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# Indoor Localization Using FM Radio Signals: A Fingerprinting Approach

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***Abstract*—Indoor positioning has become highly important because of the failure of GPS in such areas. Many Wireless Local Area Networks (WLAN) indoor localization studies use the fingerprinting technique. In this study, the new positioning system is proposed based on broadcast FM as a signal of opportunity, with significant benefits for indoor positioning. This localization system uses FM signal strength fingerprinting. The deterministic approach of fingerprinting is considered, and several algorithms are compared. The results demonstrate a minimum mean distance error of 2.96m for the K-Weighted Nearest Neighbors (KWNN) algorithm with K=6. The comparison between using fingerprinting for FM and Wi-Fi is also discussed.**

***Keywords*—Fingerprinting; FM Signal; Indoor Positioning**

## I. Introduction

The Global Positioning System (GPS) and Global Navigation Satellite Systems (GNSS) in general have been adopted as the de facto positioning technology because of the highly accurate location information they provide globally; however, this technology fails in particular environments such as indoors or urban canyons. These failures of GNSS are mainly due to the low received signal power and low visibility of satellites in urban/indoor areas. Therefore, non-GNSS navigation technologies are essential for such regions [1].

Utilizing signals of opportunity is a promising alternative navigation means of providing adequate geolocation [2]. Signals of opportunity are existing (non-navigation) radio frequency (RF) signals around us, which tend to have much higher power levels and wider coverage in urban and indoor environments than GNSS signals. Furthermore, they can penetrate buildings due to their lower frequencies [3]. Although such signals cost less than GNSS in terms of the system implementation [4], there are significant problems that need to be considered in employing each of them for positioning, owing to the fact that such terrestrial signals were not designed for location estimation.

Signals of opportunity in previous research include analogue/digital television and analogue/digital audio signals transmitted from commercial radio and television broadcasting towers [3]. They also include Global System for Mobile communication (GSM) signals from mobile telephone base stations [3]. Other types of signals of opportunity are Ultra-Wide Band (UWB), ZigBee, and Wireless Local Area Networks (WLAN) such as Wi-Fi and Bluetooth [2].

In this paper we focus on indoor navigation using broadcast FM signals - an analogue audio signal with outstanding advantages for urban/indoor positioning purposes. These benefits the ability to be received both indoors and outdoors, dense coverage in urban areas where GNSS behaves poorly, availability, low-cost and low-power hardware, high received signal power, and finally the large number of transmitters that can provide good geometry for positioning [5]. The geometry of transmitters is highly significant in the distance-based positioning techniques.

The most crucial problem of using an FM signal, however, is that they do not carry any timing information, which is a critical factor in range calculation [6]. Moreover, navigation using FM signals would be degraded, as are most radio-navigation systems, by the effects of multipath and Non-Line-of-Sight (NLOS) signals.

Measurements that can be taken from signals of opportunity for navigation purposes are based on: Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA), and Received Signal Strength (RSS). For the first three methods, the lack of timing information in FM signals is critical. Hence, some of the previous studies proposed utilizing an independent fixed position observer unit that receives all FM signals from the FM transmitters in the area, and observes the difference in synchronization between them and broadcasts transmitted signals relative information [6]. Performing TDOA range measurements for a set of unsynchronized FM sub-carrier signals by making use of an additional observer module is discussed in [7]. In addition, in order to extract timing and direction information, particular hardware with a multi-directional antenna is required [8].

The latter positioning technique is localization based on RSS and signal propagation modeling. There are two general approaches to wireless localization using the RSS technique: signal propagation modeling and location fingerprinting. The former one is not included in this paper. Fingerprinting has two stages: “training” and “positioning”. A database of the location dependent parameters collected at the reference points (RPs) is generated in the training stage, and in the positioning stage, different algorithms can be used to estimate the position of the user [9].

