Analysis of a Device-free Passive Tracking System in Typical Wireless Environments

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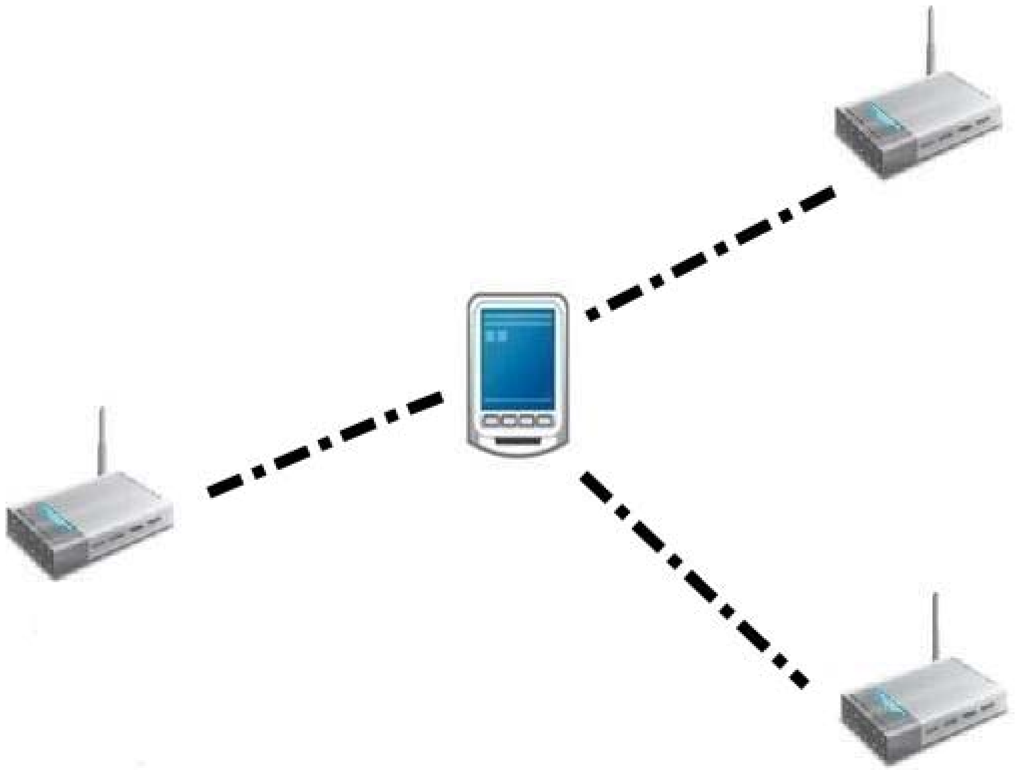
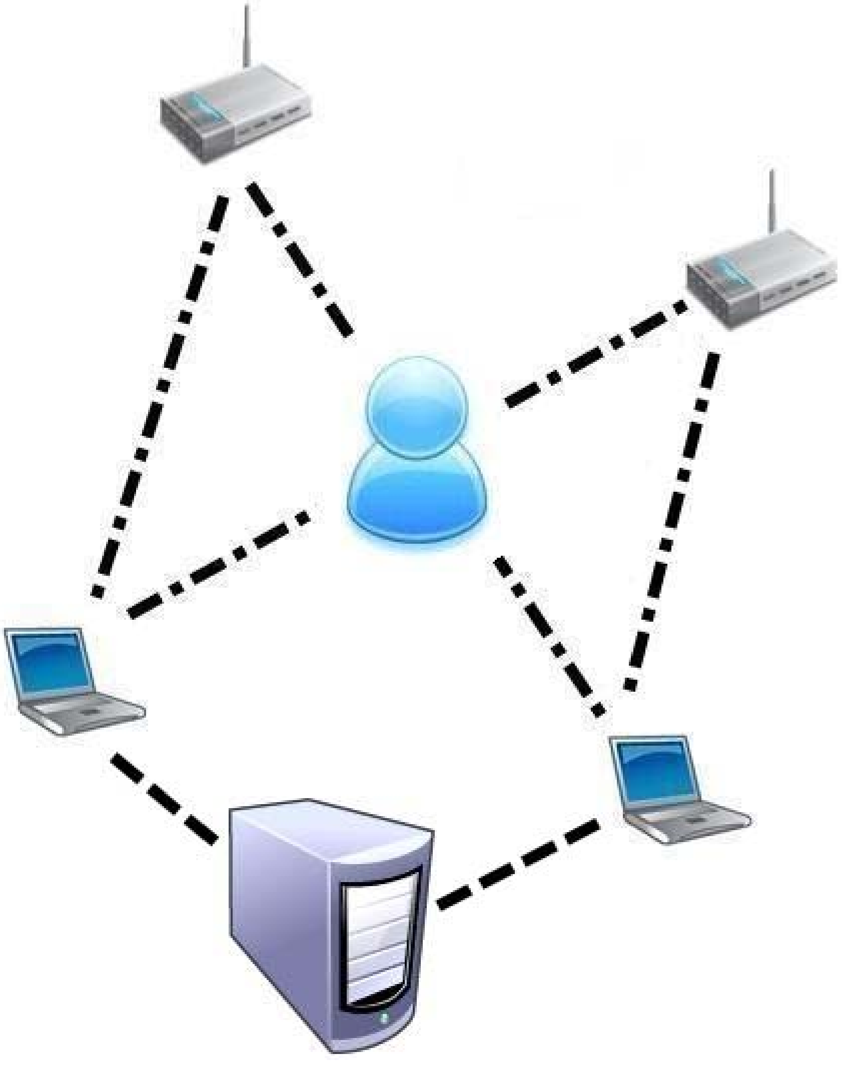
Traditional WLAN Localization

