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A Survey of WiFi Indoor Positioning Techniques

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Abstract: Despite the fact that there is a growing number of Mobile Stations (MS) equipped with built-in Global Positioning System (GPS) receivers, WiFi positioning is still a subject of interest, as GPS is usually unavailable in indoor environments. Furthermore, the increasingly denser deployment of WiFi access points (AP), coupled with the fact that most mobile devices today are WiFi enabled, makes the use of WiFi signals a superior choice for indoor positioning. Accordingly, this paper brings a literature review on Wireless Fidelity (WiFi) positioning, with a comparative analysis of several localization techniques for indoor single-floor environments.
Keywords: indoor localization, WiFi, radiofrequency fingerprinting, multi-lateration, positioning accuracy

I. INTRODUCTION

Since 1997, when the first IEEE 802.11 WiFi networks became available, Wireless Local Area Networks (WLANs) based on that standard have spread enormously. Nowadays, WiFi networks are ubiquitous in domestic, corporate and public areas. This fact, coupled with the availability of WiFi enabled smartphones, makes positioning of mobile stations (MS) in WLANs a crucial issue.

Positioning in WiFi WLANs is by no means restricted to indoor environments. However, it is in such scenarios that WiFi positioning becomes more useful, mainly due to:

- the unavailability of Global Navigation Satellite System (GNSS) signals in the majority of indoor environments;
- the lower availability of cellular signals in indoor environments (unless there are dedicated micro and pico-cells deployed specifically to provide indoor coverage);
- the high density of WiFi Access Points (APs) in indoor environments.

Practically all radio frequency (RF) positioning solutions use one of the following basic techniques:

1. cell identity (CID): which assumes that the MS is located at the coordinates of the serving station;
2. centroid: the target MS position is given by the centroid of the polygon whose vertexes are the reference stations;
3. multi-lateration: provides the MS positioning based on distance estimates between the MS and the reference stations; those estimates are obtained using time or received signal strength (RSS) measurements; multi-lateration can be either circular or hyperbolic -time difference of arrival (TDOA);
4. multi-angulation: uses angle-of-arrival (AOA) measurements between the MS and the reference stations to yield a position estimate;
5. database correlation methods (DCM): also referred to as scene analysis, pattern matching or RF fingerprinting;

Fig.1 shows the basic geometric representation of the centroid and triangulation (multi-angulation e multi-lateration) methods. In Fig.1a, the centroid of the polygon whose vertexes are the reference stations gives the position estimate (M). In Fig.1b, three reference stations provide three circular lines-of-position (LOPs) for an unambiguous MS position estimate. A LOP is the set of points at which the target MS can be located. LOPs are generated when positioning methods based on triangulation (multi-lateration or multi-angulation) are used. Different positioning techniques yield different types of LOPs: linear, circular or hyperbolic. The MS estimated position is given by the intersection of two or more LOPs.

In Fig.1c, four reference stations provide three hyperbolic LOPs for an unambiguous MS position estimate. In Fig.1d, two non-collinear reference stations provide two linear LOPs for an unambiguous MS position estimate. In all cases, one must know the coordinates of the reference stations with the highest possible accuracy.

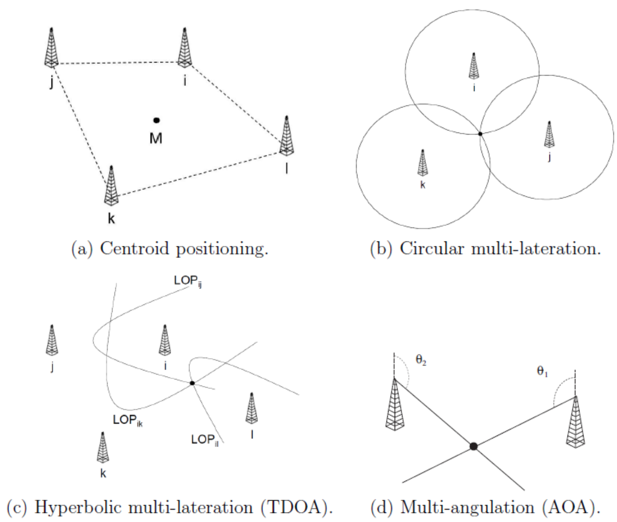

Figure 1: Centroid and triangulation (multi-lateration and multi-angulation) positioning methods.

