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Radio Fingerprinting-Based Indoor Localization: Overcoming Practical Challenges

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1 Introduction

Awareness and demand for location-based services (LBS) has grown with the ever-increasing ubiquitousness of Global Navigation Satellite System (GNSS) enabled devices. Current generation LBS drives multitudes of novel technological developments in location and context aware computing over a wide range of fields (ABI Research, 2015). This has also lead to increasing demand for LBS in environments without access to reliable GNSS, such as urban and indoor environments. Hence, many alternate approaches to providing accurate urban and indoor positioning have been developed (Torres-Solis et al., 2010). The range of applicable approaches is significantly reduced by focusing on solutions able to work on unmodified smartphones along with cheap and easy to install infrastructure. Radio fingerprinting localization (Kjærgaard, 2007) is one of the most common approaches able to overcome these restrictions.

The remainder of this chapter provides further motivation for radio fingerprinting in Section 1.1, introduces the basic methodology and assumptions in Section 1.2, and elaborates on how to overcome some of the technical challenges in Section 2. This overview is written from the point of view of a practical commercial use.[1]

1.1 Motivation

With direct line of sight to enough satellites GNSS can enable accurate location awareness at low cost to a vast range of mobile devices. However, in urban and indoor environments large infrastructure such as buildings can disrupt the signal path. In the extreme case of urban canyons only a narrow strip of sky is directly visible at street level. These disruptions

[1] Based on several years of experience deploying radio fingerprinting solutions at indoo.rs GmbH.

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can lead to complete signal loss or to signal distortion through reflection and refraction which invalidates the line of sight assumptions in the localization. Furthermore, there may be multiple signal paths of similar strengths for the same source (Braasch, 2017). Together these effects dramatically impair the applicability of satellite-based methods in such environments.

Therefore, some alternate approach must be taken, such as Ultra Wide Band (UWB) radio (Ingram et al., 2004), Radio-Frequency IDentification (RFID) (Bekkali et al., 2007; Gikas et al., 2016), optical solutions (Mautz and Tilch, 2011; Kuo et al., 2014), ultrasound (Hazas and Hopper, 2006), or dead reckoning (Jimenez et al., 2009). However, for a solution to be widely adopted it is required to work on unmodified end-user mobile devices such as smartphones. In this sense the aforementioned methods have severe shortcomings: UWB radio is unavailable to most devices, RFID methods are range limited on smartphones, optical and ultrasound methods work poorly with pocketed devices, and dead reckoning solutions with fixed sensor placement require phones to be predictably coupled to their owners.

This situation leaves solutions using the motion sensors and radio receivers commonly available on smartphones. Some possible radio solutions are impeded by requiring expensive or hard to install custom hardware. Additionally, many methods are sensitive to strong multipath and fading effects in indoor environments. Together, this reduces viability of multilateration, Angle Of Arrival (AOA) (Rong and Sichitiu, 2006), and Time Difference Of Arrival (TDOA) (Liu et al., 2007) methods. Moreover, methods operating standalone on the device are preferable, as maintaining an uninterrupted remote server connection is not always possible. Server side solutions also introduce additional latency from round trip time and increased battery drain due to data transfers, which may significantly degrade user navigation experience.

Radio fingerprinting with on-board radios can overcome all of these obstacles. With enough visible signal sources the method is robust to noise in any particular input. Depending on the device, different sources can be used, such as FM radio (Chen et al., 2012), GSM (Otsason et al., 2005), Wi-Fi (Al Nuaimi and Kamel, 2011), and Bluetooth Low Energy (BLE) (Faragher and Harle, 2015). In practice, the most common fingerprinting sources are Wi-Fi and BLE, which both offer unique and complementary features. Wi-Fi is supported on a multitude of devices, is ubiquitously installed, and has 2.4 and 5 GHz radio bands with different propagation properties. Meanwhile, BLE offers iBeacon and Eddystone devices that can be made very small, cheap and easy to install, and still have good localization performance (Zhao et al., 2014). Unlike most Wi-Fi installations, BLE setups are often optimized for localization performance. Typical BLE scan rates are faster than for Wi-Fi leading to more responsive localization. Another important difference is that on Apple iOS devices only the BLE Application Programming Interface is available to developers. In some cases it is possible to use both sources at the same time, however, as the antenna commonly is shared this may lead to poor performance. With this in mind, the remainder of the chapter is restricted to a discussion of radio fingerprinting on mobile devices with Wi-Fi and BLE receivers.

