SPATIO-TEMPORAL SIMILARITY MODEL FOR WI-FI-BASED INDOOR LOCALISATION

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Outline

• Background
• Three technologies developed
  – An Android-based smartphone app for localization and RSSI survey.
  – Data management system to interpolate and update fine-grained RSSI map.
  – A localization engine based on J2EE7 platform.
• Application scenarios
• Conclusion and Future work
Background

• Huge market for location-based services (LBS)
  – Estimated to be USD 593 billion in 2013 and more than doubling to USD 1337 billion by 2020. (Market Info Group http://www.marketinfogroup.com/location-based-services-market-technology/.)

• Problems of existing technologies
  – More than 90% of human activities are NOT covered by GPS
  – RFID requires infrastructure investment.
  – Pedestrian dead reckoning is inaccurate.
## WIFI vs. Other Solutions

<table>
<thead>
<tr>
<th></th>
<th>WIFI</th>
<th>RFID-based positioning system</th>
<th>GPS</th>
<th>Cellular Network</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Positioning Fundamental</strong></td>
<td>RSSI-based, WIFI signal map</td>
<td>Proximity</td>
<td>Satellite signal triangulation</td>
<td>Proximity</td>
</tr>
<tr>
<td><strong>Service Availability</strong></td>
<td>Indoor &amp; Outdoor Continuous positioning and location tracking as long as covered by WIFI network</td>
<td>Confined indoor Checkpoint-based No or limited information between checkpoints</td>
<td>Outdoor</td>
<td>Indoor &amp; Outdoor</td>
</tr>
<tr>
<td><strong>Accuracy</strong></td>
<td>Medium to High Up to 2m</td>
<td>Proximity Depends on the density of RFID infrastructures</td>
<td>Medium ~ 20m</td>
<td>Low 100m~2 km</td>
</tr>
<tr>
<td><strong>Range &amp; Coverage</strong></td>
<td>Long City level</td>
<td>Short Room/building level</td>
<td>Long Global</td>
<td>Long City level</td>
</tr>
<tr>
<td><strong>Deployment Cost</strong></td>
<td>Low - Medium Exploit existing WIFI infrastructures</td>
<td>Medium – High Require extra RFID infrastructures (extra cost for wiring and installation)</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Mobile Unit Cost</strong></td>
<td>Low</td>
<td>Very Low</td>
<td>Low</td>
<td>Medium</td>
</tr>
<tr>
<td><strong>Operation &amp; Maintenance</strong></td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
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</tbody>
</table>
Our research focuses on improving the accuracy of WIFI localization

- RSSI map construction is the key to accuracy

How about constructing RSSI map based on S-T characteristics?

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WIFI fingerprinting system

WIFI signatures survey with laptop / phone
Crowds Mobile localization Location estimation Database Periodical updates RSSI map Local server & localization engine

Algorithm module (ST similarity model)
Optimization module

WIFI RSSI

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Android app

User-interface
We propose an S-T similarity model

• Basic assumption
  – Infer the RSSI based on the specific characteristics of the neighborhood.

• 5 S-T metrics
  – 1) Spatial distance
  – 2) Signal similarity
  – 3) Similarity likelihood
  – 4) RSSI vector distance
  – 5) S-T reliability.
Metric 1: spatial distance

- Preliminaries
  - $S_{i,j,t_k}$: signal strength at calibration point $i$, from the $j$th AP, at discrete timestamp $t_k$, where
    - $i = 1, 2, ..., M$; $j = 1, 2, ..., N_i$; $k = 1, 2, 3$ ...
    - $N_i$ indicates the number of APs detected at Cell $i$, and $t_k$ represents the $k$th sampling timestamp.

- Definition
  - For any two specific calibration points $i_1, i_2$.
    - $Metric_1 = \| l_{i_1} - l_{i_2} \|$, where $i_1, i_2 \in 1, 2, ..., M$
Metric 2: signal similarity

- **Goal**
  - Cluster signals with similar behavior.

WIFI Signals from 15 APs, clustered into 3 groups, at a specific location

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Metric 2: signal similarity

- **Definition**
  - For two specific APs $j_1, j_2$

  $$\text{Metric}_2 = \sqrt{\frac{\sum_{i=1}^{M} \sum_{k=\text{begin}}^{\text{end}} (S_{i,j_1,t_k} - S_{i,j_2,t_k})^2}{\text{number of } t_k \text{ in } [t_{\text{begin}}, t_{\text{end}}]}}$$

  - where $i \in 1, 2, \ldots, M; j_1 \in 1, 2, \ldots, N_{i_1}; j_2 \in 1, 2, \ldots, N_{i_2}$
  - $t_k \in [t_{\text{begin}}, t_{\text{end}}]$
Metric 3: similarity likelihood

• Definition
  – The likelihood of two RSSI distributions located at two cells $i_1, i_2$, computed by histogram statistics and Gaussian statistics. For convenience of computation, this metric is represented in log scale.
Metric 4: RSSI vector distance

- **Goal**
  - The relation between spatial distance and average Euclidian distance of two RSSI series at two selected locations $i_1, i_2$

![Graph showing the relationship between Metric 1 (Spatial distance) and Metric 4 (RSSI Vector Distance).](image)

Mean spatial distance = 1.333 m
Metric 5: S-T reliability

(a) c4:ca:d9:ec:d5:50  
(b) c4:ca:d9:ec:d5:51  
(c) 58:66:ba:a0:a2:d4  
(d) 58:66:ba:a0:a2:d5  
(e) 58:66:ba:a2:aa:60  
(f) 58:66:ba:a2:aa:61  
(g) 58:66:ba:a2:a6:70  
(h) 58:66:ba:a2:a6:71

Critical APs
S-T similarity model based on 5 S-T metrics

• To filter untrusted RSSI values
• Definition
  – We define Metric 5 based on S-T correlation
  – For the $j$th AP at two selected locations $i_1, i_2$

$$Metric_5 = \begin{cases} 
  \text{constant}, & \left| \frac{S_{i_1,j} - S_{i_2,j}}{\sigma(i_2,j)} \right| > 0.9 \times CI \\
  1, & \text{otherwise}
\end{cases}$$

– where $0.9\_CI$ represents the 90% confidence interval
System deployment

Deployment framework of current WIFI localization system, with (a) smartphone app built on Android system and (b) back-end server & database.

(a) Mobile app
(b) Overall framework of the RSSI map construction
Application scenario 1: office

Spatial Distributions of the Actual Position (blue), the Calculated Position (red), and the Final Candidate Positions (green)
Accuracy of RSSI map construction
Accuracy for localization

(a) Deterministic estimation

(b) Probabilistic estimation
Application scenarios 2 & 3

- **Hong Kong Science Park**
  - 40 X 20m
  - 2-5m accuracy

- **HKU Centennial Campus**
  - 100 X 50m
  - Indoor/outdoor area
  - 2-5m accuracy
Enable crowd-sourced RSSI data collection

- Crowd-sourced RSSI map generation
  - Overcome the workload of RSSI map updates
New framework

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<th>RSSI map construction</th>
<th>Localization</th>
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<td>WIFI RSSI</td>
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<td>Database</td>
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Local server & localization engine

Location estimation

Mobile localization

Periodical updates

RSSI map

Algorithm module

Optimization module

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The optimization module

![Graphs showing improvement in error metrics over epochs.]

- Improved by 18% - 37%
- Improved by 40% - 75%
- Improved by 13% - 26%

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