- Access points
- Client device
  - Receives signals
  - Applies algorithms
  - Provides location info



Device-free Passive Localization (DfP)

- Access points (AP)
- Monitoring points (MP)
- Stream
  - (AP, MP) pair
- Human user
  - Effects on signals
- Application server (AS)
  - Collects samples
  - Applies algorithms
  - Initiates actions
- **User carries no device**



Prospective Application Areas of DfP

- Intrusion detection
- Low cost surveillance
- Border protection
- Home automation

Contributions

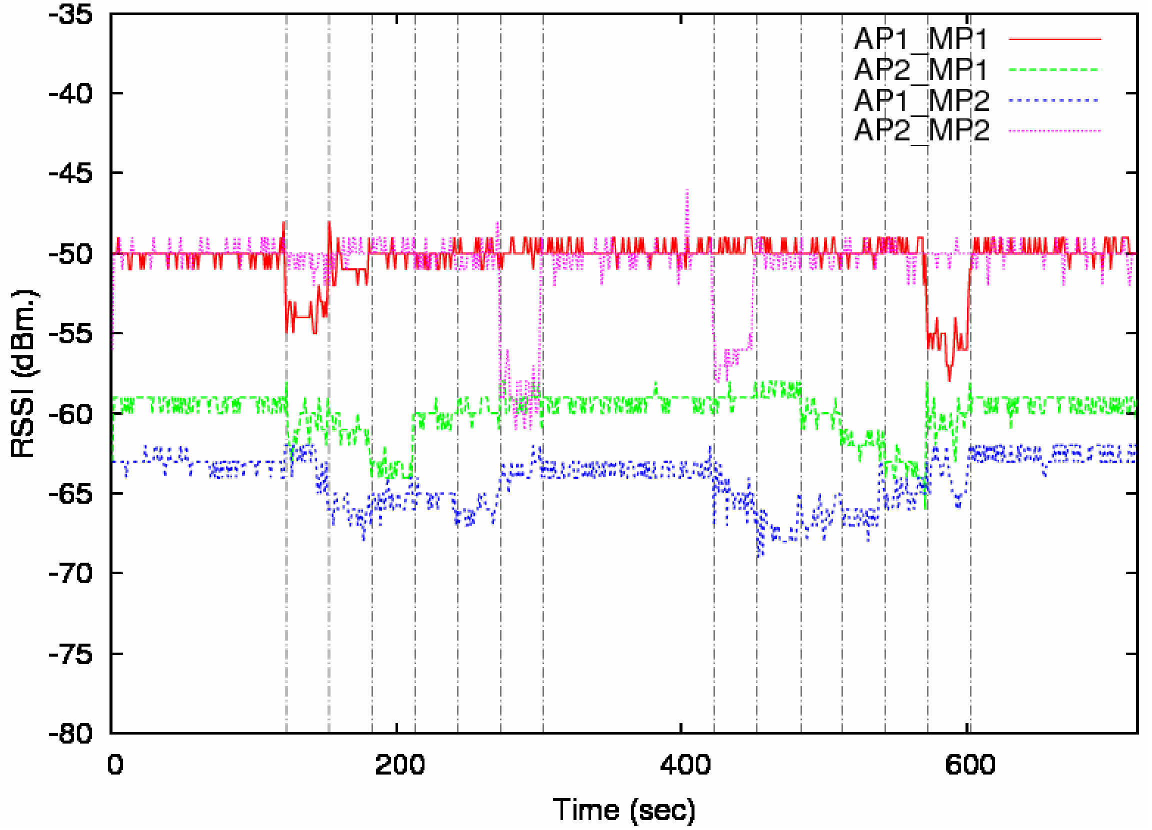
- Our previous work in MobiCom'07 provided a proof of concept of DfP in ***a highly controlled environment***.
- In this work, we present the first implementation and analysis of DfP tracking in ***typical indoor environments***.
- Compared deterministic and probabilistic approaches to the DfP tracking problem.
- Identified the main factors that affect the accuracy of DfP systems in realistic indoor scenarios.
- Provided preliminary results to stimulate further work in this area.

