

PhD Dissertation

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International Doctorate School in Information and  
Communication Technologies

DISI - University of Trento

INDOOR POSITIONING USING FM RADIO SIGNALS

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# Abstract

Location based services are becoming an indispensable part of the life. Wide adoption of the Global Positioning System in mobile devices, combined with Wi-Fi and cellular networks, have practically solved the problem of outdoor localization and opened a new market. This, however, is the case only for outdoors. There are numerous areas of ubiquitous computing, which require the knowledge of user position *indoors*. Awareness of user's location is important in such areas as smart environments, assisted daily living, behaviour analysis studies.

Over the past years, a significant effort has been dedicated to development of indoor localization systems. The results vary in characteristics, performance, and cost. Despite the effort, the existing indoor positioning systems are still limited: they either require expensive infrastructure (UWB, ultrasound), have limited coverage (Wi-Fi, Bluetooth, RFID, DECT) or low accuracy (cellular networks). The cost of commercial systems is prohibitive for their wide adoption (Ubisense).

The main objective of this thesis was to determine the feasibility of indoor positioning using FM radio signals, generated either by local transmitters or by broadcasting FM stations. The performance of FM localization cannot be simply predicted from other technologies, such as Wi-Fi or GSM, due to significantly lower frequencies (around 100 MHz vs. units of GHz) leading to differences in signal propagation. Moreover, FM represents a popular and well-established technology, readily available in many

mobile devices. At the infrastructure side, broadcasting FM stations provide almost ubiquitous coverage, while short-range FM transmitters are available license-free from conventional electronics markets.

The results indicate that indoor positioning using broadcasting FM stations outperforms in terms of accuracy both Wi-Fi and GSM indoor localization systems (for confidence levels up to 90% and in all cases, respectively). Due to the passive nature of the client devices, the system can be used in sensitive areas where local radio transmission, such as Wi-Fi or GSM, is prohibited for safety or security reasons. Finally, an FM receiver has significantly lower power consumption than a Wi-Fi module and provides 2.6 to 5.5 times longer battery life in localization mode.

## **Keywords**

indoor positioning, FM radio, signal fingerprinting

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# List of Abbreviations

AM	Amplitude modulation
AOA	Angle of arrival
CDMA	Code Division Multiple Access
CDF	Cumulative distribution function
DECT	Digital Enhanced Cordless Telecommunication
DTMF	Dual Tone Multi-Frequency
ECG	Electrocardiography
FFT	Fast Fourier transform
FCC	Federal Communications Commission (USA)
FM	Frequency modulation
FM <sub>L</sub>	FM positioning using local transmitters
FM <sub>B</sub>	FM positioning using broadcasting stations
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GP	Gaussian process
GSM	Global System for Mobile Communications
IEC	International Electrotechnical Commission
IR	Infrared
ISM	Industrial, scientific and medical radio band
kNN	K-nearest neighbor
LBS	Location-based service
LOS	Line of sight

NaN	Not-a-number
NLOS	Non line-of-sight
ODA	Open data applications
PCB	Printed circuit board
PCL	Passive coherent location
RDS	Radio Data System
RF	Radio frequency
RFID	Radio Frequency IDentification
RSS	Received signal strength
RSSI	Received signal strength indicator
s.d.	Standard deviation
SCS	Stereo channel separation
SNR	Signal-to-noise ratio
UHF	Ultra high frequency (300–3000 MHz)
UWB	Ultra wide band
VHF	Very high frequency (30–300 MHz)
Wi-Fi	Wireless fidelity; IEEE 802.11 wireless networks

# Chapter 1

## Introduction

Positioning systems have a long history, traceable back to the ancient guiding-star navigation. Since then, technological advances and the Global Positioning System (GPS) have practically solved the problem of outdoor localization. Mobile devices with GPS receivers made the technology available to wide public and created the market of location-based services.

However, there are numerous pervasive computing applications which would benefit from position information within indoor environments, where GPS signal is too weak. Indoor location awareness is important for such fields as ambient intelligence, assisted daily living, behavior analysis, social interaction studies, and myriads of other context-aware applications.

Despite the substantial research and development efforts, the existing indoor positioning systems remain too limited for wide adoption. The current de-facto standard, Wi-Fi based localization, has a limited coverage. Other systems, based on RFID, infrared, ultrasound or ultra-wide band (UWB) approaches, require specialized hardware and dedicated infrastructure, and therefore have high costs. The systems based on cellular networks, in turn, provide a good coverage, but low positioning accuracy.

