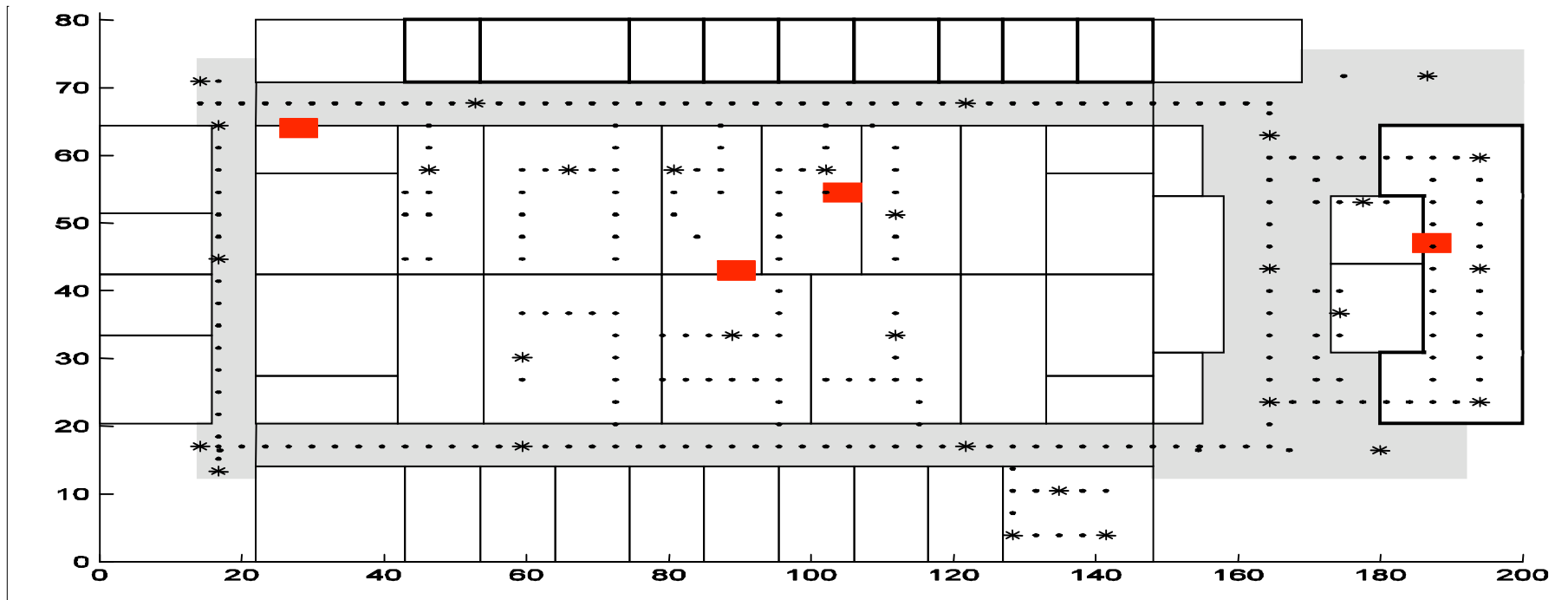
- Interpolated Map Grid: (Surface Fitting)
- Goal: Extends original training data to cover the entire floor by deriving an expected fingerprint in each tile
- Triangle-based linear interpolation using “Delaunay Triangulation”
- Advantages:
 - Simple, fast, and efficient
 - Insensitive to the tile size



Impact of Training on IMG

- Both location and number of training samples impact accuracy of the map, and localization performance
- Number of samples has an impact, but not strong!
 - Little difference going from 30-115, no difference using > 115 training samples
- Different strategies [Fixed spacing vs. Average spacing]: as long as samples are “uniformly distributed” but not necessarily “uniformly spaced” methodology has no measurable effect

