

Indoor Positioning Using FM Radio

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Andrei Papliatseyeu*, Venet Osmani, Oscar Mayora

{apapliatseyeu, vosmani, omayora} @ create-net.org

Multimedia Interaction and Smart Environments (MISE),
CREATE-NET,
Via alla Cascata 56/D, Povo, Trento, 38123, Italy.

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Abstract

This paper presents an indoor positioning system based on FM radio. The system is built upon commercially available short-range FM transmitters. To the best of our knowledge, this is the first experimental study of FM performance for indoor localisation. FM radio possesses a number of features, which make it distinct from other localisation technologies. Despite the low cost and off-the-shelf components, our FM positioning system reaches a high performance, comparable to other positioning technologies, such as Wi-Fi for example. Our experiments have yielded a median accuracy of 1.0 m and in 95% of cases the error is below 5 m.

Keywords: indoor positioning, location fingerprinting, wireless localisation, mobile technologies, ubiquitous computing.

INTRODUCTION

Location awareness is an important requirement for many modern applications, spanning from mobile maps and geotagging up to various indoor systems. Applications of indoor localisation can also be found in the realm of social sciences, allowing inference of human relationships, for example colleagues that spend time in the same office, through analysis of sub-room mobility patterns (Eagle & Pentland, 2006). In health care, indoor localisation can be used to aid elderly locate misplaced objects (such as their mobile phone), or deliver location dependent reminders. These applications can be enabled by a low-cost, sub room location solution.

The Global Positioning System (GPS) is most widely used for location sensing, but it is limited to outdoors-only applications. A body of research has addressed indoor positioning using different technologies, like ultrasound and infrared beacons, Wi-Fi and GSM networks, or other types of radios (Hightower & Borriello, 2001). Most of these systems are limited in terms of expensive/custom hardware, laborious deployment or low performance.

FM has a number of advantages over other localisation technologies, like Wi-Fi. Firstly, although Wi-Fi infrastructure is readily available in office buildings, the installation of a localisation system in domestic environment requires additional hardware. Indeed, multiple Wi-Fi access points would be required to provide positioning, since a single access point or a wireless router, typically found at home, is not sufficient. In this case, FM is a cheaper alternative to the deployment of multiple Wi-Fi access points per apartment. FM transmitters are available from many consumer electronics shops; the client device can be represented by a cellphone with an embedded FM receiver. Secondly, FM radio can be safely used in specialised environments, such as hospitals, whereas GSM, Wi-Fi or Bluetooth devices must remain

switched off due to potential interference with medical devices. Finally, FM is highly power-effective: an average FM receiver consumes about 15 mW, compared to almost 300 mW of Wi-Fi (in receiving mode) (“TDA7088”, 1996; “BCM4326”, 2006).

This paper explores the applicability of short-range FM radio transmitters for indoor positioning. We have installed our FINDR (FM INDoOR) positioning system in our lab and this paper presents performance evaluation results of the system, as well as an overview of particular properties of FM radio with respect to localisation. A same-environment comparison with a Wi-Fi-based positioning system is also provided.

The paper is organized as follows. The section that follows provides an overview of the related work. The next section introduces our approach and our experimental testbed. The following two sections present results pertaining to performance evaluation of FINDR and describe the possible application scenarios of the system. Lastly, the final section reiterates the main points and draws the conclusions.

RELATED WORK

Wireless positioning techniques

In the last decade, a large body of research has been dedicated to the development of location-aware systems. Indoors positioning systems rely on several types of sensors: infrared (IR) (Fox et al., 2003; Liao et al., 2003), ultrasound (Fox et al., 2003; Priyantha et al., 2001), digital compass (Priyantha et al., 2001), RFID (Hightower & Borriello, 2004), and various kinds of radio: GSM (Varshavsky et al., 2007), Wi-Fi (Bahl et al., 2000; Youssef et al., 2003), Bluetooth (Kotanen et al., 2003), domestic powerline (Patel et al., 2006; Stuntebeck et al., 2008), and others (Bulusu et al., 2000; Krumm et al., 2003). Such systems usually rely on one or a number of the following criteria: user proximity to some fixed beacons, time of signal

propagation, and received signal strength. In the following sections we briefly describe each of these approaches to localisation.

