Empirical Performance of Self-calibrating WiFi Location Systems

Daniel Turner
Stefan Savage
Alex C. Snoeren
UCSD
10/05/2011
Localization Outdoors

- GPS tells us where we are outdoors
- GPS + smart phone
Localization Outdoors

- GPS tells us where we are outdoors
- GPS + smart phone
  - Turn-by-turn driving directions
Localization Outdoors

- GPS tells us where we are outdoors
- GPS + smart phone
  - Turn-by-turn driving directions
  - Yelp
Localization Indoors

• Sadly GPS works poorly indoors
• Indoor localization services
  – Tour guides in museums
  – Advertising in Malls
  – The next BIG thing
• So how do we get indoor ‘GPS’
  – For next generation of applications
• How much accuracy do we need?
  – 3-5 meters depending on application
Custom Hardware

• Deploy new localization infrastructure
  – Bluetooth, RFID, Sonar, ..
    • AoA, TDoA, and Signal Decay
  – Requires special purpose infrastructure
Leveraging WiFi Infrastructure

- 802.11 (WiFi) location systems
  - Median accuracy around 3 Meters
  - Requires significant manual calibration
RSSI

• WiFi exposes Received Signal Strength Indication (RSSI)
  – measurement of the power present in a received packet
  – Higher value indicated stronger signal
  – RSSI is a unit-less quantity
Fingerprint Based Approaches
Fingerprint Based Approaches

AP 1

AP 2

AP 3

AP 4
Fingerprint Based Approaches

AP 1: 44.1 RSSI
AP 2: 22.7
AP 3: 19.8
AP 4: 35
Fingerprint Based Approaches

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<tr>
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Fingerprint Based Approaches
Fingerprint Based Approaches

AP 1: 42.1 RSSI
AP 2: 23.4
AP 3: 22.6
AP 4: 39
The Next Challenge

• Indoor localization is possible
• Can be done using only WiFi
• Can it be done w/o human calibration?
  – Only Calibration data from AP to AP transmissions
Self-Calibration

• We can leverage intra-AP transmissions to build models
Self-Calibration

• We can leverage intra-AP transmissions to build models

• Signal-Distance pairs

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Plug-n-Play for Indoor Localization

• Self-Calibrating WiFi location systems
  – Recognized that WiFi decays exponentially
  – Use models to map RSSI to distance
  – Leverage WiFi infrastructure to calibrate models
  – Published 2-5 Meters of accuracy
Published Self-Calibrating Systems

• Algorithms uses varying amounts of data to train models
  – In theory more training data should lead to better accuracy

• Triangular Interpolation and eXtrapolation (TiX) Gwon and Jain 2004
• Lease Krishnakumar et al 2004
• Bayesian indoor positioning system D. Madigan et al 2005
• Ariadne y. Ji et al 2006
• Probabilistic Method Moares and Nunes 2006
• Zero-configuration and robust indoor localization (ZCFG) Lim et al. 2006
• EZ Localization Chintalapudi et atl. 2010
Picking a System to Deploy

• There are multiple Self-Calibrating systems

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• Published performance all under 5 Meters
• Not clear which we should(n’t) use
Our Environment

• Test Environment
  – 30k Sq. Ft. per floor
  – 10 APs per Floor
  • Channels 1, 6, and 11
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Contributions

• Perform head-to-head comparisons
  – 4 different algorithms

• Algorithms don’t work as well as published
  – As much as 4x worse than previously published

• We provide insight into why not
  – Performance loss due to environmental issues
  – Performance loss due to systemic issues
Outline

• Motivation
• **Algorithms**
• Experimental set-up / results
• Causes of Error
• Conclusion


A. Overview

The table below shows the Mean RSSI values for each access point (AP) in a network.

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In this network, the Nearest AP is determined by the access point with the highest Mean RSSI.

The Nearest AP is

- \( AP_2 \) with a Mean RSSI of 47.8.

The APs in this network are labeled as AP 1, AP 2, AP 3, and AP 4.
Device | Mean RSSI
---|---
$AP_1$ | 24.4
$AP_2$ | 47.8
$AP_3$ | 45.5
$AP_4$ | 40.6

- Device is located at the AP that with the greatest RSSI
that requires no manual calibration has been proposed.

Instead, some systems require manual calibration but remain unable to surpass the accuracy of systems that use fingerprints as constraints to be solved by a genetic algorithm. They then treat the measurement as an anchor point.

When a phone is able to get a GPS lock, it opportunistically uses the measurement as an anchor point. They then treat the measurement as an anchor point.

Indoor environment

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Many of the early and still most accurate sensor-based location systems have three major manifestations: point matching, which is to evaluate self-calibrating, and probabilistic matching, which is to evaluate self-calibrating.

