Ubiquity of Wi-Fi: Crowdsensing Properties for Urban Fingerprint Positioning

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***Abstract*—Positioning systems based on location fingerprinting have become an area of intense research, mainly with the aim of providing indoor localization. Many challenges arise when trying to deploy location fingerprinting to an outdoor environment. The main problem is achieving coverage of large outdoor spaces, which needs an intensive data gathering effort. This paper proposes the use of mobile crowdsensing in order to build a fingerprint database consisting of Wi-Fi networks received signal strength measurements. Mobile crowdsensing is represented by the usage of smart-phones equipped with GPS and Wi-Fi sensors for the collection of fingerprints. The primary objective of this work is to prove the feasibility of urban positioning using Wi-Fi crowdsensed data by showing that Wi-Fi networks are ubiquitous in urban areas. We then examine the gathered data and report our findings on challenges in building and maintaining a large-scale fingerprint database, the influence of the data collection method on the Wi-Fi data and the influence of fading on measurements. As Wi-Fi access-points are shown to exhibit mobility, we also propose and analyze methods for detecting and classification of mobile and static access-points.**

***Index Terms*—crowdsourcing, ubiquitous computing, wireless sensor networks, wireless LAN, data collection.**

I. Introduction

Localization using fingerprinting is an increasingly researched topic in recent years as it offers a cost-effective alternative to cellular positioning methods [1] for mobile devices. The primary technology used by fingerprinting positioning systems is the IEEE 802.11 protocol for wireless networks also known as Wi-Fi. The majority of papers on the subject propose Wi-Fi fingerprinting positioning systems for indoor environments.

Addressing the mobile device localization problem by crowdsensing techniques is a novel solution in the context of Internet of Things development. Mobile crowdsensing is a novel data gathering technique which implies that users allow their devices to scan the environment and forward the data to the crowdsensing service, while the Internet of Things relies on sensors and machine to machine communications to better integrate the physical world with the Internet. IoT functionality can be augmented by using the density of the Wi-Fi networks for precise positioning of energy constrained devices and devices without GPS sensors.

The collection of fingerprints using mobile devices is enabled by the fact that most smartphones are equipped with satellite positioning system receivers. The collecting device will scan nearby Wi-Fi Access-Points (APs) and will log the list of visible APs, the received signal strength (RSS) together with the position of the device. The collected fingerprints are then used for Wi-Fi localization of mobile devices that do not rely upon or cannot access satellite-based positioning.

Previous work on crowdsourced or crowdsensed fingerprint positioning systems is mainly designed for indoor environments [2,3] Outdoor fingerprints are usually collected by the process of wardriving [4,5], while global localization service providers (Google, Apple, Microsoft), collect data using functions embedded in positioning software.

Building a fingerprint database for outdoor positioning is a difficult task due to challenges in offering wide coverage of the system and the need for actual data. The actuality of data is explained as the freshness of the gathered fingerprints since users can change their equipment (old equipment are removed, new ones appear) or change its location. The actuality of data should also consider the existence of mobile access-points installed in vehicles or public transport.

In order to determine the advantages and challenges of building and using a crowdsensed fingerprints database, we build our own containing more than 255000 unique access-points and 1 million measurements.

The analysis of the collected data offers the following insights:

- Wi-Fi networks are ubiquitous in urban areas and enable precise positioning. This finding is made possible by analyzing the large volume of collected data.
- Wi-Fi APs exhibit mobility.
- The data collection method has a greater influence than device heterogeneity. We show that user interaction, fading and multi-path propagation influence RSS greater than differences due to the heterogeneous characteristics of mobile devices.

The characteristics of crowdsensed Wi-Fi data hints that the method could also be used in different applications and scenarios such as: augmenting data gathering in wireless sensor networks [6], labeling of handover areas for larger coverage networks with the help of Wi-Fi networks in a multi-sensor approach characteristic for IoT development [7] or in the enhancement of power-saving algorithms for Wi-Fi client devices [8].

The remainder of the paper is organized as follows: Section 2 covers the theoretical background on fingerprinting positioning and database generation techniques. Section 3 introduces the data gathering methodology and presents results which show that Wi-Fi access-points are ubiquitous in urban areas. Section 4 describes the main challenges in building and exploiting a crowdsensed database. Section 5 summarizes the results and presents future directions.