Proximity-based

In an environment with a number of beacons with known positions, the algorithm assumes that the user's position is that of the nearest beacon. Due to its simplicity, the method is widely adapted by the systems using GSM base stations (Laasonen et al., 2004; LaMarca et al., 2005), as well as Bluetooth (Hallberg et al., 2003), IR (Fox et al., 2003) and custom radio beacons (Bulusu et al., 2000). Unfortunately, the accuracy of such systems is low and depends on the number and the density of installed beacons.

Time-based

Time-based methods employ the information about signal propagation time between the mobile device and beacons with known positions, in order to estimate the position of the mobile user. GPS is the most prominent example of this class of methods. Using the signals from a set of GPS satellites, a basic GPS receiver is able to compute its position with the accuracy of about 8 m (“GPS Performance“, 2008, p. 22). However, GPS has long start-up times (up to a few minutes) and does not work indoors and in dense urban areas, which limits GPS's applicability for ubiquitous location-based services. Ultrasonic localisation systems, like Cricket (Priyantha et al., 2001), rely on the travel time of an ultrasound pulse. While providing a good accuracy, time-based systems usually require custom hardware and expensive installation.

Signal strength-based

There are two general positioning approaches that use Received Signal Strength Indication (RSSI), namely, propagation modelling and fingerprinting. The first one attempts to build a model of the signal propagation in the space in order to estimate the distance between the

user and beacons. The fingerprinting approach, in turn, relies on a database associating RSSI measurements with corresponding coordinates and then uses machine learning algorithms in order to recognize user position among those learned during the training phase. RSSI-based methods are the most powerful, as they can provide considerably high accuracy with a few beacons.

One of the pioneering projects in RSSI-based positioning was RADAR (Bahl & Padmanabhan, 2000). The authors evaluated both propagation modelling and fingerprinting within a Wi-Fi network, and the system error was as low as 2 m (with some enhancements) (Bahl et al., 2000). With more advanced probabilistic methods, the median error of a Wi-Fi based system can reach 1.2–1.45 m (Roos et al., 2002; Youssef et al., 2003). RSSI fingerprinting has also been successfully applied for indoor localisation using GSM base stations. By employing so-called “wide fingerprints”, which included RSSIs of up to 35 GSM channels, Varshavsky et al. (2007) managed to achieve a Wi-Fi-like median positioning accuracy. However, the topology of a GSM network can be changed at any time by the network operator, thus requiring system recalibration. Patel et al. (2006) proposed a more reliable method for indoors localisation. In their system, two beacons were injecting high-frequency signals into domestic powerline. These signals could then be detected by a specialised receiver and associated with the user's position. An extended, wideband version of the system achieved a 90% accurate room recognition (Stuntebeck et al., 2008). Despite the easy installation, the system required specialised hardware with limited availability.

To the best of our knowledge, there is only one work dedicated to positioning with FM radio. Krumm et al. (2003) used prototype hand watch with an embedded FM radio, to localise using commercial FM broadcasting stations. The authors applied a Bayesian classifier to

recognize six areas of Seattle based on RSSI ranking of the local FM stations. In the best case, the recognition accuracy was 82%. Although the paper does not provide any information about error distances, the system accuracy can be estimated as hundreds of meters to kilometres, which renders it impracticable for indoor environments. Our system, instead, is based on off-the-shelf hardware and is particularly suitable for indoor use.

Regulatory considerations for short-range FM transmitters

In most countries the usage of radio-frequency transmitters is governed by special regulations. While Wi-Fi is widely adopted and generally does not require licensing, different rules may apply to short-range FM transmitters, depending on local laws.

In EU countries, the usage of short-range FM transmitters operating within 88–108 MHz frequency band is governed by European Commission Decision 2009/381/EC (“2009/381/EC”, 2009). According to it, the FM transmitters with effective radiated power of less than 50 nW do not require licensing. Complying devices bear the “CE” certification mark. In US, all radio devices must comply with the FCC Part 15 regulations. In particular, a short-range FM transmitter must produce less than 250 mV field strength in an average receiver placed 3 m away (“FCC Part 15”, section 15.239b). Certified devices have an explicit statement of their conformity to the FCC Part 15 regulations. For home-build transmitters, there is an additional limit of no more than five devices per person (“FCC Part 15”, section 15.23a).

