A Smartphone-based Indoor Localisation System Using FM and Wi-Fi Signals

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***Abstract*—Indoor localisation has the potential to revolutionise the way people navigate indoors, similar to the tremendous impact that GPS has had on outdoor navigation. A number of solutions have been proposed for indoor localisation but most rely on specialised hardware or on the presence of a strong (access point) infrastructure. Many places do not have such infrastructure, thus limiting the use of these indoor localisation technologies. We propose a smartphone-based solution using FM and Wi-Fi signals that uses commercial off-the-shelf hardware which can be connected as and when required and thus addresses some of the potential privacy concerns. We show through our experiments that the proposed system can be used even in areas with low FM and Wi-Fi signal coverage. Our system achieves a mean localisation error of 2.84 m with a 90^{th} percentile error of 4.03 m. In addition, we show the robustness of our system in a realistic and challenging environment by using a 4 month old training database.**

I. Introduction

Indoor localisation has been an area of active research due to its potential to revolutionise the way people navigate indoors, similar to what GPS did for the outdoors. Numerous RF-based approaches such as Wi-Fi [1], FM [2], [3], DVB-T [4], Bluetooth [5], ZigBee [6] and GSM [7] have already been studied, with each having its own advantages and disadvantages. Fingerprinting based approaches, especially using Wi-Fi, have been studied the most due to their low-cost, widespread availability of Wi-Fi infrastructure (especially in urban indoor scenarios), and good localisation accuracy. Most fingerprinting systems rely on a *training* phase and an *online* or *testing* phase in order to achieve the localisation objective. A user has to manually survey the indoor area and create a radio map before being able to use the system for localisation applications. Wi-Fi based localisation tends to be highly susceptible to obstructions, which represents a major limitation as even a slight change in the indoor environment would necessitate a recalibration of the radio map.

FM broadcast signals are in a unique position to overcome a number of these disadvantages:

- The frequency range of FM transmissions ($88-108$ MHz) is much lower than that of Wi-Fi (2.4 GHz or 5 GHz) or GSM (> 1900 MHz), resulting in a significant reduction in the multipath effects.
- FM has zero infrastructure costs, unlike Wi-Fi, where a sufficient number of access points are required to ensure good coverage and localisation accuracy, or Bluetooth which requires separate beacons, or DVB-T which require separate hardware.
- FM signals have a large coverage area. Signals from a single FM station can cover an area spanning several square kilometers, unlike Wi-Fi or Bluetooth.

It is estimated that people in developed countries spend around 90% of their time indoors [8]. Indoor localisation thus brings with it a number of privacy concerns. Unsecured server side processing of data can result in the location data being revealed to unauthorised people and put the concerned individual's security and privacy at risk [9].

Many localisation systems tend to rely on a high density of Wi-Fi and FM access points. Secondly, it is very difficult to implement an FM based location system on a mobile device (such as a smartphone) as the Android and iOS ecosystems do not offer any library for accessing the embedded FM chipset. A number of mobile network operators and service providers have disabled the FM chip in order to encourage streaming-based radio services [10]. According to research cited in [10], only 20% of smart phones sold in the US from January - September 2014 had FM radio activated. Microsoft has also recently confirmed that it will be removing the built-in FM radio app from Windows 10 Mobile.

In this paper, we present an FM and Wi-Fi based localisation system that can be connected to a mobile phone, as and when required, to provide localisation services. Our system utilises broadcast FM signals and can also use Wi-Fi signals whenever available. The developed localisation system is portable and can be used almost anywhere to provide good localisation accuracy. We demonstrate, through experiments carried out in two different scenarios - both scenarios with weak FM and Wi-Fi signal coverage, that the proposed system can achieve sub-3 m localisation accuracy. We also demonstrate the robustness of our system by repeating the testing phase after a period of 4 months from the initial training and achieving reasonably small localisation errors while using the original training database.

II. Related Work

RADAR [1] was one of the first systems to use Wi-Fi fingerprinting for indoor localisation. They were able to achieve

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TABLE I: Overview of existing FM localisation systems.

Reference	Hardware Platform	APs (FM, Wi-Fi)	Test Area (in m^2)
[2]	Si-4703 with laptop	32, 434	3240
[3]	FM chip on Smartphone	76, 17	72
[17]	USRP2	17, NA	253

sub-3 m localisation accuracy using only Wi-Fi signals. Recent work has focused on refining the location estimation process by using statistical methods such as the KL-divergence [11] and penalisation (or weighting) of the access points. Numerous attempts have been made to automate the training phase using techniques such as crowdsourcing [12] and machine learning [13] but with limited success.