FM radio is a popular and well-established technology. Broadcasting FM stations provide almost ubiquitous worldwide coverage, while short-

range license-free FM transmitters are available at low cost from conventional supermarkets. FM receivers, already embedded in many mobile devices, have low power consumption and do not interfere with sensitive equipment or other wireless technologies. The described features make FM radio an interesting option for a positioning system.

However, there are very few publications which have investigated the suitability of FM radio signals for localization [1, 2]. Moreover, all authors considered only outdoor scenarios. The achieved accuracy discouraged any indoor applications; no works have been published about indoor positioning using FM radio. The outdoor results, however, cannot be directly projected onto indoor scenario, as indoor and outdoor environments are notably different with regard to signal propagation [3].

The main objective of this thesis was to determine whether FM radio signals are suitable for indoor positioning. The operational frequencies of FM radio are significantly (9 to 50 times) lower than those of other technologies, such as Wi-Fi or GSM, which results in different properties of signal propagation. Thus, the FM positioning performance cannot be simply predicted from other technologies.

The main contributions of this thesis are:

- identification of FM signal features suitable for localization and discovering their limitations;
- demonstration that indoor positioning using FM signals produced by local short-range transmitters is feasible and its accuracy is comparable to Wi-Fi positioning;
- demonstration that indoor localization using signals transmitted by broadcasting FM stations (without in-building infrastructure) is feasible and outperforms GSM and, for confidence levels of up to 90%, Wi-Fi based systems;



- a novel approach for maintaining the performance of a fingerprinting-based positioning system affected by accuracy degradation;
- an analysis of how people's presence affects the FM and Wi-Fi signal strengths.

The thesis is organized as follows.

**Chapter 2** reviews the related work, motivates the selection of used methods and provides a brief review of relevant features of FM radio technology.

**Chapter 3** describes the proposed approach and identifies the properties of FM signals relevant for localization, with focus on indoor environments. It also introduces the spontaneous recalibration method to counter accuracy degradation.

**Chapters 4 and 5** present the experimental evaluation of FM positioning performance, spontaneous recalibration approach and compare the stability of FM and Wi-Fi signals in the presence of people.

**Chapter 6** details an application scenario of FM positioning.

**Chapter 7** provides the summary of contributions and directions for future work.



# Chapter 2

## Background

A localization system is a technological setup employed to determine the location of a *mobile client* within an environment. Typically, such systems also include a set of stationary devices (called *beacons* hereinafter) which interact with the mobile part. Once the position is identified, it can be reported in different formats:

**Physical** The physical location is expressed as a point within some coordinate system, either local or global (such as WGS-84 [4]).

**Relative** The relative position is expressed with regard to a local reference point. Often, the reference point is represented by a system beacon; in some cases it can also be a previously estimated client position (*dead reckoning* [5]). If the absolute coordinates of the reference point are known, it is possible to transform the relative client position into the absolute one.

**Symbolic** The symbolic position is represented by an identifier of the place the client is at. This type of position is similar to relative position, but unlike the latter, it does not have a concept of distance. A symbolic location can be converted to a physical one using a database associating location identifiers with their coordinates.

Depending on the target environment, a positioning system can be classified as either indoor, outdoor, or mixed type. This thesis focuses on localization within indoor environments, such as buildings or other enclosed spaces. For a wireless positioning system, indoor settings have a number of important differences in comparison to outdoors:

- Smaller dimensions;
- Higher density of obstacles;
- Inherently multipath propagation: signals are reflected and attenuated by walls and furniture [6];
- Large number of small-sized obstacles which scatter the signal;
- Highly dynamic environment, due to movement of people, furniture, doors, and other factors [7];
- Lower movement velocities (walking instead of driving);
- Minimal influence of weather conditions, except the cases when external beacons are used; and
- Mostly non-line-of-sight (NLOS) reception.