Agenda

- Introduction
- System Operation
- Tracking Algorithms
- Performance Evaluation
- Future Work and Conclusions

System Operation

- Main idea
  - Human effects on wireless signal propagation
  - Evident through the Received Signal Strength Indicator (RSSI)



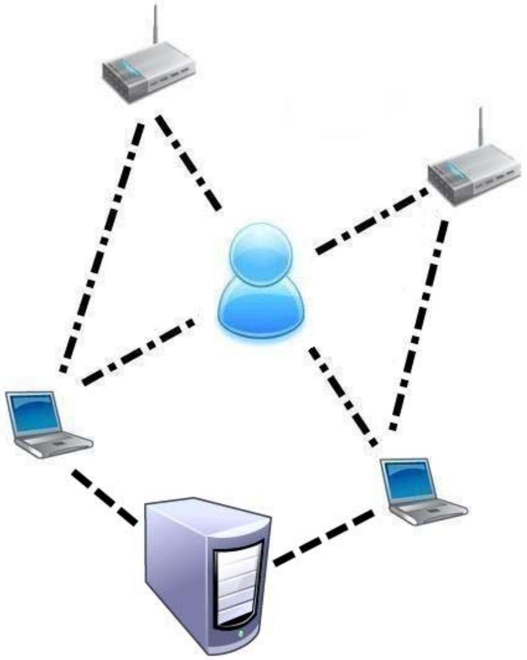
System Operation

- The system works in two phases
  - Offline phase
    - Estimates the complex relation between signal strength and the possible user locations.
  - Online phase
    - Processes received signals to estimate the current user location.

Mathematical Model

- Given M AP's and N MP's
- We get K streams where K = M * N
- Each sample is represented by a Kx1 vector "s"
  - Entries represent RSSI values for each stream

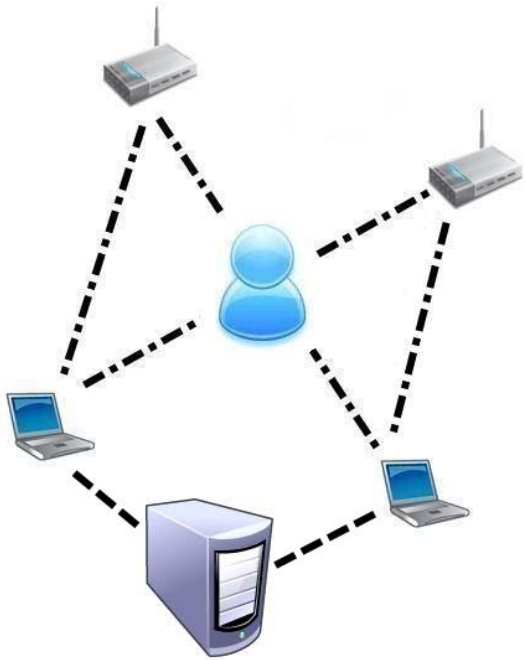
$$s = \begin{bmatrix} s_{1,1} \\ s_{1,2} \\ s_{2,1} \\ s_{2,2} \end{bmatrix}$$



Offline Phase: Passive Radio-Map Construction

- Procedure
  - The area of interest is discretized into a grid of locations.
  - A person stands at each location and samples are recorded.
  - Recorded data is processed to extract the required parameters.
  - A radio-map stores all parameters for the algorithm being used.

	S_1	S_2	…	S_q
L_1	μ_{11}	μ_{12}	…	μ_{1q}
L_2	μ_{21}	μ_{22}	…	μ_{2q}
…	…	…	…	…
L_p	μ_{p1}	μ_{p2}	…	μ_{pq}



Online Phase: DfP Tracking

- Goal: estimate the current location of the user
- Input: sample vector “s” + passive radio-map
- Approach
  - Deterministic
  - Probabilistic

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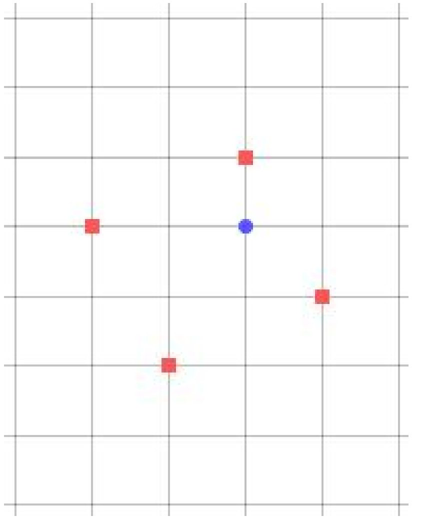
Deterministic Tracking (NNSS)