The second set of methods once again starts with the user taking a client fingerprint. Then the user computes the probability of the offline fingerprint that minimizes a similarity metric, often Euclidean.

Systems that use signal strength measurements or more specifically in the case of Wi-Fi, the received signal strength can be used for future client localization. In general, these methods take advantage of the signal strength. This nearest neighbor approach requires no calibration: a single RSSI from a client transmission labeled with the strongest RSSI and declares the client to be at the same location as the AP heard the transmission.

For example, if the system considers a simple calibration-free baseline that leverages only the four APs if a client, fingerprints are documented in the training phase, however, the baseline does not ignore packets sent from other APs labeled training phase. After the self-calibration stage, the fingerprint is labeled with the greatest RSSI.

The model uses the four APs labeled with the greatest RSSI to compute a model of the physical location of the APs to compute a model of the physical location of the APs to compute a model of the physical location of the APs.

It is convenient to think of self-calibrating algorithms as fitting into three categories based on the amount of data used to perform calibration. To assist the reader in understanding, we briefly summarize the approaches based upon manual calibration and ultrasonic acoustic waves among others.

A. Overview

The relationship between RSSI and physical location is encoded via a signal decay model of the client. The relationship between RSSI and physical location is encoded via a signal decay model of the client.

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Taking a client fingerprint, then the user computes the probability of the offline fingerprint that minimizes the metric, which is to evaluate self-calibrating.

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- Device is located at the AP that with the greatest RSSI.
Self-Calibrating System Phases

• Algorithms have two phases
  – 1) Determine distance from device and each AP
  – 2) Combine these distance estimations
• Phase 1 uses models to map distance between each AP and the device to be located
Probabilistic Method (Moares and Nunes)

- Phase 1: Building a Radio Propagation Map
  - Overlay grid w/ probability that device is present
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- Trained on 1 signal-distance pair per RPM
Probabilistic Method

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- Phase 1: Building a Radio Propagation Map

![Diagram showing radio propagation map with grid and likelihood areas]
Probabilistic Method

• Phase 2: Combing RPMs for a final estimation
  – Final probability is the product across all RPMs
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![Diagram of a building floor plan with a centered location marked at 81%]

81%
Triangular Interpolation and eXtrapolation (Gwon and Jain)

- Phase I: Distance Estimation
  - Exponential decay model
    \[ F(x) = \alpha \times e^{(\beta \times x)} \]
  - Least-squares fit over all RSSI-distance pairs
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– For AP3: \[ F(x) = 78 \times e^{(-0.09 \times x)} \]
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- For AP3: \( F(x) = 78 \times e^{(-0.09 \times x)} \)
- For AP3: \( F(47.8) = 1.3 \text{ Meters} \)
TiX

• Phase II: Location Estimation
  – Triangular Interpolation and eXtrapolation
  – Like trilateration but a bit smarter
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1.3 Meters
TiX
ZCFG (Lim et al)

• Phase 1: Distance Estimation
  – ZCFG has APs share calibration data
  – AP 1’s distance estimation is linear combination of all AP’s belief about distance between device and AP1

• Phase II: Multilateration
  – Like trilateration but w/ more than 3 distances
Outline

• Motivation
• Algorithms
• Experimental set-up / results
• Causes of Error
• Conclusion
Test Environment

• Test Environment
  – 30k Sq. Ft. per floor
  – 10 APs per Floor
    • Channels 1, 6, and 11

• Training the Algorithms
  – APs monitor bcast traffic for 10 seconds
Evaluation

• Experimental Evaluation
  – Located a laptop on a 1.5M ladder
  – Average 2 seconds worth of RSSI data per location attempt
  – 13 different locations
    • Multiple localizations in each location
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• Causes of Error
  – Height Disparity / Signal Reflection
  – Extrapolation Failures
  – Interpolation Failures

• Conclusion
Height Matters

• Access Points are mounted near the Ceiling
  – Tests took place at ‘chest’ height
• Is this height discrepancy significant?
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<tbody>
<tr>
<td>Nearest AP</td>
<td>6.7</td>
<td>6.7</td>
<td>4.8</td>
<td>1.9</td>
</tr>
<tr>
<td>Probabilistic (de Moraes &amp; Nunes)</td>
<td>6.6</td>
<td>3.37</td>
<td>2.65</td>
<td>0.72</td>
</tr>
<tr>
<td>TiX (Gwon &amp; Jain)</td>
<td>16.8</td>
<td>11.6</td>
<td>11.2</td>
<td>0.4</td>
</tr>
<tr>
<td>ZCFG (Lim et al.)</td>
<td>9.5</td>
<td>14.2</td>
<td>12.9</td>
<td>1.3</td>
</tr>
</tbody>
</table>
Signal Reflection

• Can we correct for the induced error?
  – Simply add n RSSI to each measurement?