FM POSITIONING

Our approach

The FINDR positioning system is based on a set of short-range FM transmitters as wireless beacons and a programmable radio on the client device. As most of the beacon-based positioning technologies, it has two general requirements: measuring of user-to-beacon relative

position and the ability to distinguish different beacons. In the next two sections we identify possible solutions how FM radio can address these requirements.

Relative position-dependent features

The relative position of the user with regard to a beacon can be characterised by angle between directed antennas, signal propagation time and RSSI. For the FM positioning, we have identified two features that can be used as a measure of distance between the beacons and the user.

The first feature is RSSI, defined as the amplitude of the received radio-frequency signal. Most of the current FM receivers employ RSSI value internally, to enable auto-tuning capability.

When RSSI value is not available, one can use the signal-to-noise ratio (SNR) of the demodulated signal. In this case, the beacon transmits a known periodic signal (for example, a sine wave of 1kHz) and the receiver performs a fast Fourier transform (FFT) of the demodulated signal, calculating the intensities of different frequency bands. Then, the signal-to-noise ratio is the intensity of the band of interest, divided by the average intensity of all the bands. A similar method was applied by Patel et al. (2006) to an amplitude-modulated (AM) signal. However, our experiments show that SNR of an FM signal is almost a step function, which considerably limits applicability of this approach to FM-based positioning (see “Results” section).

Distinguishing beacons

For a beacon-based positioning system, it is very important to be able to distinguish current beacon from the others. The beacons can be identified either by their carrier frequencies or by the signals they transmit (e.g. ID, name, coordinates, etc).

Unfortunately, for FM radio it is impossible to use the same frequency for all beacons. Due to the so-called “capture effect”, if a number of stations transmit on the same (or close by)

frequency, the signal from the strongest one dominates the others, while the weaker signals get attenuated (Leentvaar & Flint, 1976). Therefore, in our experiments we had to tune each transmitter to a different frequency and continuously switch between them at the receiver side. Despite this, no special network planning is required for larger-scale deployments to avoid beacons interference, as any distant interfering beacons will not be observed due to the capture effect.

Experimental setup

The FINDR was evaluated empirically in the Multimedia, Interaction and Smart Environments lab of CREATE-NET (“MISE”, 2009). The experiments were performed in a 12 x 6 m room with ordinary office furnishing. Figure 1 presents the layout of the room. A grid of 1 x 1 m cells was created for testing, and measurements were carried out in all accessible points of the grid (totally 45 points).

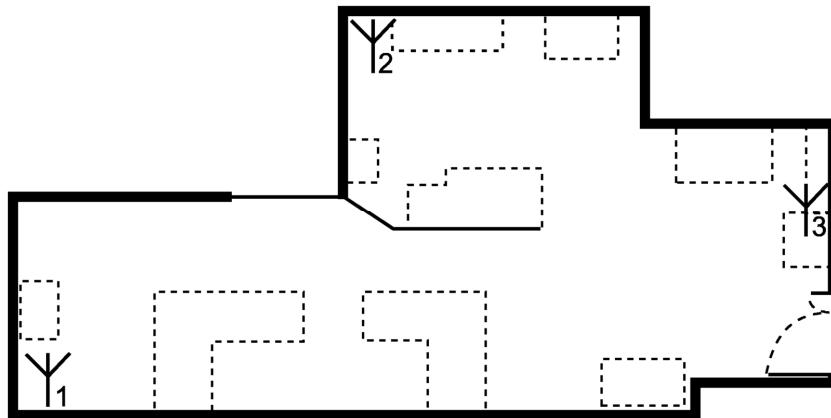


Figure 1. Floorplan of the measurement area. The antennas mark the positions of the three transmitters and the dashed lines mark room furniture.

The client device used in preliminary tests was a Nokia N800 Internet Tablet. The N800 is based on an ARM processor and features a built-in FM receiver. The N800 is running an open, Linux-based operating system, so developing low-level custom applications for the device is

relatively easy. The prototype locating software was programmed in Python and used the PyFMRadio-library to tune the FM-receiver to each of the transmitter's frequency one after another and read the signal strength from the FM-receiver hardware. The signal strength was reported on a 16-step scale (normalized to range 0...1) and was measured 300 times in a row for each frequency, with about 0.01 second between the measurements. The standard N800 headset was used as an antenna.

