FM-based Indoor Localization

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ABSTRACT

The major challenge for accurate fingerprint-based indoor localization is the design of robust and discriminative wireless signatures. Even though WiFi RSSI signatures are widely available indoors, they vary significantly over time and are susceptible to human presence, multipath, and fading due to the high operating frequency. To overcome these limitations, we propose to use FM broadcast radio signals for robust indoor fingerprinting. Because of the lower frequency, FM signals are less susceptible to human presence, multipath and fading, they exhibit exceptional indoor penetration, and according to our experimental study they vary less over time when compared to WiFi signals. In this work, we demonstrate through a detailed experimental study in 3 different buildings across the US, that FM radio signal RSSI values can be used to achieve room-level indoor localization with similar or better accuracy to the one achieved by WiFi signals. Furthermore, we propose to use additional signal quality indicators at the physical layer (i.e., SNR, multipath etc.) to augment the wireless signature, and show that localization accuracy can be further improved by more than 5%. More importantly, we experimentally demonstrate that the localization errors of FM and WiFi signals are *independent*. When FM and WiFi signals are combined to generate wireless fingerprints, the localization accuracy increases as much as 83% (when accounting for wireless signal temporal variations) compared to when WiFi RSSI only is used as a signature.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; C.2.1 [**Network Architecture and Design**]: Wireless communication

General Terms

Experimentation, Measurement, Performance

Keywords

FM, localization, mobile systems, fingerprinting, wireless

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1. INTRODUCTION

Accurate indoor positioning information has the potential to revolutionize the way people search, locate and navigate to points of interest inside buildings in a similar way that GPS revolutionized the way people navigate outdoors. For instance, a user in a mall could leverage his mobile device, equipped with accurate indoor positioning technology, to instantly search, locate and navigate with real-time turn-by-turn directions to any store in the mall. When entering a store, the user's mobile device could automatically provide directions to the exact aisle or section where the desired product is located. At the same time, businesses and advertisers could push coupons and offers to the user in real time based on his current position within the mall or the store, maximizing customer targeting effectiveness.

Enabling these scenarios has been challenging mainly due to the unavailability of GPS signals in indoor environments. In the absence of GPS, fingerprint-based indoor localization techniques have been the most accurate approach to indoor localization [1, 9, 27]. The major challenge for fingerprint-based approaches is the design of robust and discriminative signatures. The most popular approach, that does not require any hardware deployment, has been to leverage already available wireless signals (e.g., WiFi, cellular) to profile a location, usually in the form of received signal strength indicator (RSSI) values [1, 24]. In previous work, RSSI values of WiFi signals have been primarily used for this purpose, as WiFi access points are widely deployed indoors, and every mobile device is equipped with a WiFi receiver.

Even though this approach has been successful in localizing people at a coarser grain (e.g., at the building level [21]), it exhibits several limitations when considering indoor environments where a person needs to be localized at the room level. First, the operating frequency range of WiFi signals makes them susceptible to human presence and orientation as well as to the presence of small objects in a room. This introduces variability in the recorded fingerprints that can lead to localization errors. Second, several of the deployed WiFi access points are commercial in nature and employ optimizations, such as frequency hopping, to improve network's throughput. These optimizations can result in significant variations in the observed received signal strength (i.e., RSSI values change across WiFi channels), and therefore in the localization process. Third, WiFi RSSI values exhibit high variation over time that, as we show in this work, can adversely impact localization accuracy. Fourth, the area of coverage of a WiFi access point is significantly reduced in indoor environments due to the presence of walls and metallic objects, easily creating blind spots (i.e., basement, parking lots, corner rooms in a building, etc.).

To address these limitations, we study the feasibility of leveraging alternative wireless signals to *augment* or even *replace* WiFi

Signal	Frequency	Range	RX Power
WiFi	2.4 GHz, 5GHz	30 m indoor	800 mW
FM	88-108 MHz	300 km outdoor	40 mW

Table 1: Basic properties of WiFi and FM broadcast signals.

signals for fingerprinting. In particular, we propose to use FM broadcast radio signals for fingerprinting indoor environments. FM signals operate at the frequency range of 88-108MHz in the US, which makes them less susceptible to the presence and orientation of humans and small objects. Furthermore, FM signals are significantly stronger than WiFi signals in the sense that they can easily cover areas of hundreds of kilometers, while achieving good indoors penetration (Table 1). From the infrastructure point of view, there are thousands of commercial and amateur FM signals being broadcasted continuously across the world, eliminating the need for deploying any custom infrastructure. Also, most mobile devices, even the lower-end ones, are equipped with FM radio receivers that are lower power and less costly compared to the WiFi receivers (Table 1).

However, in the case of FM radio signals, the access points (FM towers) are located up to several hundred of kilometers far away from the user and transmit signals at a very high power. As a result, the recorded FM RSSI signatures might not exhibit significant variation across nearby locations, and therefore fine grain localization might not be feasible. Previous work that has already examined the use of FM radio signals for localization in *outdoor* environments has verified this intuition by demonstrating coarse-grained localization accuracies (e.g., zip code level [10] or tens of meters [8]).

In this work, we demonstrate through a detailed experimental study that FM broadcast radio signals can be used to achieve room-level indoor localization with similar or better accuracy to the one achieved by WiFi signals. Even though FM radio reception may not vary significantly across nearby *outdoor* locations, in the case of *indoor* environments the internal structure of the building can significantly affect the propagation of FM radio signals, providing enough resolution in the FM signal signatures to accurately localize mobile devices.

This paper makes the following contributions:

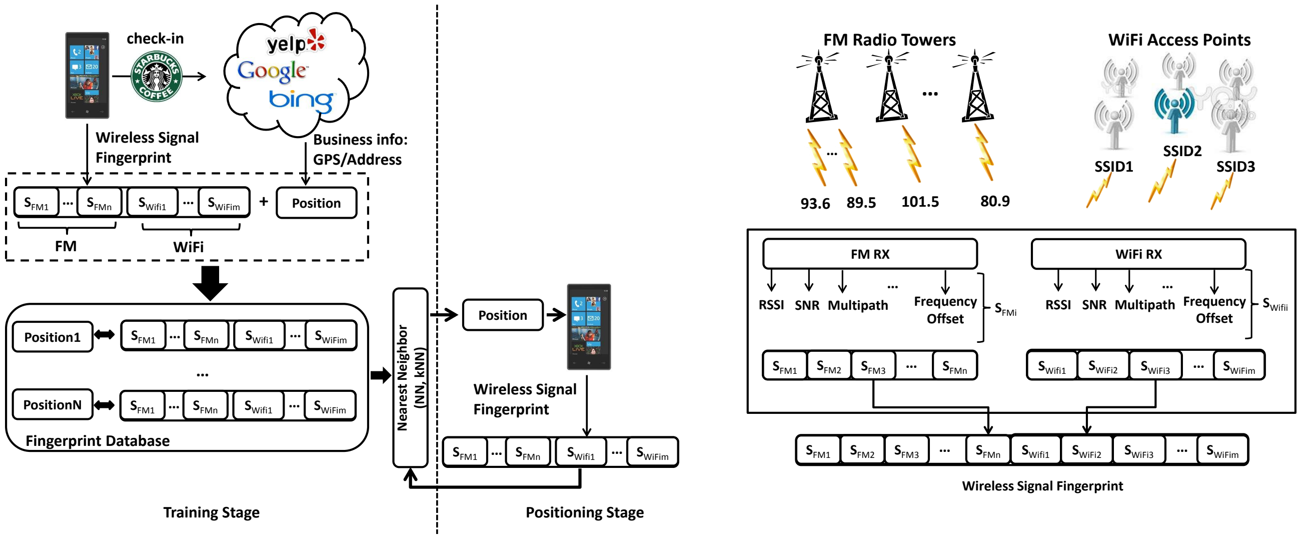
- We demonstrate through detailed experiments in 3 representative buildings across the US (a residential building, an office building, and a shopping mall) that FM radio signals can achieve similar room-level accuracy in indoor environments when compared to WiFi signals.
- We propose to exploit additional information at the physical layer, such as multipath or frequency offset information, to create more reliable fingerprinting of indoor spaces, and demonstrate through real world experiments, that this approach can improve the accuracy of FM-radio based indoor localization by more than 5% when compared to the accuracy achieved by FM or WiFi RSSI-only signatures.
- We study in detail the effect of wireless signal temporal variation and demonstrate that WiFi RSSI values exhibit significantly higher variation over time compared to FM RSSI values. This enables FM-based indoor localization to achieve approximately 57% higher room-level localization accuracy when considering temporal variations of wireless signals.
- We experimentally demonstrate that FM and WiFi signals are complementary in the sense that their localization errors are independent. Our experimental results indicate that when FM and WiFi signals are combined to generate fingerprints, the localization accuracy increases by 11% (without accounting for temporal variation) or up to 83% (when accounting for wireless signal temporal variation) compared to when WiFi RSSI only is used as a signature.