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II. Fingerprinting Theoretical Background

Fingerprinting techniques benefit from the usage of the existing infrastructure. Fingerprinting positioning is enabled by generating and maintaining radio parameters maps. The fingerprint map is then used by the positioning system in order to estimate the location of the mobile device, based on the parameters reported back.

Indoor systems are destined to operate inside buildings and can exploit knowledge of the architecture. Outdoor systems will perform in wide areas covered by the base stations of the communication and/or positioning system and rely on cellular [9] or 802.11 b/g/n technologies.

Fingerprint database and map generation can be achieved using the following techniques:

- Administrative - the task for generating and updating the fingerprint map resides solely to the system administrator. In this case, generating and exploiting the fingerprint database are two distinct steps.
- Automatic - the collection of fingerprints is achieved by the help of an automated system, for example by drones.
- Crowdsensing - the generation and update of the fingerprint map is a continuous process, and is achieved with contribution from the users of the system [3,10].

A. Crowdsensing characteristics

Choosing a method for radio map generation is mainly influenced by the scale of the desired coverage area. Outdoor and global positioning systems benefit entirely from crowdsensed data. User contributions help the positioning system by: continuous growth of the coverage area, coverage of areas restricted to public access, constant feedback that allows removal of inactive APs or the detection of mobile devices, allowing the estimation and correction of differences in user equipment, high density of fingerprints, high precision of positioning in areas most frequently visited by users - positive feedback.

B. Previous work

Previous work on outdoor Wi-Fi positioning [11,12] is mainly concerned with the evaluation of the accuracy of the positioning methods used. Reference [12] notices the influence of complex propagation phenomena that limit the precision of outdoor positioning when compared to indoor results.

The CrowdWifi method [13] is different from our approach as it is destined to work in vehicular networks with the purpose of identifying and locating roadside APs.

Reference [14] presents the design steps of an indoor fingerprint positioning systems based on crowdsourcing. Due to the indoor destination, they choose to input the position information of fingerprints with help from the user. The data collection process was supported by 14 users collecting 70000 measurements during 6 week time.

Reference [15] is aimed at maintaining the fingerprint database accuracy by user feedback. The method proposes to monitor changes in the wireless environment with help from the positioning system users, which allow the removal of inactive APs and the fast addition of new equipment. The collected database was of small scale with 8 APs and 60 fingerprints per room.

Crowdsensing as a data collection method was considered before, but the challenges arising from creating and maintaining a wide area coverage of the positioning system were not studied thoroughly. Compared to previous work, the present paper addresses problems related to the crowdsensing process as a method for urban fingerprint database construction. First, the paper establishes that Wi-Fi networks are ubiquitous in urban areas allowing the deployment of fingerprinting positioning systems. Second, the paper analyses crowdsensed fingerprint characteristics and proposes two novel methods for the identification of mobile APs. Besides, the influence of the environment on fingerprint collection is investigated, mainly concentrating on the effect of the fading phenomena.

III. Positioning Using Wi-Fi

A. Background and Methodology

Wi-Fi technology uses the 2.4 GHz ISM band and the 5 GHz band for data transmission between clients and base stations. The transmit power is usually limited at 20 dBm (100mW). Path loss, fading and human body influence will limit the coverage radius of an AP to values under 250 meters in LOS conditions and 40 meters inside buildings. In order to connect to an AP, the client must first acknowledge its presence. 802.11 protocols offer two methods for detecting the presence of an AP: active scanning and passive scanning. The scanning process provides information regarding RSS of visible AP, making possible the fingerprint collection mechanism by logging the coordinates of a Wi-Fi scan.

For the crowdsensing data gathering step we chose to use the Wigle Android Application [16] which was installed on the devices of participants. The Wigle app logs Wi-Fi passive scans and the GPS coordinates where the device was located at fixed intervals. Fingerprints were gathered permanently (24 hours a day) from all locations visited by the participants.

The data was collected using 8 smartphone devices running the Wigle app, during 6 months, in Bucharest and other areas of Romania, with a total distance ran by all participants larger than 11000 kilometers. The resulting database contains more than 255000 distinct APs and 1000000 measurements of APs.

B. Ubiquity of Wi-Fi

Wi-Fi 802.11 technology is characterized by a high density of APs in urban areas. Fig. 1 gives an insight to the density of APs near the city center of Bucharest.