In this paper, we chose the fingerprinting technique for indoor FM-based positioning since first it is an economical method because it does not need any additional hardware or infrastructure [8]. Secondly, fingerprinting is independent of the timing problem of FM signals. Finally it reduces the effect of multipath compared to other methods based on distance measurements [10]. However, it should be noted that constructing the database for fingerprinting is always time-consuming and labor-intensive [11].

More recently, the use of location fingerprinting has been investigated based on FM broadcasting signals for campus area in [8]. Also, the technique in [12] utilized some commercial short-range FM transmitters in an indoor area, and compared the positioning results with Wi-Fi positioning. The authors finally combined FM and Wi-Fi, which resulted in higher accuracy. To the best of our knowledge, there is no research on indoor positioning using FM broadcast signals.

The rest of the paper is organized as follows. Section II describes the methods utilized for FM positioning. Section III presents the experimental setup used to fulfill the FM-based positioning. The experimental results and the analysis are discussed in Section IV. Section V compares the results of our FM positioning with Wi-Fi positioning which has been formerly done in the same test bed. Finally, Section VI provides the conclusions and discusses some ideas for future work.

## II. Fingerprinting Techniques

### A. Training Stage

The first stage of the work is to establish a database for a set of $R$ known reference points (RPs), which will be used as training samples in the positioning phase. Such a database includes the $Q$ fingerprinting measurements of all $P$ FM channels sensed at each RP in a specified period of time, which is the vector of $\{RSS_{rq} = [RSS_{r1}\ RSSS_{r2} \ldots RSS_{rP}], r = 1, 2, \ldots, R, q = 1, 2, \ldots, Q\}$. The average of all measurements of each FM channel is calculated, and is logged as the reference data of that location in the database. Fig.1 illustrates the whole procedure of the training stage of FM-based fingerprinting.

### B. Positioning Stage

In this stage, the unknown location will be estimated by comparing the average of $Q$ observed measurements $\{rss_q = [rss_1\ rss_2 \ldots rss_p], q = 1, 2, \ldots, Q\}$at an unknown point with the database established in the training phase. The best match indicates the estimated position. The process of the positioning stage is shown in Fig. 1.

In the positioning phase of fingerprinting, there are two main ways to estimate a location: the deterministic and probabilistic approaches [9]. In this paper, we just analyze the deterministic approach. Three different algorithms are applied for this purpose. The first is the Nearest Neighbor (NN) algorithm [13], which is based on Manhattan distance and Euclidean distance between the observed fingerprint and those recorded in the database [14]. In this paper, we use Euclidean distance which is defined as follows:

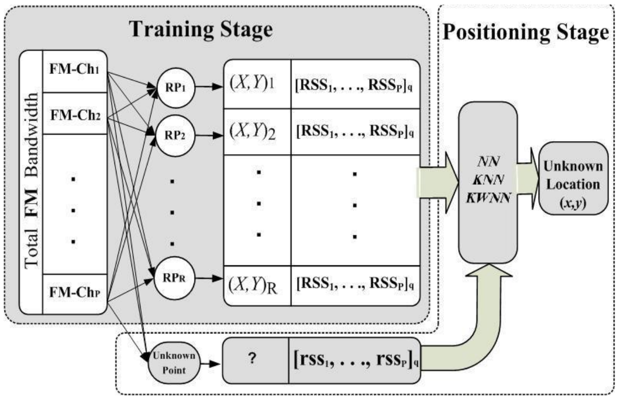


Figure 1. Two stages of location FM-based fingerprinting

$$Euclidean\ Distance = ||rss - RSS||^2 . \quad (1)$$

The second method is K-Nearest Neighbor (KNN), in which the estimated location is the average of the coordinates of K nearest points. The third algorithm which is similar to KNN is K-Weighted Nearest Neighbors (KWNN). In this method the weighted average of the coordinates of K nearest points is calculated rather than the average. The weights are the inverse of the Euclidean distance.