The relatively small dimensions of indoor environments and high density of their internal structure put stricter requirements to the positioning accuracy. Indeed, while a hundred-meter accuracy is enough to find a shopping mall, it is utterly insufficient to locate a specific shop inside. Moreover, numerous internal obstacles result in very complex propagation conditions, so that even a small change of position may lead to a significant change of signal properties. This is particularly important when the positioning system relies on distant external beacons, such as cellular or broadcasting radio stations. The signals of these beacons are powerful enough to

propagate across tens of kilometers, and free-space propagation losses are negligible at the indoor scale; in this case, signal variations inside buildings are caused mainly by fast fading due to the obstacles. In more detail this effect is analyzed in Section 5.2.1.

The following sections present an overview of state-of-the-art indoor positioning methods and some of their most notable implementations.

## 2.1 Indoor positioning methods

### 2.1.1 Proximity based

One of the simplest varieties of positioning methods is the proximity based approach, sometimes called connectivity-based. This method employs beacons with known positions and limited range, so that only one or few beacons are visible to the mobile unit at any point. The client location is then approximated as that of the nearest beacon. A more accurate estimate can be obtained by evaluating a centroid of nearby beacons' positions [8].

For a uniform grid of beacons, the worst-case accuracy of the connectivity-based approach is the grid step. While this provides an opportunity to boost the positioning accuracy by installing additional beacons, the accuracy improvement is limited due to the rapidly increasing hardware costs.

Although in comparison to other methods the proximity based approach provides relatively low per-beacon accuracy, it is widely used for its simplicity. This method is used with several wireless positioning technologies, including GSM (Cell-ID) [9], RFID [7, 10], infrared [11], Bluetooth [12], and custom radio devices [8].

### 2.1.2 Direction based

The direction-based approach leverages the information about the angle at which a signal transmitted by the mobile client arrives to the beacons (see Figure 2.1).

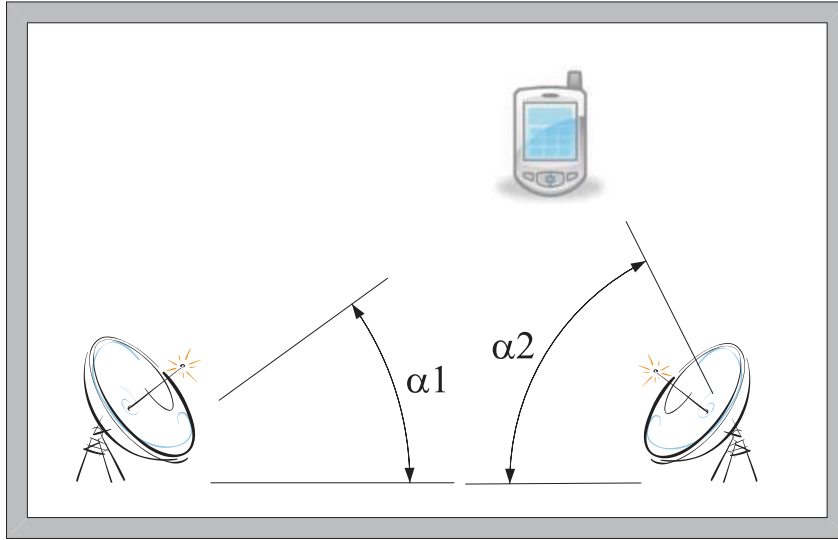


Figure 2.1: Angle-of-arrival positioning method.

In contrast to the previous method, which required a large number of beacons, the angle-of-arrival (AOA) approach requires only two beacons to estimate position in 2D (three beacons for 3D localization). On the other hand, however, angle-of-arrival measurements require highly directional antennas or antenna arrays, which increase both the cost of the system and beacons' size, so that the system might be too large for some areas. Moreover, applicability of this method in indoor environments is further limited by multipath and NLOS propagation of signals, along with reflections from walls and other objects. These factors can significantly change the direction of signal arrival and thus severely degrade the accuracy of an indoor AOA-based positioning system.

### 2.1.3 Time based (multilateration)

Time-based methods leverage the fact that the distance travelled by a signal is proportional to the propagation time. There are two main approaches based on timing information:

**Time of arrival (TOA)** approach requires that the client device and the beacons are accurately synchronized. For localization, the client device transmits a timestamped signal; when the beacons receive this signal, they calculate its travel time and thus the distance to the mobile unit. Three beacons are required to perform 2D positioning. The major drawback of the TOA approach is the need for precise synchronization of all the devices.