2. ARCHITECTURE OVERVIEW

Figure 1 provides an overview of the proposed indoor localization approach. As in most fingerprinting approaches, there is a training and a positioning stage. The training stage is responsible for collecting location-annotated wireless signal fingerprints that form the fingerprint database. The fingerprint database can be automatically crowdsourced from real mobile users as they check-in to different businesses or it can be manually created through detailed profiling. Every time a business check-in takes place, the wireless fingerprint is recorded on the mobile device and the business location is retrieved from freely available web services. The recorded wireless fingerprint is properly annotated with the business' location information and stored in the database. At the positioning stage, the mobile device records its wireless signal fingerprint and compares it against the available fingerprints in the database. The location associated to the fingerprint in the database that is the closest to the fingerprint recorded on the mobile device, in terms of a distance metric, such as euclidean distance, is assumed to be the current location of the device.

The most challenging task in fingerprint-based localization is the engineering of the fingerprint itself. To enable accurate localization, fingerprints need to be carefully engineered so that even nearby locations have sufficiently different fingerprints. Most previous approaches have adopted the received signal strength (RSSI) of nearby WiFi access points as the wireless signal fingerprint. In this work we extend this approach in two fundamental ways. First, we augment the wireless fingerprint to include the RSSI information obtained by FM radio signals. As Figure 1(b) shows, mobile devices record RSSI information from several FM radio station signals that are broadcasted from one or more radio towers. The RSSI value for each FM frequency can be used along with the WiFi RSSI values to form the wireless fingerprint. By combining WiFi RSSI with RSSI values from another wireless signal that is less susceptible to human presence and orientation, small objects, and multipath and fading due to its lower wavelength, we manage to encode a more robust profile of the location into the wireless signal fingerprint that, as it will be shown later, can lead to better localization accuracy.

Second, to enable unique fingerprints even for nearby locations, we propose to extract more detailed information, that goes beyond RSSI, at the physical layer (Figure 1(b)). Even though RSSI has been proven to be a good high-level signal indicator, it does not provide the necessary granularity to enable robust fine grain localization. For instance, RSSI values at different rooms inside a building might be identical due to different reasons such as human presence and multipath. However, lower level information at the physical layer, such as signal-to-noise ratio (SNR), and multipath indicators, can provide enough insight on *how* an RSSI value was generated. For instance, the way wireless signals are reflected in a room is unique and it depends on the room's setup and location in the building. As a result, multipath indicators might be different across rooms even though the RSSI values for these rooms might be identical. By augmenting wireless signal fingerprints with additional low level signal indicators, we enable fingerprints to capture more robust information about the wireless signal transmission *and the way it is affected from the current room's structure*. This infor-



(a) (b)

Figure 1: (a) Training and positioning stages for indoor localization (b) Signal fingerprinting using FM and WiFi radios.

mation could eventually be used to differentiate two rooms with the same RSSI values.

Note that this information could be leveraged for any wireless signal (e.g., WiFi) as long as it is exposed through the software driver. In fact, most recently Sen et al. [18, 19] exploit 802.11n PHY layer (OFDM) impulse responses and report notable localization accuracy gains. In this work, we focus on FM radio signals and therefore leverage the additional signal indicators for FM radio signals only. Nevertheless, we believe that in addition to WiFi and FM, getting additional signal indicators from the PHY layer can improve the localization accuracy of other wireless signals too.

3. EXPERIMENTAL SETUP

To evaluate the proposed approach we conducted detailed experiments in three typical building environments (Figure 2): an office building in a major corporate campus, a mall consisting of various restaurants and retail shops, and an apartment in a typical US residential building. The office and mall buildings are part of a major corporate campus located in the west coast of the US. Both buildings have a steel skeleton, and their perimeter is covered by large windows. The office building consisted of 3 different floors, with each floor containing approximately 40 rooms of $9ft \times 9ft$ size each. The mall building consisted of a single floor with a total number of 13 large rooms (i.e. $100ft \times 30ft$) of varying size and shape (Figure 2(b)). The residential building is located in a major city on the east coast of the US, and is built using steel-reinforced concrete. The particular apartment profiled in this study consisted of 5 different rooms as shown in Figure 2(c).

All buildings had exceptional WiFi and FM signal coverage. During data collection we recorded 434, 379, and 117 unique WiFi access points at the office, shopping mall, and residential buildings respectively. In every room of all 3 buildings, the FM receiver was able to tune to more than 32 FM radio stations.

3.1 Hardware

FM radio signatures were collected using the SI-4735 FM radio receiver from Silicon Labs [20] (Figure 3). The particular receiver was chosen for two reasons. First, Silicon Labs' FM radio receivers are very popular among a wide variety of consumer products such as cars, cell phones, portable media players and more. This enabled us to experiment with one of the most widely used FM receivers in the market today. Second, the particular receiver is among the few ones that expose low-level reception signal information to the application layer. In particular, besides reporting RSSI values, it provides 3 additional indicators[1] of signal reception: signal-to-noise ratio (SNR), multipath (MULTIPATH), and frequency offset (FREQOFF). SNR takes values between 0 and $128db$, and indicates how strong the received signal is compared to noise (i.e., interference, signal reflections, etc.). MULTIPATH takes values between 0 and 100, and indicates the severity of the multipath effect (i.e. the number and power of wireless signal reflections) in the current signal reception. FREQOFF mostly takes values between -10 and 10, and quantifies the difference in offset between the actual received signal and its different reflections. In general, the higher the value of FREQOFF the higher the effect of multipath and fading on the received signal. The combination of RSSI, SNR, MULTIPATH, and FREQOFF indicators represents the FM signature collected at each location during data collection (Figure 1(b)).

For embedded designs, such as cell phones, where space and size is important, the FM receiver can be connected to a patch antenna that can be directly implemented on the main PCB of the device. This would enable the device to acquire reliable signal readings, eliminating the unpredictability of loose earphone wires that are currently used as the FM antenna on most cell phones. Unfortunately, we were not able to find any patch antennas that meet the design criteria of Silicon Labs for the current FM receiver. As a result, we opted to use the typical FM antenna provided in the evaluation board. To approximate the behavior of a patch antenna, we folded the antenna as much as possible as shown in Figure 3. In our measurement setup the length of the antenna has twice the length of a typical smartphone.

WiFi signatures were collected using an 802.11a/b/g/n compatible WiFi Link 5300 card from Intel. All WiFi signatures consisted of RSSI values only. Both WiFi and FM receivers were connected to a Lenovo T61p laptop that simultaneously recorded WiFi and FM wireless signal fingerprints for a given location (Figure 3).

[1] The exact algorithm used to compute these indicators is sensitive, and is not provided by the manufacturer.

(a) Office (1 out of 3 floors) (b) Mall (c) Apartment

Figure 2: Maps of the different buildings used in our experimental study.

3.2 Data Collection and Evaluation

The goal of our experiments was to achieve accurate room-level localization[2]. In other words, given a wireless signal fingerprint from a mobile device, provide the room number where the device is located ("Position" in Figure 1 is actually a room number). To achieve this, we profiled each room in the building using both WiFi and FM signatures as described in Figure 1(b). For every room we collect the WiFi and FM signatures for 3 random points inside the room. We chose to only profile a small number of points within the room so that we can evaluate the ability of FM and WiFi signals to achieve high localization accuracy with sparse profiling, i.e., a small fingerprint database. We explore the benefit of having larger databases in Section 5.2. Depending on the experiment, multiple data collections were performed for each room over different time windows.

Specifically, at each location we record the FM signatures for 32[3] FM broadcast stations and scan the signal strengths of all available Wi-Fi access points, as described in Section 3.1. We denote $r_i, s_i, m_i, f_i \in \mathbf{R}^{32}$ as the RSSI, SNR, MULTIPATH, and FREQOFF values for the 32 FM broadcast stations at the i-th location, and similarly $w_i \in \mathbf{R}^M$ as the RSSI values for the Wi-Fi access points. Here M is the total number of Wi-Fi access points in the building, and i is the profiled location. We concatenate the signature vectors of the i-th location and denote as $a_i \in R^{128+M}$. In total, for every profiled location i within a room there are $128 + M$ values corresponding to 4 values for every one of the 32 FM channels and M values, one for every WiFi access point. As a result, the whole dataset for a given building can be written as $A = \{a_i : i = 1, 2, \ldots, 3 \times R\}$, where R is the number of rooms.