At first, all those techniques would apply to WiFi networks. However, even though there are a few exceptions (such as [1, 2]), most publications on the topic do not use methods (1) to (4). This is mainly due to the following issues:

- unlike cellular networks, round-trip delay (RTD) values are not available in WiFi networks; therefore, time-based multi-lateration would require the deployment of additional hardware;
- APs antennas are typically omnidirectional; therefore, AOA positioning would also require additional hardware (i.e., the installation of directional antenna arrays);
- WiFi positioning is most relevant in indoor environments; however, at such scenarios there are severe obstructions (such as walls, columns and furniture) between the AP and the MSs; therefore, non-line-of-sight (NLOS) propagation is prevalent, and this condition severely hinders the accuracy of circular multi-lateration, TDOA and AOA positioning;
- CID and centroid positioning require that the locations of the APs are known; however, this is hardly the case, as the APs are deployed in a chaotic manner, without a centralized coordinated effort as in cellular networks [3].

As a result, DCM becomes the mainstay technique in WiFi positioning, both in outdoor and indoor environments. This conclusion stems from the vast number of papers published on the subject if compared to other techniques. However, implementing WiFi indoor fingerprinting positioning systems is not an undertaking deprived of challenges:

- typically, extensive and time-consuming off-line training phases are required, to gather reference fingerprints to be stored in the correlation database (CDB);
- the RF environment is not stable over time: new APs are deployed, others are shut down or moved to another location, the WLANs channel frequency might change, furniture might be moved or added to the floor; consequently, the fingerprint map must be periodically updated to prevent accuracy degradation;
- implementation differences between manufacturers might result in different devices reporting distinct RSS values at the same location (the so-called cross-device effect);
- WiFi networks use an unlicensed band, so they are prone to suffer interference from external sources.

The remainder of this paper is organized as follows: Section II introduces the basic DCM elements; Section III analyzes RF fingerprinting techniques for MS location in single floor scenarios; Section IV studies other techniques used in such environments. Finally, Section V discusses some multi-floor positioning related issues, followed by a conclusion.

II. RF FINGERPRINTING SPECIFICITIES

DCM, also known as RF fingerprinting, is a class of MS positioning methods that can be applied to any wireless network. Despite their variability and broad application scope, conceptually, all RF fingerprinting location systems share the same fundamental elements: RF fingerprint, correlation database, matching function, location server, and search space reduction technique.

2.1. RF Fingerprint

An RF fingerprint is a set of location dependent RF signal parameters gathered by an MS in a given position. Those parameters can be measured by either the MS to be located or by its anchor stations. A reference or anchor station is either a fixed or mobile station, which might contain a transmitter, receiver and/or a transponder, and whose signals are used by the target MS to estimate its position, or that uses the target MS transmissions to calculate the target position. The coordinates of the reference stations must be known at all times, and with the highest possible degree of confidence.

Just like a human fingerprint, which is assumed to uniquely identify a person, an RF fingerprint is expected to unambiguously identify a geographic position. An RF fingerprint can be classified as either a target (Tfing) or reference (Rfing) fingerprint. A Tfing is the RF fingerprint associated with the MS which is to be localized, i.e., it contains signal parameters measured by the MS or by its anchor cells. The Rfings are the RF fingerprints collected or generated during the training phase and stored in the correlation database.

Several RF fingerprinting location systems employ parameters that are already available in the radio access network (RAN). These parameters are a priori location dependent and therefore each RF fingerprint can be associated with a specific position. If only RAN inherent parameters are included in the RF fingerprint, then the DCM technique can be entirely network-based. As a result, the deployment of the location system does not require any modification to existing MS.

Multi-angulation and multi-lateration positioning use signal parameters that change with the relative position between the target MS and a set of reference stations to estimate the MS location. Those techniques compute the position estimate from basic geometry, electromagnetic and signal processing principles. Those methods and RF fingerprinting differ on how they use the parameters to estimate the MS position. While in multi-angulation and multi-lateration, the position is estimated by inverting some signal parameters properties based on geometry and physics concepts, in RF fingerprinting there is no such inversion. The RF fingerprints collected by the MS are compared to previously obtained RF fingerprints to estimate the position of the collecting MS. As a result, RF fingerprinting, unlike multi-angulation and multi-lateration, does not rely on line-of-sight (LOS) geometric assumptions.