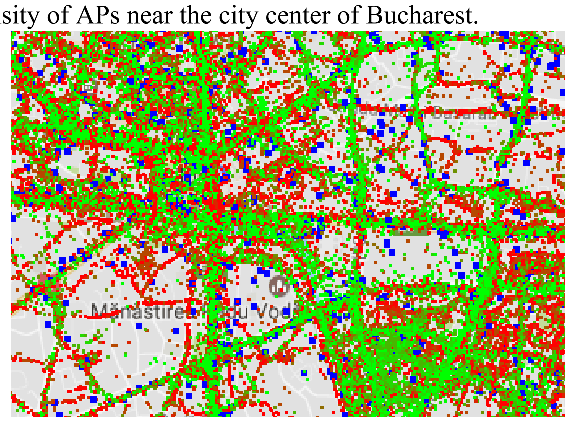

Figure 1. Crowdsensed Wi-Fi data in the center of Bucharest

By analyzing the collected data, we observed the following access-point densities, as presented in Table I, from different urban or rural areas in Romania.

TABLE I. DENSITY OF APS VISIBLE AT STREET LEVEL

Area	AP Density (AP/100 m^2)
Bucharest, Sector 3 (dense urban)	285
Bucharest, Sector 2 (dense urban)	200
Galați (urban)	150
Berceni (rural)	30

The high number of APs, visible at street level, offers unique fingerprints that contain data from numerous base stations. This increases the fingerprinting positioning accuracy by reducing the number of points where fingerprints might be similar.

In urban areas, the collected data has shown a ubiquitous presence of Wi-Fi APs with more than 90% of measurements detecting the presence of at least one access-point. Data collected in both dense urban areas, surrounding countryside and the roads between has shown that 78% of fingerprints contain data from at least two measured APs. This fact allows the usage of the broadcasted presence of an access-point to uniquely identify a location, even though it's exact position is unknown to the fingerprinting system.

The ubiquitous character of Wi-Fi networks is further proven by the following statistics, consistent with findings presented in similar papers which covered different areas [17,18]:

- 25% of all fingerprints contain at least 10 different access points;
- the average number of access points in all collected fingerprints is 7;
- the medium number of access points in urban fingerprints is 20.

IV. ANALYSIS OF CROWDSENSED FINGERPRINTS

A. *Detecting mobile access points*

The large volume of collected data ensured that it is possible to detect mobile APs. Using fingerprints from mobile APs for positioning can lead to errors that are several orders of magnitude larger than the usual coverage of a Wi-Fi AP.

We propose two methods for detecting mobile APs and we compare the results. In order to identify static APs, we consider that the maximum coverage radius of an AP is limited at 300 meters to allow for errors in positioning or the processing methods.

The first method works as follows:

1. Measurement coordinates are selected from APs that have more than one fingerprint and sorted spatially;
2. A polygon is drawn following the contour of the measurement coordinates;
3. The area of the polygon is determined; for lines (APs measured twice) we compute the perimeter;
4. We compare the area of the polygon with the area of a circle with a 300 meter radius in order to establish if it is static or mobile; similarly, if the perimeter is larger than 600 meters we consider the AP mobile.

The second method, works as follows:

1. measurement coordinates are selected from APs that have more than one fingerprint and used to generate a spatial multipoint object [18];
2. the minimum bounding box and the centroid point of the multipoint objects are calculated;
3. the maximum coverage radius of the AP is set as the maximum distance between the centroid point and the minimum bounding box;
4. APs with a maximum coverage range under 300 meters are considered static.

The second method is similar to the one proposed by [18], as it uses the idea of grouping the measurement coordinates. We chose to group them using a spatial multipoint object while the previous work uses clustering methods.

By applying the first method on fingerprints collected in Bucharest, consisting of 193842 AP and 734582 distinct measurements, we observed the following results:

- 24.03% of APs were measured only once and were excluded, as their character cannot be established;
- 75.97% were analyzed:
  - 17.27% have null area and perimeter under 600 meters - they are considered static;
  - 0.3% have null area and perimeter greater than 600 meters - they are considered mobile;
  - 56.88% have areas smaller than the threshold - they are considered static;
  - 1.52 % have a larger area than the threshold - they are considered mobile.

To summarize, 74.15 % of APs are static, 1.82% are mobile and for 24.03% we do not have sufficient data.

By applying the second method, 2.8% of APs are classified as mobile and 73.17% of them are considered static.

The first method fails to find as many mobile APs due to using the area of the contour generated by the measurements for classification. The random character of the data collection method and the fact that the collection positions are influenced by the position of driveways and sidewalks can lead to situations where the contour polygon is not symmetric, resulting in an area significantly reduced than by applying a bounding box to the measurement positions.

