A New Method for Improving Wi-Fi Based In-door Positioning Accuracy

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LBS 2014
11th Symposium on Location-Based Services
Vienna, 26–28 November 2014

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Outline

- Background
- Techniques for location tracking and positioning
- Common algorithms for location fingerprinting
- A new algorithm
- Test result
- Conclusion

Background

- **Location-based service (LBS) technologies have become an essential part of our daily lives**
  - ➢ Global revenue of LBS will generate up to US$127b by the end of 2014 (the report of Juniper Networks)
  - ➢ LBS output of China in 2013 yielded RMB￥70b
- **LBS technologies for outdoor free space are mature, e.g., usage of GPS, but for indoor environments or city canyons are problematic**
- **Increasing needs arise to locate and find people and objects in buildings/indoor-like environments**
- **Algorithm development for increasing the positioning accuracy is still desireable.**

Wide Application Areas

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Agriculture & forestry	Entertainment	Packaging
Airports & aviation	Environmental protection	Public Services
Automotive & parts	Finance & banking	Publishing & printing
Business services	Food & drinking	Real estate
Chemicals industry	Governance	Retail & wholesale
Construction	Healthcare & medication	Security
Consumer goods	Information technology	Stock raising
Defence	Logistics	Telecommunications
Education	Manufacturing	Transportation
Energy & utilities	Media	Travel & leisure

Techniques for Positioning/Location Tracking

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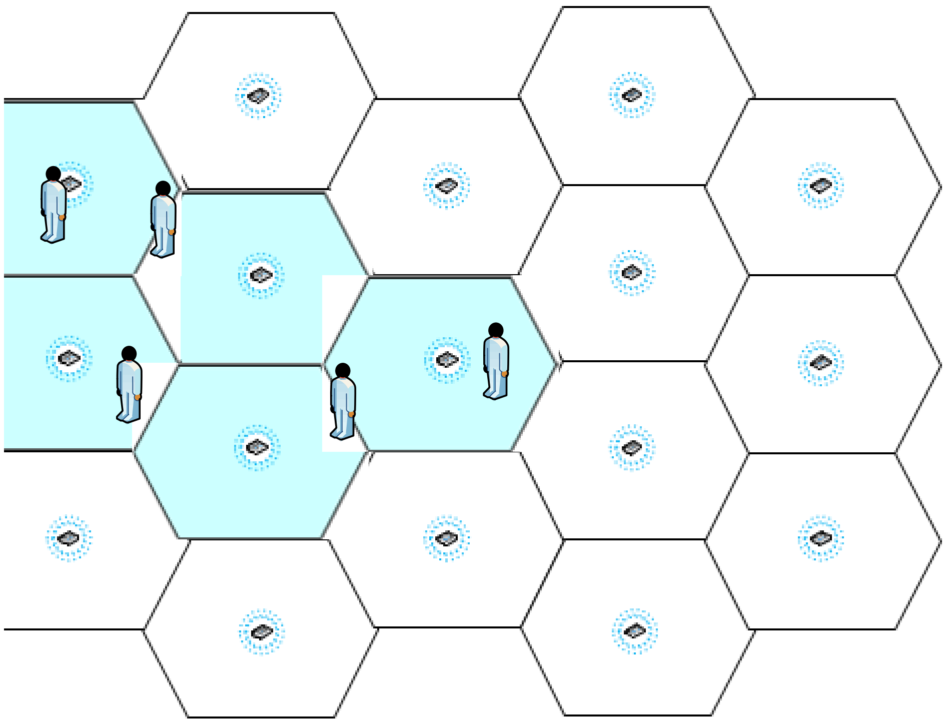
- **Measurement types**
  - ➢ Time of arrival (ToA)
  - ➢ Time difference of arrival (TDoA)
  - ➢ Angle of arrival (AoA)
  - ➢ Received signal strength indicator (RSSI)
- **Location estimation methods**
  - ➢ Cell of origin (CoO)
  - ➢ Distance-based
    - ✓e.g., trilateration
  - ➢ Fingerprinting
    - ✓pattern recognition)



Common Algorithms for Fingerprinting

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- **Probabilistic, e.g.,**
  - ✓ Bayesian

$$p(l_x|o_x) = \frac{p(l_x)\cdot p(o_x|l_x)}{\sum_{i=1}^{m} p(l_i)\cdot p(o_x|l_i)}$$

- **Deterministic, e.g.,**
  - ✓ Nearest Neighbor (NN)

$$\text{Min } \delta = \sqrt{\sum_{i=1}^{n}(S_i - S_{mi})^2}$$

  - ✓ K-NN

$$\delta = \frac{1}{K} * \sum_{i=1}^{k} \delta_i$$

  - ✓ Weighted KNN

$$\delta = \sum_{i=1}^{k}(w_i * \delta_i)$$
$$where\ (w_1 + w_2 + \cdots + w_k) = 1$$