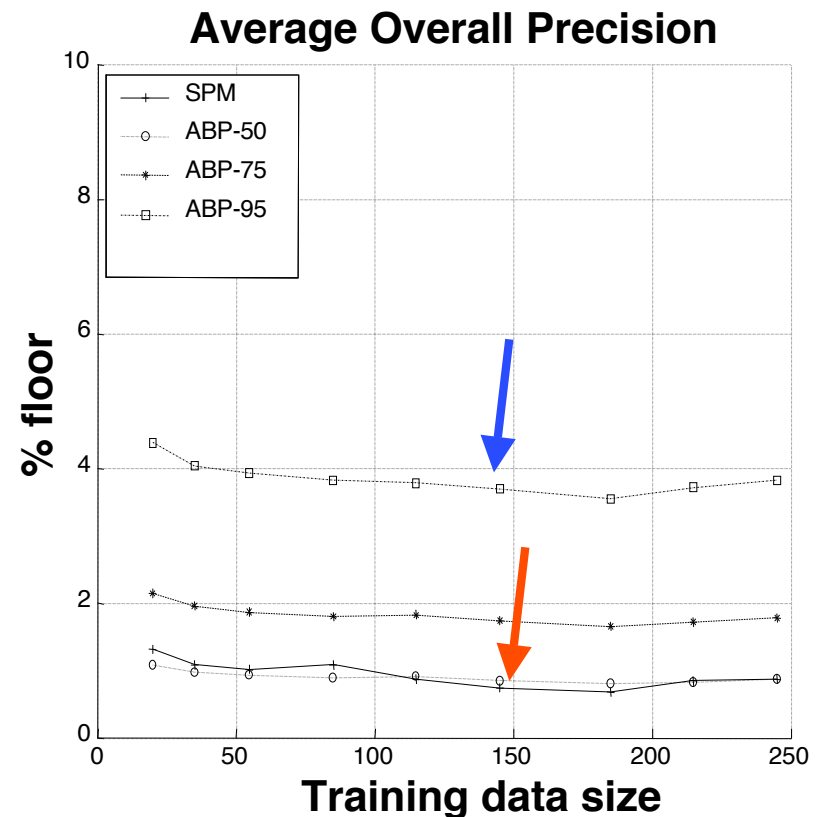
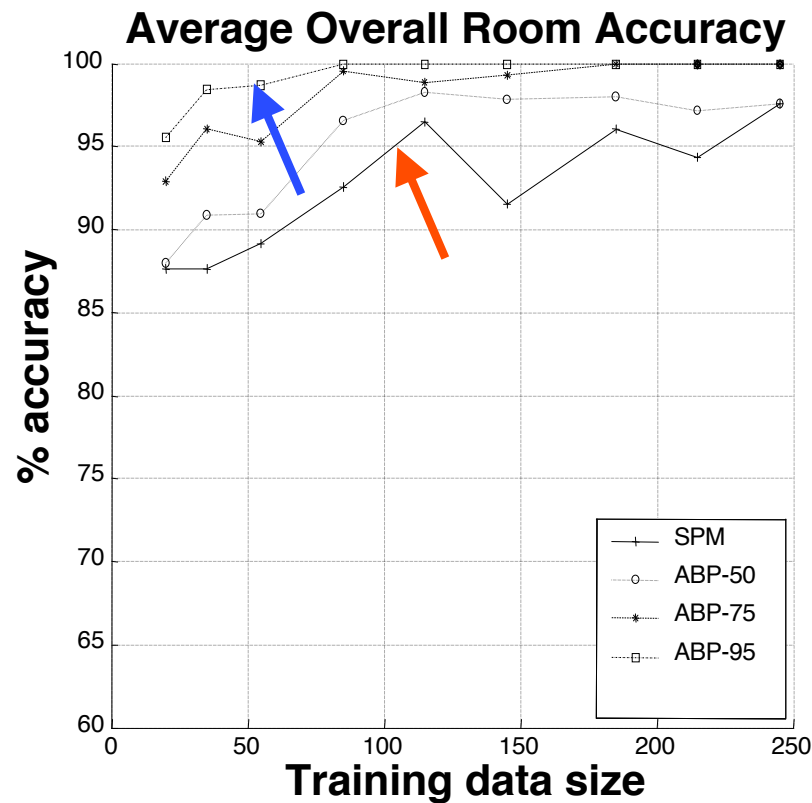
Experimental Setup



