FINDR: Low-Cost Indoor Positioning Using FM Radio

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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. The features of the FM radio which make it distinct from other localisation technologies are discussed. Despite the low cost and off-the-shelf components, the performance of the FM positioning is comparable to that of other positioning technologies (such as Wi-Fi). From our experiments, the median accuracy of the system is around 1.3 m and in 95% of cases the error is below 4.5 m.

Key words: indoors positioning, FM radio, location awareness

1 Introduction

Location awareness is an important requirement for many modern applications, spanning from mobile maps and geotagging to Internet of Things and healthcare. 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 [1]. Most of these systems are limited in terms of expensive/custom hardware, laborious deployment or low accuracy.

Our paper explores the applicability of short-range FM radio transmitters for indoor positioning. These devices are cheaply available from many consumer electronics shops. The client device can be represented by a PDA or a cellphone with an embedded FM receiver. We have installed our FM indoor positioning system (FINDR) 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.

The paper is organized as follows. Section 2 provides and overview of the related work. Section 3 then introduces our approach and our experimental testbed. Section 4 presents results pertaining to performance evaluation of the system, while Section 5 describes the possible application scenarios of the proposed system. Finally, Section 6 draws the conclusions and outlines the future work.

2 Related work

2.1 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: ultrasound [2, 3], infrared (IR) [2, 4], digital compass [3], RFID [5], and various kinds of radio: Wi-Fi [6, 7], GSM [8], Bluetooth [9], domestic powerline [10, 11], and others [12, 13]. 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 sections that follow we briefly describe each of these approaches to localisation.

Proximity-based Given 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 custom radio beacons [12], as well as Bluetooth [14], IR [2] and GSM base stations [15, 16]. Unfortunately, the accuracy of such systems is low and depends on the density and the number of installed beacons.

Time-based Time-based methods use information about signal propagation time between the mobile device and beacons with known positions, in order to estimate the position of the mobile user. The most prominent example of this class of methods is GPS. 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 [17, 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 [3], also 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 approach attempts to build a model of the signal propagation in the space in order to identify 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 statistics and 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 a rather high accuracy with a few beacons.

One of the pioneering projects in RSSI-based positioning was RADAR [18]. The authors applied both propagation modelling and fingerprinting within a Wi-Fi network, and, with some enhancements, the system error was as low as 2 m [6]. With more advanced probabilistic methods, the median error of a Wi-Fi based system can reach 1.2–1.45 m [7, 19]. RSSI fingerprinting has also been successfully applied for indoor localisation using GSM base stations. In [8], the authors employed so-called wide fingerprints, which included RSSIs of up to 35 GSM channels, and thus 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. [10] proposed a more reliable approach for indoors positioning. 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 location. An extended, wideband version of the system achieved a 90% accurate room recognition [11]. Despite the easy installation, the system requires 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. [13] described their experiments on using prototype hand watch with an embedded FM radio, to localise using commercial FM broadcasting stations. The authors applied a Bayesian classifier to distinguish 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 kilometers, which renders it impracticable for indoor environments. Our system, instead, is based on readily available hardware and is particularly suitable for indoor use.

3 FM positioning

3.1 Our approach

The proposed system employs a set of short-range FM transmitters as wireless beacons and a programmable radio on the client device. Most of the beacon-based positioning technologies have 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 three 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 HF signal. Most of the current FM receivers employ RSSI value internally, to enable auto-tuning capability.

When RSSI is not available, one can use the signal-to-noise ratio (SNR) of the demodulated signal. In this case, the beacon is set to transmit 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 intensity of the band of interest is divided by the average intensity of the all bands, thus representing signal-to-noise ratio. A similar method was applied by Patel et al. [10] to an amplitude-modulated (AM) signal. However, our experiments show that SNR of an FM signal degrades in almost binary way, thus considerably limiting applicability of this approach to FM-based positioning (see Section 4.1)

There is also another feature that depends on the signal quality and, consequently, on the distance between the transmitter and the receiver, namely, stereo channels separation. In good reception conditions the stereo channels are well separated, providing best sound quality. However, as the radio signal deteriorates, the receiver's circuitry will start to reduce the audio bandwidth and thus decrease channel separation in order to filter out the noise [20]. Ultimately, this results in a plain mono signal.

Distinguishing beacons For a beacon-based positioning system it is crucial 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. coordinates, ID, name, etc).