**Time difference of arrival (TDOA)** method uses the difference of time it takes the signal from the client to reach each of the synchronized beacons. Each time-difference measurement defines a hyperbolic line with constant distance difference between a pair of beacons; this curve specifies the possible locations of the client. Thus, two TDOA measurements (three beacons) are sufficient to acquire 2D position of the mobile unit. Clearly, the reverse approach is also possible, where the client receives timestamped signals from the beacons with known positions. The most prominent example of this class of methods is the Global Positioning System (GPS) [13], where the mobile receivers estimate their location using timestamped signals from synchronized satellites and information about satellites movement (ephemeris)). 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 [13, p. 22]. Unfortunately, GPS signal is too weak in buildings which makes the system inoperative indoors.

In contrast to the TOA method, the differential approach does not re-

quire time synchronization of the client device. The beacons, however, still must be precisely synchronized.

Due to the requirement of precise synchronization, the time-based methods require expensive specialized hardware (GPS satellites use atomic clocks for timekeeping [13]). Moreover, the accuracy of these methods indoors is limited because of inherently multipath and NLOS propagation. These issues can be alleviated by installation of a high-density beacon infrastructure, which, however, increases the hardware and deployment costs of the system.

#### 2.1.4 Signal property based

In contrast to previous approaches, which exploited either signal presence, propagation time or direction, this group of localization methods considers the characteristics of the received signal itself. These characteristics include such properties as phase, signal-to-noise ratio (SNR), and signal strength.

The most popular feature employed in wireless localization systems is received signal strength (RSS), or its representation in device-specific units, received signal strength indication (RSSI). There are two general approaches to localization using RSSI: propagation modelling and fingerprinting.

##### 2.1.4.1 Propagation modelling

The propagation modelling approach leverages the physical laws of signal propagation in order to correlate the signal strength with the travel distance. Having acquired RSSI values for three or more beacons, the mobile unit can use the propagation model in order to estimate the distances to each of the beacons, and thus own location.

Propagation models are typically expressed in terms of *path loss*, which represents how much a signal is attenuated as it propagates through space [14].



Total path loss is a rather complex function with multiple components [14, p. 15], such as:

- propagation distance (*free-space loss*),
- signal properties (such as frequency),
- terrain (hills, mountains, bodies of water),
- atmosphere condition,
- ground cover (trees, buildings) [15–17].

Indoor scenarios introduce additional components, which consider interactions with internal obstacles (reflection, refraction and attenuation) [6, 18]. Therefore, indoor propagation models should take into account layout plans of the environment.

To provide a good accuracy, a propagation model should consider as many loss factors as possible, which is often unfeasible in practice. Consequently, there are multiple different propagation models varying in complexity and included loss components [3]. However, many localization systems based on propagation modelling commonly employ simplified models, such as the one defined by the International Telecommunication Union (for indoor settings):

$$L_{total} = 20 \log_{10} f + N \log_{10} d + L_f(n) - 28 \quad dB \quad (2.1)$$

where,  $L_{total}$  is the total path loss,  $N$  is a distance power loss coefficient,  $d$  is the travel distance,  $f$  is signal frequency in MHz,  $L_f(n)$  is floor penetration loss factor in dB, and  $n$  is the number of floors between transmitter and receiver [6]. The attenuation by walls and obstacles is implicitly included into distance power loss coefficient  $N$ .

Clearly, such parameters as  $L_f(n)$  and  $N$  are environment-specific and their values should be evaluated empirically during system calibration.

Moreover, signal attenuation by floors (and walls) depends both on building materials and signal frequency (9 dB at 900 MHz and 16 dB at 5.2 GHz [6, Table 3]). If the beacons are located outdoors, the model must also consider building penetration loss, which depends on building orientation, wall materials, internal layout, floor height and windowing area [18], and varies from 7 to 27 dB [3] or from -2 to 24 dB, increasing with frequency[18].

The major advantages of the propagation modelling are straight-forward localization phase and good scalability. Creation of an accurate model, however, requires a considerable effort for evaluation of site-specific characteristics, such as power loss coefficients and floor layout. This approach is best suited for line-of-sight (LOS) and obstacle-free propagation, — conditions which are rarely met indoors. The positioning accuracy is determined by the model complexity and the quality of the environment layout plan, and is generally worse than that of fingerprinting [19, 20].

