Communication Technologies 2 (CT2)

Machine Learning:

Applications and Algorithms

Wi-Fi Fingerprinting

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Lecture in WS 2018 / 2019 29.11.2018



Outline

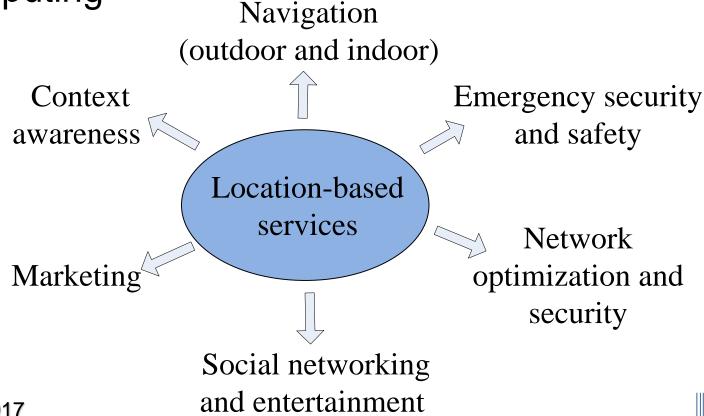


- Location-based services
- Indoor positioning
- Wi-Fi based positioning
- Wi-Fi fingerprinting system
- DCCLA algorithm
- Challenges

Location-based Services



 The location information provided is now one of the most important contexts for context-aware computing



The Global Positioning System (GPS)



- Widely used for providing positioning services.
- Require line-of-sight (LoS) transmission with the GPS satellites.
- Poor coverage for indoor environments



Source: http://www.mio.com/

Free-space Path Loss



- Assume there are no obstructions between the transmitter and receiver. The signal propagates along a straight line
- Free-space path loss is defined as the path loss of the free-space model:

$$P_L \text{ (dB)} = 10 \log_{10} \frac{P_t}{P_r} = -10 \log_{10} \frac{G_l \lambda^2}{(4\pi d)^2}.$$

d: distance between the transmit and receive antennas

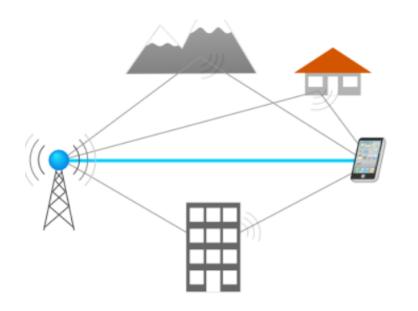
λ: the wavelength of the transmitted signal

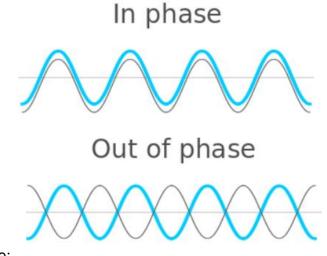
G_I: the product of the transmit and receive antenna gains

Free-space Path Loss



- Difficult to model the radio propagation in the indoor environment:
 - Multipath, fading
 - non light-of-sight transmission because of obstacles





Source:

http://wiki.yatebts.com/index.php/Radio_Propagation_Concepts

Indoor Positioning



- Different locations can be distinguished by particular features surrounded those locations
 - light, noise, temperature
 - radio signals: Bluetooth, GSM or Wi-Fi
- Good characteristic help to recognize different locations.
- The selected characteristic should be stable over time.

Wi-Fi Positioning System



- Uses the received signal strengths (RSS) from surrounded access points (AP) to locate a mobile node.
- Two methods of using the Wi-Fi RSS to determine a receiver's position
 - lateration methods
 - fingerprinting methods

Methods & positioning principle



- Time of Arrival (TOA)
- Time Difference of Arrival (TDOA)
- RSS-Based (Signal Attenuation-Based)
- Roundtrip time of flight of the signal (RTOF)
- Angulation estimation (AOA Estimation)
- Receive Signal Strength (RSS)

Trilateration methods



- Time of Arrival (TOA)
 - Measure the propagation time
 - Calculate the distance between the receiver and the transmitter.

- The clock of transmitters and receivers must be precisely synchronized



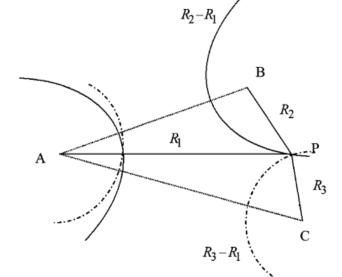
Trilateration methods



- Time Difference of Arrival (TDOA)
 - the time difference to send signal to multiple receivers
 - The hyperbolic has a constant range difference between the two measuring units.

- For each TDOA measurement, the transmitter must lie

on a hyperbolic.



Source: [2]

Trilateration methods



- RSS-Based (Signal Attenuation-Based)
 - Calculate the attenuation of emitted signal strength
 - Base on the signal path loss model, estimate the travel distance
- Roundtrip time of flight of the signal (RTOF)
 - Measure the propagation time from the transmitter to the receiver and back

Fingerprinting method



- Human fingerprint is unique
 - Collect human fingerprint and store in a database
 - To identify any person, compare his/her fingerprint with the fingerprinting database.

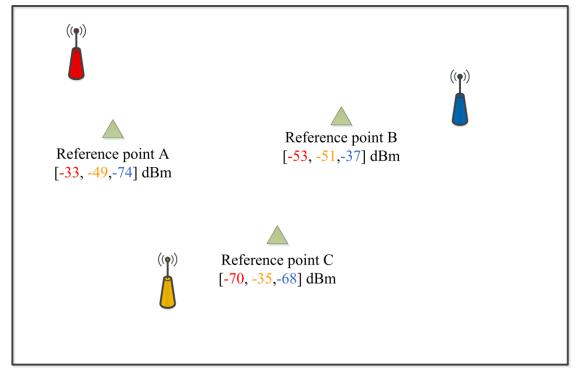


Source: [1]

Wi-Fi signal



- MAC address
- Receive signal strength (RSS)
- Service set identifier (SSID)
- Channel (frequency)