- Signal Space (SS)
  - K-dimensional Euclidean Space
  - Each stream is a dimension
  - Each location is a point
- Location estimate
  - Nearest Neighbor (NN)

$$\hat{l} = \arg\min_l D(s,l)$$

- Requirements
  - RSSI mean for each stream

Probabilistic Tracking (MAP)

- Location estimate: maximum a posteriori

$$\hat{l} = \arg\max_l P(l \mid s)$$

- Using Baye's rule

$$\hat{l} = \arg\max_l P(s \mid l) \cdot \frac{P(l)}{P(s)}$$

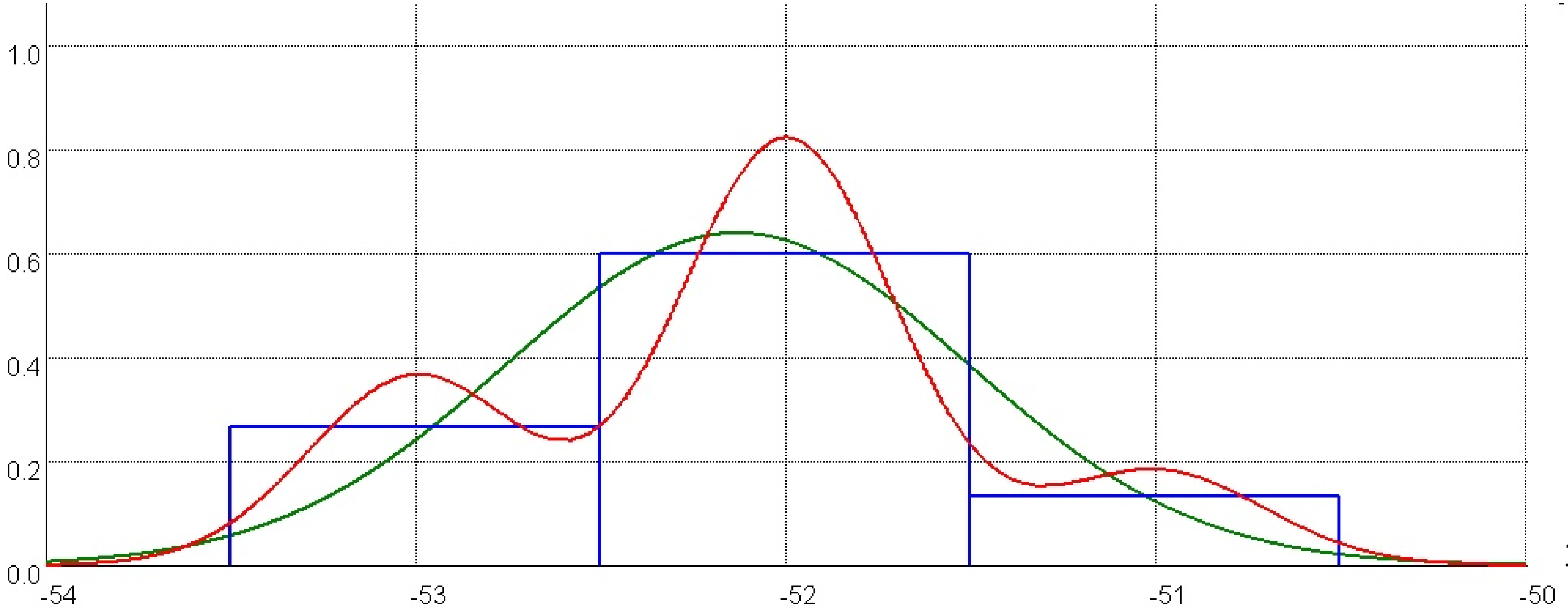
- $P(s)$ is constant and $P(l)$ is assumed constant
- Finally, assuming all streams are mutually independent

$$\hat{l} = \arg\max_l \prod_{i=1}^{M} \prod_{j=1}^{N} P(s_{i,j} \mid l)$$

- Requirements
  - $P(s_{i,j} \mid l)$ for all l, i and j
  - RSSI pdf for each stream conditioned on each location

Pdf Estimation

- Parametric estimation
  - Gaussian
- Non-parametric estimation
  - Histogram
  - Gaussian Kernel