2.2. Correlation Database

The Correlation Database (CDB) is built during the DCM training phase [4, 5], using radio propagation modelling, field measurements or a combination of both [6]. Each CDB entry is described by (f, x, y, z), where f is the Rfing associated to the point defined by coordinates (x, y, z). The structure of f may vary depending on the radio access network (RAN) technology, but some common parameters are RSS, round trip-time (RTT) and delay profiles [7]. The CDB entries should be compared to the Tfing to yield a position estimate for the MS. The MS is assumed to be located at the point whose Rfing has the largest correlation or similarity with the Tfing. Alternatively, it is possible to select the K best matches, in which case the MS location is given by a weighted average of the K best matches coordinates (i.e., the K-Nearest Neighbours (KNN)) [8].

2.3. Pattern Matching

The main engine of RF fingerprinting is the pattern matching or scene analysis algorithm. It is used to compare the Tfing to the Rfings, previously stored in the CDB. From these comparisons, one finds candidates (the positions associated to the Rfings) to estimate the location where the target RF fingerprint has been collected.

2.4. Location Server

Location Server is a term typically used to refer to network elements (hardware and software) responsible for computing the position estimate. It receives location requests from different applications or devices, consults CDBs, and estimates the location of the target MS from its RF fingerprint. In the location server, the position estimate can be computed using any supported positioning technique. In the case of RF fingerprinting, it is important to emphasize that the location server must have access to the CDB.

2.5. Search Space Reduction Technique

The CDB might be quite large and analysing all RF fingerprints stored in it might be very time consuming. To acquire a position fix within an acceptable time, some reduction in the search space (initially, all entries in the database) is welcome. Therefore, most fingerprinting location techniques employ strategies to reduce the search space within the CDB. As a consequence, the time required to produce a position fix is also reduced. Some of the techniques used in the literature are deterministic filtering [9] and optimized search using genetic algorithms [10], both applied upon RSS maps built with empirical propagation models [11]. In [12], the search space is reduced by clustering the candidate solutions. This clustering is based on the identity of the WiFi networks with the highest RSS at each measurement point.

2.6. Simplified Diagram of a DCM MS Originated Position Request

Fig.2 shows the simplified diagram of an MS originated position request. First (step 1), the MS sends a position request containing the Tfing to the location server through the radio access network (RAN). After that (step 2), the RAN communicates with the location server. The location server receives the Tfing and then queries the CDB (step 3) for the reference RF fingerprints (Rfings), returned in sequence (step 4). The location server then compares the Tfing with the returned Rfings to obtain the MS position estimate (step 5), which is sent back to the RAN (step 6) and subsequently to the MS (step 7).

From this brief description, one notes that any fingerprinting location technique has two phases. The first is the training or building phase when the CDB is built. The second is the test or operational phase, during which MS position estimates are produced from gathered RF fingerprints.

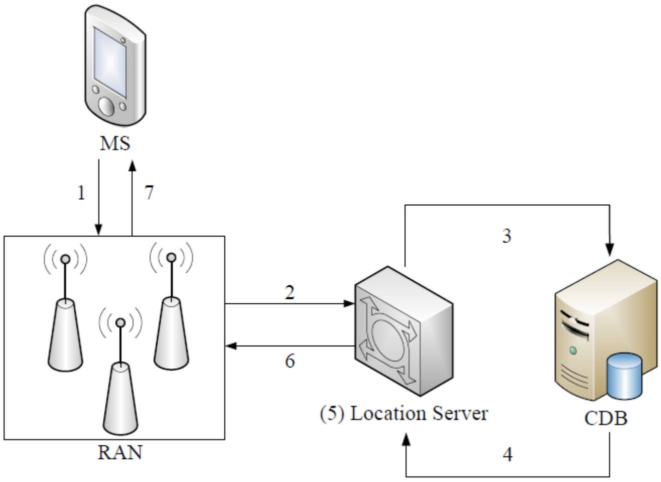

Figure 2: Diagram of RF fingerprinting location.