Wi-Fi signal



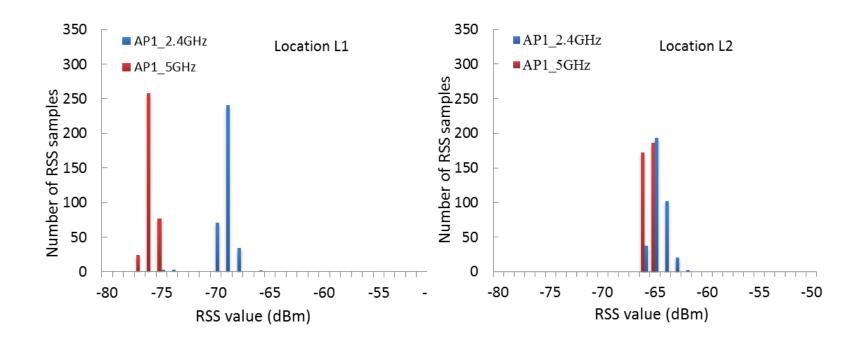
- MAC address
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Source: [1]

Wi-Fi signal





Wi-Fi RSS histogram in 2 adjacent rooms

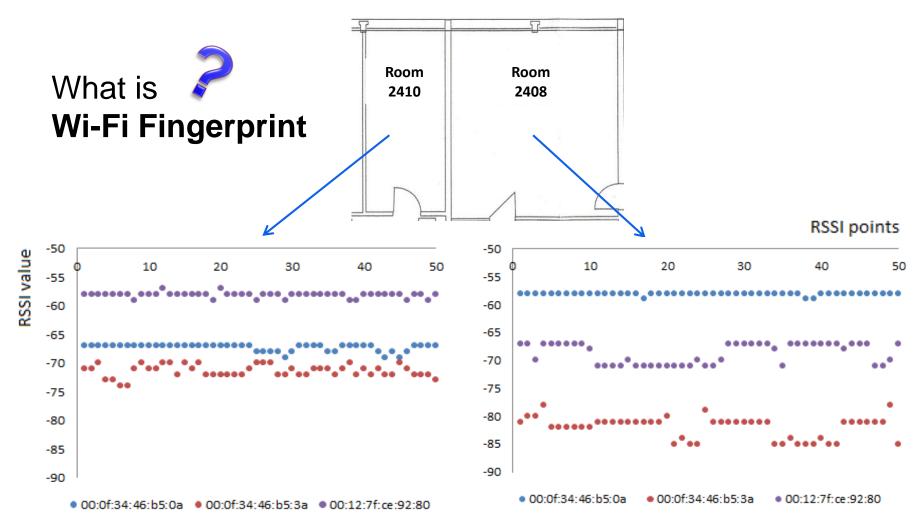
Wi-Fi fingerprinting



- The fingerprinting technique uses location specific RSSI pattern of neighboring WLAN APs to distinguish different locations
- Not require the dedicated infrastructure installation.
 - Easy to implement
 - Reduce cost

Wi-Fi fingerprinting





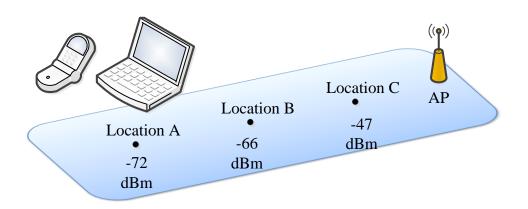
Wi-Fi fingerprint

RSSI: Received Signal Strength Indicator

Concepts



- Wi-Fi fingerprint
 - Wi-Fi information sensed at a location

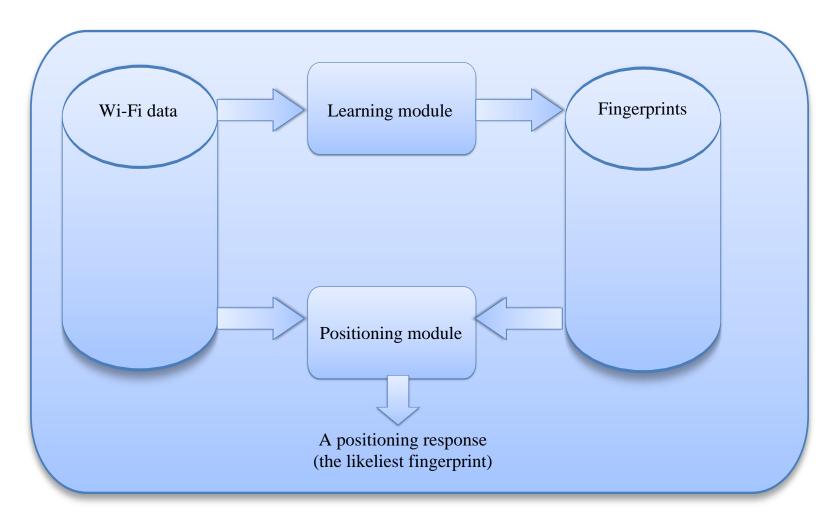


Concepts



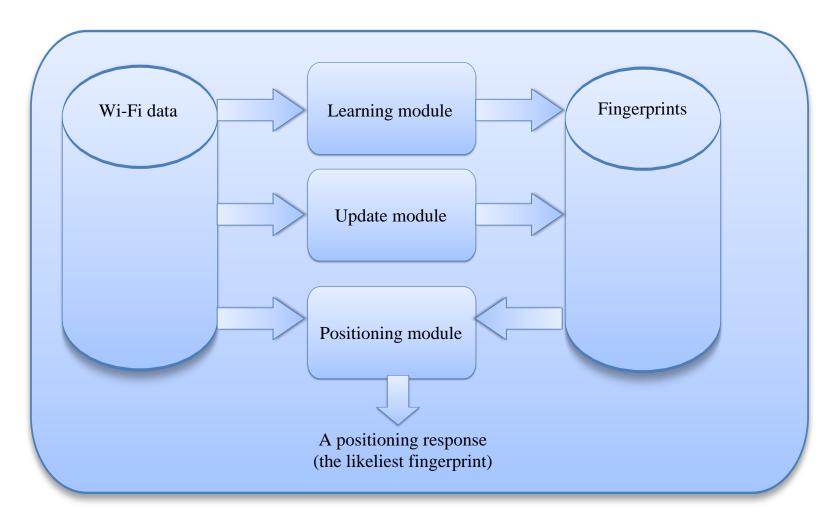
- Wi-Fi fingerprint
 - Wi-Fi information sensed at a location
- Wi-Fi fingerprinting
 - practice of recording the fingerprint of Wi-Fi signal
 - the method of finding the particular pattern of Wi-Fi signal in a particular location
- Wi-Fi fingerprint database
 - a database which contains the generated fingerprints
 - radio map





Source: [1]