  - ✓ Our new algorithm

Our Algorithm for Fingerprinting

- **Based on the NN algorithm**
- **For improving location accuracy on fingerprinting**
- **Findings used for our algorithm**
  - ➢ A former test (test environment: 56 x 18.2 x 3.3 m^3 space, 11 access points (APs) and 30 test points)
  - ➢ Findings: stronger signals presented more stability and more consistency. Therefore, our algorithm started from the surrounding APs with the strongest RSSI values observed, named the initial AP (AP_{init})

Distance Calculated from RSSI Observations (CISCO™)

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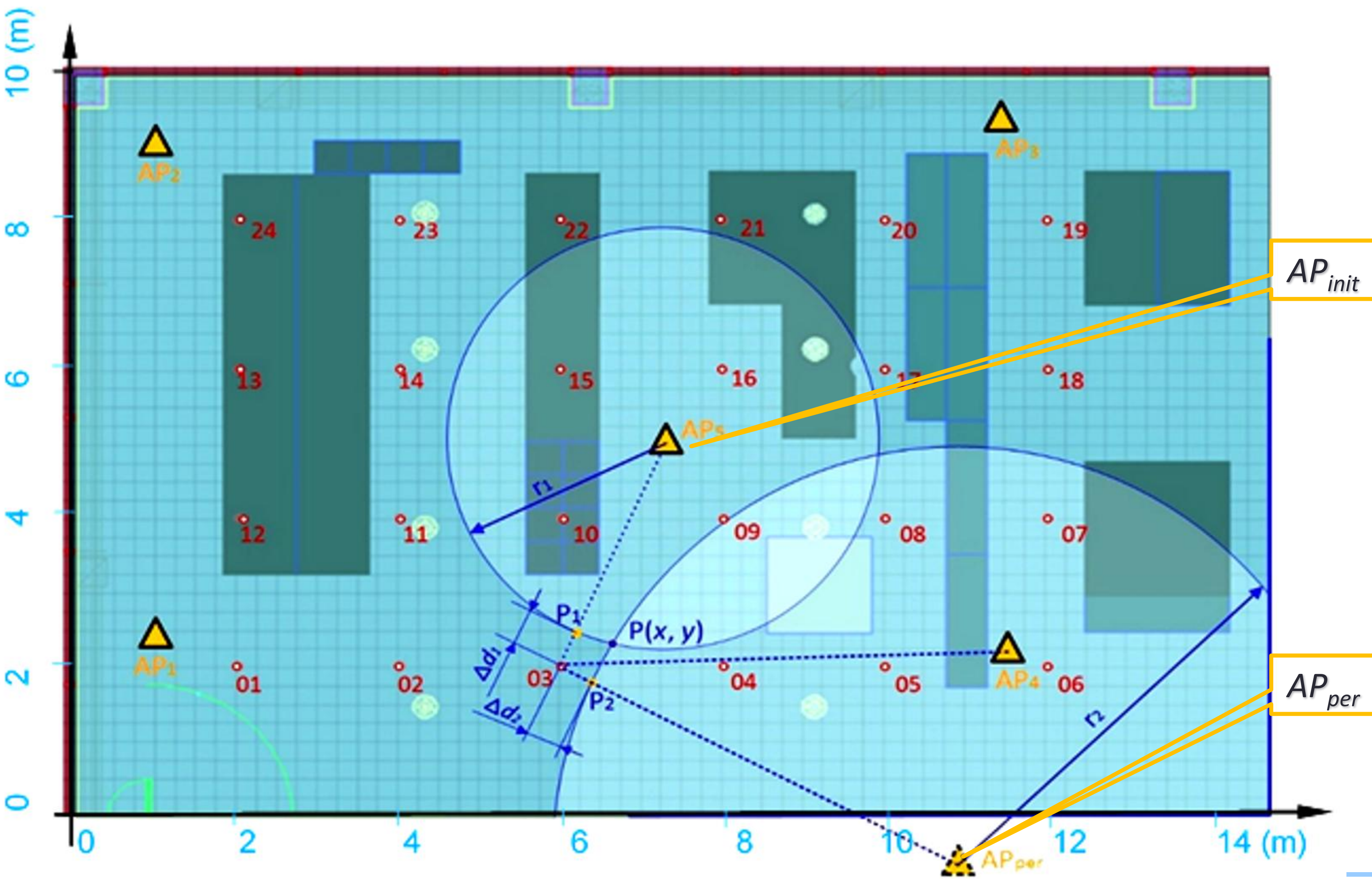
$$d = 10^{\frac{TX_{PWR} - RX_{PWR} - LOSS_{TX} - LOSS_{RX} + GAIN_{TX} + GAIN_{RX} - PL_{1METRE} - s}{10n}}$$