III. SINGLE FLOOR POSITIONING USING RF FINGERPRINTING

3.1. Nearest Neighbor in the Signal Space

One of the first RF systems for locating and tracking indoor users in WiFi networks was RADAR [13], published in the year 2000. The authors tested it in a 22×43 m^2 single-floor with 3 APs and 70 measurement points. At each measurement point, at least 20 samples (WiFi scans) were collected at four different directions (north, south, east, west), as the authors verified that, depending on the direction the user was facing, the RSS of a given AP might vary ±5 dB. For each 3-tuple (x, y, ζ), at least 20 samples were collected, where (x, y) are the measurement point coordinates and ζ is the direction the user was facing. The mean RSS per AP at each point/orientation was then calculated, yielding 70 × 4 reference fingerprints.

To compare the target and reference fingerprints, the authors introduced the concept of Nearest Neighbour in the Signal Space (NNSS), i.e., the similarity between the fingerprints was measured by the Euclidean distance in the N-dimensional RSS space. In the RADAR test bed, N = 3, as only 3 APs were used. To test the algorithm, one of the four directions at the ith measurement point was selected to be the target fingerprint (Tfing). The reference fingerprint (Rfing) of the ith point was then excluded from the fingerprint map, and the Tfing was compared to the remaining 69 × 4 Rfings. The process was repeated for i = 1, . . . , 70. The authors in [13] reported a median two-dimensional (2-D) positioning error of 2.94 meters.

The authors conducted another experiment at the same test site, with a fingerprint map (for the same 70 measurement points) built using the empirical propagation model given by

$$P(d) = P(d_0) - 10n\log_{10}\left(\frac{d}{d_0}\right) - m \times \mathrm{WAF} \quad (1)$$

where P (d) is the RSS (in dBm) at d meters from the AP, d0 is a reference distance in meters, n is the path loss exponent or slope, m is the number of walls between the AP and the current position, and WAF is the wall attenuation factor, i.e., the additional loss (in dB) introduced by each wall. Parameters d0, n and WAF were empirically defined.

In the second experiment, the median 2-D positioning error increased to 4.3 meters. CDBs built from propagation models can reduce the time consumed in the off-line phase, either at the initial CDB acquisition or its periodic updates. However, it represents a trade-off between pre-processing time (off-line) and accuracy. Besides that, modelling RF propagation in indoor environments is not an easy endeavour. In [13], the authors were able to use equation (1) to build the fingerprint map only because the locations of the three APs on the floor were known.

For clarification, consider Fig.3a, which shows a floor blueprint with the locations of four APs (white squares). The graphic scale indicates the additional loss in dB per R meters, where R is the blueprint matrix planar resolution. The floor dimensions are 20 × 40 m^2. It has a large entrance hall (left), a long corridor and three rooms, each one with just one entrance. The floor blueprint is represented as a matrix, where each element (pixel) corresponds to an R × R m^2 area. In this example, R = 0.1 m and, therefore, the blueprint is a 200 × 400 matrix.

The luminance level of the pixels is proportional to the additional loss (in dB) due to the presence of the barrier at the pixel location. Zero luminance indicates the absence of an obstacle at the pixel position. This simulation considers two types of obstacles: 30-cm thick concrete walls, with a 20 dB loss per meter, and 10-cm thick wooden doors, with an 8 dB loss per meter. Equation (1) defines the RF propagation model. The parameters values are n = 3.43, d0 = 2.5, P (d0) = −43 dBm [14]. The APs have omnidirectional antennas, so no radiation patterns were applied to generate the 2-D RSS coverage maps. The simulation does not consider multipath due to reflections from surfaces and diffraction around corners. Fig.3b shows the best server map that represents, at each pixel, the highest RSS value. Figs.3c and 3d depict the RSS (dBm) coverage maps of APs 3 and 4, respectively. The effect of the obstacles on the RF propagation is clearly distinguishable on both maps. The four RSS maps (one for each AP) can be "piled up," yielding a 200 × 400 × 4 radio map that provides a 4-element RSS vector for each pixel in the floor grid.