We also evaluate the methods by comparing their processing time. The first method is characterized by the use of a spatial sort operation, while the second method is characterized by the creation of the multipoint spatial object followed by the bounding box calculation. To compare the performances of both methods, we analyzed the time needed for completing the analysis task on sets of 50 to 650 APs and their belonging fingerprints.

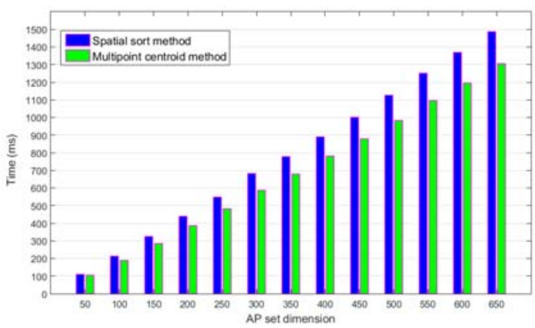

Figure 2. Performance of the proposed methods for detecting mobile APs

According to Fig. 2 the differences between the two methods are insignificant for a reduced set of APs. The difference starts to become visible for sets larger than 200 APs. This is due to the first method performing worse because of using the spatial sort operation, which has a higher calculation cost.

B. Fading influence on fingerprint collection

Using RSS measurements for fingerprinting positioning has its advantages, as mentioned before, and some challenges due to the effect of fading and the interference [18] caused by a high density of APs coexisting in a reduced area. The fading phenomena are caused by shadowing, reflection, refraction and diffraction which are specific to the environment in which the fingerprints are collected. The collection method also ensures that most of the time the collecting device is at street level while the scanned APs are inside buildings, probably at upper floors.

RSS level from an AP can vary by up to 25 dB when measured stationery due to fading effects [19]. For example, Fig. 4 presents fixed point measurements on an AP that fluctuate between -73 dBm and -94 dBm.

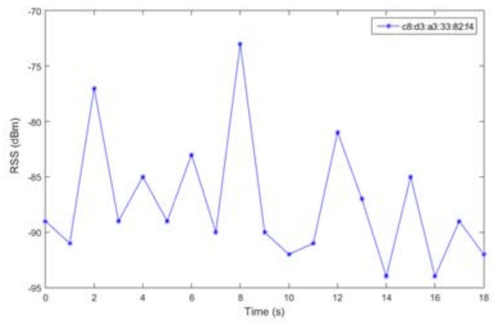

Figure 3. Fixed point RSS measurements example

The standard deviation of the RSS presented in Fig. 3 is 5.61 dB to a mean value of -87.42 dBm. The standard deviation of the signal strength is a valuable indicator for determining fading influence on signals, caused by the environment and the collection method.

Furthermore, we analyzed the RSS of three different APs from a fixed point, as shown in Fig. 4.

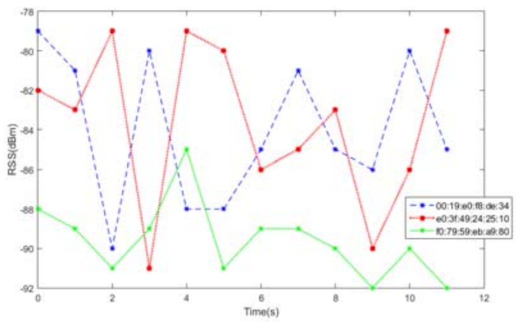

Figure 4. Fixed point RSS measurements example from 3 APs

The minimum, maximum, medium RSS expressed in dBm and standard deviation values expressed in dB are shown in Table II.

TABLE II. DENSITY OF APS VISIBLE AT STREET LEVEL

AP	Min	Max	Mean	Stdev
e0:3f:49:24:25:10	-91	-79	-83.58	4.14
00:19:e0:f8:de:34	-90	-79	-84	3.69
f0:79:59:eb:a9:80	-92	-85	-89.58	1.92

Data in the table hints to a correlation between the standard deviation value and the mean RSS value. This phenomenon can be explained by the fact that signals arriving from farther APs will reach the measurement point only on the shortest path. The multipath components will be attenuated under the sensitivity level, resulting in a lower standard deviation of the AP.

This observation hints that in order to enhance the precision of a fingerprint positioning system, fingerprints with very low or very high RSS should be used as these are less affected by fading, as shown by the standard deviation values. The usage of low RSS fingerprints is usually excluded in previous work [20], mainly due to the wider area covered by low RSS values which limit positioning accuracy. Nevertheless, our results show that the standard deviation is a useful tool in deciding which fingerprints should be included in a fingerprint database.