A typical fingerprinting-based localization scheme involves an offline phase to construct the database and an online phase for positioning unknown locations. In order to evaluate the localization performance, we emulate this two-phase process by separating the signatures into training and test sets. We first partition the whole dataset into three complimentary subsets of equal size: A_1, A_2 and A_3, where each set A_j contains one and only one location from each room. Next, we can group two subsets together as the training set, i.e., the fingerprint database, and use the third subset as the test set. We repeat this process using each of the three subsets as the test set and correspondingly the other two subsets as the fingerprint database, and report the average localization accuracy across all combinations. For each test location in the test set, we compare its signature vectors against the fingerprint database and return the location of the nearest neighbor in signal space as the localization result.

In all experiments, we report the localization accuracy when Euclidean and Manhattan distance metrics are used to compute the distance between wireless signal signatures. Even though more distance metrics have been evaluated, we opted to show only these two, as they consistently provided the highest localization accuracy across all experiments.

Figure 3: Data collection setup based on the SI-4735 FM radio receiver from Silicon Labs and the Intel WiFi Link 5300 wireless card connected to a Lenovo T61p laptop.

4. FM-BASED INDOOR LOCALIZATION

In this section, we focus on the office building environment consisting of 3 different floors and 119 rooms in total. We first investi-

[2]We focus on room-level resolution as this is the resolution at which data can be crowdsourced in a robust way from business check-in events. In Section 7, we evaluate FM's capability to achieve fine-grain indoor localization.

[3]The seek/tune time for the SI4735 FM receiver is 60 ms per channel, and the power-up time is 110 ms. It takes approximately 2 seconds to scan 32 FM radio stations.

Signature Type	Distance Metric	
	Euclidean	Manhattan
FM RSSI	85%	87%
Wi-Fi RSSI	76%	88%

Table 2: Room level localization accuracy for 119 rooms on 3 floors using FM and WiFi RSSI values as signatures.

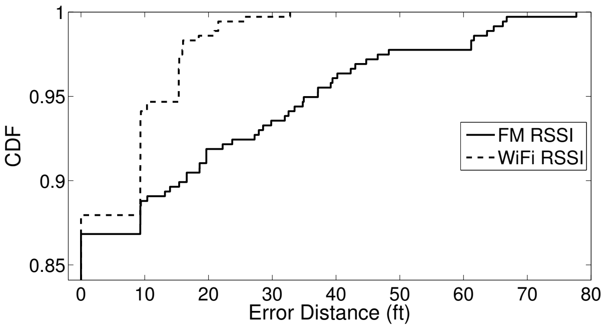


Figure 4: Distribution of the localization errors for FM and Wi-Fi RSSI. The nearest neighbors in signal space are determined using the Manhattan distance between the RSSI vectors.

gate the performance of using RSSI values alone for both FM (i.e., r_i) and Wi-Fi signals (i.e., w_i). Next, we use more signal quality indicators for FM (i.e., s_i, m_i, f_i) to see whether extracting more information from the physical layer can improve the localization accuracy. Last, we combine the FM and Wi-Fi vectors to investigate the effect on the localization accuracy and perform sensitivity analysis on the number of FM radio stations and WiFi access points used for fingerprinting.

4.1 RSSI-based Indoor Localization

Table 2 lists the room level localization accuracy results when signature vectors consist of FM or WiFi RSSI values only. It is clear that FM and WiFi RSSI values achieve similarly high accuracies that are close to 90%. Of the two distance metrics, Manhattan distance (i.e., the L_1 norm) yields slightly higher accuracy than Euclidean distance (i.e., the L_2 norm).

Figure 4 shows the distribution of the localization errors in terms of physical distance when using FM and WiFi RSSI signatures. Although both signals exhibit similar room level accuracies (Table 2), the localization errors are lower in the case of WiFi. In other words, when WiFi localization erroneously predicts rooms, those rooms are closer to ground truth compared to FM-based localization. This is expected given that there are orders of magnitude difference between WiFi and FM signals in terms of both deployment density and communication range. In general, a WiFi access point is only visible in a subset of the rooms in the building. This significantly limits the search space, and therefore the localization error that is generally lower than $30ft$. Conversely, in the case of FM signals, there are only a handful of radio towers at a given region that might be tens or even hundreds of kilometers away from the building. These FM signals can be received throughout the whole building, making every room in the building a possible candidate location.

This effect is better illustrated in Figures 5(a) and 5(b), where the Manhattan distance between every pair of profiled locations is shown when FM RSSI and WiFi RSSI signatures are used respectively. In the case of WiFi signatures (Figure 5(b)), errors are usually constrained within the vicinity of the diagonal (3 squares along the diagonal, where each square corresponds to one of the 3 floors profiled) mainly due to the communication range of access points. Very rarely the distance between WiFi RSSI vectors is low for distant locations in the building. On the other hand, the error profile of FM RSSI signature is the exact opposite (Figure 5(a)). The effect of the three squares shown in Figure 5(b) has disappeared, but now distant locations in the building can generate low distance values. As a result, even though FM and WiFi achieve similar localization accuracy overall, the localization error of FM signals is higher in terms of absolute physical distance.

Signature Type	Distance Metric	
	Euclidean	Manhattan
FM RSSI	85%	87%
FM SNR	80%	84%
FM Multipath	68%	76%
FM Frequency Offset	53%	53%
FM All	81%	91%
FM All Normalized	90%	93%

Table 3: Room level localization accuracy for 119 rooms on 3 floors using additional FM signal signatures. Combining multiple signal indicators in a single signature provides more accurate localization.

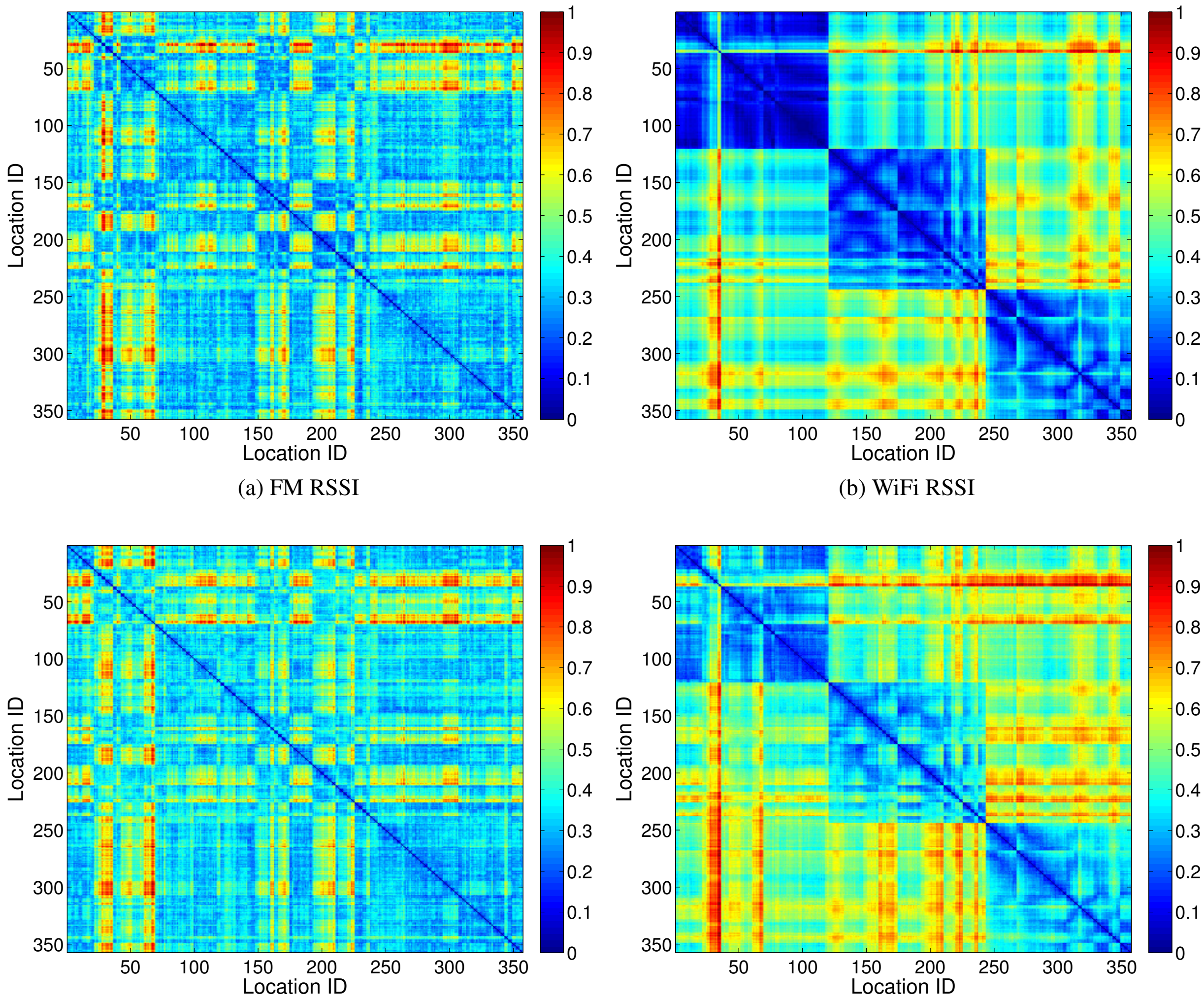
4.2 Robust Fingerprinting by Exploiting the Physical Layer

To further increase localization accuracy and to constraint errors, in this section, we leverage additional information at the physical layer to generate more robust signatures. The SI4735 FM receiver provides three additional signal quality indicators (SNR, MULTIPATH, and FREQOFF) as described in Section 3. Each of these signal indicators could be used as an individual signature, or they could all be combined with RSSI to form a single more detailed signature. The additional signal indicators can enhance the resolution of FM signatures by providing more insight about signal reception. Signal-to-noise ratio, multipath, and frequency offset, all capture detailed information about the wireless signal reception and *the way it is affected from the current room's structure and position in the building*.