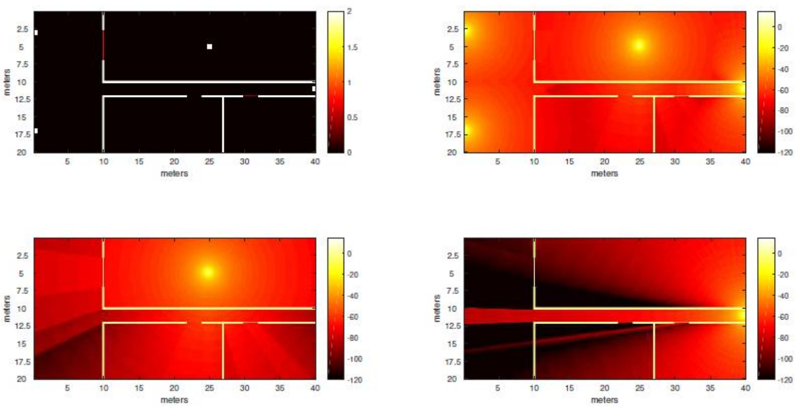

Figure 3: (a) APs locations and floor blueprint; (b) Best server map; (c) AP-3 and (d) AP-4 RSS maps.

3.2. Context-Aware Radio Maps

Changing environmental factors – such as air humidity, open or closed doors, and the presence of people – can interfere with the propagation conditions, altering the RSS at each point, in relation to the time when the fingerprint map was built. The authors in [15] tried to evaluate the quantitative effect of those environmental factors (air humidity, doors, and people) in WiFi indoor positioning accuracy. The presence of people has an effect similar to obstacles blocking the RF propagation. Open and closed doors have an effect comparable to changes in the floor layout. An atmosphere with high humidity is expected to absorb more energy of the propagating RF signal than a dry one.

They built context-aware radio maps which the target MS selects based on the current indoor environmental conditions. As the authors assumed two possible states for each of the three environmental factors (humidity – high or low; doors – all closed or all open; people – no people or people blocking the RF path), they built six fingerprint maps. They deployed one AP in each of the five rooms on a single floor and collected at least 200 WiFi scans along a corridor for each set of environmental factors. During the on-line test phase, the target MS queried humidity sensors, radio frequency identification tags (RFID) and Bluetooth devices, so that it could select the best context-aware radio map to use. Such map is the one that better matches the environmental conditions at the time of the test. The RFID tags detected if the doors were open or closed. The changes in the average propagation loss between fixed Bluetooth transmitters and the target MS identified the no-people or people blocking condition.

Tables 2.1 and 2.2 show accuracy degradations of 1.1 meters – when a low humidity radio map is applied in a high-humidity environment – and 1.9 meters – when a no-people-blocking radio map is employed in a people-blocking test environment. However, Table 2.3 indicates that the worst scenario occurs when there is a mismatch in the open/closed doors condition: the average location error increases from 2.1 meters to 7.2

meters (more than three times the original value) when an all-doors-closed radio map is used in an all-doors-open test environment.

The system proposed in [15] can still be classified as DCM for WiFi 2-D indoor positioning because even though it employs non-WiFi devices – humidity sensors and Bluetooth transmitters – those were not used in the position fix. They just helped to select the context-aware radio map better suited to the current test conditions.

To the best of our knowledge, this is the first experimental setup developed to quantitatively evaluate the effect of changing environmental dynamics in WiFi indoor localization. However, it has some severe limitations, if considered for a practical large-scale implementation, as it requires:

1. the deployment of additional hardware;
2. that users carry Bluetooth-enabled devices;
3. that users keep their MS's built-in Bluetooth adapters on.

Even though item 2 is a quite reasonable requirement considering currently available smartphones, item 3 is not, as the majority of users keep their Bluetooth adapters off most of the time to increase battery lifetime.

Table 2.1: Impact of Relative Humidity (RH) on average DCM positioning accuracy (all-doors-closed and no-people-blocking).

Average Accuracy	40% RH Radio Map	70% RH Radio Map
40% RH environment	2.1 m	3.7 m
70% RH environment	3.1 m	2.6 m

Table 2.2: Impact of people blocking on average DCM positioning accuracy (40% RH and all-doors-closed).

Average Accuracy	No-people-blocking radio map	People-blocking radio map
No-people-blocking environment	2.1 m	4.3 m
People-blocking environment	4.0 m	2.5 m

Table 2.3: Impact of open/closed doors on average DCM positioning accuracy (40% RH and no-people-blocking).