Unfortunately, due to the properties of FM, it is impossible to use the same frequency for all beacons. Due to the so-called "capture effect", when a number of stations transmit on the same (or close by) frequency, the signal from the strongest one will dominate the others, while the weaker signals get attenuated [21]. Therefore, in our experiments we had to tune each transmitter to a different frequency and 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.

3.2 Experimental setup

The system was evaluated with empirical measurements in the Multimedia, Interaction and Smart Environments (MISE) lab of Create-Net [22]. The room dimensions were 12 x 6 m, and the room contained 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 46 points).

The receiving device used in the tests was a Nokia N800 Internet Tablet. The N800 is an 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

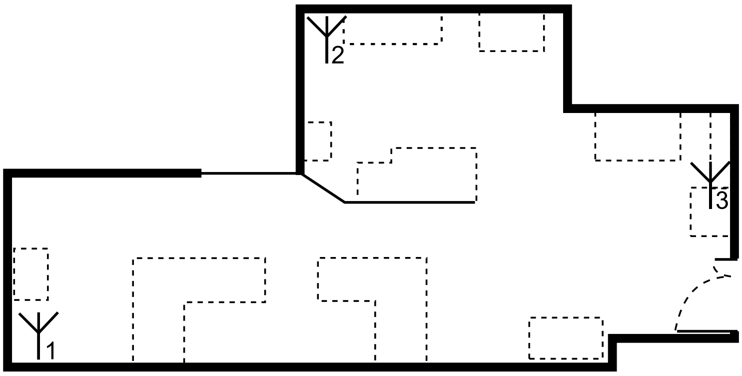


Fig. 1. Floorplan of the measurement area. The antennas mark the positions of the three transmitters and the dashed lines mark room furniture.

read the signal strength from the FM-receiver hardware. The signal strength was reported on a 16-step scale (normalized to range $0 \dots 1$) 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.

Fig. 2. MP3 player with an embedded FM transmitter, connected to power adapter. The antenna is not connected.

The transmitter used was a König mp3 player, which features 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. Initially, the whole FM band was scanned and manually checked for frequencies with little interference from local FM-radio stations. The transmitters were then tuned to these frequencies. To avoid the effect of battery degradation, the transmitters were powered by USB power adapters.

4 Results

4.1 RSSI dependency on distance

In order to estimate the feasibility of the FM positioning system, we first carried out a test to see which of the features discussed in Section 3.1 are more suitable for positioning. Stereo channel separation method has not been implemented yet and will be addressed in the future work.

The RSSI dependence on the distance from the transmitter is presented in Figure 3. To avoid any interference from the testbed's furniture, this test was performed outdoors. The graph is relatively smooth and monotone starting from 0.5 m, and proves RSSI to be a good feature for positioning. Eventual plateau-looking areas can be explained by the limited number of RSSI levels recognized by our receiver.

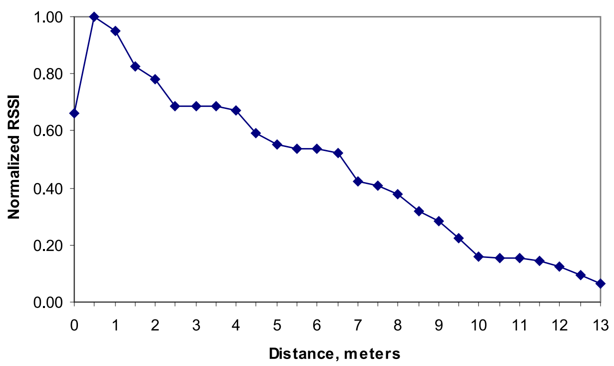


Fig. 3. RSSI dependence on distance.

Figure 4 corresponds to the indoors measurements and shows the RSSI from each of three transmitters while the user was moving horizontally (as of floorplan in Figure 1) from Transmitter 1 to Transmitter 3. The dependencies are not very smooth, which is caused by the distortions from the furniture and multipath propagation. Nevertheless, the general trends are clearly observable.

For the RSSI$_{SNR}$ method, the transmitter was set to broadcast a continuous DTMF signal for digit "1" (1209 Hz and 697 Hz). At the receiver side, the audio signal from an FM radio 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 as follows:

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

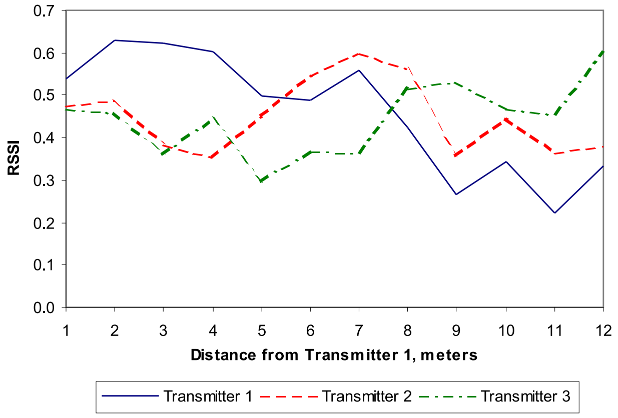


Fig. 4. RSSI variation while moving from Transmitter 1 to Transmitter 3, with Transmitter 2 placed between them.