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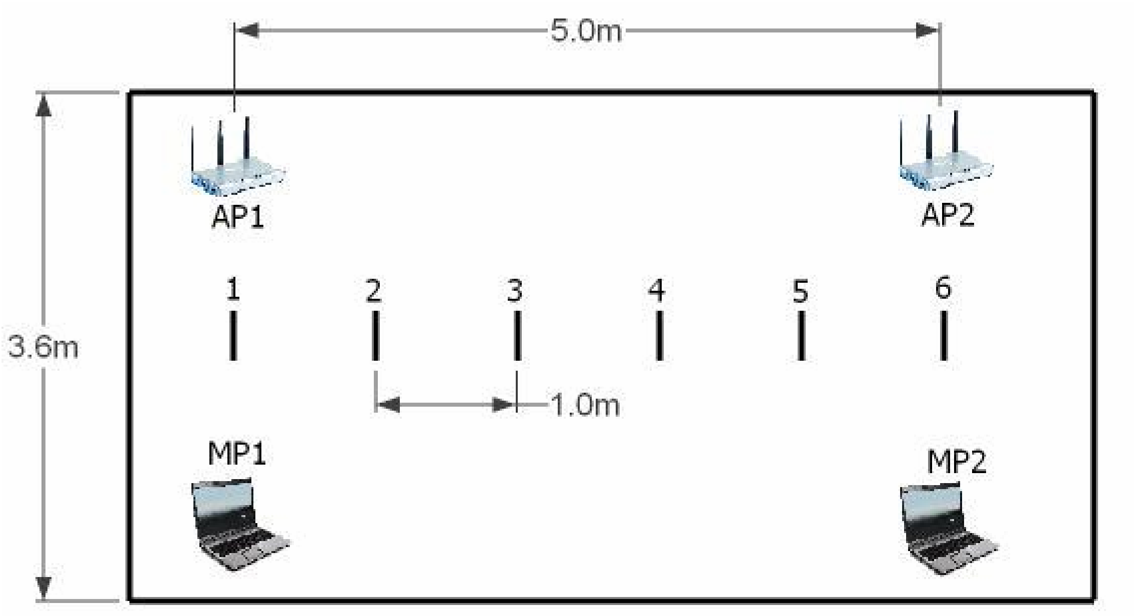
Performance Evaluation

- Methods
  - Cross validation
  - Independent test sets
- Metrics
  - Distance error
  - Probability of error

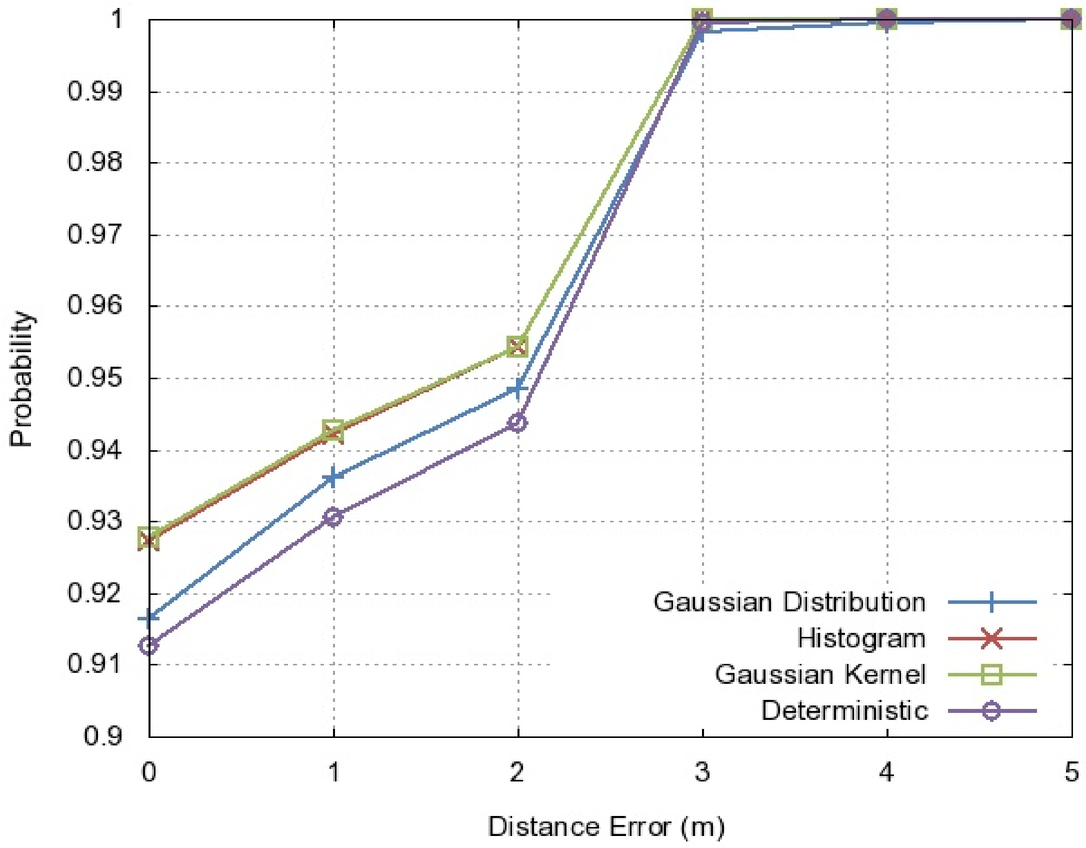
Testbed

- Typical living room discretized into 6 locations
- 2 AP's and 2 MP's (IEEE 802.11b)