For the evaluation of positioning accuracy of FM and Wi-Fi we used an HTC Artemis smartphone, which features a set of built-in wireless modules, including GSM, Wi-Fi, Bluetooth, and an FM tuner. The data collecting software was written in C# using .NET Compact Framework. The FM module was controlled through the routines implemented in a low-level C++ library. The FM signal strength was reported as integer values in range from 0 to 45. For each location, one hundred of FM and thirty Wi-Fi RSSI samples have been recorded. The standard headset was used as an FM antenna.

The transmitters used were König MP3 players ("König MP3 player", 2009), which feature a built-in FM-transmitter (Figure 2). To increase the range of the transmitters, a 1.8-meter audio cable was connected to the player's audio output to act as an antenna. Before the experiment, the whole FM band had been scanned and manually checked for frequencies with little interference from local FM radio stations; the transmitters were then tuned to these frequencies. The transmitters were powered by USB power adapters, to ensure that RSSI was not affected by battery charge level.



**Figure 2. MP3 player with an embedded FM transmitter,
connected to power adapter. (The antenna is not attached.)**

Experimental procedure

In general, the experiment has been planned and performed as follows.

First of all, we conducted a number of tests to determine which of the FM signal features discussed above demonstrate the best dependency on the distance between the transmitter and receiver. A suitable function should have been monotone and with distinct values at different distances. As a result, the signal strength (RSSI) was chosen.

At the next stage, the data acquisition has been performed. For each point of the grid (x, y) , a number of RSSI measurements $RSSI(x, y)$ were recorded from the FM and Wi-Fi beacons. These measurements, along with the corresponding coordinates formed a dataset of location fingerprints. Finally, the performance of the two positioning technologies was evaluated using leave-one-out approach and K-Nearest Neighbour (kNN) classifier (see pseudocode in Figure 3). The evaluation results and further details are presented in the next section.

```

// $D_{xy}$  is the domain of possible coordinate values

errorDistances = { } //the list of absolute error distances

for each (x, y) ∈  $D_{xy}$  do {

    testSet = { input: RSSI(x, y), output: (x, y) }

    trainSet = { input: RSSI(i, j), output: (i, j) }, for (i, j) ∈  $D_{xy}$ , where  $i \neq x$  and  $j \neq y$ 

    //Estimating coordinates by RSSI fingerprint, using kNN classifier

    classifierResult = kNN(trainSet.input, trainSet.output, testSet.input)

    errorDistance = euclidianDistanceBetweenPoints(classifierResult, testSet.output)

    errorDistances.add(errorDistance )

}

//Given the error distances, calculate and plot the error cumulative distribution function (CDF)

plotCDF(errorDistances);

```

Figure 3. The pseudocode of performance evaluation algorithm.

RESULTS

RSSI dependency on distance

In order to estimate the feasibility of the FM positioning, we first carried out a test to see which of the position-dependent features discussed above are more suitable for positioning.

The RSSI dependence on the distance from the transmitter is presented in Figure 4. This test was performed outdoors to avoid any influence of the testbed's furniture. The graph is relatively smooth and monotone starting from 0.5 m, and proves RSSI to be a good feature for

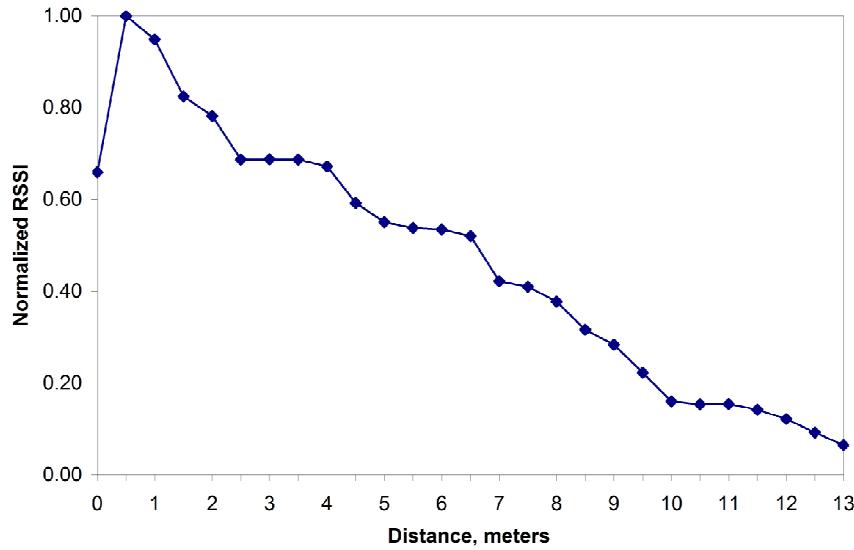


Figure 4. RSSI dependence on distance (Nokia device).