where,

d:	distance between the user and the associated AP in metres;
RX_{PWR}:	detected RSSI value from the user's smartphone in dB;
TX_{PWR}:	transmitter output power in dB;
$Loss_{TX}$:	sum of all transmitter-side cable and connector losses in dB;
$Gain_{TX}$:	transmitter-side antenna gain in dBi;
$Loss_{RX}$:	sum of all user-side cable and connector losses in dB;
$Gain_{RX}$:	user-side antenna gain in dBi;
PL_{1Meter}:	reference path loss for the distance of 1 meter and for the desired frequency, in dB;
n:	path loss exponent for the environment;
s:	standard deviation associated with the degree of shadow fading present in the environment.

Principle of the New Algorithm (1)



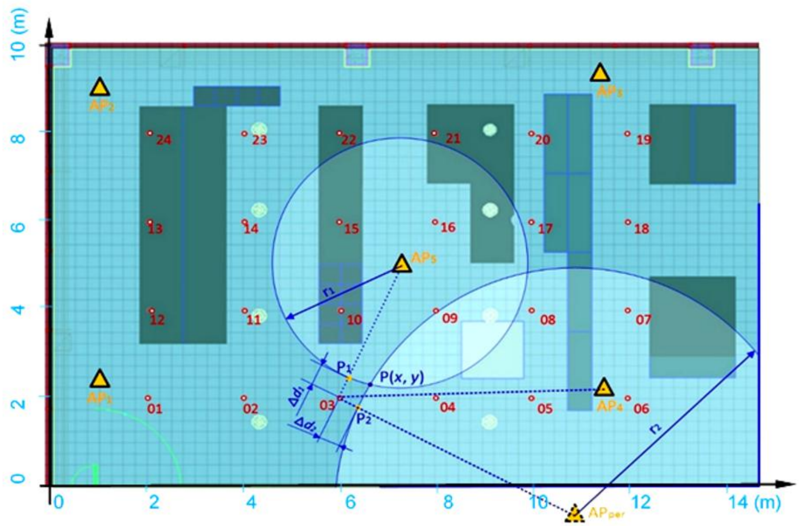
Principle of the New Algorithm (2)

Averaging a few observations for each reference point (RP):

$$\bar{S}_{RPk} = (\overline{RSSI}_{RPk}^{AP1}, \overline{RSSI}_{RPk}^{AP2}, \ldots, \overline{RSSI}_{RPk}^{APn})$$

User's P_{init} is determined by the RP with the minimum δ_k:

$$\delta_k = \sqrt{\sum_{i=1}^{n} (RSSI_{usr}^{APi} - \overline{RSSI}_{RPk}^{APi})^2}$$



Principle of the New Algorithm (3)

Calculate the differences:

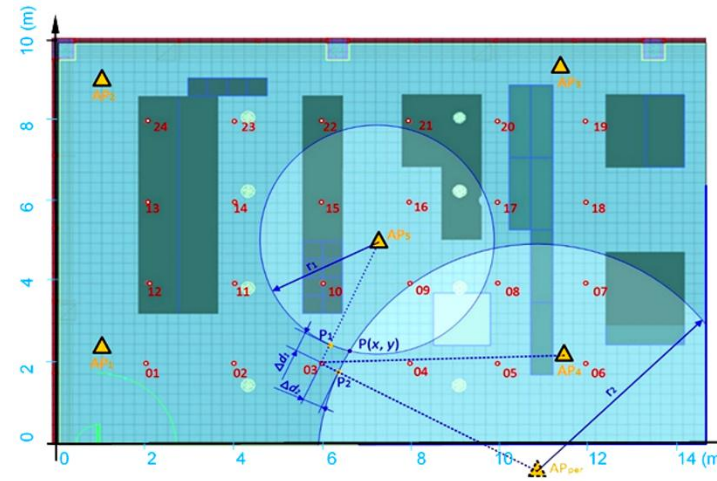
$$\Delta d_1 = d_{1\text{est}} - \overline{d_{1\text{est}}}$$
$$\Delta d_2 = d_{2\text{est}} - \overline{d_{2\text{est}}}$$

$$r_1 = D_1 + \Delta d_1$$
$$r_2 = D_2 + \Delta d_2$$

$$r_1 = \sqrt{(x - x_{init})^2 + (y - y_{init})^2}$$
$$r_2 = \sqrt{(x - x_{per})^2 + (y - y_{per})^2}$$

Proper geometry configuration

User's location: P (x, y)