When combining multiple signal indicators into the same signature, calculating the distance between signatures becomes more challenging. Different signal indicators have different value ranges that could result into biasing the distance calculation (i.e. higher value/range indicators become more important). For example, the multipath value range is between 0 and 100 whereas the frequency offset value is usually in the range of -10 to 10. Therefore, we normalize the value of each signal indicator using the standard deviation of the signal indicator's values in the fingerprint database. For example, we can compute the standard deviation for the RSSI signatures as

$$\delta_r = \left[\frac{1}{N|D| - 1} \sum_{i \in D} \sum_{j=1}^{N} (r_{ij} - \overline{r}) \right]^{\frac{1}{2}} \quad (1)$$

where D represents the set of location indices that are in the fingerprint database, and r_{ij} is the RSSI value of the j-th FM broadcast station at the i-th location. $\overline{r}$ is the average RSSI value in the database, $|D|$ is the cardinality of the set D, and $N = 32$ is the number of FM broadcast stations. Using the standard deviation, we



(a) FM RSSI

(b) WiFi RSSI

(c) FM ALL Normalized

(d) FM & WiFi ALL Normalized

Figure 5: The Manhattan distance of signature vectors between all pairs of profiled locations in the office building and for 4 different signature types. The distances are normalized by the maximum pairwise distance in each figure to have the same range of $[0, 1]$ across all figures. Diagonal values are 0 as they are the distances between identical vectors that correspond to the same locations.

can normalize the RSSI signatures as

$$\hat{r}_i = \frac{r_i}{\delta_r}, \quad \forall i \in D \cup T, \tag{2}$$

where T represents the set of location indices that are in the test set. All signal indicators' values are normalized in the same way, enabling us to compute un-biased distance values between signatures.

Table 3 lists the room level localization accuracy when each signal indicator is used as a single signature, and when all signal indicators are combined together into a single signature. The "FM All" signature corresponds to combining all *raw* signal indicator values into a single signature. The "FM All Normalized" signature corresponds into combining all *normalized* signal indicator values into a single signature.

It is clear that among all individual signal indicators, RSSI achieves the best accuracy. On the other hand, multipath and frequency offset indicators seem to not be able to provide the necessary resolution to achieve accurate localization on their own. However, com-

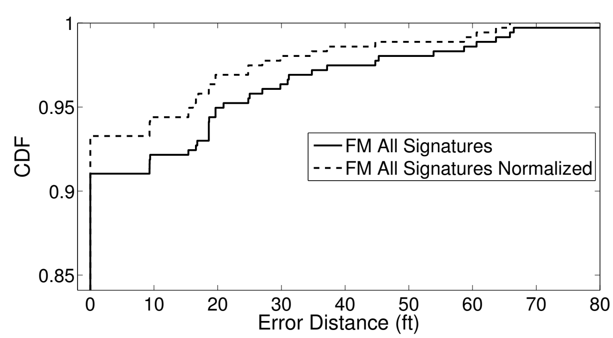


Figure 6: Distribution of the localization errors when combining all available signal indicators from the FM signals into a signature. The nearest neighbors in signal space are determined using the Manhattan distance between the signature vectors.

Signature Type	Distance Metric	
	Euclidean	Manhattan
FM All	81%	91%
FM All Normalized	90%	93%
Wi-Fi RSSI	76%	88%
FM & Wi-Fi All	93%	98%
FM & Wi-Fi All Normalized	94%	98%

(a) Room level localization accuracy

True	Floor #	2	2	2	2	2	3	3
	Room #	3	12	16	19	35	21	23
Predicted	Floor #	2	2	2	2	2	3	3
	Room #	5	11	17	20	36	19	24

(b) Error location list for FM & Wi-Fi All Normalized

Table 4: Room level localization accuracy for 119 rooms on 3 floors. Table (a) shows the localization accuracy achieved across different signature types. Table (b) shows a complete list for the room and floor numbers of the incorrectly identified locations when using the normalized FM and WiFi signatures with the Manhattan distance metric.

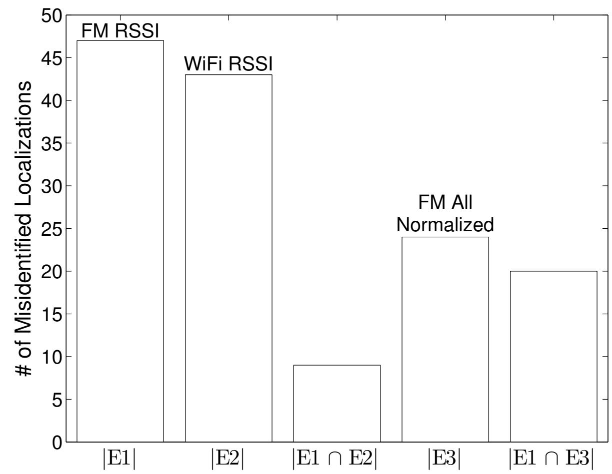


Figure 7: E1 and E2 represent the set of locations that are misidentified by FM RSSI only and WiFi RSSI only respectively. E1 $\cap$ E2 are the set of locations that misidentified by both FM and WiFi RSSI signatures. $|$E1 $\cap$ E2$| \ll |$E2$|$, suggesting that FM and WiFi positioning errors are not correlated. As a comparison, E3 denotes the set of misidentified locations using the FM All normalized signature.

bining all signal indicators into a single signature achieves higher accuracy than any individual signal indicator. This highlights the benefit of extracting more information from the physical layer and reflects the intuition that each type of signal indicator can capture a unique set of interplays between the propagating radio wave and its surrounding environment.

The impact of the additional signal indicators on the localization accuracy of FM signature is better illustrated in Figures 5(a) and 5(c), where the Manhattan distance between every pair of profiled locations is shown when the FM signature ignores or takes into account the additional signal indicators. By comparing Figures 5(a) and 5(c), it is obvious that when all signal indicators are leveraged in the FM signature, the distance matrix appears to be significantly less noisy, in the sense that the distances between non-neighboring locations in the matrix are significantly higher compared to the FM RSSI matrix. As a result, higher localization accuracy is achieved when all FM signal indicators are combined into a single signature.

Furthermore, Table 3 shows that normalizing the signatures, as described above, can further improve localization accuracy. When compared to Table 2, FM-based localization achieves 5.7% higher localization accuracy compared to the WiFI RSSI signatures.

Normalization not only improves accuracy, but also constraints the error when wrong predictions are made. Figure 6 shows the distribution of the localization errors for FM-based fingerprinting. Normalization increases the percentage of correctly identified locations, and also reduces the errors for the incorrectly identified locations.

4.3 Combining FM and Wi-Fi

In this section we investigate whether the FM and WiFi signal indicators could be combined into a single signature to further improve indoor localization accuracy.

Table 4(a) lists the room level localization accuracy when WiFi and all FM signal indicators are combined into a single signature. The combination of WiFi and FM signals can eliminate almost all localization errors, achieving 98% accuracy; an 11.3% increase compared to WiFi RSSI fingerprinting (Table 2). This suggests that the localization errors generated by the FM signatures are not correlated with the errors generated by WiFi signatures. To further investigate the correlations, we collect and count the number of locations misidentified by each signature, as shown in Figure 7. E1 and E2 are the set of locations misidentified by FM RSSI and WiFi RSSI respectively. The fact that $|$E1 $\cap$ E2$| \ll |$E2$|$ indicates the set of locations misidentified by FM RSSI rarely overlap with those by WiFi RSSI. As a comparison, we also collect the locations misidentified by all normalized signatures of FM and denote as set E3. One can see that $|$E1 $\cap$ E3$| \approx |$E3$|$, and therefore the locations misidentified by FM all normalized signatures highly overlap with those misidentified by FM RSSI. Overall, one can see that FM localization errors are not correlated with the WiFi errors. On the other hand, using more FM signatures removes many of the localization errors by FM RSSI.

