A Comparative Survey of WLAN Location Fingerprinting Methods

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http://math.tut.fi/posgroup/
Outline

- Radio map
- Static location estimation
  - Deterministic methods
  - Probabilistic methods
- Filtering approach
  - Kalman filter
  - Bayesian filter
- Conclusion
Radio map
The radio map is $\mathcal{M} = \{\mathcal{M}_i\}$, where $\mathcal{M}_i = (B_i, R_i)$.
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Example of cells $B_i$ and RSSI means $\bar{a}_{i,j}$
Effect of radio map density

Cell size $\approx$
- 120 $m^2$
- 60 $m^2$
- 30 $m^2$

![Bar chart showing ME/m for different methods and cell sizes.](image-url)
Effect of orientation

![Bar chart showing the comparison of various methods: Histog. comp., Histogram, NN Method, Parametric, and Kernel. The chart compares Still and Rotating conditions.]

- Histog. comp.: Higher ME/m for Still condition.
- Histogram: Higher ME/m for Rotating condition.
- NN Method: Similar ME/m for both conditions.
- Parametric: Lower ME/m for Still condition.
- Kernel: Lower ME/m for Rotating condition.
Effect of calibration time
Static location estimation
Deterministic vs. Probabilistic framework

Det. estimate:

\[ \hat{x}_{\text{Det.}} = \sum_{i=1}^{M} \frac{w_i}{\sum_{j=1}^{M} w_j} p_i, \]

where all weights \( w_i \) are nonnegative.

For example: \( w_i = \frac{1}{\|y - \bar{a}_i\|_1} \).
Deterministic vs. Probabilistic framework

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For example: 

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w_i = \frac{1}{\|y - \bar{a}_i\|_1}.
\]

**Nearest Neighbor (NN):**

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\hat{x}_{\text{Det.}} = p_i,
\]

where \( i = \arg\max_i (w_i) \).
Deterministic vs. Probabilistic framework

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For example:

\[ w_i = \frac{1}{\|\bar{y} - \bar{a}_i\|_1}. \]

Nearest Neighbor (NN):

\[ \hat{x}_{\text{Det.}} = p_i, \]

where \( i = \text{argmax}_i(w_i) \).

Pro. estimate:

\[ \hat{x}_{\text{Pro.}} = \sum_{i=1}^{M} \frac{|B_i| p(y|i)}{\sum_{j=1}^{M} |B_j| p(y|j)} p_i, \]

where \( |B_i| \) is volume of \( B_i \) and \( p(y|i) \) is likelihood inside cell \( B_i \). Here we use uniform prior.
Likelihood approximations

$p(y|i)$

RSSI

- RSSI histogram
- Gaussian kernel, width=0.8
- Exponential kernel, width=0.8
- Exponential kernel, width=2
## Summary of static estimators (meters)

<table>
<thead>
<tr>
<th>Method</th>
<th>ME</th>
<th>Median</th>
<th>RMSE</th>
<th>Max</th>
<th>95th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Histo. comp</td>
<td>7.0</td>
<td>5.0</td>
<td>11.0</td>
<td>106</td>
<td>19.4</td>
</tr>
<tr>
<td>NN</td>
<td>5.6</td>
<td>4.4</td>
<td>8.8</td>
<td>120</td>
<td>13.7</td>
</tr>
<tr>
<td>Histogram</td>
<td>5.5</td>
<td>4.3</td>
<td>8.4</td>
<td>105</td>
<td>14.2</td>
</tr>
<tr>
<td>Parametric</td>
<td>5.5</td>
<td>4.3</td>
<td>8.7</td>
<td>106</td>
<td>13.1</td>
</tr>
<tr>
<td>Kernel</td>
<td>5.4</td>
<td>4.1</td>
<td>8.9</td>
<td>99</td>
<td>12.3</td>
</tr>
</tbody>
</table>
Filtering approach
Position Kalman Filter (PKF)

Initial state: \( x_0 \)

Motion model: \( x_{k+1} = F_k x_k + w_k \)

Measurement model: \( y_k = H_k x_k + v_k \)

PKF uses the static solutions as a meas..

P-model: \( F_k = I \) and \( H_k = I \)

PV-model: \( F_k = \begin{bmatrix} I & \Delta t I \\ 0 & I \end{bmatrix} \) and \( H_k = \begin{bmatrix} I & 0 \end{bmatrix} \)
Bayesian filtering

\[ p(x_k | y_{1:k}) = \frac{\left\{ \begin{array}{l} p(y_k | x_k) \\ p(x_k | y_{1:k-1}) \end{array} \right\} \int p(y_k | x_k) p(x_k | y_{1:k-1}) \, dx_k}{\text{normalization}} \]

current meas.  state model and past meas.
Bayesian filtering

\[ p(x_k | y_{1:k}) = \frac{\underbrace{p(y_k | x_k)} \cdot \underbrace{p(x_k | y_{1:k-1})}}{\int p(y_k | x_k) p(x_k | y_{1:k-1}) \, dx_k} \]

normalization

\[ p(x_k | y_{1:k-1}) = \sum_{i=1}^{M} \frac{\beta_{k}^i}{|B_i|} \chi_{B_i}(x_k), \]

where \( \beta_{k}^i = \sum_{j=1}^{M} \pi_{i,j} \beta_{k-1}^j \) and \( \pi_{i,j} = P(x_k \in B_i | x_{k-1} \in B_j) \).
Summary of filtering approach

- Histog. comp.
- Histogram
- NN
- Parametric
- Kernel

Methods:
- ME / m
- Static
- KF, constant velocity
- KF, stationary
- Graph state model
Conclusion

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