Average Accuracy	All-doors-closed radio map	All-doors-open radio map
All-doors-closed environment	2.1 m	4.6 m
All-doors-open environment	7.2 m	2.8 m

3.3. On-demand Radio Maps for Client-Based Solutions

DCM indoor positioning solutions might be classified either as MS-assisted or MS-based. In the MS-assisted case, a location server calculates the MS position using fingerprints sent by the target MS and querying a server-based CDB. In the MS-based case, the MS calculates its position querying a client-based CDB, i.e., a fingerprint map stored in the MS itself 3. In the case of a server-based CDB, the location server might have to deal with several simultaneous location requests, and a search space reduction technique might significantly reduce the delay of each position fix. In the case of a client-based CDB, a search space reduction technique, besides speeding up the position fix acquisition time, also reduces the network load (as the MS downloads smaller fingerprint maps) and the required storage space at the MS. In [16], the authors proposed two techniques to diminish the search space in client-based solutions: Intersection of Access Points (IAP) and Union of Access Points (UAP).

In IAP, the target MS downloads only the Rfings containing at least all the Aps detected in the WiFi scan. In UAP, the MS downloads the Rfings containing at least one of the APs detected in the WiFi scan. The authors also defined a criterion called N-Group to trigger a fingerprint data query (i.e., the query and download of an updated search space from the location server to the client-based CDB) whenever more than N APs changed in two consecutive WiFi scans. The higher the N, the lower the frequency of fingerprint data queries. The objective of N-Group was to reduce the frequency of data queries, without degrading positioning accuracy. The client-based CDB is usually a subset of the server-based CDB.

Their experimental testbed comprised 25 APs and was set on the second floor of an office building with 57 × 32 m^2 on the campus of the University of Manheim. The off-line training phase used 130 measurement points disposed in a regular grid with 1.5-meter spacing. In the test phase, 46 points were randomly chosen. Both in the training and test phases, 110 WiFi scans were collected per point. The average accuracy was 3 meters, using no search space reduction 4. Then, the value of N was progressively increased when using IAP and UAP, and three parameters were monitored: positioning accuracy, fingerprint map query frequency, and search space size (measured by number of points, i.e., Rfings). The authors in [16] observed that, when using UAP, the search space reduction was negligible: the average search space size was 129. However, when using IAP, the average search space size shrank to 12. With IAP, when increasing N from 1 to 10, the positioning error augmented almost
20% (from 3 meters to 3.5 meters).

3.4. ANN-Based Pattern Matching

The authors in [17] use a feed-forward artificial neural network (ANN) to establish a relationship between input WiFi RSS vectors and locations. In an indoor environment, they deployed three APs in a 28×15 m^2 floor and selected 125 points, collecting 400 samples per point. The samples collected at 110 points were used to train the ANN. The remainder points were used to test it. The ANN had three inputs (the RSS values of each AP), 18 neurons in the hidden layer and two outputs (planar coordinates x and y). As in [28], the experimental accuracy was excellent: 61% of the test patterns had errors lower than 1.8 meters, and 85% had errors smaller than 3 meters. However, there is no guarantee that ANN-based pattern matching algorithms will yield such high accuracy in more complex scenarios, such as in multi-story buildings, or when radio maps built with propagation models are used in the supervised training.

3.5. RF Fingerprinting using Parameters other than RSS

All DCM techniques studied so far in this chapter used RF fingerprints containing only mean RSS values, which are relatively simple to measure and are readily available in WiFi networks. These traits made RSS fingerprinting a practical solution for WiFi localization systems. The core difference between distinct implementations lies mostly on how the target and reference fingerprints are compared, i.e., on which pattern matching technique (NNSS, RSS rank correlation, ANN-based) is used. However, other parameters can be employed in the RF fingerprint.