Chen et al. [2] showed that FM is a viable alternative to Wi-Fi signals, especially in indoor environments. FM signals when combined with Wi-Fi were shown to be complementary and to cancel each other's errors, improving the accuracy by up to 80%. Popleteev [3] used short-range FM transmitters over a small area along with signals from the broadcast FM stations to achieve improved localisation accuracy. Carvalho et al. [14] used FM and DVB-T fingerprinting using software defined radio (SDR) to provide sub-meter localisation accuracy.

Anyplace [15] is one of the most accurate mobile phone based applications for indoor localisation. It relies on Wi-Fi and inertial sensors that are built into most modern smartphones to provide an accurate estimation of the path followed by the user. The COEX navigation system [16] allows users to navigate using a floor map and the fingerprint database of the site. However, all these systems rely on strong Wi-Fi coverage and fail in areas with a small number of access points. In Table I, we list some of the existing FM based localisation systems in the literature. Most of these systems use a large number of FM stations and Wi-Fi APs while our proposed system uses only 10 FM stations and 27 Wi-Fi APs, which is substantially lower.

III. System Design

An overview of the proposed system is shown in Fig. 1 and described in the following sub-sections.

A. Hardware

We use the Silicon Labs Si-4703 evaluation board connected to an Arduino Uno to collect the FM RSSI signatures. The Si-4703 was connected to an Arduino which was in turn connected to the smartphone through an OTG cable. The smartphone serves the dual purpose of supplying power to the Arduino system and being the processing platform for the RSSI data via an Android application. Considering the lack of homogeneity in mobile phones, service providers or carriers, as well as the operating systems in facilitating access to the embedded FM chip, we decided to use a standalone FM receiver as described above.

B. Detection of Active Broadcasting Stations

The FM band in India is $87.5 - 108$ MHz, with a spacing of 100 kHz between each channel. Clearly, not all the 205

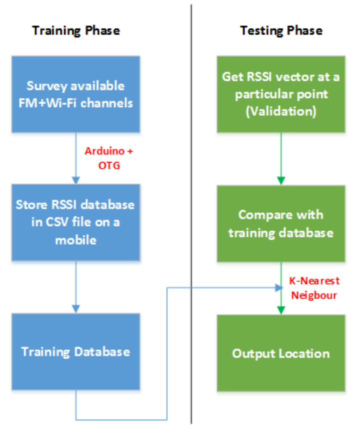

Fig. 1: Flow diagram of the proposed system

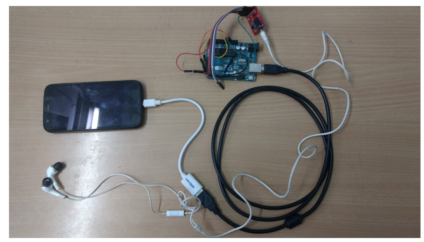

Fig. 2: Experimental Setup: Si-4703 FM Radio Receiver connected to a Moto G smartphone using an Arduino Uno and an OTG cable.

possible FM channels would be active at a given location. A peak detection algorithm with an appropriate RSSI threshold was designed to identify the active channels. However, a major challenge with the channel seeking algorithm is the time required to scan each FM channel frequency. Scanning 205 FM channels requires around 10 s at a given location or training point, which makes the process time consuming. To overcome this, we make the following assumption: *The overall set of (possibly) active radio stations will remain the same as long as the localisation area is small in comparison to the typical range of FM tower transmissions.* This assumption is reasonable as FM signals typically have a range of tens of kilometers and the indoor localisation area is very small compared to the FM range. Thus, the channel seeking is done only once at the beginning of the training phase, after which the active radio stations are stored in an array as reference for use during the training and online phases. This speeds up the channel scanning process, allowing us to measure the FM RSSIs as quickly as the Wi-Fi RSSIs.

C. Software

The measured FM RSSI vector or data is written to a CSV (comma separated value) file for further processing. We used the open source libraries *usb-serial-for-android* [18] and the *Mathertel Radio* [19] for this purpose. The former acts as an interface between the Arduino board and the Android OS while the latter allows us to control the Si-4703 board. The Wi-Fi RSSIs are collected directly on the mobile phone using the in-built Wi-Fi transceiver chipset. An Android application was developed specifically for this purpose.