positioning. Eventual plateau-looking areas can be explained by the limited number of RSSI levels recognized by the receiver.

corresponds to the indoors measurements and shows the change of RSSI levels from each of three transmitters while the user was moving from Transmitter 1 to Transmitter 3 (as of floorplan in Figure 1). The graphs are not very smooth, which is caused by the distortions from the furniture and multipath propagation. However, the general trends are clearly observable.

For the RSSI_{SNR} method, the transmitter broadcasted a continuous dual tone multi-frequency (DTMF) signal corresponding to digit “1” (1209 Hz and 697 Hz). At the client side, the received audio signal from was sampled by a laptop sound card at 8 kHz sampling frequency and transformed to the frequency domain using 1024-band FFT. For each point, 32 spectra were recorded and then averaged. RSSI_{SNR} was then calculated by the following formula:

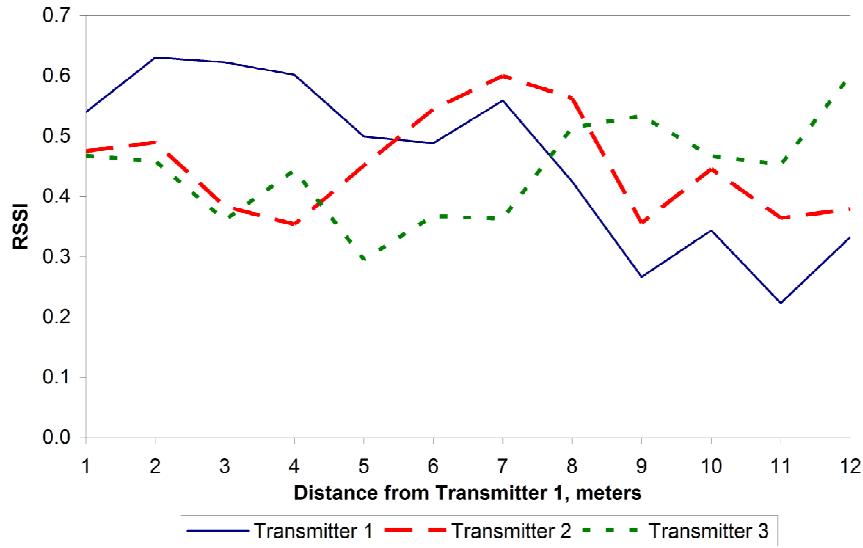


Figure 5. Change of RSSI levels while moving from Transmitter 1 to Transmitter 3, with Transmitter 2 placed between them (Nokia device).

$$RSSI_{SNR} = \frac{band_{697Hz} + band_{1209Hz}}{mean(all_bands)}$$

The experimental results exhibited no clear dependency of $RSSI_{SNR}$ from the distance to the transmitter (see Figure 6). In range from 0.5 m to 3.6 m the mean $RSSI_{SNR}$ value barely changed, between 3.6 m and 4.5 m it became unstable, and then rapidly degraded to the noise level. Such behaviour can be explained by the capture effect, which improves the post-detection SNR for non-linear modulations (such as FM) when the pre-detection SNR is above a certain threshold, “capture threshold”; below this threshold the SNR drops dramatically (Linnartz, J. P., 1993). In our case, the capture effect is complemented by the receiver noise-reduction circuitry which automatically mutes the audio output if the received signal is too weak (“TDA7088”, 1996).

Thus, due to intrinsic properties of FM, $RSSI_{SNR}$ is almost a step function of distance. Therefore, we did not consider $RSSI_{SNR}$ for further experiments.