## III. Experimental Setup

### A. Experimental Test bed

The experimental test bed is located on the 4th floor of Electrical Engineering building at University of New South Wales (UNSW). The layout of the test bed is shown in Fig. 2. The test bed has dimensions of 11m by 23m, and consists of 7 rooms, which are a typical indoor office environment, and the corridor. The crosses represent RPs and the squares are the test points. This is the same test bed as used for Wi-Fi positioning in [15] because we want to compare our result with Wi-Fi positioning results.

In our experiment, there are 150 RPs ($R$=150), and 28 test points (TPs). The RPs are gridded as well as possible. They are close to or aligned with the corners, doors and windows, which could be easily identified on the map and in the real test bed. The points that people are most likely to require are chosen as the TPs. There are 17 FM channels sensed at each RP ($P$=17), which cover whole FM bandwidth from 88MHz to 108MHz.

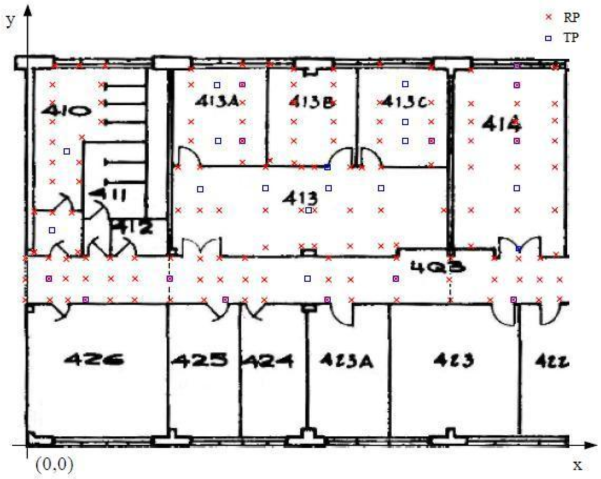


Figure 2. Experimental layout for FM-based fingerprinting

At each RP the user faces north first, and records the RSS of the sensed FM channels. Then the orientation is changed to south and the RSS values are logged. A total of 120 measurements are made at each point within 12 seconds ($Q$=120). The data were collected in one day over the weekend, so that not many people were present.

### B. Data Acquisition

The investigation of signal of opportunity data is based on a Software Defined Radio (SDR) approach. The equipment used here is the Universal Software Radio Peripheral (USRP2) manufactured by Ettus Research LLC. It captures and stores the raw spectrum for post-processing. USRP2 is used with GNU Radio software, an open source package of signal processing blocks written in Python and run on the Ubuntu platform. In addition, the TVRX daughterboard manufactured by Ettus Research LLC was used with USRP2. It can receive 50MHz-870MHz, which covers the FM signal bandwidth. For the receiver antenna, we use a v-shaped “Rabbit ear” antenna, a kind of dipole antenna.

## IV. Experimental Result and Analysis

To evaluate the performance of our indoor FM-based positioning, the experimental results of the mentioned test bed using NN, KNN, KWNN algorithms are analyzed from three different aspects: K value, data acquisition time, and sensed channel numbers. The errors between the estimated and true location are calculated as a Euclidian distance. The mean distance error using the three algorithms is calculated.

Fig. 3 shows the relationship between mean distance error and the value of K. When K is equals to 3, the error is less than 20cm higher than K equals to 2, which can be ignored. However, the general trend of the figure is going down to the minimum error and then going up. The optimal value of K is when the mean distance error is minimum. The results indicate that this happens when K equals 6 for both KNN and KWNN methods. Also, K equals 5 is slightly less accurate than the results of K=6. Thus, for the rest of the paper we just consider four algorithms: KNN (K=5, 6) and KWNN (K=5, 6). Moreover, Fig. 3 demonstrates that the weighted average of nearest neighbors gives improved results compared to NN and even KNN. But no algorithm always provides the best result [15].