It should be noted that commonly absolute radio fingerprinting positioning is augmented by fusing it with estimates based on on-board motion sensors, for instance, using Pedestrian Dead Reckoning (PDR) (Ettlinger et al., 2017; Pratama et al., 2012) and Kalman filters (Burgess and Dong, 2016), or by exploiting local disturbances to the geomagnetic field (Li et al., 2016; Guo et al., 2014).

1.2 Radio Fingerprint Localization Assumptions

At its core, radio fingerprinting relies on premeasured radio reference maps with point measurements. Each reference point contains a set of measured received signal strength indicator (RSSI) readings (fingerprints) from identifiable sources. Positions are estimated by comparing a new RSSI measurement to the radio map, and computing a position from the most similar reference points. This approach makes several basic assumptions:

Environment No major change has taken place in the radio environment since the creation of the radio map.

Transmitters Transmitters are fixed in place, transmit at a constant signal strength, and they are uniquely identifiable.

Reference point Reference points see enough visible signals with enough variations to provide a location unique hierarchy.

Receivers Radio receiver characteristics of locating devices and mapping devices are similar.

As long as these assumptions hold, relatively good localization is possible with residuals in the range of 2–5 m. With infrastructures that obfuscate transmitter ID or modulates transmission power, localization becomes inaccurate or unfeasible. Over time small changes to the radio environment are inevitable, and subsequently the localization accuracy will deteriorate unless the radio map is updated. These changes can have many causes, for example, architectural modifications such as the addition of walls or partitions, installation of doors or windows; interior changes such as displacement of tables or white boards; or changes in the radio infrastructure through aging or replacement of beacons, or new sources of interference such as microwaves or Wi-Fi infrastructure. However, if sufficient sources are visible, it can be several years until such random environment changes are larger than the inherent noise in the RSSI measurements. Certain enterprise systems sometimes randomize transmitted Basic Service Set IDentifier (BSSID) (unique transmitter identifier), share it between multiple physical devices, transmit multiple virtual devices from the same physical unit, or dynamically throttle the transmission strength. Furthermore, mobile access points and beacons are not uncommon and cannot be assumed to stay in place for any extended period of time. The presence of such unreliable transmitters likely will degrade localization accuracy, and should be filtered both from observations and the radio map. For opportunistic approaches using whatever signal sources are available filtering is essential for consistent results. The reference points should be dense enough so that neighboring points are similar but not identical, furthermore it is preferable that the reference point density is uniform throughout the building. Finally, the receiving (locating) devices should give comparable results to the devices used in mapping, and not be too sensitive to device posture, for example, hand held, placed in pocket, carried in hand bag, placed on desk, etc.

2 Fingerprinting Challenges

As described in Section 2.1, the similarity between an observation and the reference points can be estimated by comparing the signal sets. Special care has to be taken to ensure that signals are comparable, and that missing signals due to packet collisions, or weak signal strength are handled correctly. Once similarities to all reference points are estimated, they should be used to infer the position of the observations. There are many ways to do this, as outlined in Section 2.2. Which combination of similarity and estimation is most suitable may depend on environment, devices in use, and overall requirements of a solution. Furthermore, differences in device receiver characteristics must be taken into account, as follows in Section 2.3. Finally, as shown in Section 2.4, a radio map has to be available and up-to-date with the physical conditions at the time of localization.