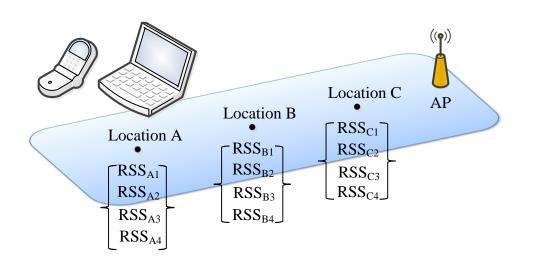




Source: [1]



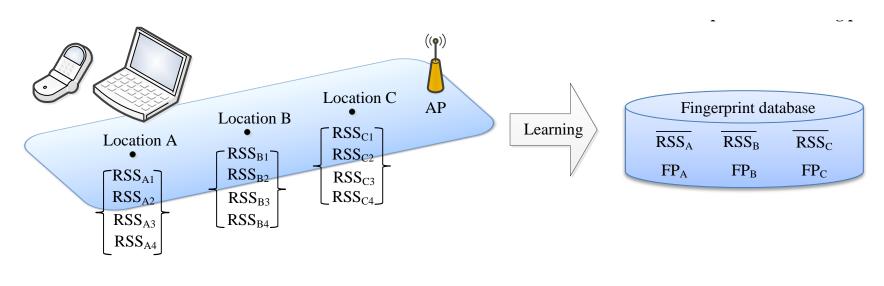
- Learning phase (training, offline phase)
 - Collecting Wi-Fi data
 - Generating Wi-Fi fingerprint: building a database containing Wi-Fi fingerprints



Source: [1]



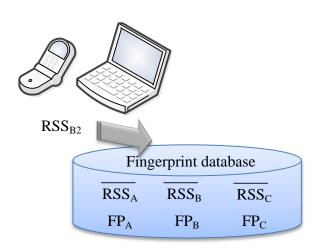
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Source: [1]



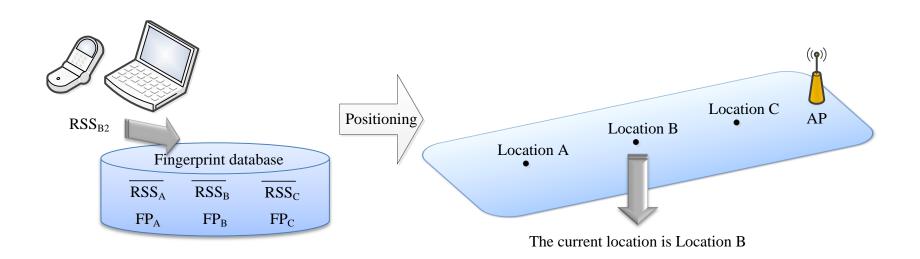
- Positioning phase (testing, online phase)
 - Comparing the current Wi-Fi scans with the FP database to infer the location



Source: [1]



- Positioning phase (testing, online phase)
 - Comparing the current Wi-Fi scans with the FP database to infer the location



Source: [1]

Components of Wi-Fi fingerprinting System



- Wi-Fi APs
 - broadcast Wi-Fi signal
- Mobile devices
 - collect the Wi-Fi RSS from APs
 - manage fingerprint database
 - execute the learning and positioning algorithms
 - user interface (UI)
- Users
 - carry the mobile device in their daily lives
 - interact with the mobile device through the UI.

Components of Wi-Fi fingerprinting System



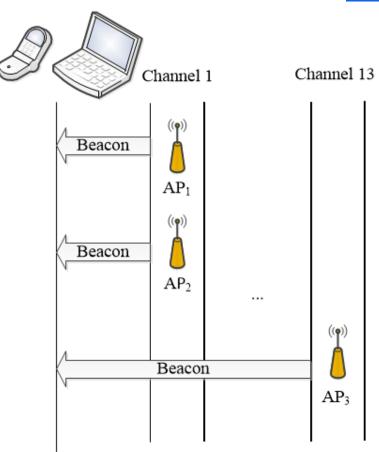
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May be done on a computer

Scanning methods



- Passive scanning
 - Moves to each channel in the channel list
 - Listen to the beacon frames from nearby APs



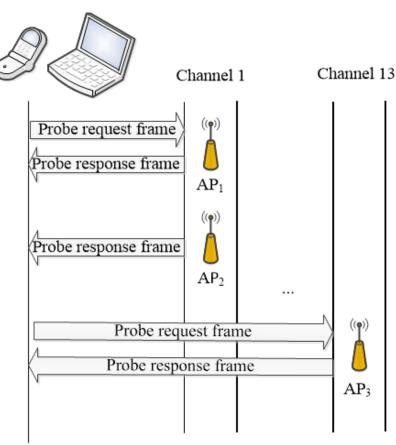
Passive scanning

Source: [1]

Scanning methods



- Active scanning:
 - Mobile device transmits a Probe Request frame on each of the channel
 - Wait to receive response from any APs
 - Move on to the next channel
 - This process is iterated until all channels have been scanned



Active scanning

Source: [1]

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Wi-Fi collection approaches



Grid-based

- split a selected area into many small grids
- measure Wi-Fi signal in those grids
- Interpolation-based
 - measure Wi-Fi data in observed locations
 - based on the fingerprints of the observed locations, interpolate fingerprints for other locations
- Path survey (War-driving)
 - collect Wi-Fi data when moving
 - record the walking distances at the same time

Wi-Fi collection approaches



Dead Reckoning

- infer location based on previously determined locations
- combine with the traveled distance and the direction of movement

Place learning

 discover the significant locations where people spend much time by analyzing various sensor data

Crowdsourcing

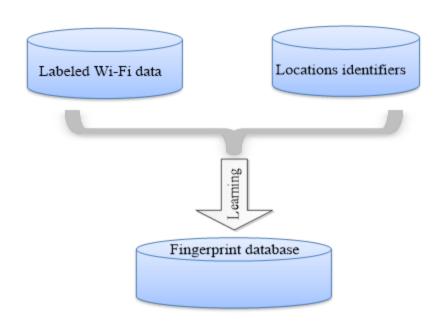
 Using raw Wi-Fi data, fingerprints contributed by different users, devices

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Learning approaches



- Supervised
- Semi supervised

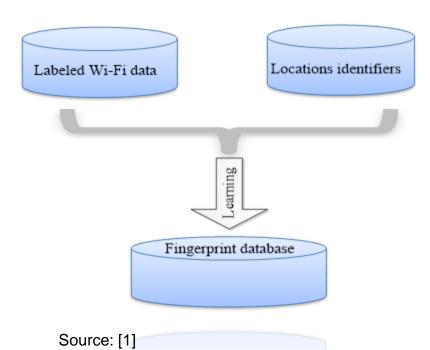


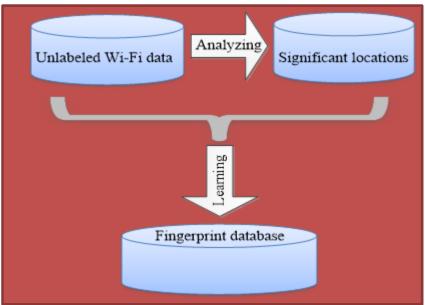
Source: [1]