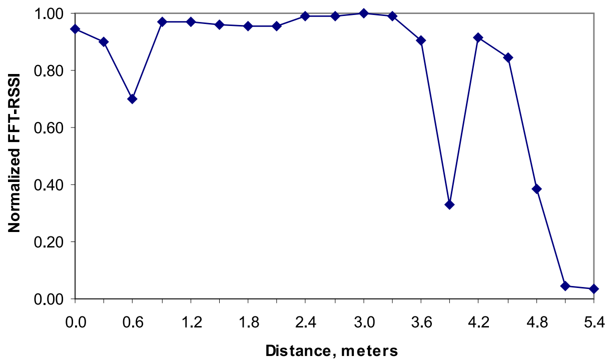


Fig. 5. RSSI_{SNR} dependence on distance.

The experiment discovered no clear dependency of RSSI_{SNR} from the distance to the transmitter (see Figure 5). 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 a 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 [23]. 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 [24].

Thus, RSSI_{SNR} dependency on the distance is almost binary due to intrinsic properties of FM. Therefore, we did not consider RSSI_{SNR} for further experiments.

4.2 2D positioning

To estimate the system accuracy in two-dimensional positioning, we have used fingerprinting approach with two evaluation methods: leave-one-out validation and an independent test set. In leave-one-out method, 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) [18]. Besides that, in order to estimate the real-world system accuracy, we have tested the system on an independent data set collected by another person.

For classification, a k-nearest neighbour (kNN) method was used [25]. The kNN classifier evaluates the distance from the test point to all the training points, and selects the labels (classes) of the k nearest training points. From these k labels, the prevailing one is returned as the classification result. For our task, we employed the Euclidean distance measure. The optimal value of k ($k = 9$) was selected by leave-one-out validation and then reused for cross-person evaluation.

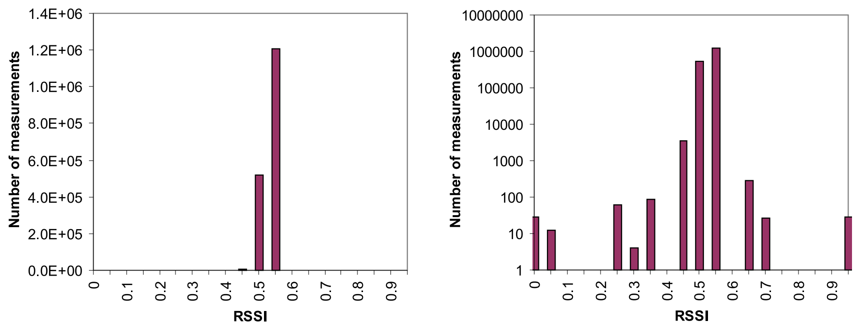
Fig. 6. Error distributions for two-dimensional positioning.

The error distance distributions for both approaches are shown in Figure 6. The baseline performance is represented by a random classifier. The median accuracy for the leave-one-out evaluation method is 1.3 m, falling to about 4.5 m at 95% confidence level. The evaluation on an independent test set demonstrates expectably better result for small errors: 29% of places are recognized correctly. The median accuracy is better than 1.3 m. Despite the long tail, caused by distant outliers, in 95% of the cases the positioning error stays below 6.8 m.

4.3 RSSI stability over time

For a fingerprinting-based system, it is very important that the values measured during calibration phase do not drift over time. Otherwise, the system accuracy may diminish significantly, and the system will require recalibration. It has been demonstrated, that many current fingerprinting-based systems are affected by the signal stability problems [11, 26].

In order to estimate the stability of the FM signal strength, we placed a transmitter 4 meters apart from the receiver and left it recording the RSSI over the weekend. However, in four hours the device 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.



(a) Normal scale (b) Logarithmic scale

Fig. 7. RSSI distribution for 4-hour long measurements.