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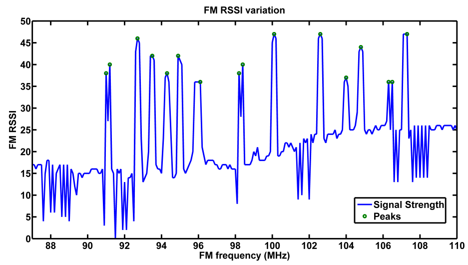

Fig. 3: Typical plot of FM RSSI measurement: Peaks identified before processing are shown with circles. Peaks very close to each other correspond to the same FM station.

IV. Experimental Methodology

A. Experimental Setup

The experimental evaluation of our system was carried out in the Bharti School building at the Indian Institute of Technology Delhi campus under two different movement patterns:

- Scenario 1: Track covering 64 m^2, shown in Fig. 4a.
- Scenario 2: Linear track of length 21 m, shown in Fig. 4b.

The training grid points were chosen on a uniform grid with the grid cell being a square of size 1 m^2. Authors in [20] have demonstrated that the probability of exact localisation decreases as the grid cell size becomes smaller. Based on existing work in the literature, an area of 1 m^2 provides the best balance between localisation accuracy and resolution. The linear track was used to check the accuracy of our system for simultaneous localisation and mapping (SLAM) applications. The measurements in the second experiment were taken at intervals of 0.5 m. The true location is recorded manually at each of the training points. The two training data sets contained 50 and 40 training grid points, respectively. The building has an average signal strength coverage of FM stations and Wi-Fi access points (AP), with a total of 10 FM stations and 27 Wi-Fi APs. Since the FM signal coverage in this building is much lower than in typical environments, we believe it would a true test of the proposed system.

The user and mobile phone orientation are kept the same throughout the experiment in order to avoid such variations from affecting the localisation analysis and results. The mobile phone is held in the user's hand with its orientation being in the direction of the user's movement. We used a Motorola Moto G running the Android 5.1.1 operating system for all the experiments. Apple Earpods were used as an FM antenna. Though less accurate than a conventional antenna, the use of earphones allows us to replicate real life setting as closely as possible, by using only off-the-shelf hardware.

B. Data Analysis

1) Training Phase

During the training phase the RSSI measurement vectors were recorded at each of the pre-determined grid points throughout the experiment area. The signal strengths of the FM radio stations were stored in a vector $s_i^{FM} \in \mathbf{R}^{M_f}, (M_f = 10)$. Similarly, the RSSI of the Wi-Fi access points were stored in a vector $s_i^{WF} \in \mathbf{R}^{M_w}, (M_w = 27)$, where M_w is the total number of Wi-Fi access points across the N training grid points. The missing (or out-of-range) access points in each Wi-Fi RSSI measurement are set to -100, indicating they were not visible. Finally, the FM and Wi-Fi RSSI vectors at each point were combined to form a single vector $s_i \in \mathbf{R}^{M_f+M_w}$. The vectors $\{s_1, s_2, \ldots, s_N\}$ are stored as the training data.

2) Localisation Phase

During the localisation phase, the RSSI measurement is recorded by the user at any point in the test area. The k-nearest neighbour (KNN) algorithm (with $k = 3$) was used to compare the measured RSSI vector with the training data set. The algorithm estimates the user location as the centroid of the three *nearest* locations that are determined by using an appropriate distance metric to compare the measured and training RSSI vectors. We used the Euclidean and Manhattan distances as the distance metrics.

Consider two RSSI vectors given by $\mathbf{p} = [p_1, p_2, \ldots p_M]$ and $\mathbf{q} = [q_1, q_2, \ldots q_M]$, where $M = M_f + M_w$ is the dimensionality of the RSSI vector.
Euclidean distance between the two vectors is given by:

$$\mathbf{E}(\mathbf{p}, \mathbf{q}) = \sqrt{\sum_{i=1}^{M} (p_i - q_i)^2}$$

Manhattan distance between the two vectors is given by:

$$\mathbf{M}(\mathbf{p}, \mathbf{q}) = \sum_{i=1}^{M} |p_i - q_i|$$

User location estimate = $(L_1 + L_2 + L_3)/3$

where L_1, L_2, and L_3 are the locations which are 'nearest' in the RSSI fingerprint database to the measured RSSI vector.

3) Algorithm Analysis

A variety of algorithms and distance metrics are available in the literature for analysing the RSSI data. However, most of the available techniques have large computational requirements, which necessitates moving the computations to the cloud. We decided to focus on carrying out the computations locally on the mobile device, which would also assuage some of the privacy or security concerns. Thus we had to come up with an algorithm that would have very low computational requirements.