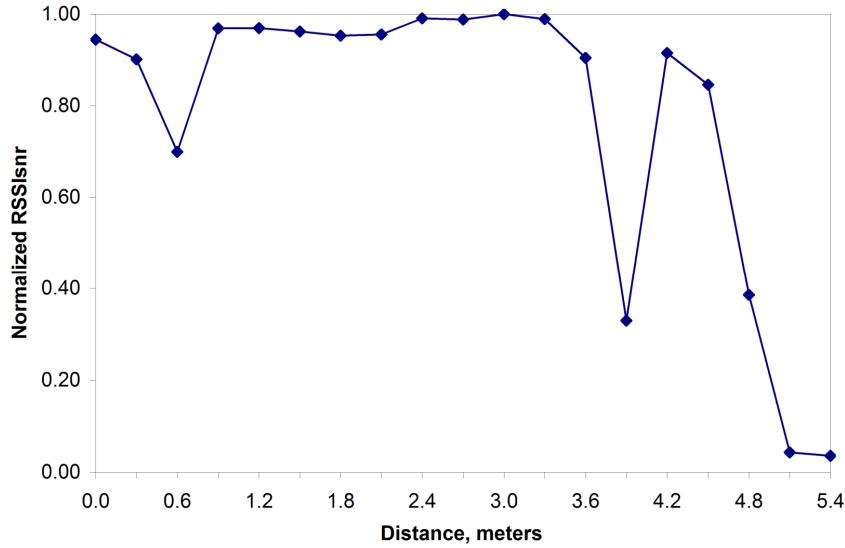


Figure 6. RSSI_{SNR} dependence on distance (Nokia device).

2D positioning

To estimate the FINDR accuracy in two-dimensional positioning, we have used a fingerprinting approach with leave-one-out validation, in which we sequentially selected one of the RSSI measurements and excluded all the measurements related to the same coordinates from the training set. The selected measurement was then used as test data. It should be noted however, that leave-one-out evaluation tends to worsen the actual positioning accuracy, as the classifier is unable to recognize the class it has not been trained on (that is, the error distance is always greater than zero) (Bahl & Padmanabhan, 2000).

In this experiment, a k -nearest neighbour (kNN) method was used for classification (Mitchell, 1997). The kNN classifier evaluates the distance from the test RSSI sample to all the training RSSIs, and selects the labels (classes) of the k nearest training RSSI samples. From these k labels, the prevailing one is returned as the classification result. In FINDR, we employed the Euclidean distance measure. The optimal value of k ($k = 9$) was selected by leave-one-out validation.

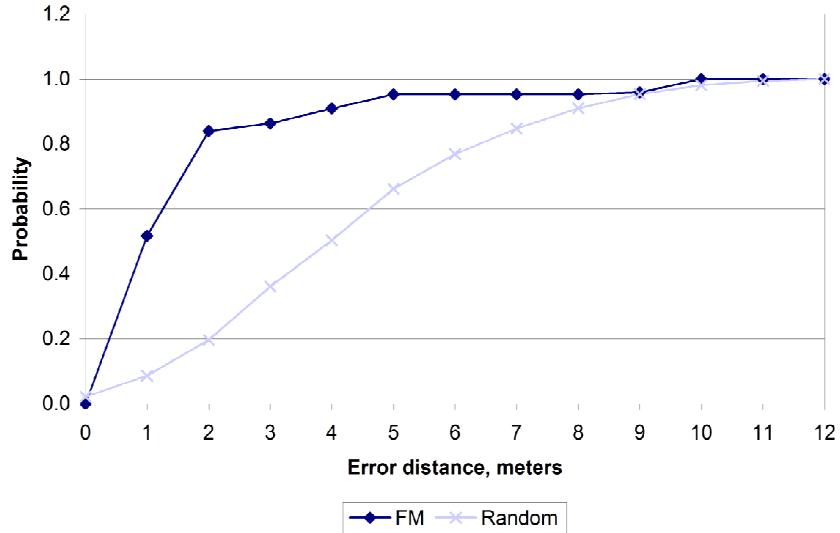


Figure 7. Error distributions for two-dimensional positioning (HTC device).

The error distance distribution is shown in . The baseline performance is represented by a random classifier, which returns random location disregarding the input RSSI values. The median accuracy is about 1.0 m, falling to about 5.0 m at 95% confidence level. The long tail of the distribution is caused by a single distant outlier.