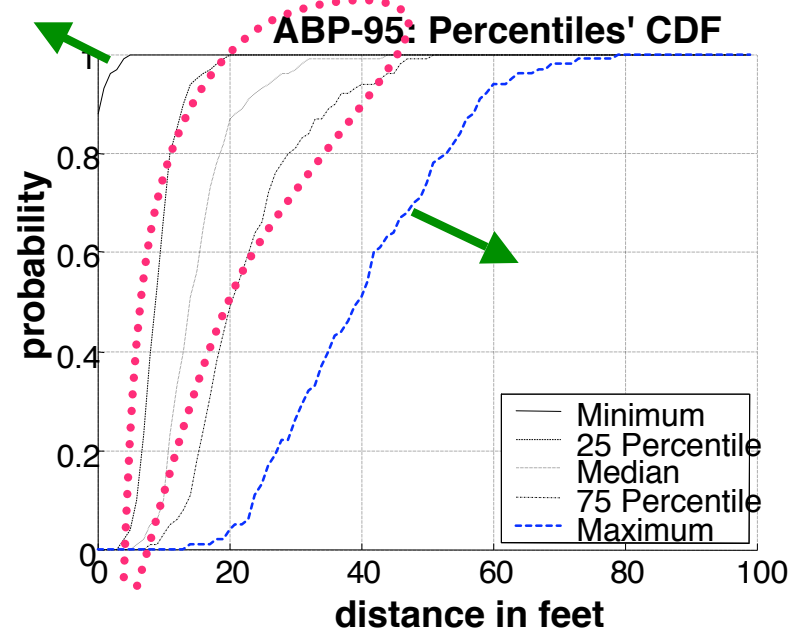
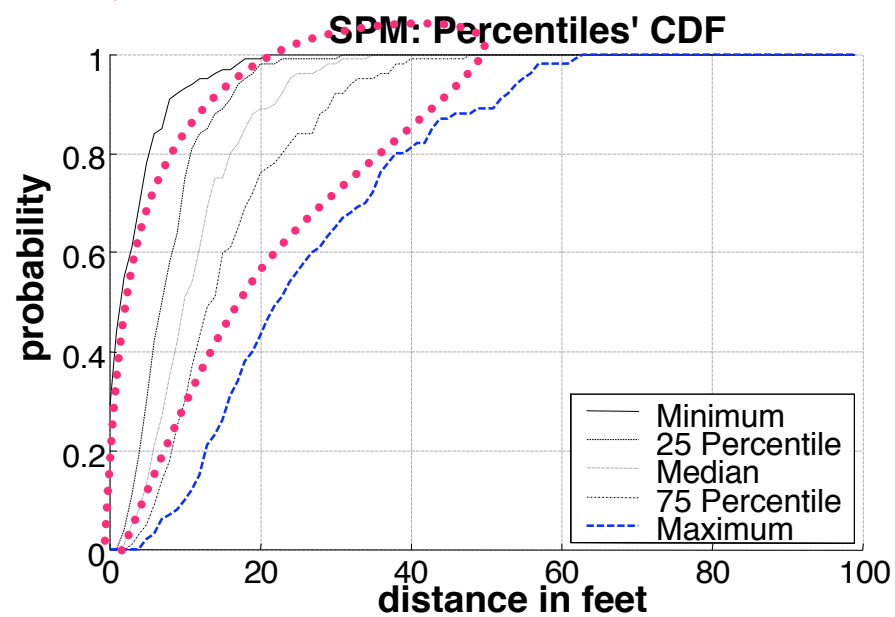
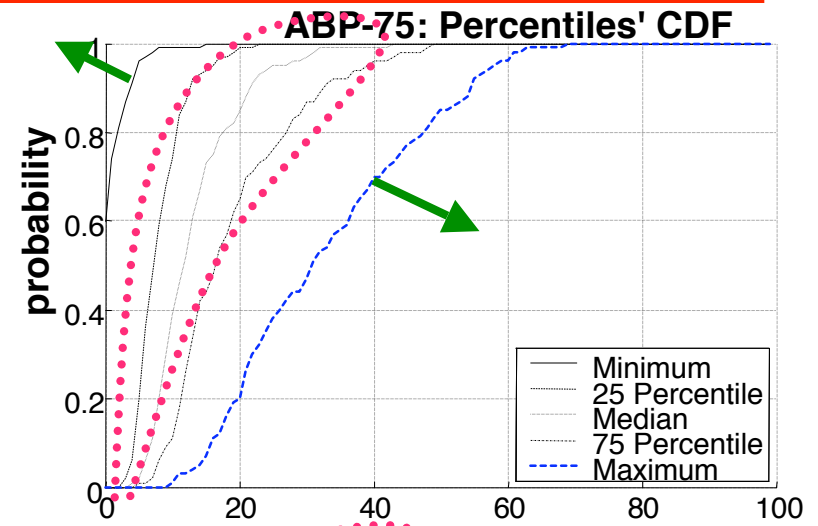
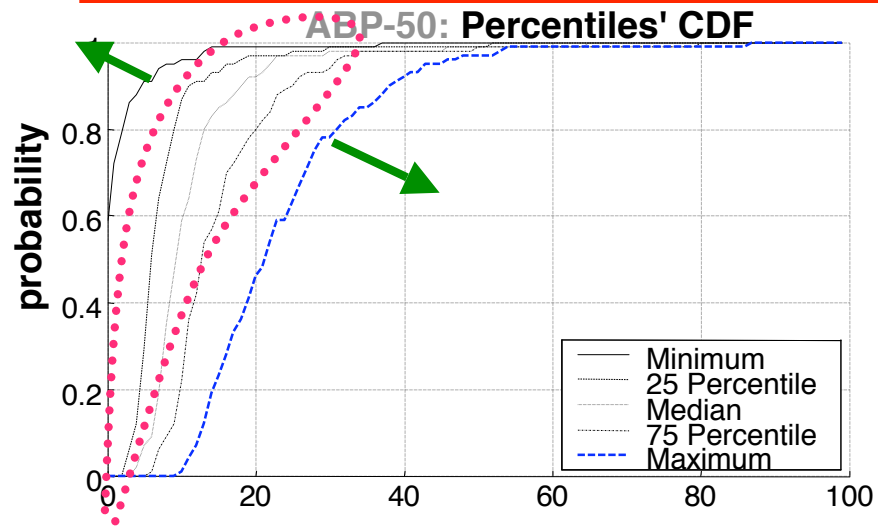
- CoRE
- 802.11 data: 286 fingerprints (rooms + hallways)
- 50 rooms
- 200x80 feet
- 4 Access Points

Area-based Approaches: Accuracy-Precision Tradeoffs

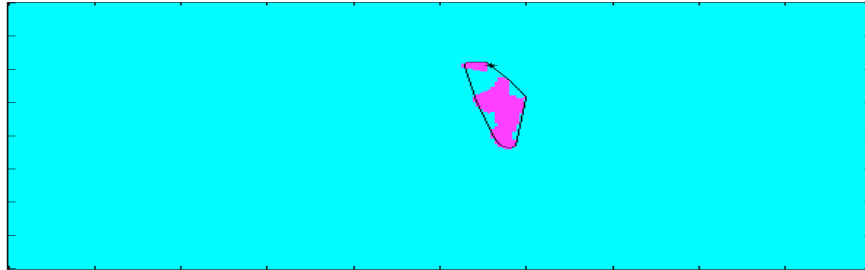
- Improving Accuracy worsens Precision (tradeoff)