We used the UJIndoorLoc database [21], a freely available Wi-Fi fingerprinting database to carry out our initial algorithm development. KNN algorithm with $k = 3$ and the Euclidean distance metric provided the highest accuracy among all the algorithms tested. KNN algorithm, with its high accuracy and low computational requirements, proved to be the best choice.

V. Experimental Results

A. Experiment Scenario 1

The first experiment was conducted in a 64 m^2 area on the second floor of the Bharti School building (refer Fig. 4a). Table II shows the mean and 90$^{\text{th}}$ percentile localisation errors. The CDF curves are plotted in Fig. 5 and Fig. 6. Based on our experiments and contrary to the observations of many other works in the literature, we find FM to be a better localisation methodology with a mean error of 2.84 m using the Euclidean and 3.48 m using the Manhattan distance metric. Combining FM and Wi-Fi fingerprints provides a substantial improvement

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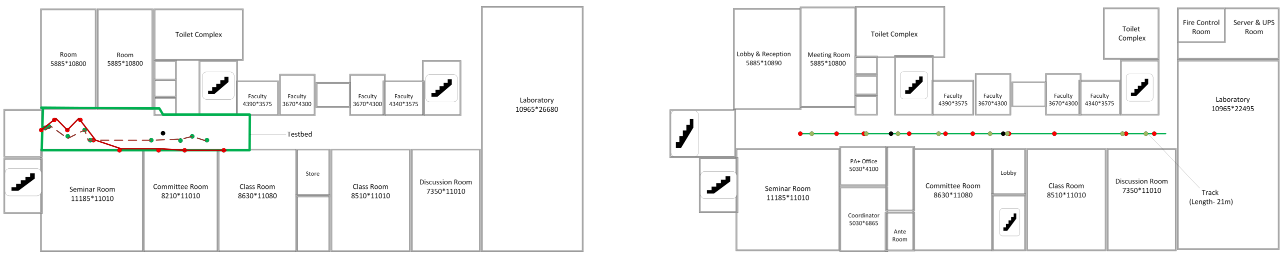

(a) (b)

Fig. 4: Floor plans for the two experiments: (a) Track covering 64 m^2 on the second floor, (b) track of length 21 m on the ground floor; Red circles indicate the true path followed in (a) and (b); Dashed line in (a) shows the estimated path. Green points indicate the estimated positions in (a) and (b). Black points indicate those points with substantial error.

TABLE II: Mean and 90th percentile localisation errors

Localisation Type	Euclidean Distance	Manhattan Distance
FM Mean	2.84 m	3.48 m
FM 90th	4.03 m	4.66 m
Wi-Fi Mean	4.92 m	5.31 m
Wi-Fi 90th	9.09 m	9.09 m
FM + Wi-Fi Mean	3.72 m	3.47 m
FM + Wi-Fi 90th	7.18 m	7.18 m

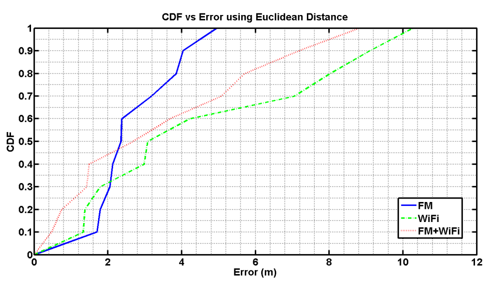

Fig. 5: CDF plot for Euclidean distance metric

in the accuracy as compared to using only Wi-Fi. However, the combined method is still less accurate than the one using only FM. This indicates that though a richer fingerprint can provide better localisation accuracy, it may not be more accurate than the constituent technologies.

One of the reasons why FM provides such good localisation accuracy could be due to the experimental environment. The experiment was conducted on the second floor of a highly enclosed building resulting in significant changes in the FM RSSI vector at each location. However, the Wi-Fi RSSIs do not show a significant change in such environments.

Both Wi-Fi and FM + Wi-Fi also show significantly higher

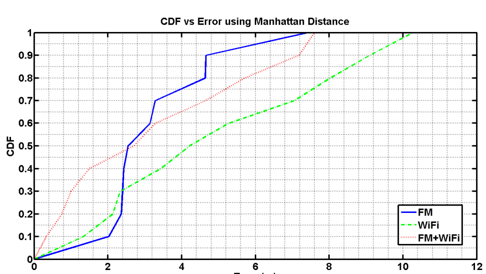

Fig. 6: CDF plot for Manhattan distance metric

TABLE III: FM localisation error (m)

Localisation Type	Euclidean Distance	Manhattan Distance
FM Mean	2.67 m	5.75 m
FM 90th	5.65 m	8.87 m

90th percentile errors than FM. The higher errors can only be attributed to obstructions (such as walls) and the resultant multipath, as all other parameters have been kept constant. This indicates that Wi-Fi based localisation is much more sensitive to obstacles as compared to FM in indoor environments.