Comparison with Wi-Fi

Wi-Fi (IEEE 802.11) is currently de-facto standard for indoor positioning, used in many commercial systems, such as Ekahau and Skyhook (“Ekahau RTLS”, 2009; “Skyhook”, 2009). In order to prove the viability of the FM positioning, we compared it with the Wi-Fi-based approach.

The data has been collected simultaneously for FM and Wi-Fi, in the same environment, with the same device (HTC Artemis). For each of 46 locations, we have recorded 100 FM and 30 Wi-Fi signal-strength samples. The resulting dataset contained data from 3 FM transmitters (as depicted in Figure 1) and 19 Wi-Fi access points, with unknown locations. To make the comparison fair, we evaluated the positioning accuracy for all the possible combinations of 3

Wi-Fi access points out of 19. The set with the best median accuracy was then used for comparison. The evaluation method was the same as the one described in previous section.

Due to the firmware limitations, the device reported Wi-Fi RSSI data in a rather coarse manner: there were only 6 different RSSI values (from -90 dB to -50 dB with step of 10 dB, corresponding to “Very low” and “Excellent” extreme signal strengths, while 0 corresponded to “No signal”). In this regard, to make the comparison fair, we converted the original FM RSSI values (integers from 0 to 45) to 6-level range, as of Table 1. This expectably worsens the performance of FM (cf. and Figure 8), but provides an insight into relative performance of FM and Wi-Fi positioning.

Table 1. FM RSSI level conversion

Original FM RSSI	6-level FM RSSI	Wi-Fi RSSI
40 to 45	-50	Excellent
30 to 39	-60	Very good
20 to 29	-70	Good
10 to 19	-80	Low
1 to 9	-90	Very low
0	0	No signal

The comparison results are presented in Figure 8. As evidenced from the figure, our FM and Wi-Fi positioning systems exhibit similar performance in terms of accuracy.

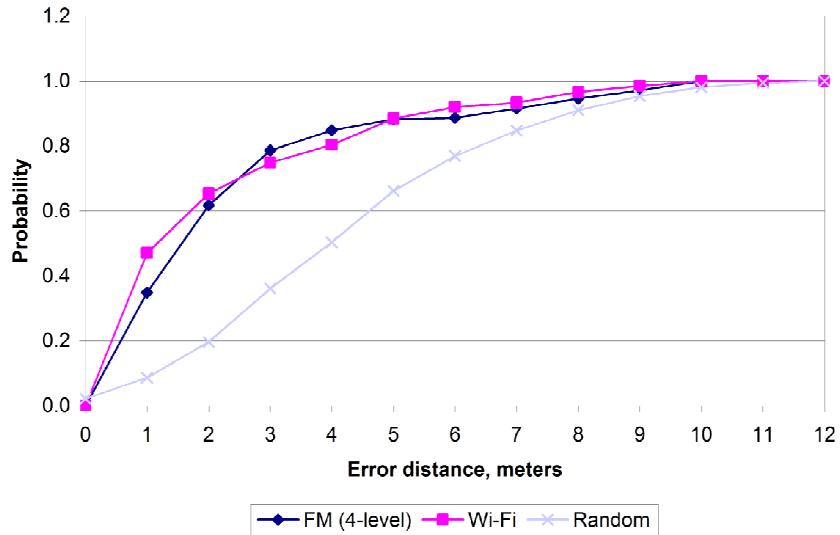


Figure 8. Comparison of Wi-Fi and FM error distributions (HTC device).

Given the other characteristics of FM, such as price (an FM transmitter is up to 10 times cheaper than a Wi-Fi access point), power effectiveness (15 mW of FM radio compared to 300 mW of Wi-Fi), safety in specific environments (an FM receiver is not found to interfere with medical or other sensitive equipment, unlike Wi-Fi devices) and availability (FM tuners are built into various mobile devices like cellphones or PDAs), we can conclude that the FM positioning is a viable alternative to Wi-Fi-based location systems.

RSSI stability over time

Any fingerprinting-based positioning system relies on the assumption that RSSI levels remain stable after the calibration phase. Otherwise, the system accuracy may diminish significantly, and the system will require recalibration, which is laborious and time-consuming. It has been demonstrated, that many current fingerprinting-based systems are affected by the signal stability problems (Kaemarungsi, 2006; Stuntebeck et al., 2008).

