

# Robust and Undemanding WiFi-fingerprint based Indoor Localization with Independent Access Points

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## 1. WIFI BASED INDOOR LOCALIZATION SYSTEM

Our proposed localization system is similar to existing WiFi-fingerprint localization systems. It works by first collecting received signal strength (RSS) values of access points (APs) from different reference points in the area of interest. This initial training can be done either manually or by crowd-sourcing. The WiFi-fingerprint map is generated from collected RSSs at all reference points. However, instead of utilizing unreliable absolute RSS values, our system uses RSS differences between every pair of APs as a fingerprint metric. This fingerprint metric is denoted as AP-Sequence. The AP-Sequence is used to partition the area of interest into small regions. Each small region is associated with unique ordered RSS sequence. The WiFi-fingerprint map consists of this small regions.

Figure 1 illustrates a high-level application scenario of AP-Sequence fingerprint localization. When a user A wants to know her location, she first scans the RSS values of APs in her proximity. For example, the user A scans wireless channels and observes  $AP_1$ ,  $AP_2$  and  $AP_3$  with RSS values of  $-42$  dBm,  $-65$  dBm, and  $-72$  dBm, respectively. Based on the relative difference between RSS values of the three APs, the AP-Sequence of  $\langle 1, 2, 3 \rangle$  is generated. Essentially, it is an ordered sequence of APs from high to low in terms of RSS strength. Then the user A uploads AP-Sequence  $\langle 1, 2, 3 \rangle$  to AP-Sequence fingerprint map server for localization. The AP-Sequence of  $\langle 1, 2, 3 \rangle$  is compared to AP-Sequence fingerprint map and she is ultimately localized to a region associated with the best matching AP-Sequence.

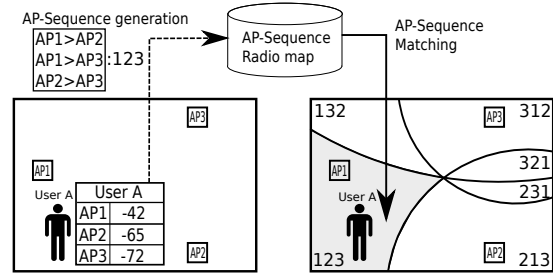


Figure 1: System overview

There are two important steps need to be addressed for the AP-Sequence fingerprint localization: Fingerprint map construction and AP-Sequence matching for localization.

## 2. FINGERPRINT MAP CONSTRUCTION

The fingerprint map is constructed by partitioning the area of interest into a set of small regions by circular boundaries. To partition the area, the locations of APs are required, which are readily available in most commercial and industrial buildings. Each pair of APs is associated with one circular boundary. Suppose there are AP 1 and AP 2 in the area. Then this pair of APs will be associated with a circular boundary. This circular boundary divides the area into two regions. One region contain AP 1 and the other region contains AP 2, respectively. If a point lies inside of the circle containing an AP 1, it indicates that the RSS value of AP 1 at that point is likely to be greater than RSS value of AP 2 measured at the same point. Theoretically, any points lie on the circular boundary sees equal RSS values from both AP 1 and AP 2. Suppose,  $d_1$  and  $d_2$  are distances from AP 1 and AP 2 to a point on the circular boundary, respectively. Then, the exact location of this circular boundary depends on the the transmission power difference between two APs and defined by the following equation [1].

$$P_{AP1} - P_{AP2} = 10\eta \log(d_1/d_2),$$

where  $\eta$  represent a path loss exponent and  $P_{AP1}$  is trans-

mission power of AP 1. The center of circle lies on the line intersecting both APs.

Unfortunately, users often don't have access to this information about the transmission power and many WLAN changes this transmission power dynamically overtime. Instead of acquiring this information manually, our system estimates the locations of circular boundaries based on the RSS values collected during the initial training phase. After adjust all the circular boundaries, subregions are created from intersections of these circular boundaries. Each subregion is associated with a unique AP sequence. It is sorted list of APs in the increasing order of their RSS values measured within the subregion. Since a WiFi scan from one reference point often detects several APs, training from few reference locations is sufficient for obtaining a complete AP-sequence fingerprint map. Finding optimal locations of circular boundaries can be formulated as a mix integer linear programming which minimize the incorrectly classified reference points.

### 3. AP-SEQUENCE MATCHING

In order to determine a user's location, we first obtain a RSS values from all nearby APs and generate ordered AP-Sequence by comparing their RSS values. Even though RSS values are not always stable over time, our empirical experiments show that the AP-Sequence of an AP pair typically remains stable if their measured RSS difference is greater than 10 dBm. Similar observations are reported in [3, 2]. Therefore for a given AP pair, if their measured RSS difference is greater than 10 dBm, we define it as a reliable AP pair. Our sequence matching scheme compares the number of reliable AP pairs appeared in the AP-Sequence of individual regions. Then, the user is estimated to be located at the center of the region with the AP-Sequence that most closely matches to the measured AP-Sequence. It is possible that there are more than one region with the same number of reliable AP pairs. To break ties, we use user's previously estimated location and choose the region closest to it.

### 4. DEPLOYMENT REQUIREMENT

Here we describe demonstration version of our system. This system may be different from an actual system. The actual system is server based design since it should be able to simultaneously handle very large number of users. However, the basic design and approach would be identical for both the demonstration version and the actual system.

#### 4.1 Hardware requirement

Any fingerprint-based localization system requires a set of access points. For this competition, we do not require any Internet access through the access points. Therefore, we will simply deploy five to ten wireless routers in the area of interest. The wireless routers will be placed at the random locations depends on the availability of power sockets. Our system is robust against dynamic power controlling among different access points. To emulate that, we will deploy different brands of wireless routers with different transmission power settings.

One android smartphone and a custom-made application will be used for fingerprint map construction and localization. This means fingerprint map will be precomputed and stored in the smartphone itself. The AP-Sequence finger-

print map will be displayed on the application. For the case of multiple users, application along with the precomputed fingerprint map will be transferred manually to other user's android smartphones.

### 4.2 System calibration

Our system requires little initial training, but it would still require 2D floor plan map, preferably in a vector format. We can construct the fingerprint map either manually or from crowdsourcing. In the manual training, we first collect the RSS values of APs from many reference locations in the targeted area and then construct the AP-Sequence fingerprint map. Therefore, we require an easy access to the target site. For crowdsourcing based calibration, the user can either act as a volunteer for calibrating the fingerprint map or a user who would like to know their current location. If users already know their current locations, they can upload these along with their associated WiFi scans. The AP-Sequence fingerprint map updates continuously according to these volunteers' input. If two different volunteers upload their WiFi scans at different time, most recent input carries more weight during the calibration process. Also, if the location of volunteer used in the calibration is too far from the AP, that input is not considered during the calibration process. The exact weighting of inputs depends on the dynamics of wireless channel and the transmission power of APs.

For localization, the user simply scans available access points for localization and the scanned RSS values of all access points are matched to precomputed fingerprint map within the same smartphone. User is localized to the center of the region with highest matching score.

For the case of multiple users, the precomputed fingerprint map will be transferred manually to other user's android smartphones. Better localization accuracy is expected if more users participate on the calibration of fingerprint map.

### 5. REFERENCES

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