The complementary nature of FM and WiFi signals is clearly illustrated in Figure 5. Initially, FM RSSI signatures (Figure 5(a)) provide high localization accuracy, which further increases when the additional signal indicators are leveraged (cleaner distance matrix in Figure 5(c)). However, errors are still distributed throughout the building, in the sense that signature distances even for distant locations in the building are low. On the other hand, localization errors in WiFi RSSI signatures are mostly constrained to only nearby locations as demonstrated by the 3 dark squares in Figure 5(b). When FM and WiFi signal indicators are combined into a single signature (Figure 5(d)), the benefits of both FM and WiFi signals show up in the resulting distance matrix. FM signatures significantly reduce the dark square effect which is the main source of errors in the case of WiFi signals (Figure 5(b)). At the same time, WiFi signals reduce the number of cases where distant locations have low distance values, the major source for errors in the case of FM signals. As a result, a mobile device can leverage its ability to receive both signals to effectively enhance localization accuracy with marginal overhead.

Table 4(b) lists the floor and room numbers of the locations that are identified incorrectly when combining the normalized FM and WiFi signatures (i.e., the last row of Table 4(a)) with the Manhattan distance. A total of seven test locations (2% of the 357 locations)

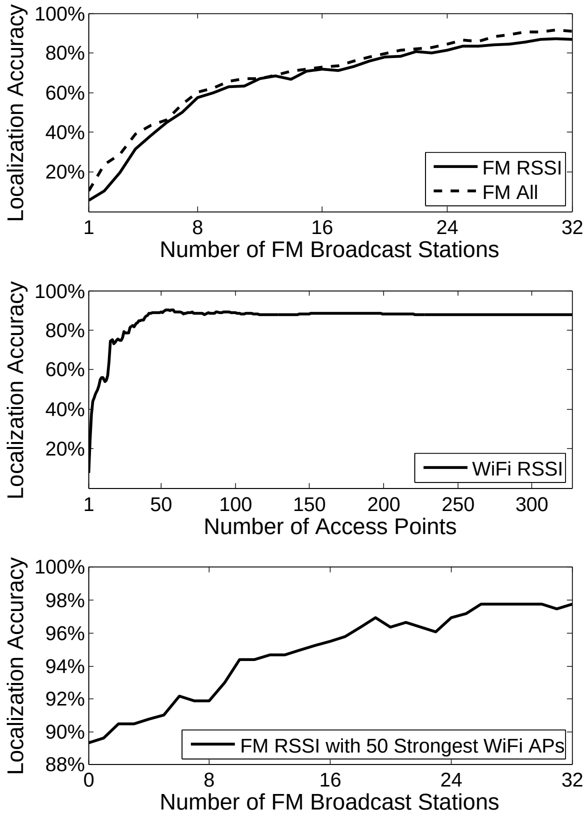


Figure 8: The sensitivity of localization accuracy on the number of FM broadcast stations and WiFi access points. Stations and access points are added in descending order of their average signal strength. In the last graph we employ the 50 strongest WiFi access points and only vary the number of FM radio stations.

are misidentified. However, all the erroneously predicted rooms are on the same floor and nearby the true rooms.

4.4 Sensitivity Analysis on the Number of FM Stations and WiFi Access Points

So far we have been using the signatures from all 32 FM broadcast stations and 434 visible WiFi access points in the office building for indoor localization. However, it is unclear how many FM radio stations and WiFi access points are actually needed to provide accurate localization. To answer this question, we perform a sensitivity analysis where we withhold a certain percentage of FM radio stations and WiFi access points, and rerun the nearest neighbor based localization algorithms. Specifically, we sort the FM stations and WiFi access points in descending order of their RSSI values averaged over all locations. At each step, we incrementally add one station/access point at a time, and rerun the localization algorithm. As a result, when we evaluate the localization performance with n stations, we use the n strongest stations in terms of their average RSSI values.

Figure 8 shows the localization accuracy achieved when different number of FM radio and WiFi access points are used. It is clear that for both signals, additional infrastructure leads to higher accuracy. To achieve the maximum localization accuracy (i.e., accuracy when all radio stations or access points are used), 30 FM radio stations and approximately 50 WiFi access points are required. In the case

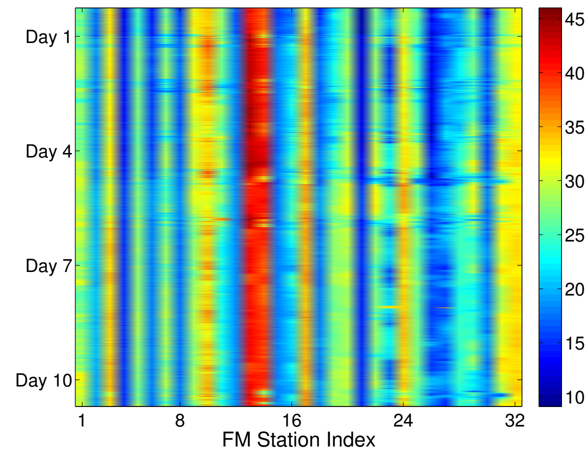


Figure 9: Raw RSSI values in dBμV of the 32 FM broadcast stations over the course of 10 days. Results for the rest 3 FM signal indicators are not shown in the interest of space.

of FM, the accuracy increases very fast till around 8 stations, but it does not saturate afterwards. Instead it keeps rising, but at a lower pace, indicating that a large number of radio stations is required to achieve high localization accuracy. In the case of WiFi, given the high density of access points and their limited communication range, the number of useful access points saturates relatively fast at around 50 access points.

When we start by using the 50 strongest WiFi access points as the base line, the localization accuracy increases as we are incrementally adding FM stations, and seems to saturate at the point where 25 radio stations are used (bottom graph of Figure 8).

5. TEMPORAL VARIATIONS

The results in the previous section are derived without considering the temporal variations of FM and WiFi signals. However, it is known that signal signatures are likely to change overtime. For example, Haeberlen et al. [9] achieve 95% room level localization accuracy using WiFi RSSI signatures when the test and training data are collected in close time proximity. With data from different time and day, however, the localization accuracy drops to 70%, as pointed out in [22].

In this section we explore the temporal variations of the broadcasted FM signals and the impact on localization accuracy. First, we continuously monitor the FM signals for ten days at a fixed location in one room to gain intuition on how signatures vary over time. To quantify the impact of temporal variations on localization accuracy, we collect fingerprints for the 40 rooms on the 2nd floor on different days and run the localization algorithm against fingerprint databases that were recorded at different points in time.

5.1 Continuous Monitoring of FM Signals Over Ten Days

Figure 9 shows the raw RSSI values of the 32 FM stations at a fixed location in one room over the course of ten days. This room is a regular office and therefore its door and furniture could change states due to the presence of humans. The room is at the perimeter of the office building and has a window that faces a busy street. We note that there were rainy, cloudy, and also sunny days during the experiment. We configured the receiver to record all signal in-

Signature Type	Distance Metric	
	Euclidean	Manhattan
FM RSSI	100%	100%
FM SNR	100%	100%
FM Multipath	100%	100%
FM Frequency Offset	99%	77%
FM All	100%	100%
FM All Normalized	100%	100%

Table 5: Room level localization accuracy using the data collected at a fixed location over the course of ten days as the test set, against the fingerprint database collected in Section 4. The first three measurements taken at the fixed location were inserted into the fingerprint database.

dicators for the 32 FM broadcast stations once per three minutes. Therefore, Figure 9 includes more than 4000 rows of data.

Figure 9 shows that, overall, RSSI values at a given frequency do not change drastically over time. However, all FM stations seem to exhibit fluctuations in RSSI values, but to a different extent. For instance, FM station 27 seems to exhibit way larger fluctuations in RSSI values when compared to FM station 21. We believe that this is due to the fact that different radio stations are broadcasted from different radio towers and at different transmission power levels.

In order to quantify whether these fluctuations would impact this room's localization result, we use the first three rows of data in conjunction with the fingerprints collected in section 4 as the fingerprint database, and use the rest of the rows in Figure 9 as the test set. Table 5 lists the percentage of rows that are identified correctly. The localization accuracies are consistently high for all signature types except frequency offset. This suggests that as long as a location has been profiled before, the temporal variations should not cause this location to be mislabeled in the future.

5.2 Collecting Fingerprints on Different Days

In this section, we extend the temporal variation analysis to multiple locations. Specifically, we collect four additional sets of fingerprint measurements for the 40 rooms on the second floor in exactly the same way as before, but on different days. We chose to study the second floor because this floor exhibits most localization errors as shown in Table 4(b).