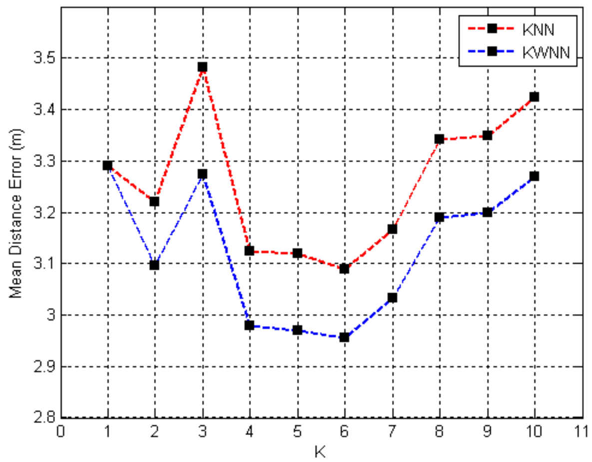


Figure 3. Mean distance error using KNN and KWNN methods for different K

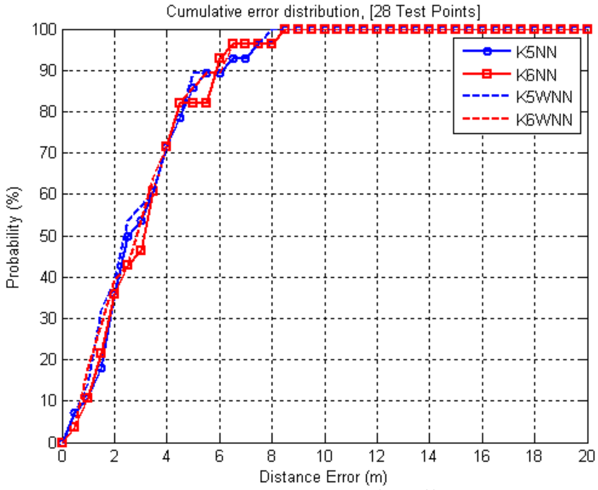


Figure 4. Deterministic approach results for different algorithms

The cumulative distribution function (CDF) of the error is plotted in Fig. 4 for different algorithms. It can be observed that the error at the 67th percentile is 3.8m and 3.7m for K6NN and K6WNN methods, respectively. When the 95th percentile is considered, the error is 6.5m and 6.4m.

A second approach is to evaluate the effect of the number of measurements made at each RP or similarly the corresponding period of data acquisition time. It is plotted in Fig. 5 for KNN and KWNN methods. The results indicate that 12 seconds of data provide higher accuracy than fewer ones. However, the highest error difference for each algorithm is about 40cm which is quite low. It is an important result since helps reduce the labor work and amount of recorded data in training stage.

The number of sensed FM channels in our experiment is 17. However, there are some channels which are broadcasting from the same antenna. Therefore, a third approach is to examine the effects of frequency diversity as separate from transmitters’ location diversity. We just select one channel among other channels broadcasting from one location, which decreases the number of sensed channels to 9. The comparison between the mean distance errors for $P$=17 and $P$=9 are shown in Table I. The results show that the number of sensed FM channels does have an effect. Without changing the number of transmitter locations, the extra signals improve accuracy from about 4m to about 3m.

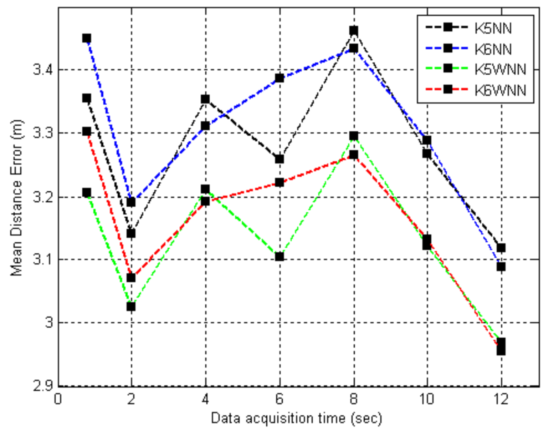


Figure 5. Mean distance error in different data acquisition time for four algorithms of KNN and KWNN (K=5, 6)