To further validate the observations, we analyzed the database as follows: we chose all APs with more than 10 fingerprints, we calculated mean RSS and standard deviation of the collected fingerprints for each AP and finally, we mediated the value of the resulting standard deviation for APs with similar mean RSS value.

The standard deviation of all selected fingerprints is 6.36 dB, with a mean RSS value of -83.7 dBm.

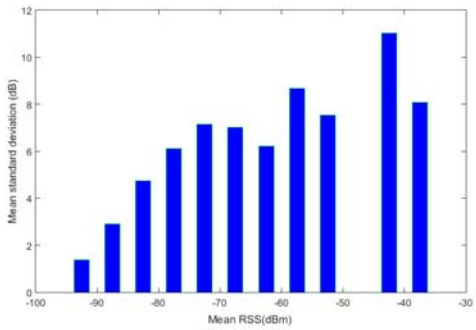

Figure 5. Mean standard deviation for APs with specific mean RSS value

Fig. 5 show that APs with mean RSS values under -80 dBm, have a standard deviation under 5 dB, being less affected by fading and multipath propagation. The correlation between the low values of the standard deviation and the mean RSS, hints that the impacting fading has components generated by multi-path propagation [21]. Multipath effects are lower for APs with lower mean RSS, since NLOS components are attenuated under the sensitivity level of the receiver.

C. Mobile Device vs. Collection Method influence on fingerprints

In order to determine if the mobile device or the collection method had a greater influence on the measured RSS, we analyzed the histograms for fingerprints captured with different devices. Table III presents the RSS parameters (minimum, maximum, medium RSS in dBm and standard deviation values in dB) of different devices, similar to values expressed in [22].

TABLE III. RSS PARAMETERS FOR DIFFERENT DEVICES

Device	Min	Max	Mean	Stdev
Samsung Galaxy A5 2016	-100	-16	-83.53	6.21
Samsung Galaxy J5	-97	-20	-85.24	6.4
Samsung Galaxy A3	-99	-37	-86.56	7.3

By analyzing the histograms, the mean and the standard deviation values, we observe that the fingerprints captured with the different devices show similar statistics, concluding that the data collection method combined with fading effects have a more significant influence on the collected measurements than device heterogeneity.

D. RSS Histogram analysis

Previous work on fingerprint databases model RSS distribution using Gaussian or log-normal distributions [23-25]. A general model for RSS distribution has yet to be set, as crowdsensed fingerprint systems for outdoor environments have not been studied well in the literature. Normal distributions of 802.11 RSS values were proposed in previous work [24,25], but the fingerprint positioning systems had an indoor destination.

In order to fit a distribution to the recorded RSS values, the RSS histogram for all collected fingerprints is plotted in Fig. 6. Histogram analysis can be conducted for values collected in only one fixed point or for the entire crowdsensed database. RSS values will vary for different points and moments, but analyzing the whole database is useful in determining what type of fading influences the collected fingerprints.

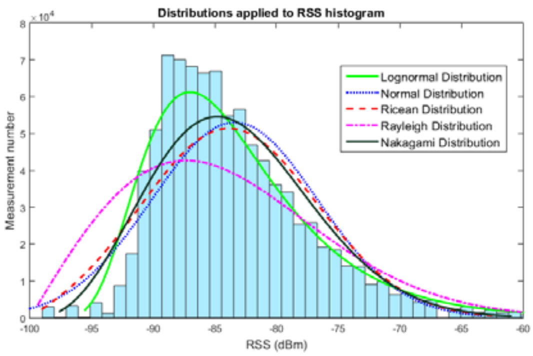

Figure 6. Distributions applied to RSS histogram

RSS histograms can be asymmetric or multimodal so modeling them with a normal distribution can be difficult. Left skewness of the log-normal RSS distributions can be explained by the fact that the variance of low RSS values is higher than that of high RSS values. When collecting fingerprints at a distance from the AP, the sensitivity of the receiver will impose a lower limit on RSS values, resulting in a right skewness of the histogram.

RSS distribution fitting can help to determine which type of fading is influencing the collected measurements. Reference [26] proposes the following distributions for different fading types: Gaussian distribution with mean equal to the RSS mean for flat fading; Log-normal distribution for slow fading due to shadowing effects; Rayleigh or Ricean distribution for fast fading due to multipath propagation.