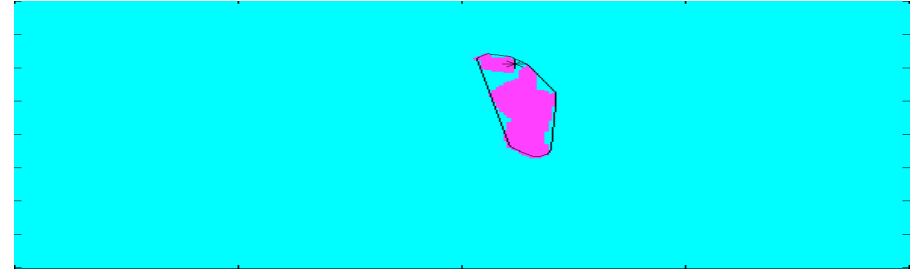
A Deeper Look Into “Accuracy”



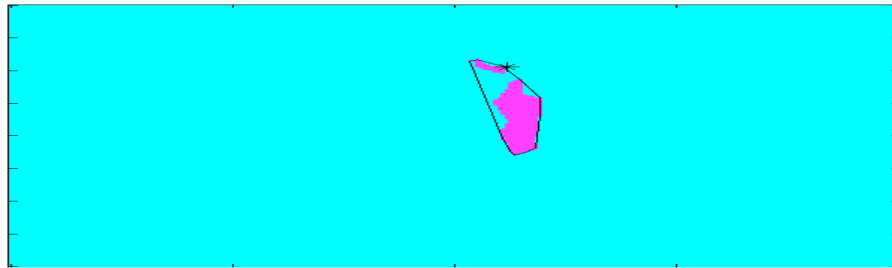
Sample Outputs



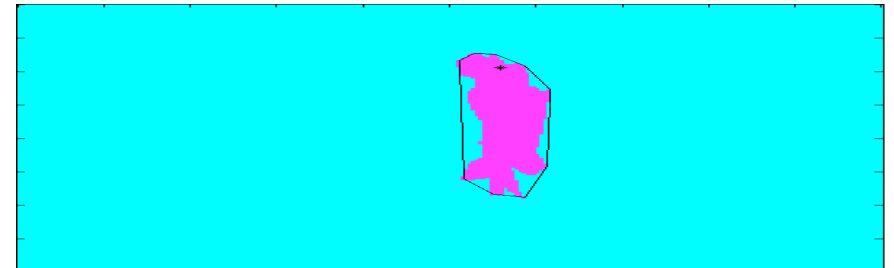
ABP-50



ABP-75



SPM



ABP-95

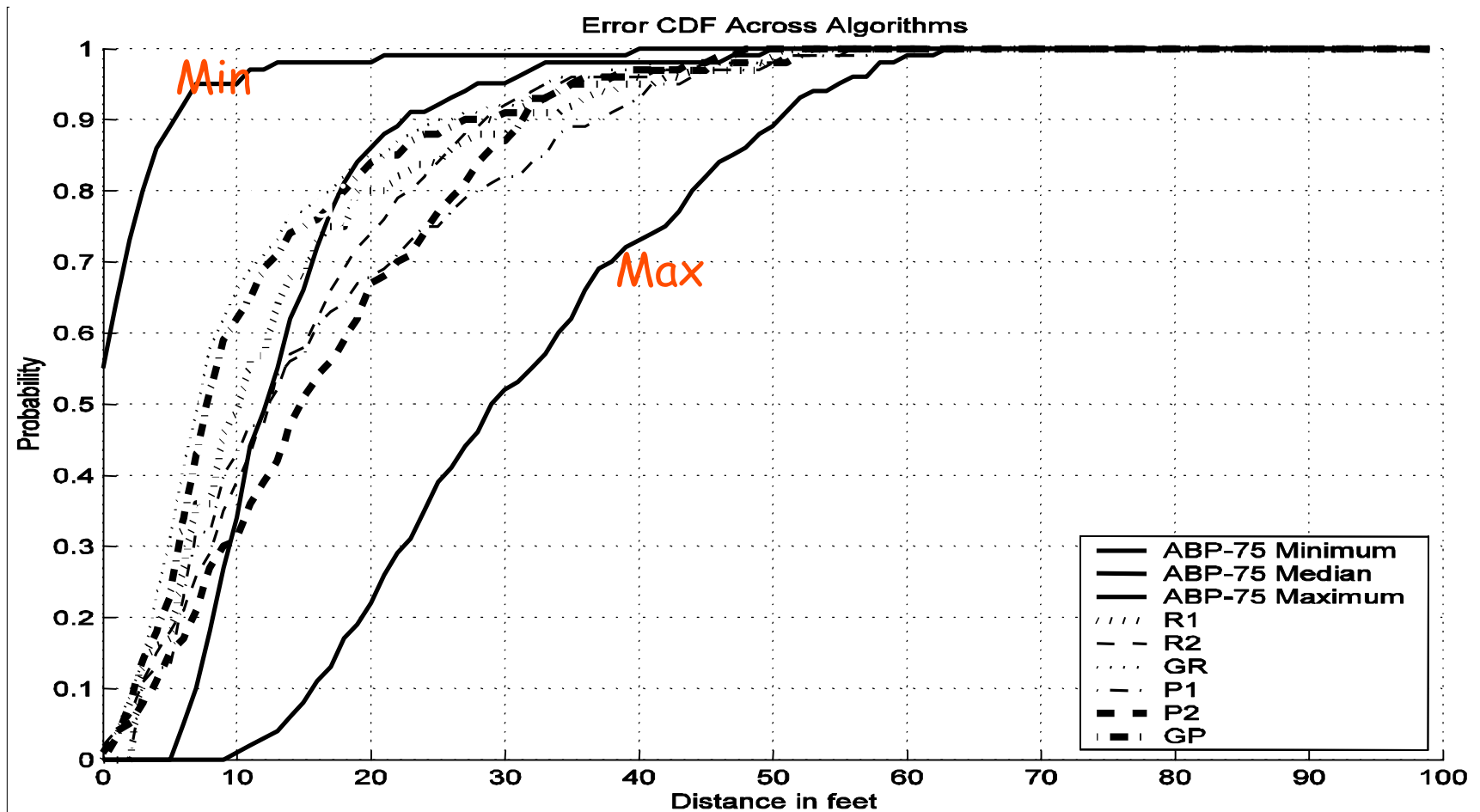
- Area expands into the true room
- Areas illustrate bias across different dimensions (APs' location)