Learning approaches



- Supervised
- Semi supervised
- Unsupervised





Fingerprint feature



MAC_i: MAC address

 RSS_i : averaged

received signal

strength of AP_i

of AP

- Deterministic technique
 - Mean RSS value

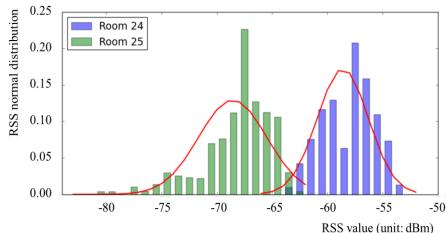
$$FP_{l} = \{MAC_1 : \overline{RSS_1}, \dots MAC_p : \overline{RSS_p}\} | (p \in \mathbb{N}_+)$$

Wi-Fi scan

$$S_l^i = \{MAC_1: RSS_1^i, ..., MAC_p: RSS_p^i\} \mid (i, p \in \mathbb{N}_+)$$

- RSS range

- RSS histogram



Source: [1]

Fingerprint feature



- Deterministic technique
 - Wi-Fi ratio: the RSS ratio between pairs of APs $r(AP_i, AP_j) = \frac{RSS_i}{RSS_j} | (i, j \in \mathbb{N}_+; i < j)$
 - RSS difference: the differences between pairs of APs $d(AP_i, AP_j) = RSS_i RSS_j \mid 1 \le i < j \le n$
 - AP rank: rank values are assigned to APs based on their RSS

$$FP_l = \{1: MAC_i, \dots, p: MAC_i\} \mid (RSS_i \geq RSS_j; i, j, p \in \mathbb{N}_+)$$

-The response rate: the times of sensing the AP divided by the times of scans.

MAC_i: MAC address of AP_i

RSS_i: received signal strength of AP_i

Fingerprint feature



Probabilistic technique

- Gaussian distribution
 - In case the RSS values of an AP are distributed as a Gaussian model.
 - A statistical signature, as a fingerprint, is generated for each location by using the Gaussian model.
- Non-Gaussian distribution
 - In case the RSS distribution is non-Gaussian, an improved double-peak Gaussian distribution has been proposed to approximate the RSS distribution.
- Log-normal distribution
 - The RSS distribution may be asymmetric

Accuracy

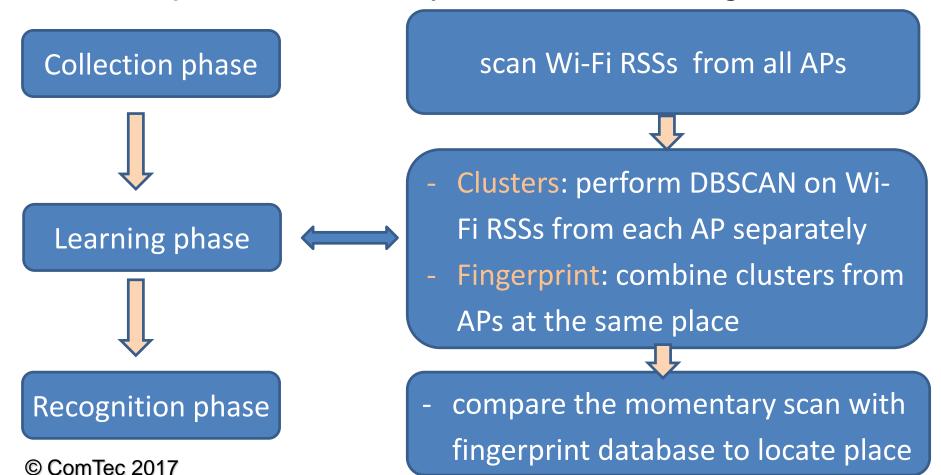


- In meter
 - how close is the estimated location to the true location indicated as error distance (m)
- Room level
 - locating a user within a room

DCCLA algorithm



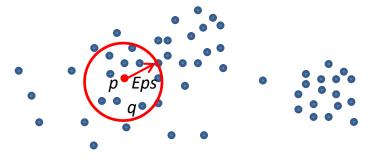
- Wi-Fi Fingerprinting-based localization
- Unsupervised Density-based Clustering method



Density-based clustering



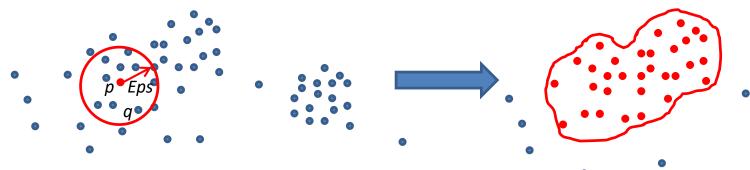
- the density-based spatial clustering of applications with noise (DBSCAN) algorithm utilizes concepts of neighborhood and neighborhood-density to extract clusters.
- 2 parameters
 - Eps: radius of the neighborhood
 - MinPts: minimum number of points in a cluster



Density-based clustering



- the density-based spatial clustering of applications with noise (DBSCAN) algorithm utilizes concepts of neighborhood and neighborhood-density to extract clusters.
- 2 parameters
 - Eps: radius of the neighborhood
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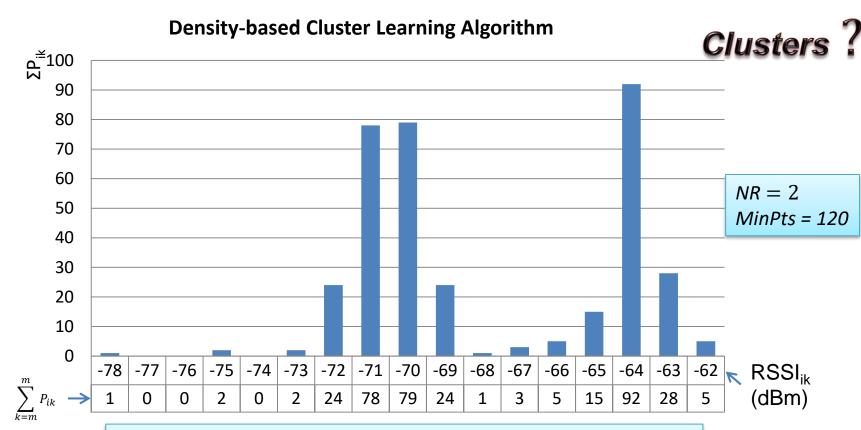
Discover clusters