In order to estimate the stability of the FM signal strength in FINDR, we set the receiver to record the RSSI from the transmitter placed 4 meters away, and left the devices running for

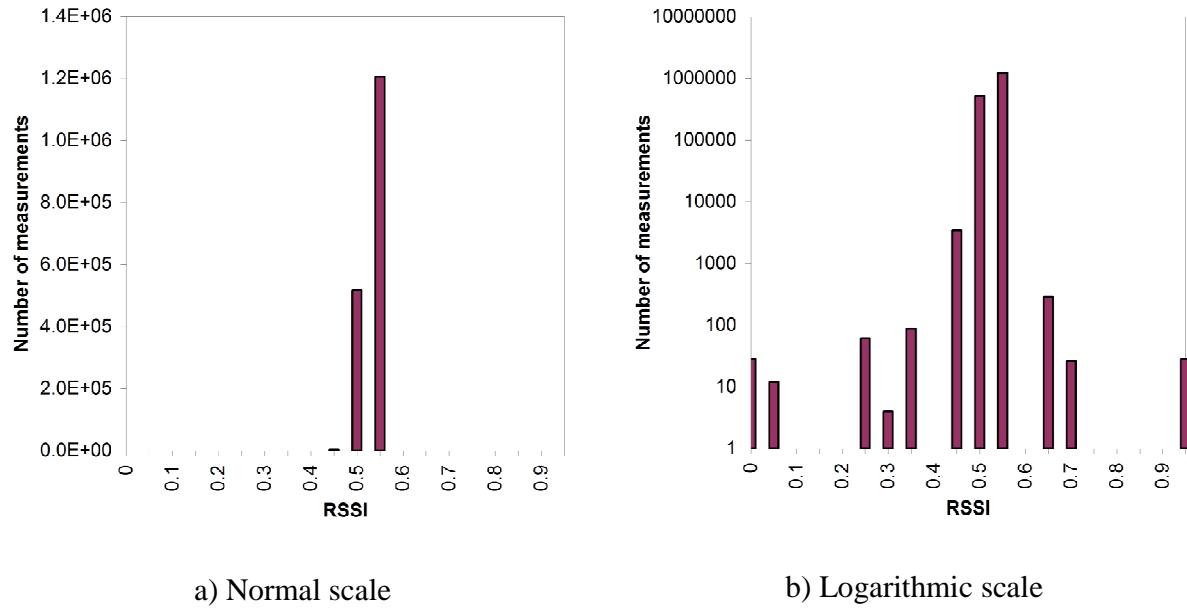


Figure 9. RSSI distribution for 4-hour long measurements (Nokia device).

weekend. Unfortunately, in four hours the receiver ran out of memory and only 1.7 million samples have been recorded. Their mean value was 0.57975 and the variance was 0.00097.

The RSSI distribution in Figure 9 demonstrates the FM RSSI to be rather stable. The two peaks on Figure 9a are different by one quantization step only. There are about 4000 outliers, which constitute only about 30 seconds of the whole 4-hour dataset. Although the readings are limited, the obtained results are a good indication that the system will maintain high positioning accuracy for longer period, without frequent recalibration needed to address RSSI drift.

CONCLUSION

This paper presented the FINDR, an indoor positioning system based on FM radio technology. The system is a low-cost solution that does not require any specialised hardware. FM transmitters, used as beacons, are easily available in the most of electronics shops. Virtually any cellphone or PDA with an embedded FM tuner can be used as a client device. The results of the system evaluation show a median accuracy of about 1.0 m and 5.0 m at 95% confidence level. A

comparison with a Wi-Fi positioning system deployed in the same environment showed that FM and Wi-Fi have a similar performance.

As a positioning technology, FM has a number of advantages over Wi-Fi. FM transmitters are easily available from consumer electronic shops and are 3 to 10 times cheaper than Wi-Fi access points. Unlike Wi-Fi modules, an FM receiver is a zero-emission device, which makes it safe for use in sensitive environments where Wi-Fi is restricted. Moreover, a typical FM receiver consumes only about 15 mW of battery power, one twentieth of Wi-Fi consumption (“TDA7088”, 1996; “BCM4326”, 2006). Although Wi-Fi infrastructure is readily available in many office buildings, it is uncommon to have more than one access point at home, which is insufficient to provide localisation. Given these considerations, FM positioning is a more cost-effective alternative for positioning than Wi-Fi.

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