Comparison With Point-based localization: Evaluated Algorithms

- **RADAR**
 - Return the “closest” fingerprint to the RSS in the training set using “Euclidean Distance in signal space” (R1)
- **Averaged RADAR (R2), Gridded RADAR (GR)**
- **Highest Probability**
 - Similar to ABP: a typical approach that uses “Bayes’ rule” but returns the “highest probability single location” (P1)
- **Averaged Highest Probability (P2), Gridded Highest Probability (GP)**

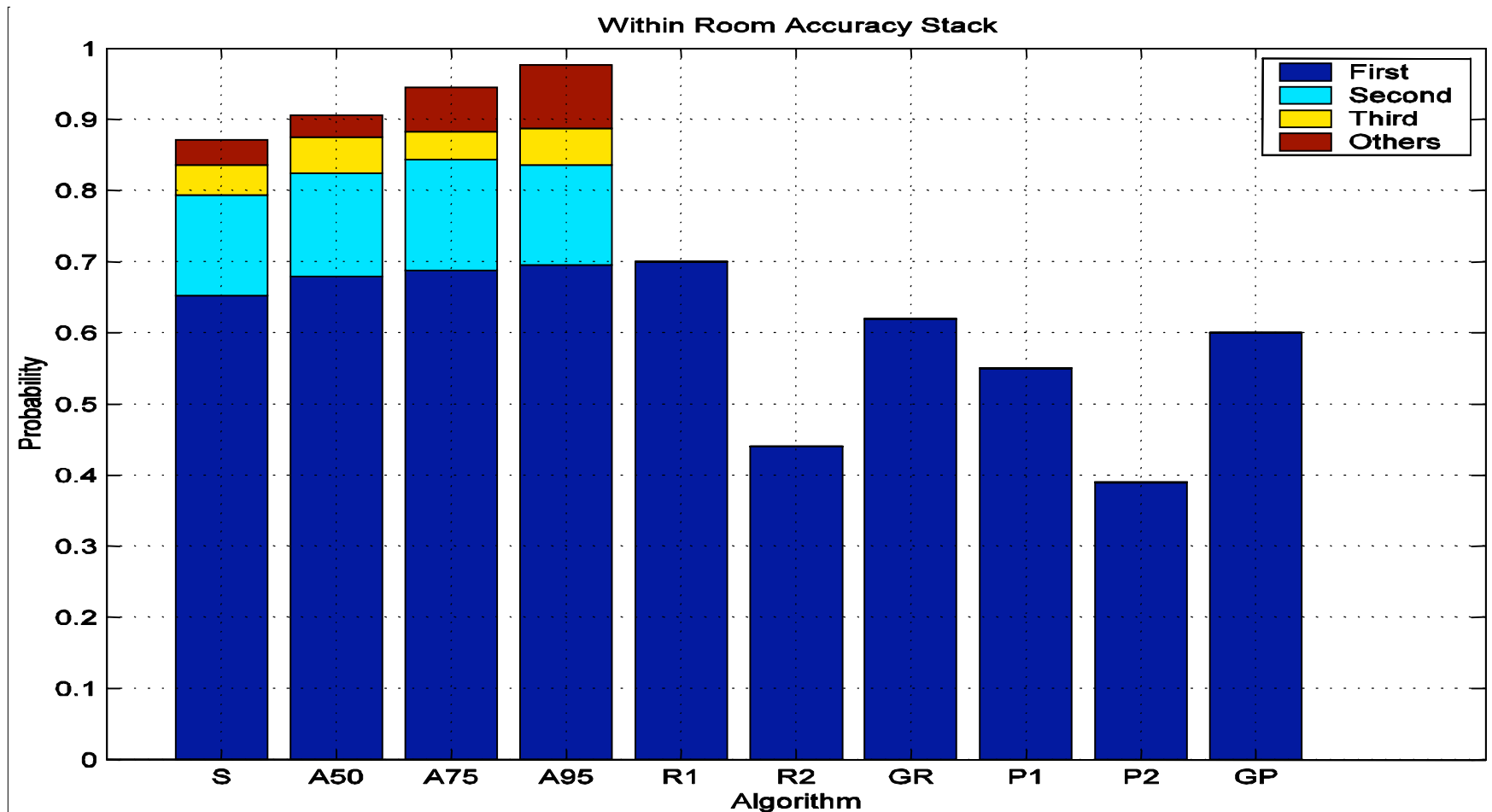
Comparison With Point-based Localization: Performance Metrics