The RSSI distribution in Figure 7 proves the FM RSSI to be rather stable. The two peaks are different by one quantization step only. There are about 4000 outliers, which constitute only about 30 seconds of the whole 4-hour dataset. Note that the measurements have been done by a receiver that distinguishes only 16 RSSI levels; a more advanced receiver could improve both the distribution detail and the positioning accuracy.

5 Application Scenarios

The need for finding one's position has sprung up a number of technologies that fulfil this purpose with varying degrees of success. While outdoor positioning is a relatively mature technology (i.e. GPS), the indoor localisation has been proven an interesting research challenge. The interest in indoor positioning has been fuelled by the potential it offers in creating novel applications that can span across diverse domains. Applications ranging from locating lost keys within home, up to detecting mobility patterns of elderly that aid disease diagnosis, are made possible by utilising technologies that offer relatively precise location information, while considering the cost benefits. FM localisation method, described thus far, is such technology that can give rise to a number of interesting applications.

Applications that make use of localisation can be found in the realm of social sciences, amongst other domains. Localisation can be utilised to infer mobility patterns of users. A study, described in [27], tracked location of 100.000 mobile phones. Analysis of the data revealed that users have predictable mobility behaviour patterns, which authors were able to infer by analysing only half of the data collected. However, this study was limited since location data was based on GSM localisation, thus had a low granularity, typical of a GSM cell tower range.

FM localisation will allow analysis of data that has much higher localisation granularity, by simply utilising a mobile phone with built-in FM receiver. This information then can be used, not only to infer mobility patterns, but by using the concept of group location, the social network of a user can also be deduced. In other words FM localisation method will allow inference of human relationships, for example colleagues that spent time in the same office, through analysis of sub-room mobility patterns.

Naturally, localisation technology is applicable to a number of other domains, including health care, where it can be used to aid elderly locate misplaced objects (such as their mobile phone), or even deliver location dependent reminders - locking the front door when entering the house for instance. These applications can be enabled by a low-cost, sub room location solution, which FM positioning is able to provide.

6 Conclusion

This paper presented an indoor positioning system based on FM radio technology. The system is a low-cost solution that does not require any specialised hardware, thus is easily deployable. FM transmitters, used as beacons, are easily available in the most of electronics shops. Virtually any cellphone or PDA, with an embedded FM receiver can be used as a client device. The preliminary results of the system evaluation show a median accuracy of about 1.3 m and 4.5 m at 95% confidence level that is favourably comparable to other state-of-the-art positioning systems.

In the future we plan to conduct a more comprehensive system evaluation using probabilistic classifiers and perform a same-environment comparison with other positioning systems. These results will be applied to a number of previously described application domains.

References

[1] J. Hightower and G. Borriello. Location systems for ubiquitous computing. *Computer*, 34(8):57–66, 2001.

[2] D. Fox, J. Hightower, L. Liao, D. Schulz, and G. Borriello. Bayesian Filtering for Location Estimation. *IEEE Pervasive Computing*, 2003.

[3] N.B. Priyantha, A.K.L. Miu, H. Balakrishnan, and S. Teller. The cricket compass for context-aware mobile applications. *Proceedings of the 7th annual international conference on Mobile computing and networking*, pages 1–14, 2001.

[4] L. Liao, D. Fox, J. Hightower, H. Kautz, and D. Schulz. Voronoi Tracking: Location Estimation Using Sparse and Noisy Sensor Data. In *Proc. of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS'03)*, 2003.

[5] J. Hightower and G. Borriello. Particle Filters for Location Estimation in Ubiquitous Computing: A Case Study. In *Proceedings of the Sixth International Conference on Ubiquitous Computing (Ubicomp)*, pages 88–106. Springer, 2004.

[6] P. Bahl, V.N. Padmanabhan, and A. Balachandran. Enhancements to the RADAR User Location and Tracking System. *Microsoft Research: Redmond, WA*, 2000.

[7] MA Youssef, A. Agrawala, and A. Udaya Shankar. WLAN location determination via clustering and probability distributions. In *Pervasive Computing and Communications, 2003.(PerCom 2003). Proceedings of the First IEEE International Conference on*, pages 143–150, 2003.

[8] Alex Varshavsky, Eyal de Lara, Jeffrey Hightower, Anthony LaMarca, and Veljo Otsason. GSM indoor localization. *Pervasive and Mobile Computing*, 3(6):698–720, December 2007.

[9] A. Kotanen, M. Hännikäinen, H. Leppäkoski, and T.D. Hämäläinen. Experiments on local positioning with Bluetooth. In *Proceedings of the International Conference on Information Technology: Coding and Computing (ITCC'03)*, pages 297–303, 2003.