We first study the pairwise localization performance between two datasets, where one dataset is chosen as the test set and a different dataset is chosen as the fingerprint database. Note that this way the size of the test set is the same as that of the fingerprint database. We run the nearest neighbor localization algorithm on all combinations of pairs of datasets (i.e., 20 pairs across 5 datasets) and present the average room level localization accuracy in Table 6(a). Compared to the results in Table 4, it is obvious that temporal variations of the signal signatures can lead to noticeable degradation of localization accuracy. WiFi RSSI signatures seem to be affected the most by temporal variations as the localization accuracy decreases by 44% (from 88% to 49%) in the presence of temporal variations. On the other hand, FM signatures seem to be less susceptible to temporal variations, as the localization accuracy decreases by only 13% (from 93% to 81%), and the achieved accuracy remains above 80%. In general, because of the differences in frequency and wavelengths between FM and WiFi signals, WiFi signals are more susceptible to human presence/orientation, and to the presence of even small objects in the room. However, both human presence and setup of objects in a room changes over time, significantly lowering the localization accuracy of WiFi RSSI-based fingerprinting.

Signature Type	Distance Metric	
	Euclidean	Manhattan
FM RSSI	78%	77%
FM All	79%	82%
FM All Normalized	75%	81%
Wi-Fi RSSI	43%	49%
FM & Wi-Fi All	85%	89%
FM & Wi-Fi All Normalized	80%	90%

(a) Pairwise: same size test and training sets

Signature Type	Distance Metric	
	Euclidean	Manhattan
FM RSSI	91%	92%
FM All	91%	92%
FM All Normalized	88%	91%
Wi-Fi RSSI	57%	61%
FM & Wi-Fi All	94%	96%
FM & Wi-Fi All Normalized	91%	95%

(b) One versus many: four datasets in the fingerprint database

Table 6: Room level localization accuracy for 40 rooms on the second floor. Table (a) lists the localization accuracy where one dataset is chosen as the test set and a different dataset as the fingerprint database. Table (b) includes four datasets in the fingerprint database.

The signature that is affected the least by temporal variations is the one that combines WiFi RSSI and the 4 FM signal indicators. In particular, localization accuracy decreases by only 8%, and absolute accuracy is 90%. Note that these observations are consistent with the observations in Section 4.3, indicating that WiFi and FM errors are uncorrelated.

As more data is crowdourced or manually collected over time, the quality of the fingerprint database improves. The rationale is that more datasets that are collected across different days can potentially capture more patterns of the signal signatures in the temporal domain. Table 6(b) quantifies the impact of the size of the fingerprint database on the localization accuracy. It lists the results of using four datasets as the fingerprint database and one dataset as the test set. It loops through the five different combinations and reports the average numbers. Clearly, adding more datasets into the database can lead to notable gains in the localization accuracy, indicating that a bigger fingerprint database can better cope with temporal variations.

We note that during the course of our experiments, most of the changes in the environment were the movements of people, chairs, doors, and other smaller objects. Our experimental results indicated that both WiFi and FM signals are susceptible to these changes, however, FM signals are affected significantly less compared to WiFi. More dramatic changes such as moving big metal shelves should affect the signatures to a larger extent for both WiFi and FM signals, but have not been studied in this work.

6. DIFFERENT TYPES OF BUILDINGS

In this section, we investigate whether the results obtained in office environments can apply to other types of buildings and geographic regions in the US.

Signature Type	Distance Metric	
	Euclidean	Manhattan
FM RSSI	77%	80%
FM All	65%	72%
FM All Normalized	67%	71%
Wi-Fi RSSI	94%	97%
FM & Wi-Fi All	94%	98%
FM & Wi-Fi All Normalized	96%	98%

(a) Pairwise: same size test and training sets

Signature Type	Distance Metric	
	Euclidean	Manhattan
FM RSSI	87%	90%
FM All	79%	82%
FM All Normalized	92%	87%
Wi-Fi RSSI	97%	100%
FM & Wi-Fi All	97%	100%
FM & Wi-Fi All Normalized	97%	100%

(b) One versus many: four datasets in the fingerprint database

Table 7: Table (a) lists the localization accuracy where one dataset is chosen as the test set and a different dataset as the fingerprint database. Table (b) includes four datasets in the fingerprint database.

6.1 Shopping Mall

Shopping malls are different from office buildings in many aspects. The ceilings are taller and the rooms are sparser and bigger, which makes malls resemble outdoor environments more than office buildings do. Given that FM-based indoor localization depends on the internal structure of the building to achieve high localization accuracy, it is unclear whether FM signatures can be used in this type of environments.

We opted to collect fingerprint measurements at the first floor of a two-story mall building that hosts various restaurants and retail shops (Figure 2(c)). We collected five fingerprint datasets on three different days. For each dataset, we take measurements in 13 rooms and at 3 random locations for each room. Therefore, every dataset includes a total of 39 locations. The first 4 datasets are collected during a weekend, and the 5th dataset is collected on a Wednesday afternoon. Table 7(a) shows the average pairwise localization accuracy across all possible combinations of database and test datasets. Interestingly, FM signatures perform slightly worse compared to the office building (cf. Table 6), but WiFi signatures perform significantly better. The degradation of FM signatures' accuracy can be attributed to the fact that mall buildings resemble more of outdoor environments as the impact of the internal structure of the building on signal propagation is lower compared to office buildings. On the other hand, WiFi signatures can more reliably distinguish the 13 rooms because of the large size and clear spatial separation of these rooms, to the extent that some of them are covered by completely different sets of access points. Nevertheless, combining WiFi and FM signatures still provides the highest positioning accuracy.

Table 7(b) shows the localization accuracy when using only one dataset as the test set and the remaining four datasets altogether as the database. Similar to the case of the office building environment, having more fingerprints in the database increases localization accuracy.

Signature Type	Localization Accuracy
FM RSSI	100%
WiFi RSSI	90%
FM & WiFi All	97%
FM & WiFi All Normalized	100%

Table 8: Localization accuracy for 5 rooms in a residential building when the Manhattan distance metric is used.

6.2 Residential Building

Residential buildings differ from office and mall buildings in size, shape, structure and often building materials. In this section, we study the performance of FM based indoor localization in an apartment unit that has multiple rooms of various sizes (Figure 2(b)). This apartment is located on the east coast of the US, and therefore the list of FM stations are completely different from the ones used in the office and mall buildings which are on the west coast. Nevertheless, we still chose 32 audible stations such that the number of stations remains consistent.

We collected two datasets on two different days. Each dataset gathered measurements in 5 rooms and at 3 random locations per room. We chose each of the two datasets in turn as the test set and fingerprint database to evaluate the positioning accuracy. Table 8 shows the average room level localization accuracy for FM and WiFi signatures. Overall, both FM and WiFi signatures demonstrate above 90% accuracy in this environment, with FM signatures achieving perfect room-level localization accuracy. These results are comparable to the results at the office and mall buildings, suggesting that: (1) the achieved localization accuracies are independent of the building type, and (2) the FM based indoor localization approach is applicable to other geographic regions with different FM broadcast infrastructure.

7. FINE-GRAIN LOCALIZATION AND DEVICE VARIATIONS

So far, we have been focusing on room-level localization as this is the resolution at which data can be crowdsourced reliably from current business check-in events. However, it is still feasible to collect more fine-grained, location annotated indoor fingerprints through detailed profiling. To study the feasibility of using FM radio signals to perform fine-grain location estimation, we performed experiments along the hallway on the second floor of the office building.

Specifically, we gathered FM and WiFi signatures at 100 locations that formed a straight line along the hallway, with the distance between every two adjacent locations being approximately one foot (± 0.06 ft). We collected a total of three datasets in different days to capture the temporal variation of signal signatures. The exact same locations were profiled in all three datasets. The coordinates of each location were measured accurately using a laser distance meter.

7.1 Leave One Out Evaluation

For each one of the three datasets, we perform the leave-one-out evaluation. In particular, we remove one and only one location at a time from the dataset and compare its signature against the other 99 signatures in the dataset. The position of the closest signature is assumed to be the position of the test location. In such an evaluation, a robust signature scheme should always return one of the two neighboring locations to the test location.

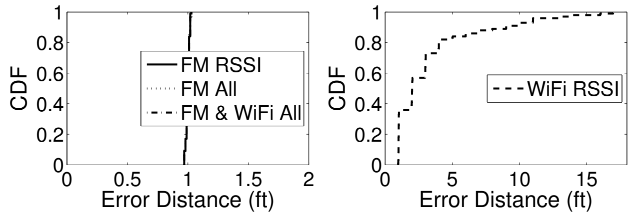


Figure 10: Distribution of the leave-one-out localization errors for FM and WiFi RSSI signals. The nearest neighbors in signal space are determined using the Manhattan distance between the RSSI vectors.