The aforementioned possibility is explored in [7], where the authors compared the accuracy of DCM techniques applied to 2.4 GHz WiFi indoor positioning using RSS, Channel Impulse Response (CIR), Channel Transfer Function (CTF) and Frequency Coherence Function (FCF)-based fingerprints. The CIR to the impulse transmitted by the jth AP is given by

$$\mathbf{h}_j(t) = \sum_{i=1}^{M} a_i e^{-j\phi_i \delta(t-\tau_i)} \quad (2)$$

where a_i, ϕ_i and τ_i are the amplitude, phase and delay of the ith received multipath component; M is the number of multipath components and δ (t) denotes the impulse function. Equation (2) shows that, in multipath propagation conditions, the receiver detects multiple delayed and attenuated copies of the transmitted impulse. By taking the CIR with respect to different APs at the same position, it is possible to build an RF fingerprint given by [$h_1(t)$ . . . h_N (t)], where N is the number of APs. Note that each element of the fingerprint is an M-element vector, so the CIR-based fingerprint is an M × N matrix. The CIR is expected to carry the multipath information that is unique to each location. However, the possible accuracy is limited by the signal bandwidth: higher bandwidths are equivalent to higher time-domain resolution, which allows detecting (separating) more multipath components (i.e., increasing M).

CTF is the Discrete Fourier Transform (DFT) of the CIR. A CTF-based fingerprint can then be formed, which will have the same dimensions of the CIR-based fingerprint. The same applies when using FCF-based fingerprints, where the FCF for the jth AP at a given measurement position is the complex autocorrelation of the CTF.

The authors set up an experimental testbed in a 30 × 25 m^2 single-floor with 3 APs. A total of 152 measurement points were chosen with a fixed distance of 1 meter between adjacent points. Amidst those points, 51 were randomly selected for the test, and the remainder composed the CDB. Euclidean distance in the signal space was used to compare the target and reference RSS-based fingerprints (the higher the distance, the lower the similarity). For the CIR, CTF and FCF-based fingerprints, vector correlation (dot-product) was used (the higher the dot-product, the higher the similarity). Then, weighted K-Nearest Neighbors (w-KNN) was applied. In w-KNN, the position estimate is given by

$$(\hat{x}, \hat{y}) = \frac{\sum_{i=1}^{K}(w_i x, w_i y)}{\sum_{i=1}^{K} w_i} \quad (3)$$

where K is the number of neighbors, w_i and (x_i, y_i) are the weight and the reference coordinates of the ith neighbor point, respectively. The weight w_i is directly proportional to the similarity between the target and ith reference fingerprints.

FCF-based fingerprints achieved the best results: an average error of 2.5 meters, with almost no variation as the number of neighbor points in the w-KNN algorithm increased from 1 to 10. RSS-based fingerprinting was the technique that benefited the most from the use of w-KNN: the average error dropped from 3.5 meters (for K = 1) to 2.8 meters (for K = 9). CTF performance was a little worse than FCF, and CIR was the worst of all, with errors between 3 and 4 meters for K ranging from 2 to 10 (for K = 1, the CIR-based fingerprinting error was 4.2 meters). Even though FCF-based fingerprinting performed better in the test, if one considers practical larger implementations, the accuracy gain will most likely not compensate the increased complexity of obtaining those measurements (which would involve the deployment of additional hardware to the pre-existing WiFi network infrastructure), if compared to the relative simplicity of measuring RSS.

IV. SINGLE FLOOR POSITIONING USING OTHER TECHNIQUES

4.1. Fingerprinting + RSS-Based Multi-Lateration

In [14] the authors proposed a hybrid positioning scheme with two phases. In the first phase, RF fingerprinting identifies the room where the MS is most probably located. In the second phase, RSS-based multi-lateration locates the MS within the pre-selected room.

The testbed was a 17 × 23 m^2 floor (comprising 7 rooms and a large corridor) with 5 APs. The radio map for the fingerprinting algorithm was built using RSS mean values obtained from WiFi scans collected at 14 locations. The DCM similarity measure was the Euclidean distance. The WiFi 802.11b/g scans collected at another

100 points (12 samples per point) were used to calibrate the empirical propagation models. Path loss equation (2.1) was employed to estimate the RSS. The distances between the MS and the APs were obtained by taking the inverse of the path loss equation. A total of nine symbolic locations were defined: the seven rooms plus two sections of the corridor. For each AP and each symbolic location, different path loss equation parameters – reference distance, RSS at the reference distance, attenuation slope – were defined.

