The Airplace Indoor Positioning System

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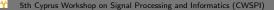


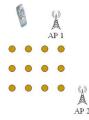


WiFi RSS Fingerprinting



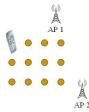






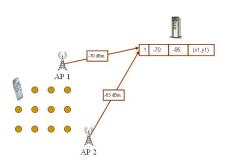
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 - n APs deployed in the area
 - Fingerprints $r_i = [r_{i1}, \dots, r_{in}]^T$
 - Averaging $\overline{r}_i = \frac{1}{M} \sum_{m=1}^M r_i(m)$
- Online phase: Positioning
 - Fingerprint $s = [s_1, \dots, s_n]^T$ is observed
 - Obtain an estimate
 ℓ using the radio





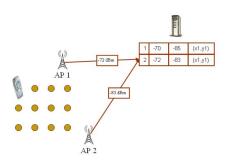
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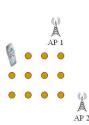
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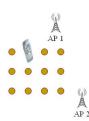






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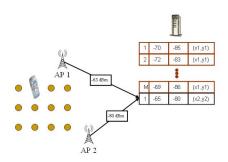






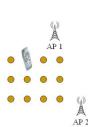
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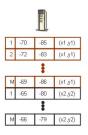




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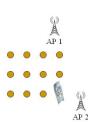


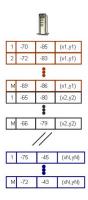




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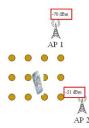


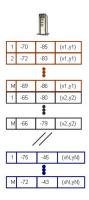




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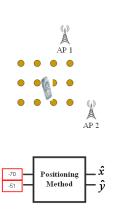


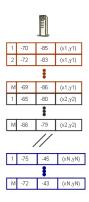




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Airplace System

Terminal-based Infrastructure-assisted Architecture

- Low Communication Overhead: Avoids uploading the observed RSS fingerprint to the positioning server
- User Privacy & Security: Location is estimated by the user and not by the positioning server





RSS Logger Application

Facilitates collection and storage of the RSS data on the device.

- Developed around the Android RSS API for scanning and recording data samples in specific locations
- User-defined number of samples
- Users can contribute their data to Airplace for constructing and updating the radiomap through crowdsourcing





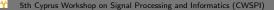
Distribution Server

Constructs the RSS radiomap and disseminates it to the requesting clients.

- Listens for connections from clients, that either contribute their RSS data or request the radiomap for positioning
- Parses all available RSS log files and merges them in a single compact radiomap file
- ► Fine tunes algorithm-specific parameters and stores them in a configuration file which is distributed with the radiomap

Start Run	Stop Running Indoor Module	51	ate: Running	Start Running Outdoor	Module
	Starting Indoor Radio Map module Indoor Radio Map module started on j Ustening for connections (Indoor mod	solybibilo-laptop with IP:PORT lej	[127.0.1.1:65510]		
Server Pending C	onnections Outdoor Mode				
A/A		Port	Time Connected	Type	Data Excl





Find Me Application

Implements the positioning client running on the users device.

- Connects to the server for downloading the radiomap and algorithm-specific parameters
- ► Algorithm bank with several algorithms (KNN, MMSE, etc.)
- Dual Operation Mode: Online (real-time positioning) or Offline (evaluation of algorithms)





Thank you for your attention Questions?

Contact

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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 $\{\ell'_1, \ldots, \ell'_i\}$ 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:
$$K \neq 1$$
, $w_i = \frac{1}{\|\overline{r}_i - s\|}$

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*.

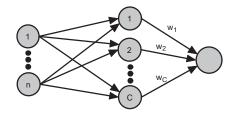
$$p(\ell_{i}|s) = \frac{p(s|\ell_{i})p(\ell_{i})}{p(s)} = \frac{p(s|\ell_{i})p(\ell_{i})}{\sum_{i=1}^{l} p(s|\ell_{i})p(\ell_{i})}$$
(2)
$$p(s|\ell_{i}) = \prod_{j=1}^{n} p(s_{j}|\ell_{i})$$
(3)

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

Positioning variants

- Maximum Likelihood: $\hat{\ell} = \arg \max_{\ell_i} p(s|\ell_i)$
- Maximum A Posteriori: $\hat{\ell} = \arg \max_{\ell_i} p(s|\ell_i) p(\ell_i)$
- Minimum Mean Square Error: $\hat{\ell} = \mathbf{E}[\ell|s] = \sum_{i=1}^{l} \ell_i p(\ell_i|s)$

Radial Basis Function Networks



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

- ► *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