Datasets	Signature Type	Localization Error (ft)	
		50%	90%
1 vs 2	FM RSSI	0.02	2.02
1 vs 2	WiFi RSSI	4.97	15.00
3 vs 1&2	FM RSSI	0.01	1.00

Table 9: Localization errors using FM and WiFi RSSI signatures in the hallway using the Manhattan distance to determine the nearest neighbor in signal space. All datasets were taken at different days. Datasets 1 and 2 were taken using the same FM receiver, while dataset 3 leveraged a different FM receiver of the exact same type.

Figure 10 shows the distribution of the localization errors for FM and WiFi RSSI signatures across all 3 datasets. FM RSSI signatures provide highly accurate positioning with errors around 1 ft. Recall that the 100 locations formed a line with the distance between two neighboring positions set to one foot (± 0.06 ft). This indicates that each location is identified as one of its two neighbors on the line. On the other hand, WiFi RSSI signatures exhibit significantly larger errors, with the 90 percentile error approximating 10 ft.

Figure 11 visualizes the spatial resolution of the FM and WiFi RSSI signatures by plotting the Manhattan distances between all pairs of locations for one of the three datasets collected. The distances are linearly mapped to the [0,1] range for each signature such that the graphs are directly comparable. The diagonals are always zero because the vectors are identical for the same location. By comparing Figures 11(a) and 11(b), it becomes apparent that not only FM RSSI signatures have the necessary spatial resolution for accurate fingerprinting, but they provide significantly finer-grain resolution compared to WiFI RSSI signatures. In the case of FM signals, the RSSI distances are low only for the same or neighboring locations. In most other cases, the FM RSSI signatures differ significantly. Conversely, in the case of WiFi signals, RSSI distances are low even for locations that can be more than $15ft$ far away from each other, leading to high localization errors as shown in Figure 10.

7.2 Temporal and Device Variation

All 3 datasets were collected at different days, and the third dataset was collected using a different FM receiver chip of the same model and manufacturer. This allowed us to study how temporal and device variations affect the accuracy of fine-grain localization.

First, we examine temporal variations using datasets 1 and 2. We let one of them be the test set and the other be the fingerprint database, and then flip their roles to compute the average localization error. The 50th and 90th percentile errors are shown in Table 9. Both FM and WiFi RSSI signatures show higher localization errors compared to Figure 10, due to temporal variations. Nevertheless, FM still outperforms WiFi significantly.

To study the effect of device variations, we choose dataset 3 as the test set (fingerprint database) and one of the other two datasets in turn as the fingerprint database (test set), and compute the average CDF of localization errors. The results are summarized in the last row of Table 9. Note that the results are subject to both temporal and device variations since dataset 3 was collected in a different day too. Even under device variations, the localization error does not increase significantly as compared to temporal-only variations. In fact, the localization error seem to be slightly lower with device variations. These variations are most likely due to the random changes in the environment, indicating that device variations do not notably affect the localization performance.

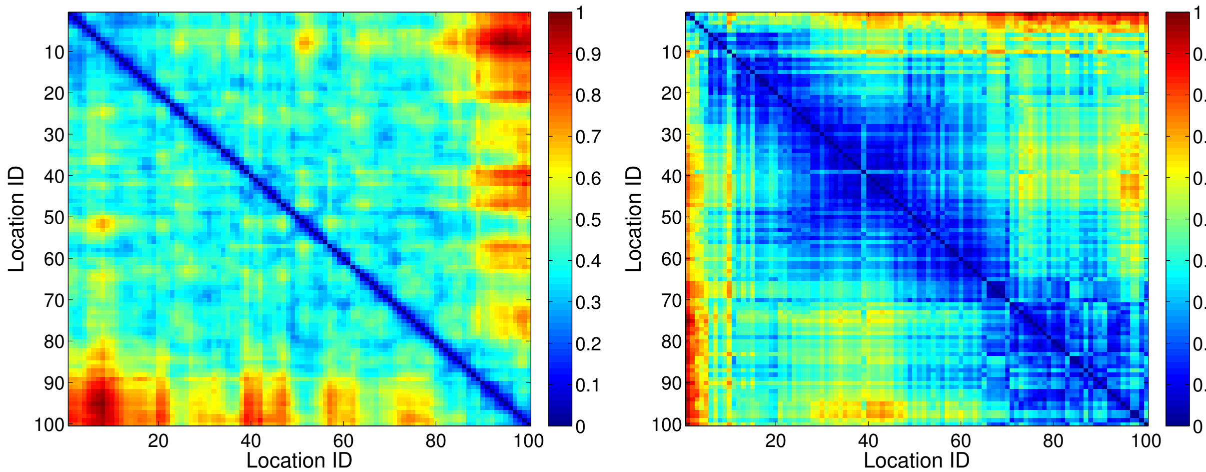
8. RELATED WORK

Previous approaches to fingerprint-based indoor localization can be roughly classified into two categories: *infrastructure-based* and *infrastructure-less* approaches. *Infrastructure-based* approaches rely on the deployment of customized RF-beacons, such as RFID [13], infrared [25], ultrasound [17], Bluetooth [3], and short-range FM transmitters [11]. The advantage of these approaches lies on the fact that the deployed beacons can be carefully engineered/optimized for indoor localization, and of course they can be deployed at the necessary density to provide accurate indoor positioning. However, the high overhead of deploying custom hardware usually prohibits the feasibility of infrastructure-based approaches.

Infrastructure-less approaches, on the other hand, do not require any hardware to be deployed, as they leverage already available wireless signals to profile a location, usually in the form of RSSI values. The state-of-the-art approach to signal fingerprinting relies on WiFi signals as WiFi access points are widely deployed indoors, and every mobile device is equipped with a WiFi receiver. The early RADAR [1] indoor localization system demonstrated the effectiveness of WiFi fingerprinting by achieving localization accuracies in the range of 2 meters. More recent work [9, 27] reported higher accuracy by statistically modeling the signal strength as Gaussian distributions. WiFi signals, however, operate at the 2.4GHz or 5Ghz range that makes them particularly susceptible to multipath, fading, small objects and most importantly to human presence. In particular, human body and its orientation can drastically impact WiFi RSSI values. As a result, profiling of locations becomes extremely tedious as for every location signatures need to be recorded for different body orientations [1]. Also, in agreement with our findings, the temporal variations of WiFi RSSI values tend to be high due to the sensitivity of the signal to the presence of humans and small objects. Most recently, Sen et al. [18, 19] exploit 802.11n PHY layer (OFDM) impulse responses and report more robust localization performance. On the other hand, commercial WiFi-based localization systems (e.g., Skyhook [21]) focus more on coarse-grained localization (e.g., 70 meters in Skyhook [6]) to alleviate the need for war-driving inside buildings.

Varshavsky et al. developed GSM fingerprint-based indoor localization systems that can achieve slightly worse accuracy to that of WiFi based systems [14, 24]. The key concept of their system is to record fingerprints from not only the six surrounding GSM stations, but also farther away stations whose signal can still be heard by the mobile phones.

Recently, Tarzia et al. explored the possibility of using acoustic background spectrum for room-level localization [22]. Their localization system takes advantage of the observation that each room tends to have its own unique background noise. Using currently available smartphones and their embedded microphones, they demon-



(a) FM RSSI

(b) Wi-Fi RSSI

Figure 11: The Manhattan distance between the RSSI vectors measured at 100 evenly spaced $(1ft)$ locations in the hallway of an office building. The distances are normalized by the maximum pairwise distance in each figure to have the same range $[0, 1]$ across the two figures. Diagonal values are 0 as the RSSI values for the same location are identical.

strate room level accuracies around 70% from an experiment involving 33 rooms.

Chung et al. investigated indoor localization with geo-magnetic sensors [5]. Their system is based on the observation that the steel and concrete skeletons of buildings can distort the geomagnetic field, such that fingerprinting is feasible. The localization error of this system is within 1 meter 88% of the time. However, the values of the geo-magnetic sensors change drastically even for nearby locations, requiring enormous profiling. Furthermore, the proposed system uses custom-made geo-magnetic sensors that is unclear how they can be reliably integrated into current phones.

In this paper, we consider FM broadcast radio signals for fingerprint based indoor localization. Because of the lower frequency, FM signals are less susceptible to human presence, multipath and fading, they exhibit exceptional indoor penetration, and according to our experimental study they vary less over time when compared to WiFi signals. From the infrastructure point of view, there are thousands of commercial and amateur FM signals being broadcasted continuously across the world, eliminating the need for deploying any custom infrastructure. Also, most mobile devices, even the lower-end ones, are equipped with FM radio receivers.