- perform DBSCAN on each AP to discover highdensity clusters.
- cluster: consecutive RSS range with high RSS density

Fingerprint

Clusters appear at the same time from different APs

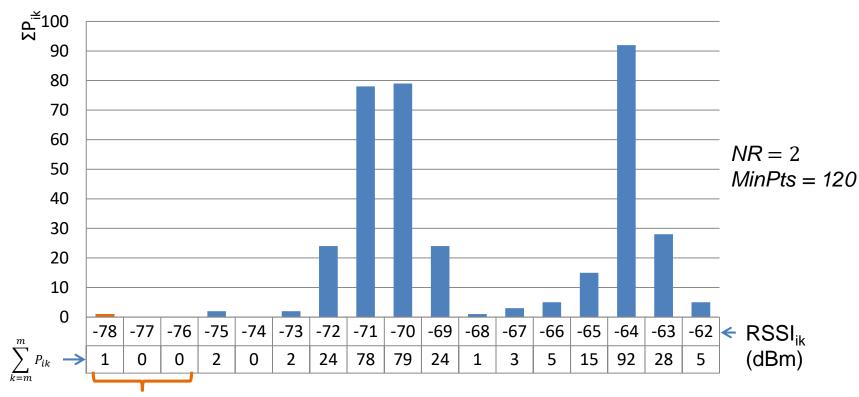




Data in a Wi-Fi database: collected in room 2408 between 09:00 -09:30 on 15.08.2012. *MAC_i* = 00:0f:34:46:b5:0a $\sum_{k=-78}^{-62} P_{ik} = 359$



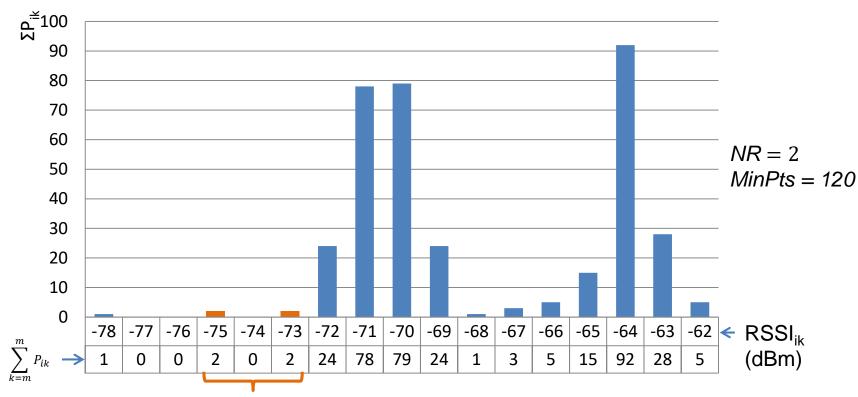
Density-based Cluster Learning Algorithm



$$\rho(P_{ik}) = \sum_{k=-78}^{-76} P_{ik} = 1 < 120$$



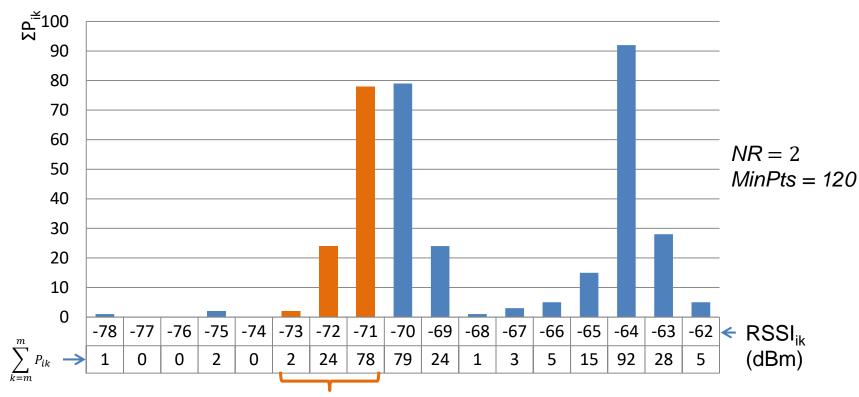
Density-based Cluster Learning Algorithm



$$\rho(P_{ik}) = \sum_{k=-75}^{-73} P_{ik} = 4 < 120$$



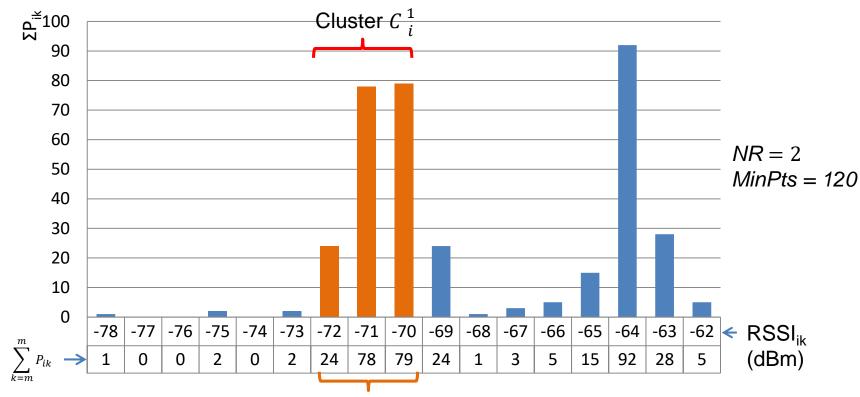
Density-based Cluster Learning Algorithm



$$\rho(P_{ik}) = \sum_{k=-73}^{-71} P_{ik} = 104 < 120$$



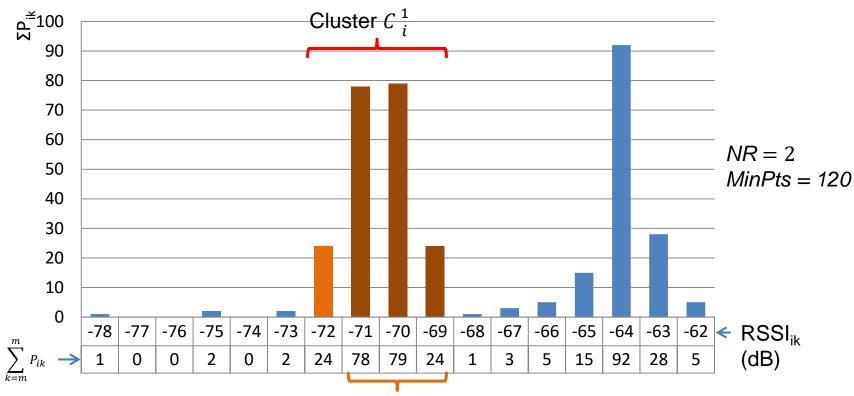
Density-based Cluster Learning Algorithm