The RSS histogram, shown in Fig. 6, is right-skewed with a value of the skewness of 1.59. This is due to the receiver sensitivity which does not allow receiving signals with values lower than -100 dBm and due to the data collection method which implies a minimum distance of 10-20 meters between collecting device and AP.

The kurtosis coefficient is a measure to whether the data is peaked or flat relative to a normal distribution [22]. If the data is peaked near the mean the kurtosis coefficient is higher while a flat top near the mean corresponds to a low kurtosis. The kurtosis value of the collected measurements is 8.61. Normal distributions have kurtosis values near 3. This signifies that the RSS histogram is significantly peaked near the mean. This is consistent with observations in [22].

The following statistical parameters, shown in Table IV, were used for determining the fit of the distribution to the histograms: NlogL- negative of the log likelihood. BIC – Bayesian information criterion and AIC – Akaike information criterion.

TABLE IV. STATISTICAL PARAMETERS FOR DISTRIBUTION FITTING

Distribution	**NlogL**	**BIC**	**AIC**
Lognormal	1.807×10^6	3.614×10^6	3.614×10^6
Nakagami	1.842×10^6	3.685×10^6	3.685×10^6
Rician	1.865×10^6	3.730×10^6	3.730×10^6
Normal	1.866×10^6	3.732×10^6	3.732×10^6
Rayleigh	2.173×10^6	4.347×10^6	4.347×10^6

The lognormal distribution has the highest precision in fitting the histogram values, pointing out that collected fingerprints are most likely to be influenced by slow fading due to shadowing. This is true considering the data is collected at street level while APs are probably behind the walls of the buildings.

The Ricean and the Nakagami distributions behave similarly. The Nakagami fading model is suitable to situations when the received signal is composed of a major component which is not mandatory LOS and few other secondary components. The Nakagami and Ricean distribution fit the histogram for values under -85 dBm.

The normal distribution is not best fitted for the urban outdoor scenario, as shown by the parameters.

The Rayleigh distribution is characteristic of environments highly impacted by multipath propagation, where most likely the LOS component is nonexistent. Rayleigh fading is specific to urban cellular communications in dense urban environments where the distance between transmitter and receiver is between 300 and 1000 meters. The collection method makes it likely that between the transmitter and receiver exists at least one wall. The reduced coverage of Wi-Fi APs limits the distance at which multipath components can be received, as proven before. This is visible by the fact that the Rayleigh distribution does not fit well the values of the histogram.

V. CONCLUSION

Offering Wi-Fi fingerprint positioning in urban areas has not been studied well, mainly due to the difficult task of collecting the fingerprints in all coverage areas. For this problem, we propose the use of a crowdsensed fingerprint database.

Building such a database requires time and a significant effort. In order to collect the data for the study, 5 month time and more than 11000 driven kilometers were necessary.

To determine the possibility of deploying an urban Wi-Fi fingerprint positioning system, we first prove the ubiquitous character of Wi-Fi in urban areas.

We analyze the collected fingerprints and we highlight important aspects that must be taken into consideration when deploying a Wi-Fi fingerprinting positioning system:

- the density of APs is highly correlated with the population density;
- APs exhibit mobility - we propose two methods for detecting static and mobile APs and we analyze their performances;
- RSS measurements are affected by fading - we examine the standard deviation of RSS values collected from APs and we propose this as a tool to enhance the quality of the data used for fingerprinting;
- The crowdsensing collection method influences fingerprints - by comparing different devices histograms we find they are statistically similar due to the data collection process;
- RSS histogram analysis offers insights into the environment impact on measurements - we conclude that the lognormal distribution models the RSS histogram with the best accuracy.

Also, some privacy concerns arise by studying the collected data: APs can be localized with a high precision due to their reduced coverage; constructing large volume databases containing positioning information is a task at the hands of researchers and minor player, not only of global location based service providers; analysis of gathered data can offer insights on private information such as the fact that an AP is mobile or that it was moved from one part of the city to another; APs can be used to precisely track persons, as shown in [27], followed by the detection of the significance of the location to the users, such as homeplace or workplace [28].

Future work will be concentrated on designing an urban Wi-Fi fingerprint positioning system that can rely on the constructed database. We will focus on evaluating the impact of the standard deviation of fingerprints on positioning accuracy and use the lognormal distribution for probabilistic position estimation, as it was proven to best fit the RSS histograms for collected fingerprints.

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