- Traditional error along with percentiles CDF for area-based algorithms (min, median, max)
- Room-level accuracy



CDFs for point-based algorithms fall in-between the min, max CDFs for area-based algorithms

Point-based algorithms perform more or less the same, closely matching the median CDF of area-based algorithms



Similar top-room accuracy

Area-based algorithms are superior at returning multiple rooms,
yielding higher overall room accuracy

If the true room is missed in point-based algorithms the user has no clue!

Conclusion

- Area-based algorithms present users a more intuitive way to reason about localization uncertainty
- Novel area-based algorithms and performance metrics
- Evaluations showed that qualitatively all the algorithms are quite similar in terms of their accuracy
- Area-based approaches however direct users in their search for the object by returning an ordered set of likely rooms and illustrate confidence

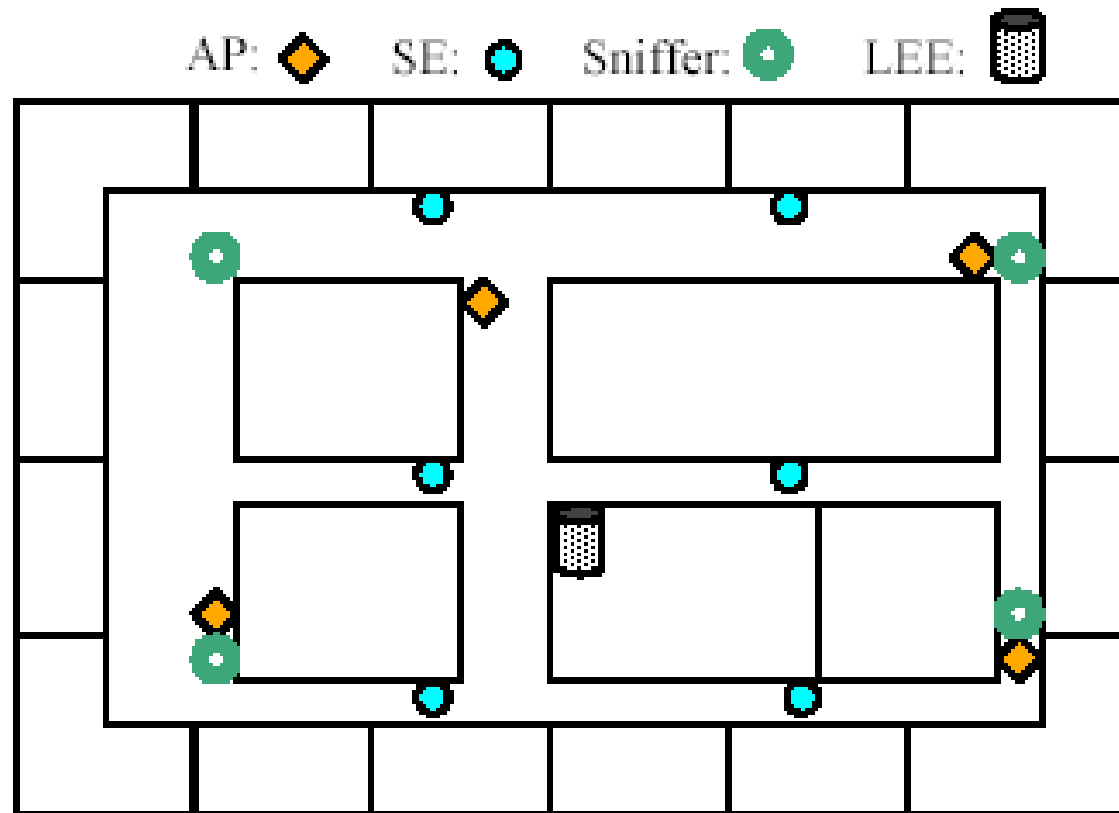
System for LEASE: Location Estimation Assisted by Stationary Emitters for Indoor RF wireless Networks

P. Krishnan, A.S. Krishnakumar, W.H.
Ju, C. Mallows, S. Ganu
Avaya Labs and Rutgers

LEASE components

- Access Points
 - Normal 802.11 access points
- Stationary Emitters
 - Emit packets, placed throughout floor
- Sniffers
 - Read packets sent by AP, report signal strength fingerprint
- Location Estimation Engine (LEE)
 - Server to compute the locations

LEASE system



LEASE methodology

- SE emit packets
- Sniffers report fingerprints to LEE
- LEE builds a radio map via interpolation
 - Divide floor into a grid of tiles
 - Estimate RSS of each SE for each tile
 - Result is an estimated fingerprint for each tile
- Client sends packet
 - Sniffers measure RSS of client packet
 - LEE computes location of client based on the map.