$$\rho(P_{ik}) = \sum_{k=-72}^{-70} P_{ik} = 181 \ge 120$$



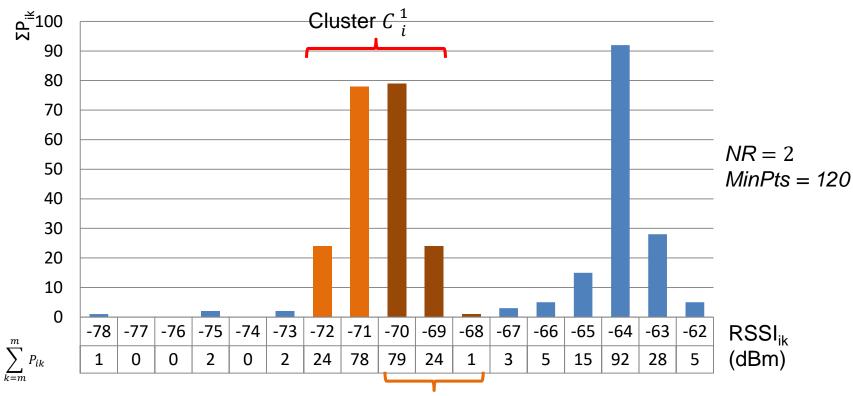
Density-based Cluster Learning Algorithm



$$\rho(P_{ik}) = \sum_{k=-71}^{-69} P_{ik} = 181 \ge 120$$



Density-based Cluster Learning Algorithm

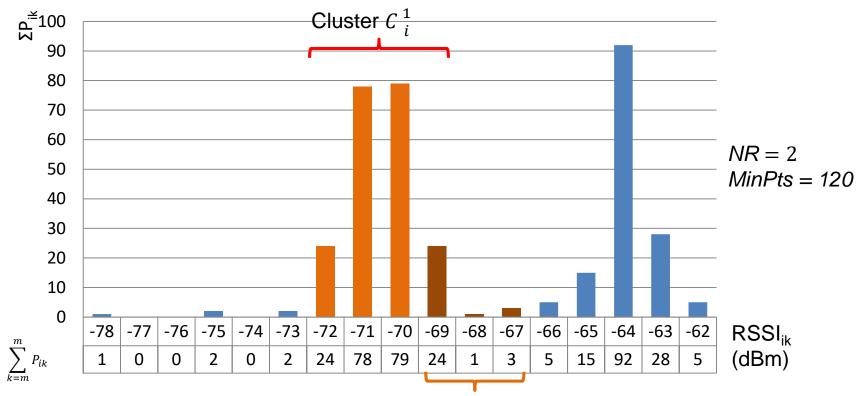


$$\rho (P_{ik}) = \sum_{k=-70}^{-68} P_{ik} = 104 < 120$$

Note: if ρ (P_{ik}) < 120, the density check will continue, since P_{ik} with RSSI_{ik}=-69 dB still belongs to the cluster C_i^1



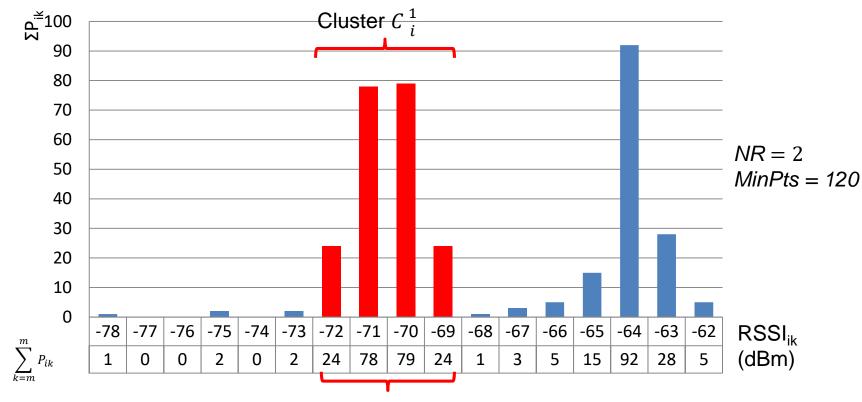
Density-based Cluster Learning Algorithm



$$\rho(P_{ik}) = \sum_{k=-69}^{-67} P_{ik} = 28 < 120$$



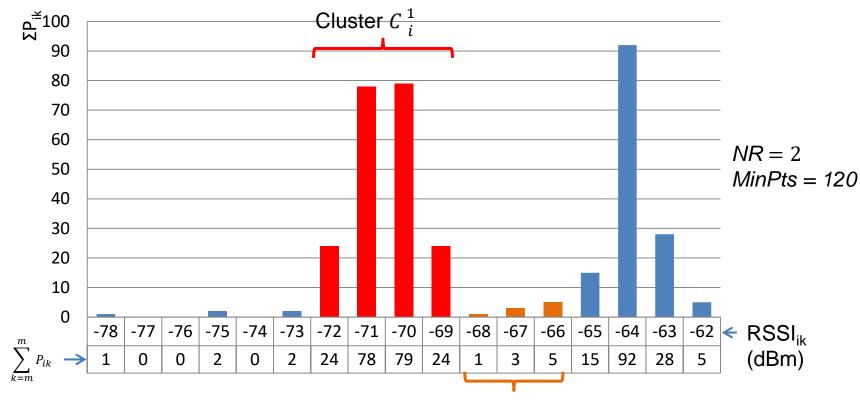
Density-based Cluster Learning Algorithm