FM radio based localization systems have been studied before in the context of *outdoor* localization. Krumm et al. measured the signal strength from a set of FM broadcasting stations in outdoor environments and used the strength rankings to distinguish 6 suburbs [10, 26]. Also in outdoor environments, Fang et al. compared the performance of FM radio signals and GSM signals using a spectrum analyzer [8]. They report that both signals achieve similar accuracy in the order of tens of meters using the fingerprinting approach. In this work, we consider FM radio signals for *indoor* localization, and we experimentally demonstrate that higher accuracies can be achieved indoors. This is due to the impact that the internal structure of the building has on the FM radio signal propagation. The internal walls, floors, and ceilings affect FM radio signal propagation enabling higher spatial resolution in the recorded RSSI signatures.

In parallel with our work, Andrei et al. [16], as well as Moghtadaiee et al. [12] explored FM broadcast signals for indoor localization. Andrei et al. reported median localization error of 0.91 meters when leveraging FM RSSI signatures [16]. However, this is preliminary work that only included profiling a single room in a building. More recently, Moghtadaiee et al. measured RSSI values of FM broadcast radios in several rooms with USRP2, and reported a mean localization error of 2.96 meters using fingerprinting[12].

Our work differs from these approaches in four fundamental ways. First, to the best of our knowledge, this is the first large scale study of using FM radio signals for the purpose of indoor localization. We collected measurements in more than 100 rooms on multiple floors, buildings and regions in the US. The volume of experimental data enabled us to investigate room level as well as fine-grain localization performance in the 2D, as well as in the 3D space. Previous work has only evaluated 2D errors, yet at a much smaller scale. Second, we go beyond RSSI-based fingerprinting. We propose and evaluate the use of additional signal strength indicators at the physical layer to create more robust and discriminative signatures. Third, we study in detail the impact of temporal and device variations on the localization accuracy for both WiFi and FM signals. Fourth, we experimentally demonstrate that WiFi and FM errors are independent, and that the two signals can be combined to generate signatures that can achieve up to 83% higher localization accuracy when accounting for wireless signal temporal variations.

Last but not least, energy efficiency is an important consideration when designing localization systems [6, 7, 15]. FM receiver consumes significantly less power compared to the receivers for WiFi and GPS, and thereby can be integrated into general localization systems to tradeoff accuracy and efficiency by duty-cycling various components.

9. CONCLUSIONS

We have presented and evaluated a new approach to fingerprint-based indoor localization that leverages FM broadcast radio signals. Our experimental results show that when FM RSSI values are combined with additional information about signal reception at the physical layer to form the wireless signal signature, localization is 5.7% more accurate than WiFi-based techniques. Furthermore, we experimentally demonstrated that due to differences in operating frequency and wavelength, FM signals are more robust to temporal variations when compared to WiFi signals. More importantly, we have shown that FM and WiFi signals exhibit uncorrelated errors. The combination of FM and WiFi signal indicators into a single signature provides up to 83% higher localization accuracy than when WiFi only signals are used.

FM infrastructure is already widely deployed across the world, and many of the mobile devices include FM receivers. With minor modifications in the hardware of commercial devices and the inclusion of patch FM antennas, the proposed approach could be immediately deployed in the wild. In fact, on most smartphones today there is a single chip that houses all wireless infrastructure (WiFi, Bluetooth, FM radio etc.) such as the BCM4329 from Broadcom [2], WiLink 7.0 from Texas Instruments [23], and CSR9000 from Cambridge Silicon Radio [4]. Most, if not all, of the chip vendors include FM radio components that in general constitute of only a small fraction of the overall chip. This makes the cost impact of FM radio minimal. RSSI information is already available on most radio chips, and localization using RSSI can already achieve satisfactory accuracy. On the other hand, from the FM chip vendor's perspective, there are no major obstacles or limitations in exposing this information to the application layer. We believe that accurate indoor localization can justify and motivate chip vendors to easily expose this information to the application layer.

Based on our intuition and the experimental results for FM signals, we believe other signals such as AM and TV broadcast radios can also be used for localization. Also, combining more signals into a richer fingerprint should further increase the localization performance.

10. ACKNOWLEDGMENTS

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11. REFERENCES

[1] P. Bahl and V. N. Padmanabhan. RADAR: An In-Building RF-based User Location and Tracking System. In *Proceedings of INFOCOM*, 2000.

[2] Broadcom. Low-Power 802.11n with Bluetooth 2.1 + EDR and FM (Tx and Rx), 2008.

[3] R. Bruno and F. Delmastro. Design and analysis of a bluetooth-based indoor localization system. In *Personal Wireless Communications*, Lecture Notes in Computer Science. 2003.

[4] Cambridge Silicon Radio. CSR9000.

[5] J. Chung, M. Donahoe, C. Schmandt, I.-J. Kim, P. Razavai, and M. Wiseman. Indoor location sensing using geo-magnetism. In *MobiSys '11*, 2011.

[6] I. Constandache, R. R. Choudhury, and I. Rhee. Towards mobile phone localization without war-driving. In *Proceedings of the 29th conference on Information communications*, INFOCOM'10, pages 2321–2329, Piscataway, NJ, USA, 2010. IEEE Press.

[7] I. Constandache, S. Gaonkar, M. Sayler, R. R. Choudhury, and L. P. Cox. Enloc: Energy-efficient localization for mobile phones. In *INFOCOM*, pages 2716–2720, 2009.

[8] S.-H. Fang, J.-C. Chen, H.-R. Huang, and T.-N. Lin. Indoor localization using fm radio signals: A fingerprinting approach. In *IWCMC '08*, 2008.

[9] A. Haeberlen, E. Flannery, A. M. Ladd, A. Rudys, D. S. Wallach, and L. E. Kavraki. Practical robust localization over large-scale 802.11 wireless networks. In *MobiCom '04*, 2004.

[10] J. Krumm, G. Cermak, and E. Horvitz. Rightspot: A novel sense of location for a smart personal object. In *UBICOMP '03*, 2003.

[11] A. Matic, A. Popleteev, V. Osmani, and O. Mayora-Ibarra. Fm radio for indoor localization with spontaneous recalibration. *Pervasive Mob. Comput.*, 6, December 2010.

[12] V. Moghtadaiee, A. G. Dempster, and S. Lim. Indoor localization using fm radio signals: A fingerprinting approach. In *2011 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, September 2011.

[13] L. M. Ni, Y. Liu, Y. C. Lau, and A. P. Patil. Landmarc: indoor location sensing using active rfid. *Wirel. Netw.*, 10, November 2004.

[14] V. Otsason, A. Varshavsky, A. L. Marca, and E. de Lara. Accurate gsm indoor localization. In *UbiComp'05*, September 2005.

[15] J. Paek, K.-H. Kim, J. P. Singh, and R. Govindan. Energy-efficient positioning for smartphones using cell-id sequence matching. In *Proceedings of the 9th international conference on Mobile systems, applications, and services*, MobiSys '11, pages 293–306, New York, NY, USA, 2011. ACM.

[16] A. Popleteev. *Indoor positioning using FM radio signals*. PhD thesis, University of Trento, April 2011.

[17] N. B. Priyantha, A. Chakraborty, and H. Balakrishnan. The cricket location-support system. In *Mobicom '00*, 2000.

[18] S. Sen, B. Radunovic, R. R. Choudhury, and T. Minka. Precise indoor localization using phy layer information. In *Proceedings of the 10th ACM Workshop on Hot Topics in Networks*, HotNets '11, pages 18:1–18:6, New York, NY, USA, 2011. ACM.

[19] S. Sen, B. Radunovic, R. R. Choudhury, and T. Minka. Spot Localization using PHY Layer Information. In *MobiSys '12*, 2012.

[20] Silicon Laboratories. Si4735 Broadcast AM/FM/SW/LW Radio Receiver IC Rev D60, 2011.

[21] Skyhook, Inc. http://www.skyhookwireless.com/.

[22] S. P. Tarzia, P. A. Dinda, R. P. Dick, and G. Memik. Indoor localization without infrastructure using the acoustic background spectrum. In *MobiSys '11*, 2011.

[23] Texas Instruments. WiLink 7.0 single-chip WLAN, GPS, Bluetooth and FM solution, 2010.

[24] A. Varshavsky, E. de Lara, J. Hightower, A. LaMarca, and V. Otsason. Gsm indoor localization. *Pervasive Mob. Comput.*, 3, December 2007.

[25] R. Want, A. Hopper, V. Falcão, and J. Gibbons. The active badge location system. *ACM Trans. Inf. Syst.*, 10, January 1992.

[26] A. Youssef, J. Krumm, G. Cermak, and E. Horvitz. Computing location from ambient fm radio signals commercial radio station signals. In *IEEE Wireless Communications and Networking Conference, WCNC*, 2005.

[27] M. Youssef and A. Agrawala. The horus wlan location determination system. In *MobiSys '05*, 2005.