Our experiments show that a richer fingerprint can only be effective for localisation when the experimental area has a strong signal coverage for each of the constituent signal types. Relatively weak signal coverage of even one constituent can negatively impact the accuracy of the overall system. The addition of Wi-Fi RSSIs to the FM RSSI fingerprint increased the localisation error (as compared to only FM) due to the poor quality of the Wi-Fi fingerprint.

B. Experiment Scenario 2

The second experiment was conducted on the ground floor of the Bharti School building. All the data points were taken on a 21 m long linear track (refer Fig. 4b). This was done to compare the localisation resolution achievable using FM and Wi-Fi signals. Previous work has been limited in this regard, with most work being done in areas with strong signal coverage. The resulting localisation errors are shown in Table III. Surprisingly, the Wi-Fi RSSIs did not show any variation throughout this experiment. The Wi-Fi RSSI vector remains the same at all the 40 test points and thus no results are available in this experiment for the Wi-Fi based localisation. Thus, FM again performs better than Wi-Fi with a mean localisation error of 2.67 m using the Euclidean distance metric and 5.75 m using the Manhattan distance metric. This shows that FM provides a much better resolution than Wi-Fi, especially in areas with relatively weak Wi-Fi coverage. Euclidean distance tends to smooth out the errors, as seen in Fig. 7, illustrating its superiority as a distance metric, especially when used with KNN based approaches in linear tracks. The accuracy obtained during linear movement makes FM suitable for SLAM applications, especially when used in combination with other localisation approaches such as those based on sensor fusion and computer vision.

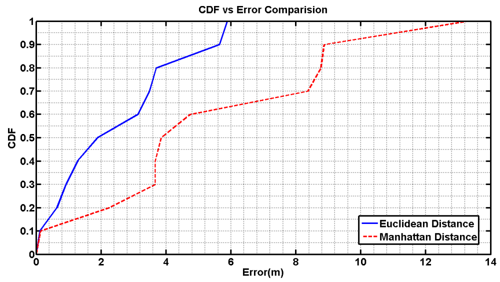

Fig. 7: CDF plots for linear movement

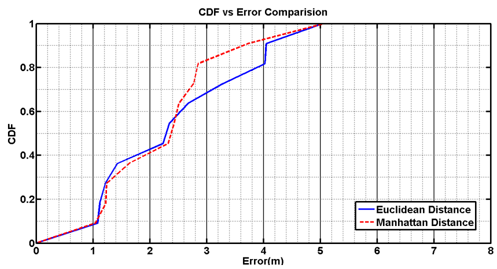

Fig. 8: CDF plots using the old training database

C. Robustness to Changes in Indoor Environment

To check the robustness of our system, we repeated the testing phase again on the second floor of the Bharti School building, 4 months after our original experiments. This time, we measured RSSIs at few random points within the same 64 m^2 test area. The localisation system gave a mean error of 2.59 m with 90^{th} percentile error of 4.03 m when we use the KNN algorithm with the Euclidean distance metric. Using Manhattan distance gave a lower mean localisation error (2.44 m), which indicates that the Euclidean distance metric may not be superior in all cases. In spite of the experiment being held after 4 months, our localisation system gave good accuracy. This analysis shows that the localisation system and the FM training database is robust to not just changes in the indoor environment, but also the passage of time.

VI. Conclusion and Future Work

In this paper, we have demonstrated a smartphone-based indoor localisation system using FM and Wi-Fi signals. This system can be connected as and when needed and works even in the absence of infrastructure such as Wi-Fi access points. We achieved sub-3 m localisation error even in areas with limited signal coverage. We tested our system in two different scenarios and FM showed better localisation resolution and accuracy in both scenarios. FM was also shown to give extremely good accuracy with a relatively old training database, thus minimising the need for repeating the labourious training process. This shows the robustness of the system to changes in the indoor environment with time. Our results in such an environment are comparable to existing systems despite weaker signal coverage and without the use of additional hardware such as an external antenna. Future work will be aimed at combining the results of the system with the inertial sensors on a mobile phone in order to achieve better localisation accuracy. We also plan to improve our system design so that it can be easily integrated with a smartphone, thus improving the system's usability. An indoor localisation *chip* which is fully integrable with smartphones would be the ideal solution.

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