$$C_{i}^{1} = \{MACi, -72dB, -69dB\}$$



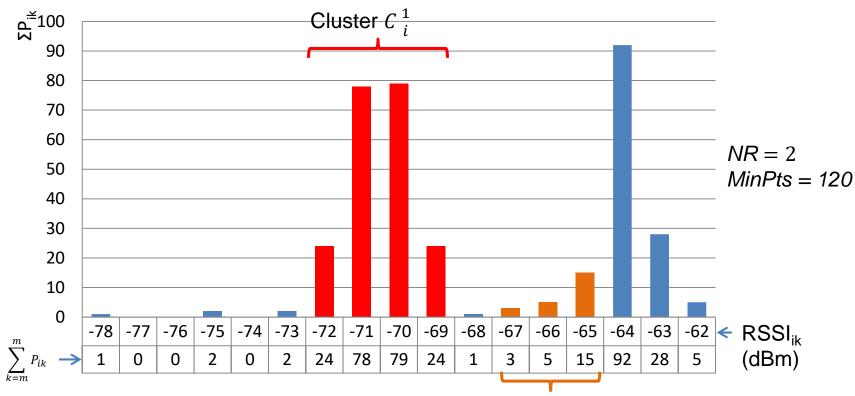
Density-based Cluster Learning Algorithm



$$\rho(P_{ik}) = \sum_{k=-68}^{-66} P_{ik} = 9 < 120$$



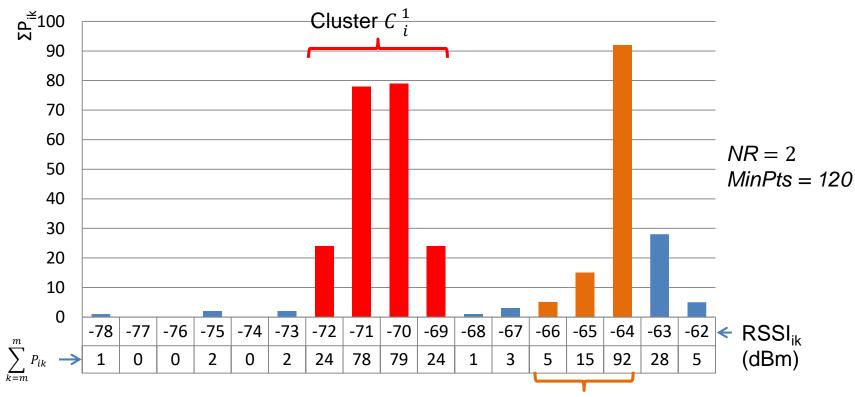
Density-based Cluster Learning Algorithm



$$\rho(P_{ik}) = \sum_{k=-67}^{-65} P_{ik} = 23 < 120$$

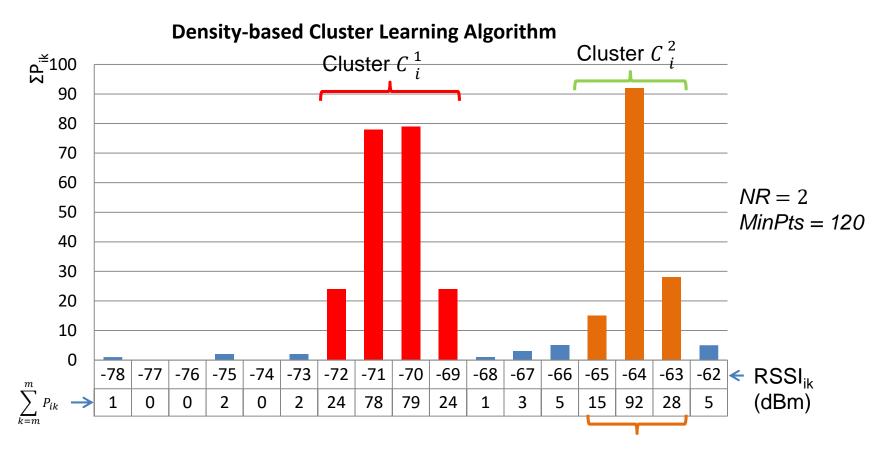


Density-based Cluster Learning Algorithm



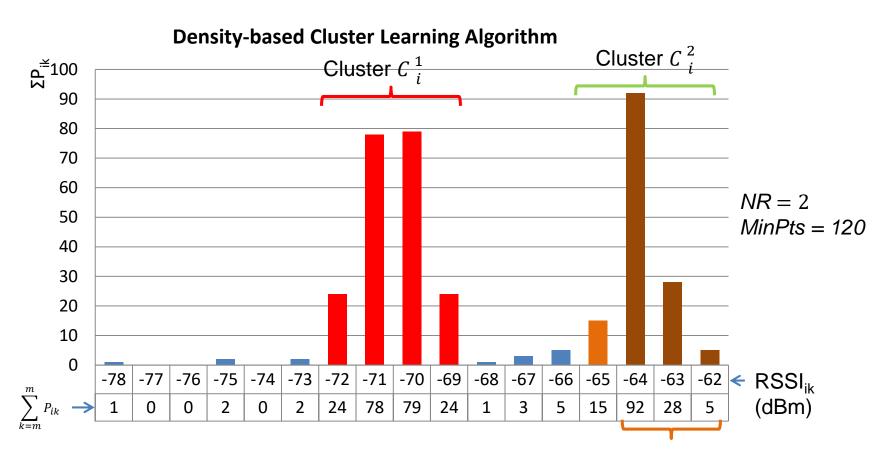
$$\rho(P_{ik}) = \sum_{k=-66}^{-64} P_{ik} = 112 < 120$$





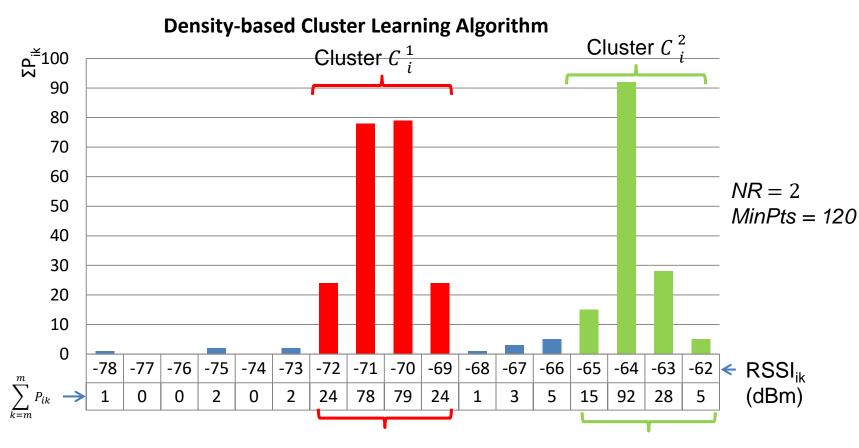
$$\rho (P_{ik}) = \sum_{k=-65}^{-63} P_{ik} = 135 \ge 120$$