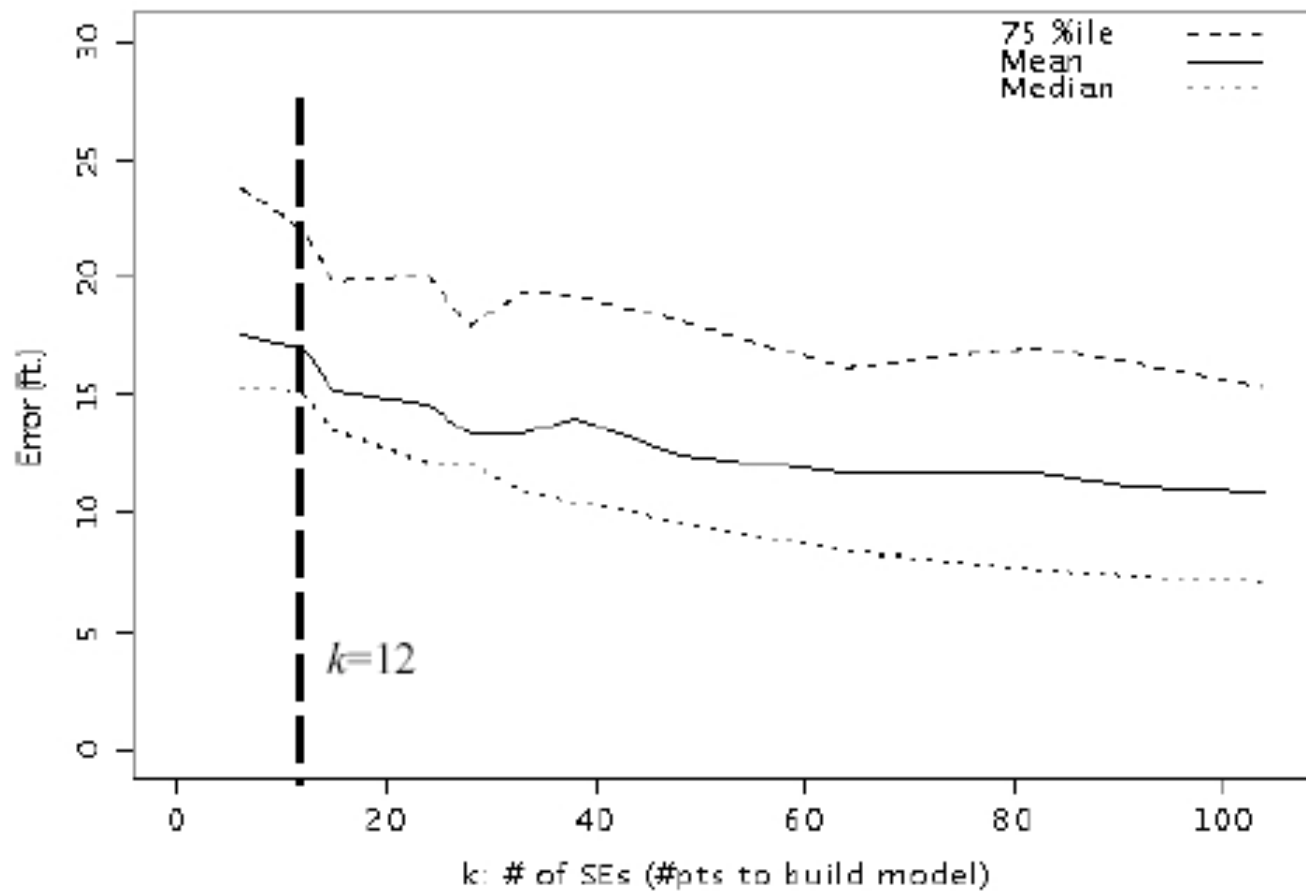
Building the map

- For a each sniffer:
 - have X, Y, RSS (“height”) for each AP
 - Use a generalized adaptive model to smooth the data.
 - Use Akima splines to build an interpolated “surface” from the set of “heights” over the grid of tiles
 - Each tile(3ftx3ft) has a predicted RSS for the sniffer
- Note complexity vs. the Delaunay triangles for SPM, APB algorithms.