Table I. MEAN DISTANCE ERROR FOR DIFFERENT FM CHANNEL NUMBERS

| | K5NN | K6NN | K5WNN | K6WNN |
|---|---|---|---|---|
| 17 channels | 3.12 | 3.09 | 2.97 | 2.96 |
| 9 channels | 4.12 | 4.08 | 4.03 | 4 |

## V. COMPARING RESULTS OF FM VERSUS WI-FI POSITIONING

In order to have a good comparison between navigation using FM signals and Wi-Fi signals, we chose the same test bed as was used for Wi-Fi positioning in [15]. To investigate the effect of the number of RPs in location estimation, the number of RPs is intentionally reduced to 99, 66, 33, and 16. But the RPs are still gridded as evenly as possible in the test area. Hence in total 5 fingerprinting databases were generated for each of both cases. In order to have the same conditions to evaluate the performance, again we consider K equals 2, 3, 4, 5, and 6.

Fig. 6 shows the average of the positioning error using all the algorithms mentioned above for FM and Wi-Fi positioning systems. When the number of RPs increases, the accuracy of the estimated location increases. But when the density of the RPs is high, the rate of increase of the accuracy decreases. This figure also indicates that Wi-Fi positioning has higher accuracy. This can be expected since the Wi-Fi transmitters are very close to the receiver and because they are short-range, their RSS varies rapidly in a small region. However, FM-based positioning gives reasonable results for indoor positioning and will cost much less than Wi-Fi in terms of receiver simplicity, FM availability and coverage, and sensitivity to the environment. FM stations, unlike Wi-Fi access points, are not turned on and off and moved, requiring frequent database updates.

## VI. CONCLUSION AND FUTURE WORK

GPS as a globally accepted technology has an operational difficulty in urban and indoor areas. Utilizing terrestrial signals of opportunity instead of or in addition to GPS can be helpful for navigation in such regions. In this study, a new positioning method based on broadcast FM broadcasting signals is proposed because of their outstanding benefits for indoor positioning, such as the ability to be received both indoors and outdoors, dense coverage in urban areas, availability, low-cost and low-power hardware, and high received signal power. For navigation purposes, the fingerprinting method is utilized, in which the RSS of the FM signals are taken to build a data map and post-processing. The experiment for estimating unknown locations by the deterministic approach was carried out with results demonstrating a minimum mean distance error of about 3m. The comparison between our FM-based positioning results and Wi-Fi positioning results from the same test bed show the higher accuracy of Wi-Fi positioning; however, the accuracy from FM costs much less due to availability of FM signals and simplicity of the receivers.

For the next stage, we plan to analyze the probabilistic approach of location fingerprinting for our FM-based positioning and examine more fully the effects of transmitter location and frequency diversity. We will also examine outdoor applications, and transitions from indoors to outdoors.

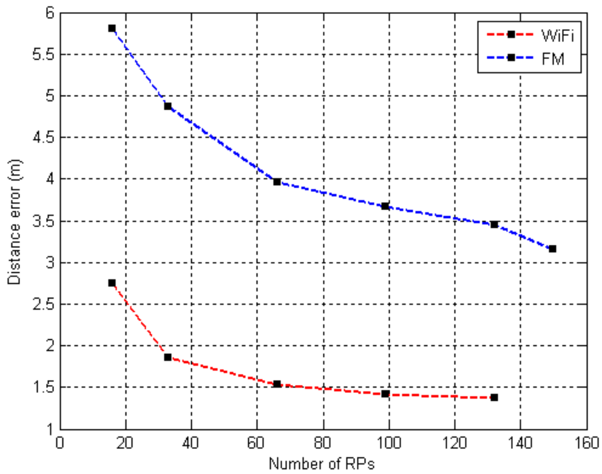


Figure 6. Mean of average distance errors for FM and Wi-Fi positioning in the same test bed

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