$$\rho(P_{ik}) = \sum_{k=-64}^{-62} P_{ik} = 125 \ge 120$$





 $C_{i}^{1} = \{MACi, -72dB, -69dB\}$ $C_{i}^{2} = \{MACi, -65dB, -62dB\}$

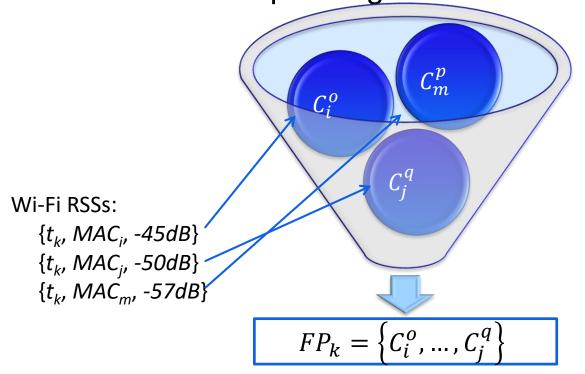
Positioning phase



Compare the current Wi-Fi RSSs with learned Wi-Fi fingerprints

The user returns to a location corresponding to this

fingerprint



Source: [1]

Common Positioning approaches

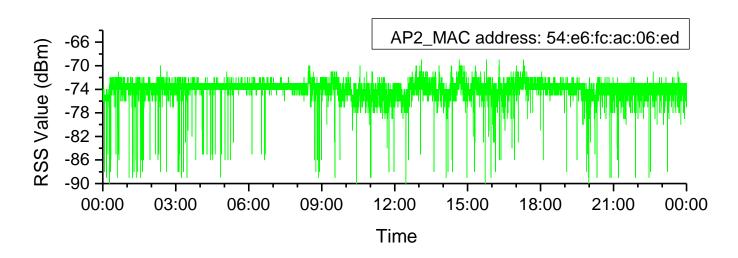


- Nearest neighbor
 - Euclidean distance, Manhattan distance
- Probabilistic framework
 - Estimating the likelihood function, e.g., histogram, kernel, Gaussian
- Neural network
- Support vector machine
- Filtering approaches

RSS fluctuation



- Human presence
- **Obstacles**
- Change of environment

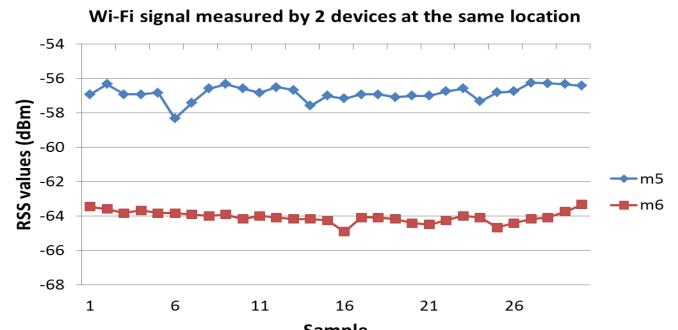


Source: [1]

Device heterogeneity



- Different devices are used in the training phase and positioning phase
- Those devices may have different Wi-Fi chipset, different antenna gain

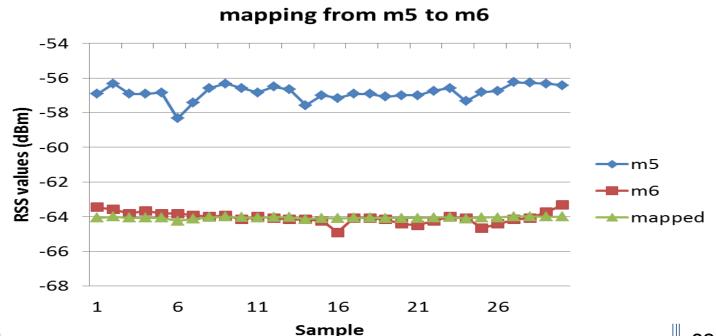


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Solving Device heterogeneity



- Mapping device
 - Manual calibration
 - Linear transformation method
 - Ranking method



Solving Device heterogeneity



- Extract features that do not depend on hardware
- Spatial mean normalization (SMN)

$$\bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i$$
 $\hat{x}_i = F(x_i | 1, ..., N)) = x_i - \bar{x}$

- Signal strengths difference (SSD) $d(AP_i, AP_j) = RSS_i RSS_j$
- Hyperbolic Location Fingerprinting (HLF)

$$r(AP_i, AP_j) = \frac{RSS_i}{RSS_j} \qquad nlr(AP_i, AP_j) = \log r(AP_i, AP_j) - \log(\frac{1}{RSS_{max}})$$

2.4 GHz vs 5 GHz



 The free space path loss index depends on the frequency of the signal

$$P_L \text{ (dB)} = 10 \log_{10} \frac{P_t}{P_r} = -10 \log_{10} \frac{G_l \lambda^2}{(4\pi d)^2}.$$

- The output power limit is different
- Different characteristic:
 - Scattering inside the building
 - Damping through water
 - Wall penetration
 - Fast fading

Other factors



- Energy consumption
- Response rate
- Fingerprint database
- Different frequency
- Number of scan per location estimate
- Influence of the number of Wi-Fi APs
- Combination with other sensors

References



- Y. Xu, "Autonomous Indoor Localization Using Unsupervised Wi-Fi Fingerprinting," PhD. Dissertation, Kassel University Press, 2015.
- 2. H. Liu, H. Darabi, P. Banerjee, and J.Liu, "Survey of Wireless Indoor Positioning" Techniques and Systems", IEEE Transactions On Systems, Man, And Cybernetics— Part C: Applications And Reviews, Vol. 37, No. 6, November 2007.
- 3. S. Das, T. Teixeira, and S. F. Hasan, "Research Issues related to Trilateration and Fingerprinting Methods", International Journal of Research in Wireless Systems, Volume 1, Issue 1, November, 2012.
- 4. E. Ester, H. Kriegel, J. Sander and X. Xu, "A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise", 2nd International Conference on Knowledge Discovery and Data Mining, 1996.
- 5. S. Shin, A. G. Forte, A. S. Rawat, and H. Schulzrinne, "Reducing MAC Layer Handoff Latency in IEEE 802.11 Wireless LANs", Proceeding MobiWac 2004.
- 6. B. Bing (Editor), "Wireless Local Area Networks The New Wireless Revolution," Wiley-Interscience, 2002.
- 7. A. Goldsmith, "Wireless Communications," Cambridge University Press, 2005.