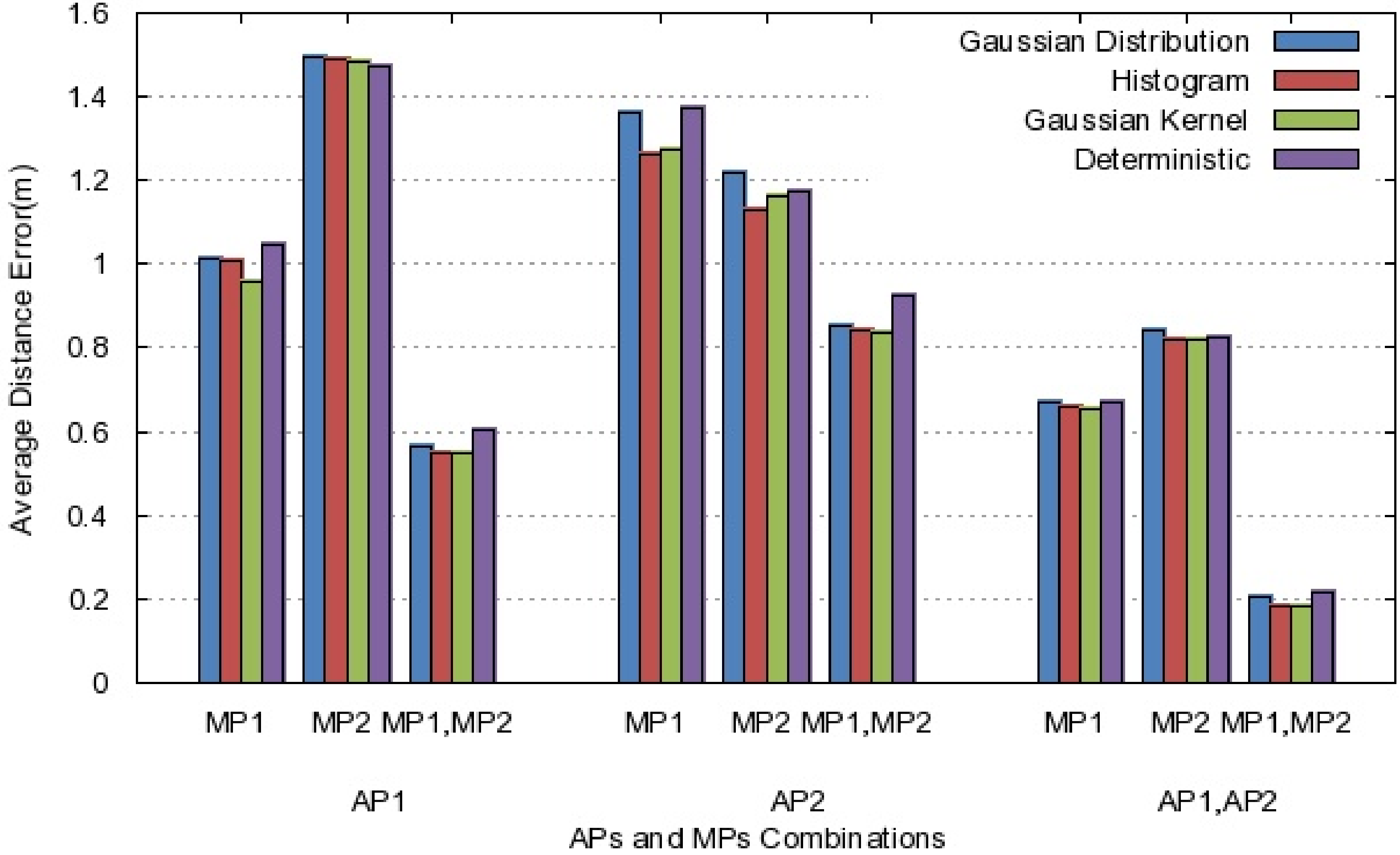


Cross-Validation (Ideal Case)

	Average Distance Error	Probability of Error
Gaussian Distribution	0.201 m	0.0835
Histogram	0.176 m	0.0727
Gaussian Kernel	0.175 m	0.0723
Deterministic	0.214 m	0.0874