2.1 Fingerprint Point Similarity

A radio fingerprint $\vec{x}$ is a set of observable signals under some given conditions. In a space equipped with N transmitters a fingerprint can be expressed as the vector

$$\vec{x} = \{x_0, \ldots, x_N\}, \tag{1}$$

where x_i is the RSSI obtained for transmitter i. It should be noted that x_i does not have to be a single reading, it can be a time series of observed RSSI or a set of summary statistics such as mean μ_i, standard deviation σ_i, and number of readings n_i. In principle, these vectors are sparse and may not have an entry for each of the N possible transmitters. This can be due to signal loss from announcement package collisions during measurements, or the RSSI is below the sensitivity threshold of the measuring device. A reference measurement $\vec{y}$ is simply a fingerprint observation made at a known position $\vec{p}$

$$\vec{y} = \{\vec{p}|x_0, \ldots, x_N\}. \tag{2}$$

A reference map is a set of many reference measurements taken at M different positions

$$\mathbf{Y} = \{y_0, \ldots, y_M\}. \tag{3}$$

The radio map Y then can be thought of as a sparse $M \times N$ matrix of readings and a set of M point locations.

Given an observation and the reference measurements, some measure of similarity (or inversely, distance) needs to be found to gauge which reference points are closer to the observation. For this to work it is important that the assumptions on an unchanged environment and fixed transmitters are fulfilled. Furthermore, in situations with few visible transmitters the similarity estimates will have very large uncertainties that are likely to lead to poor location estimates.

The distance between the sets is commonly expressed as the Minkowski distance

$$d(x,y) = \left(\sum_{i=0}^{n} |x_i - y_i|^{\alpha} \right)^{1/\alpha}, \tag{4}$$

which for $\alpha = 1$ corresponds to Manhattan (City block or Taxi) distance, and for $\alpha = 2$ to Euclidean distance. To use the distance as a similarity S it is commonly inverted to give a measure that decreases with distance, for example, $S(x,y) = d(x,y)^{-1}$ or $S(x,y) = a - d(x,y)$. A possible improvement is to weight the difference by reference variance σ_i^2, which for $\alpha = 2$ and assuming no off-diagonal covariances corresponds to the Mahalanobis or normalized Euclidean distance

$$d(x,y) = \left(\sum_{i=0}^{n} \frac{|x_i - y_i|^2}{\sigma_i^2} \right)^{1/2}. \tag{5}$$

Both of these measures with varying p and many other variants occur in fingerprinting solutions, and the right choice of similarity measure can reduce location uncertainty by 30% (Retscher and Joksch, 2016; Torres-Sospedra et al., 2015).

A nonlinear transformation of variables can further improve localization by another 10%, for instance, using exponentiation, powers, or z-score (Torres-Sospedra et al., 2015; Burgess et al., 2016). This can be explained by considering the logarithmic distance relation of RSSI. Close to the source, signals have a strong distance dependence, which gets much weaker further away. Thus, one should not expect optimal results when treating all signal strengths the same. In addition to transforming signals, they can also be subject to threshold to reject weak signals. This may reduce the noise sensitivity, at the cost of shorter range for the transmitters. However, this often does not have a large positive impact on localization accuracy (Torres-Sospedra et al., 2015). Furthermore, the calculated distance may be transformed in turn, to better correspond to a distance estimate.

As signal strength is not linear, some methods approach the problem by only considering the RSSI ordering between the two sets using rank-based methods such as Spearman's Footrule, F, and Kendall's τ, K (Kumar and Vassilvitskii, 2010; Machaj et al., 2011). In these approaches the observations $\vec{x}$ and $\vec{y}$ are sorted by RSSI and only the order of the transmitters is retained as $\vec{x}'$, $\vec{y}'$. For instance with an observation $\vec{x} = \{-30, -20, -40\}$ the ranking vector becomes $\vec{x}' = \{2, 1, 3\}$. Spearman's Footrule measures the disarray as the sum of the absolute difference between ranks in a signal.

$$F(\vec{x}', \vec{y}') = \sum_{i} |\vec{x}_i' - \vec{y}_i'|. \tag{6}$$

Kendall's τ counts the number of pairs of transmitters that are in opposite order in the two observations, as follows

$$K(\vec{x}', \vec{y}') = \frac{2}{n(n-1)} \sum_{i,j \in N} 1 \text{ if } i, j \text{ in opposite order in } \vec{x}' \text{ and } \vec{y}' \text{ else } 0. \tag{7}$$