As the floor blueprint and the APs locations are known, by identifying which room the target MS is located in, it is possible to select a specific propagation model and also compute additional losses due to obstructions (walls). Attenuation factors obtained during the experiment for different types of walls are listed in Table 2.4. The values of P (d_0) for each AP (WX-1590 SparkLAN) were measured at a reference distance of d_0 = 2.5 meters, and their values ranged from −46.7 dBm to −43.7 dBm.

In the test phase, 30 locations were selected. In the first stage, fingerprinting achieved a symbolic location identification accuracy (room or corridor section) of 97%. In the second stage, multi-lateration using specific (for each AP and each symbolic location) calibrated propagation models achieved a mean 2-D positioning accuracy of 1.83 meters. However, when applying fingerprinting only (using a radio map with 33 reference fingerprints instead of only 14), the planar error was 1.78 meters, i.e., approximately the same accuracy.

Table 2.4: Wall Attenuation Factor (WAF) for different types of walls [14].

Type of Obstacle	WAF (dB)
Very Thick Concrete Wall	12.6
Thick Concrete Wall	9.5
Concrete Wall	5.5
Soft Partition	0.8

4.2. Multi-Lateration using an RTS/CTS Distance Estimator

In [1] the authors explored the use of the Request-to-Send (RTS)/Clear-to-Send (CTS) two frame exchange mechanism in the WiFi Medium Access Control (MAC) sub-layer to obtain range estimates between the MS and the AP. The RTS/CTS scheme is part of the medium access control in WiFi WLANs [18]. It reduces collisions by defining periods during which the wireless medium is reserved for only one station. Before transmitting a data frame, a station sends an RTS frame to the AP. The RTS informs the time that will be needed to transmit the subsequent data frame. Upon reception of the RTS, the AP sends a CTS frame. All nearby stations, on reception of the RTS and/or the CTS frames, refrain from transmitting for the required duration.

The distances estimates obtained using the aforementioned scheme would later be applied to locate the target MS by circular multi-lateration. As there is no synchronization between the AP and the MSs in WiFi networks, the time-of-flight cannot be measured directly. Instead, it is obtained from the roundtrip-time (RTT) between the MS and the AP. The target MS transmits an RTS at instant t_i. Upon reception, the AP replies with a CTS, which is received by the target MS at instant t_f , yielding

$$\mathrm{RTT} = t_f - t_i \quad (4)$$

If the processing time Δt at the AP is known, it can be subtracted from the RTT value. The outcome is divided by two, producing a time-of-flight, that, once multiplied by the speed of propagation of the radio wave (c), provides a distance estimate given by

$$d = \frac{c(\mathrm{RTT} - \Delta t)}{2} \quad (5)$$

At least three distance estimates from different APs are required for a position fix. The authors performed an indoor test along a $50 \times 4.3\ m^2$ corridor. During the test, there was always a line-of-sight between the target MS and each AP. On average, the ranging estimates had an error under 4 meters. However, the authors did not report the positioning accuracy achieved using those range estimates in circular multi-lateration. This location technique has two major drawbacks:

- it requires the deployment of additional hardware (a printed circuit board with an Intersil HFA3861B base-band processor) at each MS to allow measuring the RTT;
- to operate, the system needs that the RTS/CTS exchange is activated; however, in most networks this scheme is disabled (or is only used to reserve the medium for the transmission of large data frames), as it introduces additional traffic and delay in the network.

V. CONCLUSION

This work presented a comprehensive survey on WiFi indoor positioning techniques, grouping and analysing the key aspects of several papers on the subject. Most solutions rely on RSS fingerprinting, applying features as NNSS, context-aware radio maps and ANN-based pattern matching to improve accuracy. A few researchers use other parameters to compose the RF fingerprint (such as CIR, CTF, and FCF), as well as alternative techniques to reduce the search space within the radio map (such as IAP and UAP).

As a conclusion of this study, one could add that an arbitrarily high location precision in WiFi networks can certainly be obtained in well-controlled environments with the deployment of a very high number of APs. Nonetheless, the main research focus on this area lies in seeking the best precision in chaotic environments, where most of the times not even the location of the APs is known. This allows the easy deployment and use of localization systems in a wider range of situations, with minimum cost and delay.

Another conclusion is that, due to the intrinsic characteristics of in-building RF propagation, fingerprinting seems to be the best alternative for WiFi indoor positioning.

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