• RSSI vs. time
  – Ceiling; Ladder; Floor Height
Can we correct for the induced error?

- Simply add $n$ RSSI to each measurement?

$\text{RSSI vs. Ceiling; Ladder; Floor Height}$
Signal Reflection

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Signal Reflection

• Can we correct for the induced error?
  – Simply add n RSSI to each measurement?
• RSSI vs. time
  – Ceiling; Ladder; Floor Height
• Different locations different results
Beyond Reflection

• Signal reflection causes some degradation
  – 1-2 Meters

• Experiments found more than 2 meters of accuracy difference from published values

• What other issues could be responsible?
Calibration Data

• Does our calibration data accurately capture decay
  – Order of magnitude less AP/sq. ft. than previous works

<table>
<thead>
<tr>
<th>Study</th>
<th>Square Feet</th>
<th># of Aps</th>
<th>Aps/Sq. Ft.</th>
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<tbody>
<tr>
<td>Prob (de Moraes &amp; Nunes)</td>
<td>1,722</td>
<td>4</td>
<td>0.0023</td>
</tr>
<tr>
<td>TiX (Gwon &amp; Jain)</td>
<td>6,717</td>
<td>4</td>
<td>0.0006</td>
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<tr>
<td>ZCFG (Lim et al.)</td>
<td>598</td>
<td>6</td>
<td>0.01</td>
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<tr>
<td>Cisco Recommends</td>
<td>3,000-5,000</td>
<td>1</td>
<td>0.0002-0.0003</td>
</tr>
<tr>
<td>UCSD CSE Building</td>
<td>30,000</td>
<td>10</td>
<td>0.0003</td>
</tr>
</tbody>
</table>
Signal Degradation due to Walls
Signal Degradation due to Walls
Signal Degradation due to Walls

![Diagram showing signal degradation due to walls between access points (AP1, AP2, AP3)].
Signal Degradation due to Walls
Signal Degradation due to Walls

- Wall placement causes signal degradation
Degraded Training Data

• APs have 4-6 signal-distance pairs for training
  – Distance ranges from 5-35 Meters
  – RSSI ranges from 45-10
  – Expect to fit exponential decay
Degraded Training Data

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  - Distance ranges from 5-35 Meters
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  - Expect to fit exponential decay

Effect of multiple walls
When Walls Get in the Way

- Common for AP to have wall between it and all other training APs
- Yet, device to locate has line of sight
When Walls Get in the Way
When Walls Get in the Way
When Walls Get in the Way
When Walls Get in the Way

- Probabilistic method doesn’t handle this well

![Map and graph showing device location and RSSI vs. distance data.](image)
When Walls Get in the Way

- Probabilistic method doesn’t handle this well
  - We instituted a filtering scheme to help

[Map and chart showing device location and RSSI vs. distance]
When Walls Get in the Way

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- TiX handles this scenario much better
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But not always
Extrapolation Failures

• Called extrapolation failures because they occur beyond training data
• Sometimes filtering is effective
  – Median improved 2.1 M for Probabilistic method
• Made two attempts to filter ZCFG
  – Increased median error by 0.5 Meters
• Possible to overcome with additional APs
  – Excessive AP density impacts WiFi performance
Good Training Data Isn’t Enough

• Not all failures can easily be overcome
Good Training Data Isn’t Enough

• Not all failures can easily be overcome

Similar RSSIs at different distances
Good Training Data Isn’t Enough

- Not all failures can easily be overcome

**Diagram:**
- **Similar RSSIs at different distances**
- **1 wall between APs**
Decay Isn’t Always Exponential

- 10 RSSI variation in under 3 Meters due to walls
Decay Isn’t Always Exponential

- 10 RSSI variation in under 3 Meters due to walls
Decay Isn’t Always Exponential

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Decay Isn’t Always Exponential

• 10 RSSI variation in under 3 Meters due to walls

Line of sight to AP
Decay Isn’t Always Exponential

- 10 RSSI variation in under 3 Meters due to walls
Interpolation Failures

• Called interpolation failures because they occur in-between training data

• This isn’t fixable with extra training data
  – Walls add unpredictable decay

• Even the sophisticated algorithms can’t overcome these issues
  – In fact most do worse
Summary

• Indoor Localization is in demand
• Achieving less than 5m accuracy w/o site survey is still an open problem
  – Improved filtering mechanisms
  – Novel models that better isolate signal from noise in training data