As ordering is not affected by scaling or offset, these approaches are insensitive to device gain settings. Furthermore, they often produce more robust results than metric similarities. However, some information is lost as the amount of difference leading to rank difference is lost. This is especially at weak signal strengths, where noise can give significant contribution to rank order. Here thresholding can help alleviate the impact of noise. Transformations and rank-based methods can also help to reduce device heterogeneity issues outlined in Section 2.3.

Moreover, it is common that some of the readings in the sparse reference vector lack a common reading for the same transmitter in the observation vector. This is a big problem, as the similarity measures rely on pairwise comparisons between the two sets. Signals can be cut out by the device because they are too weak or because of collisions. The probability that a signal disappears from an observation is inversely correlated to its strength, thus making it a bigger problem for weak signals.

There are several approaches to dealing with missing signals. The simplest approach is to only consider the observations common between the observation and reference point. However, the set of common transmitters is expected to be smaller with increasing distance between observation and reference. For many distance measures this introduces a bias going against the true distance as fewer terms are included in the sums. Thus, this can lead to degraded performance unless compensated for. A more refined approach is to only consider the transmitters visible in the observation, and to fill in some default missing value for missing transmitters in the reference points. Typically, the minimal observable signal is used (e.g., -100 dB) for this. This works and is in common use in practical applications. However, it is a rather blunt approach as the *true* signal could be much stronger or weaker than the default value. In the extreme case where no common signal is seen between the observation and reference, clearly this approach does not produce a meaningful result. The probability that a signal disappears depends on the location, which could be used as an observable in its own right in addition to RSSI to strengthen localization. Optimizing which similarity estimate to use and whether or not to transform RSSI or similarity value is not trivial. Furthermore, the similarity estimation is deeply entangled with the subsequent error estimation. In practice, it is safest to try multiple approaches using well-understood testing data.

2.2 Location and Error Estimation

The most common way to obtain a location from reference points with similarity estimates is the k-nearest neighbors (kNN) (Bahl and Padmanabhan, 2000) and its weighted k-nearest neighbors (WkNN) (Shin et al., 2012) variant. Assuming $k = 1$, the position is assigned to be at the most similar fingerprint point, while the average position is taken for higher k. Like the choice of similarity measure, the optimal value for k is best determined empirically as it depends on the radio environment. Using WkNN, the average points are weighted by similarity, which to some extent reduces the impact of k. While position estimation is straightforward with this method, accurate error estimation is not (Zhuo et al., 2012). Typically some empirical relation to the average distance between reference points and estimate is employed. It should be noted that the kNN methods may be biased by an uneven distribution of reference points. Such unevenness may cause problems in manually measured maps, where it is difficult to ensure perfect reference point distribution. However, unevenly distributed points can also be used to improve results by biasing localization toward much traveled trajectories such as corridors and doorways. To obtain a uniform point density, uneven points can be interpolated to fixed grid, for example, through a Gaussian process, or simple nearest neighbor interpolation.

It is also possible to employ probabilistic methods to try to find the location, for instance, through maximum likelihood methods (Mirowski et al., 2014). However, usually this is orders of magnitude slower than kNN, and still not guaranteed to give better results. Further approaches use the radio map as training data for machine learning approaches such as support vector machines (Wu et al., 2004) or neural networks (NN) (Gogolak et al., 2011). By learning through the map, these approaches tend to avoid the tuning issues with similarity measures and avoid parameters like k. In principle, also localization error can be determined through machine learning when there is enough labeled high-quality training data available. Machine learning methods are less transparent than kNN, and thus less robust to noise and map degradation unless specifically trained for these situations.