Effect of the Number of Streams



Increasing the number of streams decreases the distance error

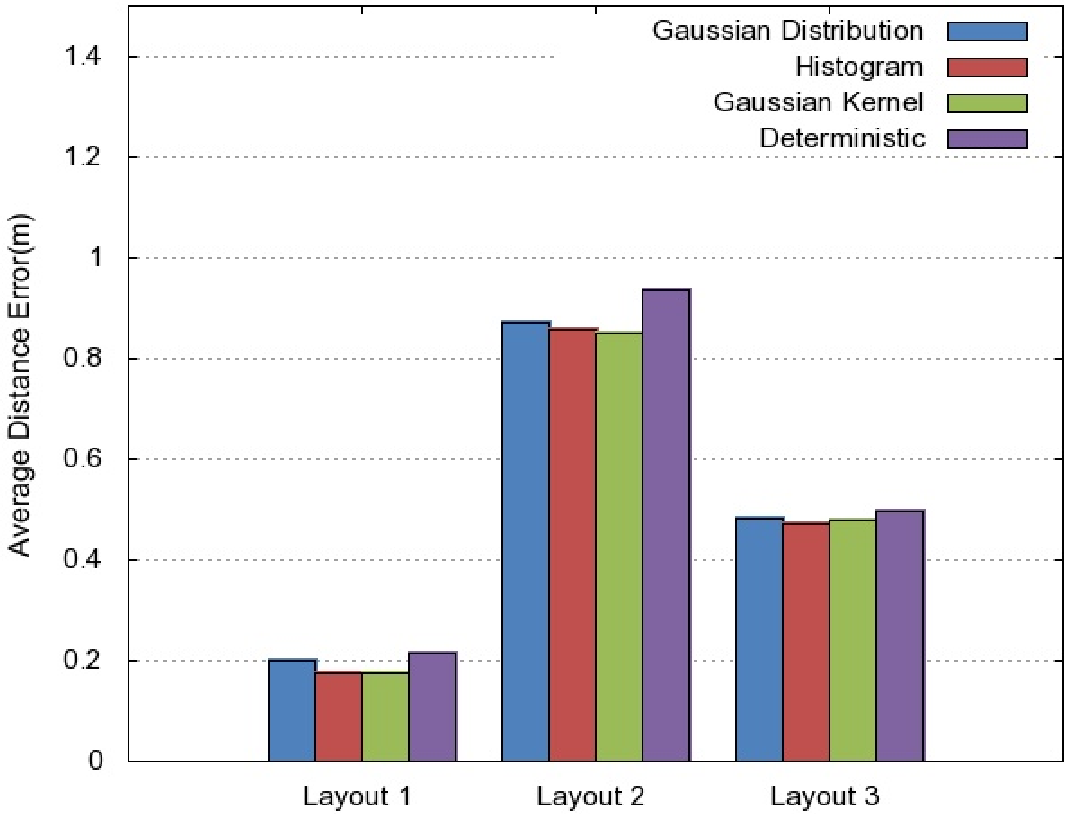
Effects of Time and User Orientation

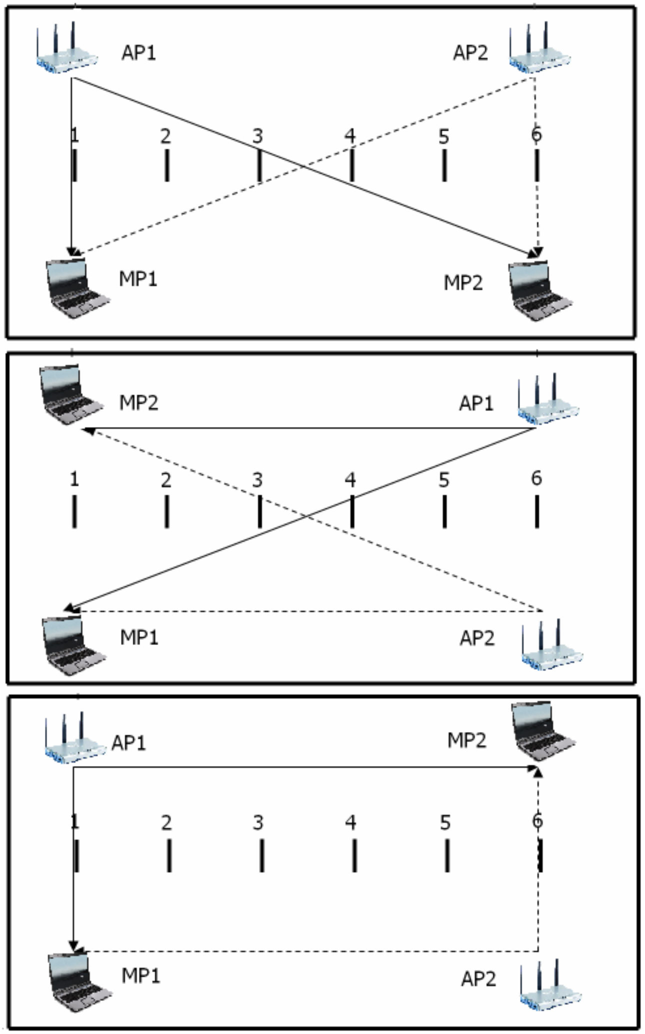
- Results of the Gaussian Kernel Method:

	Time	Orientation	Average Distance Error
Cross-Validation	Same	Same	0.175 m
Independent Set 1	Different	Same	0.358 m (2x)
Independent Set 2	Different	Different	0.586 m (3x)
Random Location Selector	N/A	N/A	1.940 m (11x)

The worst case accuracy is 3 times better than random selection

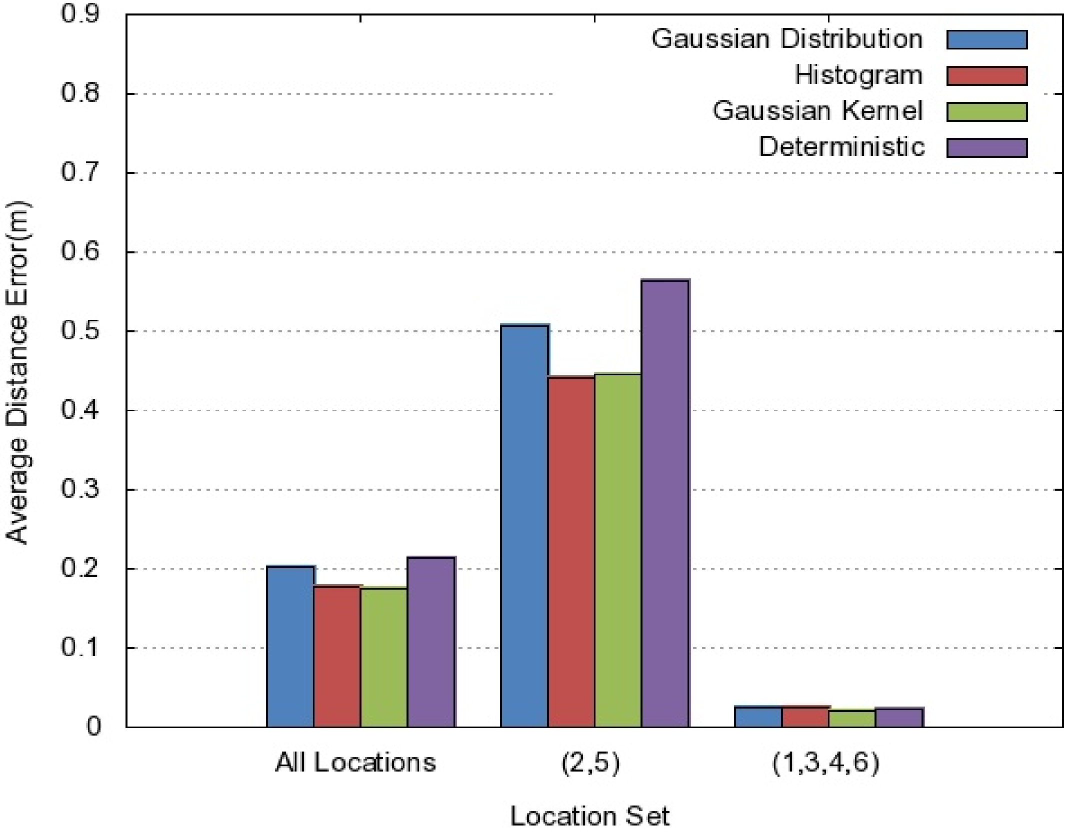
Effect of the Configuration

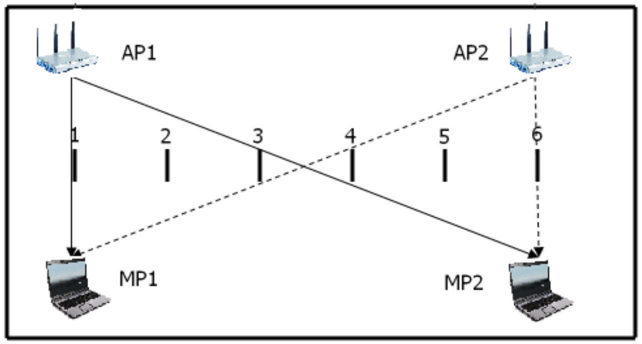




Configuration effect is more significant than the localization algorithm

Effect of the Location Set





Uncovered locations cause most of the errors

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Future Work

- Devise a robust method to select optimal configurations for a given area.
- Enable the system to adapt to changes in the monitored environment.
- Study large scale deployments of DfP systems.
- Upgrade to multi-target tracking.

Conclusions

- Probabilistic algorithms outperformed the deterministic algorithm.
- Non-parametric probabilistic technique outperformed the parametric one.
- Main factors that affect the accuracy of DfP systems
  - Number of streams
  - Time
  - User state
  - Configuration
  - Location-set

Thank You!

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