[10] Shwetak N. Patel, Khai N. Truong, and Gregory D. Abowd. PowerLine Positioning: A Practical Sub-Room-Level Indoor Location System for Domestic Use. In Paul Dourish and Adrian Friday, editors, *Proceedings of the 8th International Conference on Ubiquitous Computing (UbiComp 2006)*, volume 4206 of *Lecture Notes in Computer Science*, pages 441–458, Orange County, CA, USA, September 17–21 2006. Springer Berlin / Heidelberg. doi: 10.1007/11853565_26.

[11] Erich P. Stuntebeck, Shwetak N. Patel, Thomas Robertson, Matthew S. Reynolds, and Gregory D. Abowd. Wideband powerline positioning for indoor localization. In *Proceedings of Ubicomp 2008*, 2008.

[12] N. Bulusu, J. Heidemann, and D. Estrin. GPS-less low-cost outdoor localization for very small devices. *Personal Communications, IEEE*, 7(5): 28–34, 2000.

[13] J. Krumm, G. Cermak, and E. Horvitz. RightSPOT: A Novel Sense of Location for a Smart Personal Object. In Anind K. Dey, Albrecht Schmidt, and Joseph F. McCarthy, editors, *Proceedings of the 5th International Conference on Ubiquitous Computing (UBICOMP 2003)*, volume 2864 of *Lecture Notes in Computer Science*, pages 36–43, Seattle, WA, USA, October 12-15 2003. Springer Berlin / Heidelberg.

[14] J. Hallberg, M. Nilsson, and K. Synnes. Positioning with Bluetooth. In *Proceedings of 10th International Conference on Telecommunications (ICT 2003)*, volume 2, pages 954–958, 23 February–1 March 2003. doi: 10.1109/ICTEL.2003.1191568.

[15] K. Laasonen, M. Raento, and H. Toivonen. Adaptive On-Device Location Recognition. In *Proc. Pervasive*, volume 3001 of *Lecture Notes in Computer Science*, pages 287–304. Springer, 2004.

[16] A. LaMarca, Y. Chawathe, S. Consolvo, J. Hightower, I. Smith, J. Scott, T. Sohn, J. Howard, J. Hughes, F. Potter, J Tabert, P. Poweldge, G Borriello, and B Schilit. Place Lab: Device Positioning Using Radio Beacons in the Wild. In Hans W. Gellersen, Roy Want, and Albrecht Schmidt, editors, *Proceedings of the 3rd International Conference on Pervasive Computing (Pervasive 2005)*, volume 3468 of *Lecture Notes in Computer Science*, pages 116–133, Munich, Germany, May 8–13 2005. Springer.

[17] US Department of Defence. GPS SPS Performance Standard. Online: `http://www.navcen.uscg.gov/gps/geninfo/2008SPSPerformanceStandardFINAL.pdf`, September 2008.

[18] P. Bahl and V.N. Padmanabhan. RADAR: an in-building RF-based user location and tracking system. In *Proceedings of INFOCOM 2000, Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies.*, volume 2, pages 775–784, 26-30 March 2000. doi: 10.1109/INFCOM.2000.832252.

[19] T. Roos, P. Myllymäki, H. Tirri, P. Misikangas, and J. Sievänen. A Probabilistic Approach to WLAN User Location Estimation. *International Journal of Wireless Information Networks*, 9(3):155–164, 2002.

[20] Kazunari Honjo and David L. Simpson, Jr. Stereo fm receiver, noise control circuit therefor. US Patent 5432854, July 1995.

[21] K. Leentvaar and J. H. Flint. The capture effect in FM receivers. *IEEE Transactions on Communications*, 24:531–539, May 1976.

[22] `http://www.create-net.org/mise`.

[23] JPL's Wireless Communication Reference Website. Analog Transmission over Fading Channels. Online: `http://www.wirelesscommunication.nl/reference/chaptr05/analog/analog.htm`. (As accessed on 2008.11.20).

[24] TDA7088 Datasheet, 1996.

[25] T. Mitchell. *Machine Learning*. ISBN 0070428077. McGraw Hill, 1997.

[26] K. Kaemarungsi. Distribution of WLAN Received Signal Strength Indication for Indoor Location Determination. In *Proceedings of the 1st International Symposium on Wireless Pervasive Computing*, pages 1–6, 2006.

[27] Kerri Smith. Mobile phones demystify commuter rat race. *Nature News*, June 4, 2008.