Often a preselection phase is applied before location estimation. Preselection can improve calculation speed, reduce memory requirements, and to reduce the risk of large position outliers, *jumps*. In this phase, reference points clearly not compatible with observation are filtered out based on which signals were recently visible. If the preselection can operate with only partial summary information, it can dramatically improve calculation speed and reduce memory footprint, as both directly depend on the number of points to consider (Burgess et al., 2016). Furthermore, the number of reference points available grows with the square of distance to the observation. Clearly incompatible reference points can be identified from having few observation matches and significant difference in RSSI. Jumps occur when there are one or a few observation scans with very few visible transmitters. With fewer transmitters to discriminate with, a larger number of references will give plausible matches. As the similarity gradient is weaker with few readings the final position essentially is a random point inside the matched references. By restricting the range of reference points to consider, the magnitude of these jumps can be reduced.

It is essential that the observation occurs within the range of selected points as most fingerprinting approaches are restricted to producing results in the convex hull of the selected reference points. Preselection can be done by rejecting reference points with less than N matching networks to the observation, through spatial clustering (Ma et al., 2008), or simply by reducing the map by joining nearby fingerprint points. In clustering approaches, nearby points with similar properties are grouped into clusters, for instance, through k-means clustering. The joining approach works similarly but relies on partial hierarchical clustering. Aggregates for the clusters are compared to the observation and references in close clusters are used as preselected points. Further improvements of localization can be attained through the use of a Kalman filter (Yim et al., 2008), which considers the previous estimate and current observation to produce a smooth new estimate.

As with similarity measures, finding the optimal localization strategy is not trivial. Machine learning approaches often are able to show the highest accuracy, at the cost of training data volume and robustness. Trying all combinations of localization algorithms, similarity measures, and tunable parameters also may lead to problems with overtraining (Murphy, 2012). Commonly, an empirical trial and error approach is taken to find a combination of methods good enough for the application at hand.

2.3 Device Heterogeneity

The mobile device market is highly heterogeneous, with a large number of distinct device producers, chipsets, revisions, and firmware updates. Different devices measuring the same transmitter in identical conditions often still report different RSSI, typically by a constant offset or in some cases a linear term (Dong et al., 2017). This is a common problem, as very often the choice of locating terminal (i.e., smart phone make and model) is not influenced by the LBS provided. A difference in RSSI characteristics will bias the similarity estimates. If this difference is large it can severely impact localization accuracy.

Device heterogeneity can be handled by avoiding it altogether or by transforming values to a common scale. The aforementioned rank-based similarity methods from Section 2.1 avoids the problem by ignoring the RSSI value and only considering the sort-order of detected transmitter (Kumar and Vassilvitskii, 2010; Machaj et al., 2011). This works as the strongest network will have the highest rank in both reference and observation, regardless of scaling and offsets difference from gain or bias in the receiving antennas. Another approach is to employ differential fingerprinting where the constant offset is removed by comparing differences between RSSI within the observation to difference within the references (Laoudias et al., 2013). For example, consider an observation reference pair taken at the same location but with a 10-dB offset in the reference: $\vec{x} = \{-30, -50\}$, $\vec{y} = \{-40, -60\}$. Without knowing the offset the points will not be considered similar with Minkowski distances. With differential fingerprinting, instead internal pairwise differences are considered $\vec{x}^{\dagger} = \{-30 - -50\} = \{20\}$, and $\vec{y}^{\dagger} = \{-40 - -60\} = \{20\}$, and the Minkowski distance will be 0. However, these approaches do not work when trying to combine statistics from multiple measurements, for instance, when making a radio map.

If the range of possible RSSI values is exactly known for a transmitter, it is trivial to make a linear transformation to clamp the signals to a predetermined range. However, if the devices have different sensitivity (i.e., lower minimal RSSI threshold) this approach may lead to biased estimates. Furthermore, care has to be taken with special values, that is, $\pm\infty$, not-a-number (NaN), or *magic* values such as 0 or -100 dB. Thus, some sort of predetermined linear fit from simultaneous measurements between devices often is used, either through manual or automatic procedures (Dong et al., 2017). In practice, this entails having two devices measuring the same signal over the full range of relevant signal strengths, and then make a fit to the scatter plot of one device against the other. This has to be done between all potential devices and some standard device to provide universal standardization. It should be noted that maintaining a database with cross-calibration between all common devices is a daunting and error prone task.