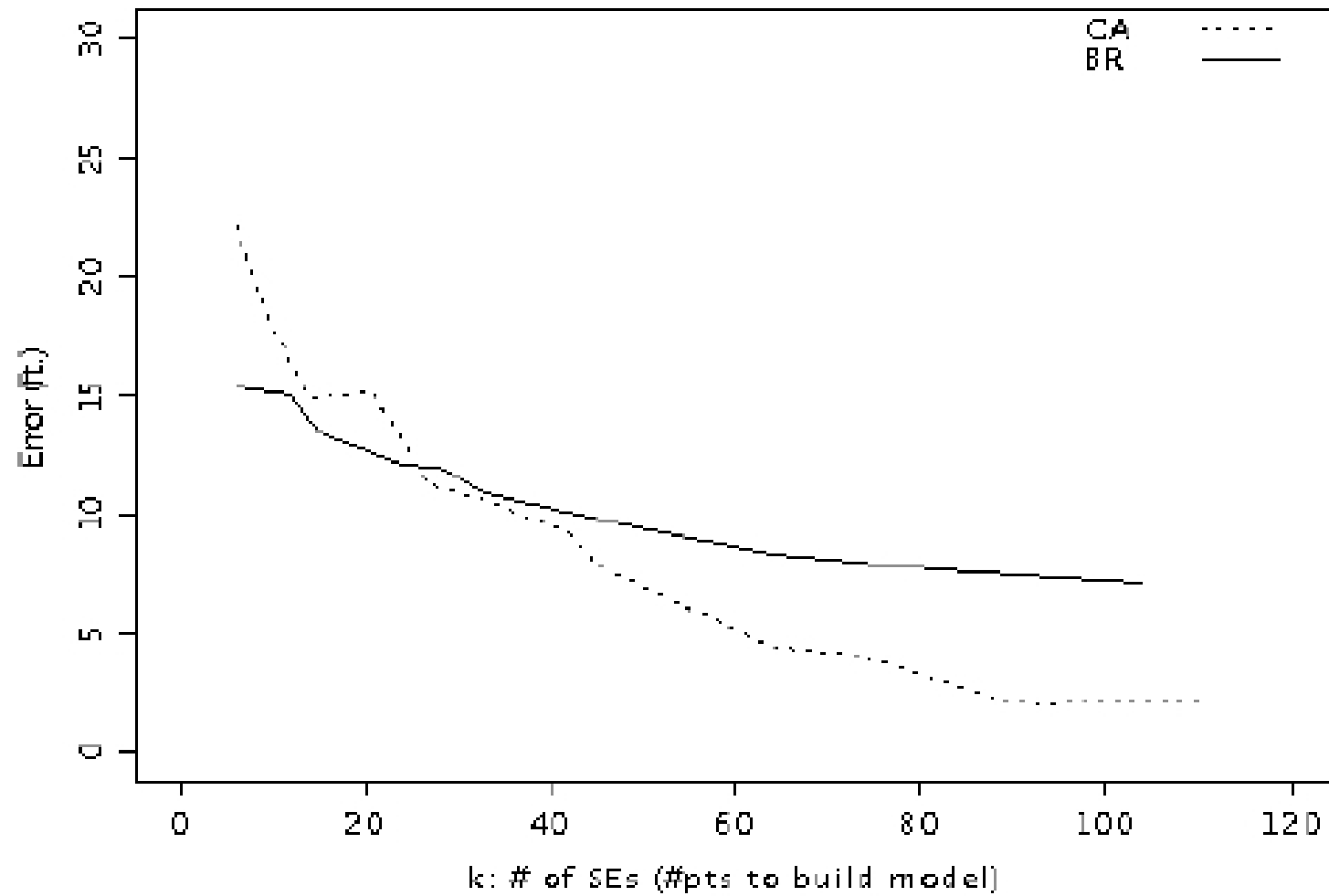
Matching the Clients

- Sniffers receive RSS of a client packet
- Find the tile with the closest matching set of RSSs
- Compute the distance in “signal space”
 - $\text{Sqrt}((\text{RSS}-\text{RSS})^2 + (\text{RSS}-\text{RSS}) \dots$
- Full-NNS: match the entire vector for each RSS
- Top-K: match only the strongest K-signals

Error vs. # of SEs



Median error by site



Metric

- Want to combine several factors into a single numeric value to judge the localization system
- Factors:
 - Area covered (A)
 - (more -> better)
 - # of fingerprints (k)
 - (more -> worse)
 - Localization error (m)
 - (more -> worse)

Metric (lower is better)

of fingerprints Relative weights

Scaling Constant

Median error

$$\Delta(i, j) = \frac{ck^i m^j}{A}$$

Area of location system

Detailed description: The diagram illustrates the components of the metric $\Delta(i, j)$. The formula is $\Delta(i, j) = \frac{ck^i m^j}{A}$. Arrows indicate the following mappings: 'Scaling Constant' points to the constant 'c'; '# of fingerprints' points to the base 'k' of the term k^i ; 'Relative weights' points to the base 'm' of the term m^j ; 'Median error' points to the term m^j itself; and 'Area of location system' points to the denominator 'A'.

Using the Metric

Technique	$\epsilon(1,3)$ (ft)	$\epsilon(2,3)$ (ft)
RADAR [4]	21.2	1484.0
Ref. [25]	1.7	188.6
LEASE(12) @BR	1.2	18.7
LEASE(28) @BR	1.5	41.8
LEASE(38) @BR	1.3	50.1

Note, areas for first 2 are normalized to the Corridors (whole floor doesn't count)

Questions:

- What are meaningful numbers?
- What to count in A ?
 - Corridor only?
 - What happens to m vs A ?
 - E.g. if we measure only in the corridors, but then try to localize in the rooms?
- What should the weights be?