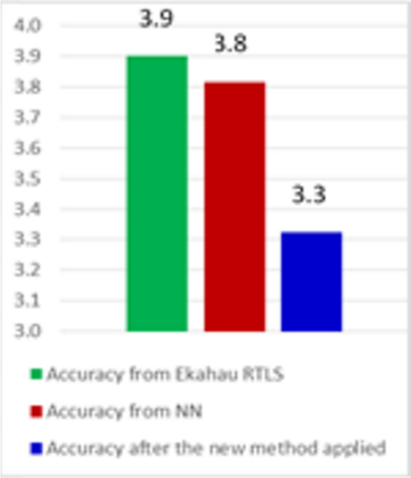


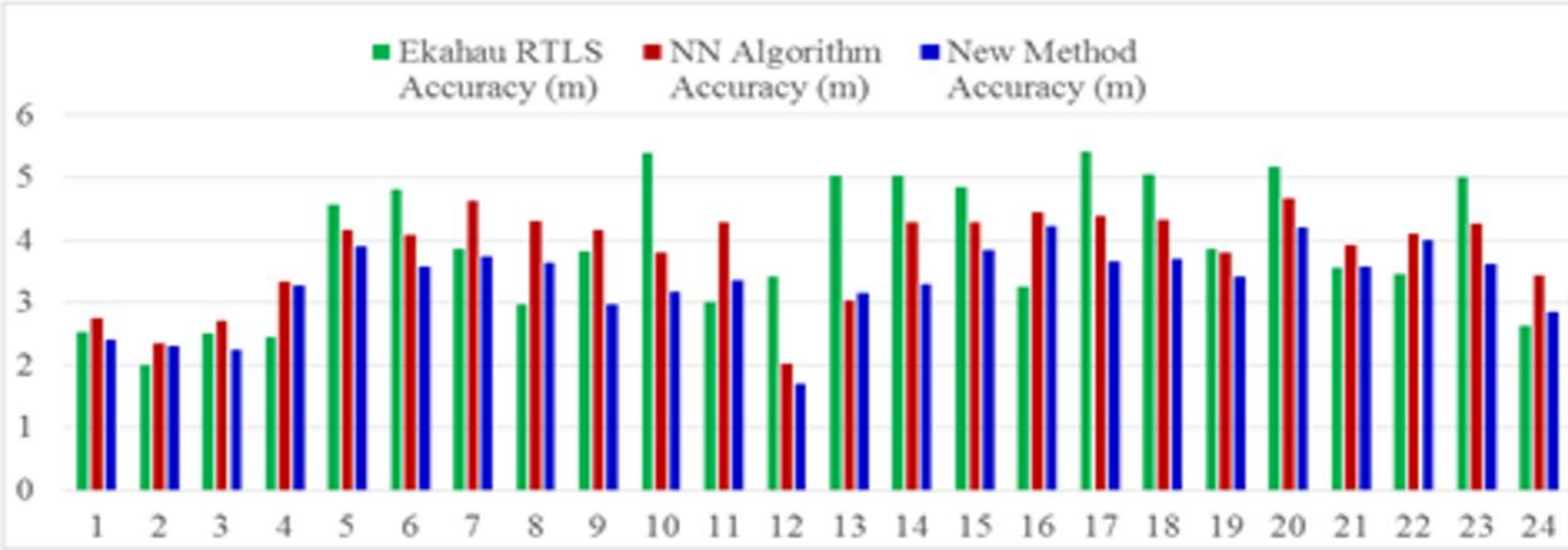
True distance D (m)	Estimated distance $\bar{d}$ (m)	*Estimated distance* d (m)	$\Delta d = d - \bar{d}$ (m)	$r = D + \Delta d$	Final P(*x*, *y*)
$D_1 = 3.15$	$\overline{d_1} = 1.50$	$d_1 = 1.25$	$\Delta d_1 = -0.25$	$r_1 = 2.90$	The nearer intersection point of the circles (r_1 & r_2)
$D_2 = 5.68$	$\overline{d_2} = 1.64$	$d_2 = 1.37$	$\Delta d_2 = -0.28$	$r_2 = 5.40$	

Analysis of the Test Results

Statistics results of 30 test points calculated by:

$$\delta_{RMS} = \sqrt{\frac{1}{m}\{\sum_{k=1}^{m}[(x_k - x_{ek})^2 + (y_k - y_{ek})^2]\}}$$





Conclusion and Future Work

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- **A new method for indoor positioning is proposed**
- **The new method is based on the NN algorithm with an improvement on location accuracy of half a meter**
- **The differential approach provides a new way for systematic error elimination to improve position estimates**
- **Future work:**
  - ✓ 3D implementation
  - ✓ investigation of the variation of RSSI observations from a particular AP at different times
  - ✓ Accuracy comparasion between KNN, Weited-KNNS

Thank you!

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