The Airplace Indoor Positioning System

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WiFi RSS Fingerprinting

Where am I?
Fingerprint-based Positioning

- **Offline phase**: Build RSS radio map
  - $n$ APs deployed in the area
  - Fingerprints
    $$ r_i = [r_{i1}, \ldots, r_{in}]^T $$
  - Averaging
    $$ \bar{r}_i = \frac{1}{M} \sum_{m=1}^{M} r_i(m) $$

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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
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?

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Deterministic Approach

Deterministic positioning methods

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

$$\hat{\ell} = \sum_{i=1}^{K} \frac{w_i}{\sum_{j=1}^{K} w_j} \ell'_i$$

where $\{\ell'_1, \ldots, \ell'_l\}$ denotes the ordering of reference locations with respect to increasing distance $\|\bar{r}_i - s\|$.

$K$-Nearest Neighbor (KNN) variants

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

Probabilistic positioning methods

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

\[
p(\ell_i|s) = \frac{p(s|\ell_i)p(\ell_i)}{p(s)} = \frac{p(s|\ell_i)p(\ell_i)}{\sum_{i=1}^{l} p(s|\ell_i)p(\ell_i)}
\]

\[
p(s|\ell_i) = \prod_{j=1}^{n} p(s_j|\ell_i)
\]

$p(s|\ell_i)$ 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: $\hat{\ell} = E[\ell|s] = \sum_{i=1}^{l} \ell_ip(\ell_i|s)$
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