2.4 Obtaining and Updating Radio Maps

The radio map is the set of all reference points $Y = \{\vec{y}_1, \ldots, \vec{y}_M\}$. For optimal results, these maps should span the entire navigable area with a uniform point density and high-quality point estimates. The distribution of the reference points through the building affects the localization. If the density of points is too low important features may be missed, resulting in poor accuracy. On the other hand, too high density increases storage, memory, and computational load without improved localization accuracy. Nonuniform point densities may lead to problems when tuning localization algorithms to work optimally with the radio map. Another consideration is that most localization algorithms only produce results interior to the radio map and thus the radio map should span every navigable position. Common point densities range from 1 to 10 m. While only hexagonal grids can give truly uniform point density in two dimensions, often square grids are employed for the sake of simplicity. In practice it may not be possible to measure uniformly, and thus less rigid approximate grids also are common.

Creating accurate radio maps is a resource intensive task (Kaemarungsi and Krishnamurthy, 2004) that additionally requires regular updates due to the evolving radio environment. Manual measurements performed at each reference point is the most straightforward approach to obtaining radio reference maps. It should be noted that the quality of the measurements also affects the localization quality. For instance, low statistics leaves high uncertainty in RSSI estimates, and offsets between actual and reported point locations distort positioning. Measuring conditions such as the user partly shading the signal path, the influence of surrounding crowds, or dynamic environment can further degrade reliability of estimates. Measurements may take up to a minute per reference point, which for a 1000 m^2 venue and 1 m fingerprint density can mean over 15 h of measurements. For typical commercial deployments the radio map needs to be updated every 6–12 months in the author's experience. The amount of measurements and the care needed in making them have been a limiting factor in the commercial adoption of fingerprinting solutions in the indoor navigation market.

Numerous technologies have been developed to lower the cost of radio map creation. For instance, some use collected RSSI and precise transmitter location knowledge (Koo and Cha, 2012), and others propose ray-tracing to calculate fingerprints (Raspopoulos et al., 2012; Renaudin et al., 2017; Tayebi et al., 2009). Several employ Simultaneous Localization And Mapping (SLAM) algorithms (Frese et al., 2005; Ferris et al., 2007; Huang et al., 2011; Murphy, 2012; Koller and Friedman, 2009) to replace costly point-by-point measurements with simple continuous measurements along paths. From the author's practical experience with SLAM approaches they are able to reduce measurement time by a factor of 10 for initial mapping. By crowdsourcing some trajectories from navigating users, it is possible to use SLAM to update radio maps and thus circumventing the need for any additional dedicated measurements beyond initialization (Rai et al., 2012; Laoudias et al., 2013). It should be noted that crowdsourcing poses many privacy concerns, as well as potentially costly amounts of calculations.

3 Summary and Conclusions

In this chapter, the popularity of radio fingerprinting for indoor localization has been explained. The basic assumptions made on radio environment, transmitter, radio fingerprint reference points, and receiving devices have been clarified. After this introductory part follows a discussion on some of the challenges that arise when attempting to satisfy these basic assumptions. Here details are given on how radio map reference point similarity is calculated, how device heterogeneity can be handled, and how radio maps are built. In measuring fingerprint similarity the utility of nonlinear RSSI transformations, the use of rank-based methods to avoid otherwise cumbersome device heterogeneity, and possible dangers when missing signals are discussed. Outlines are given to how location and error estimation can be done using common kNN methods as well as with advanced machine learning alternatives. Furthermore, methods to address device heterogeneity have been elaborated. Finally, an overview of challenges and approaches related to creating maps has been given.

There is no single perfect solution for any one of the problems mentioned above, and certainly not for a combined localization system. Instead, approaches are selected by what fits the intended application best, that is, high accuracy, low latency, low computational complexity, low memory usage, robustness to noise, etc. In general this selection is best done using dedicated evaluation data taken in realistic conditions.

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