#### 2.1.4.2 Signal fingerprinting

The signal fingerprinting is an empirical approach, which makes no assumptions about the environment or signal propagation paths therein [21]. This method includes two stages: calibration and localization. The calibration phase is a site survey comprising the collection of signal characteristics (*signal fingerprints*) at predefined points, and building a database which matches fingerprints with their locations. During the localization phase, the mobile client acquires a fingerprint and the positioning system utilizes the calibration data and appropriate algorithms to determine the location to which the collected fingerprint most probably belongs.

The machine learning methods which associate fingerprints with positions during the localization phase, employ various approaches: deterministic and probabilistic [20, 22–24], classification and regression [25–27]. The most popular approach is k-nearest neighbour [28], which can be attributed

to its intuitiveness and good positioning results [22, 23, 25]. However, more advanced methods can also be used: artificial neural networks [22, 23], Bayesian inference [1, 29], support vector machines [30] or their combinations [31].

The major drawback of the fingerprinting approach is the laborious and time-consuming calibration process. Several works found that the calibration efforts can be significantly reduced with minimal impact on localization accuracy [19, 27, 32, 33]. Also, there are methods for automatic acquisition of the calibration data, either with [7, 19] or without auxiliary hardware [32, 34].

Another problem is that the localization performance of a fingerprinting based system is prone to degradation due to changing conditions in the environment, which result in changes in signal propagation. The dynamic factors are air humidity, opening doors and windows, movement of people and furniture [7, 35, 36]. To maintain the positioning accuracy in a dynamic environment, the calibration process should be periodically repeated to update the training dataset.

To address this, some projects employ a variety of sensors that provide the system with updated fingerprints from predefined points in the area of interest. Chen et al. [7] designed a Wi-Fi based positioning system that uses RFID based sensors to provide the system with reference locations as a user passes by. Assuming that the user walking speed is constant, the system is able to periodically update the calibration data even between the RFID readers. Another approaches employ a set of stationary signal sniffers [37] or a mobile robot capable of autonomously collecting Wi-Fi signal strength measurements in different locations [19].

This thesis, in turn, addresses the problem by introducing the novel concept of spontaneous recalibration, which does not require any additional hardware (see Section 3.5.1). The literature suggests that this method has

never been presented before.

Despite the described limitations, the fingerprinting approach provides the best accuracy in complex environments [20, 21], such as indoors, and works well with reflected, diffracted, and scattered signals with either LOS or NLOS reception. Moreover, in contrast to all other methods, fingerprinting does not require any knowledge about beacon positions, which makes this method the only option for a positioning system leveraging external beacons, such as cellular network nodes or broadcasting FM stations. The described reasons have motivated the use of the fingerprinting approach in this thesis.

### **2.1.5 Summary**

Table 2.1 summarizes the localization methods discussed above.

Table 2.1: Summary of indoor positioning methods.

Method	Indoor accuracy	LOS/NLOS	Affected by multipath	Cost	Note
Proximity	low to high	both	no	low to high <sup>1</sup>	<ul style="list-style-type: none"> <li>• Accuracy can be improved by additional beacons, which, however, increase the cost.</li> <li>• Beacon locations must be known.</li> </ul>
Direction (AOA)	medium	LOS only	yes	high	<ul style="list-style-type: none"> <li>• Accuracy depends on antenna's angular characteristics.</li> <li>• Beacon locations must be known.</li> </ul>
Time (TOA, TDOA)	high	LOS only	yes	high	<ul style="list-style-type: none"> <li>• Requires precise time synchronization.</li> <li>• Beacon locations must be known.</li> </ul>
Propagation modelling	medium	LOS only	yes	medium	<ul style="list-style-type: none"> <li>• Requires the knowledge of floor layout and building materials.</li> <li>• Beacon locations must be known.</li> </ul>
Finger-printing	high	both	no	medium	<ul style="list-style-type: none"> <li>• Requires laborious calibration.</li> <li>• Beacon locations are not required.</li> </ul>

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<sup>1</sup>The cost of a proximity-based system depends on the number of beacons, which, in turn, depends on the desired accuracy.

## 2.2 State of the art wireless indoor positioning systems

This section presents a review of most notable state-of-the-art indoor positioning systems. The main focus is put on the radio based systems, because unlike other signals, such as ultrasound, infrared or visible light, the radio waves can penetrate walls and thus are suitable for NLOS conditions inherent to indoor environments.

### 2.2.1 Wi-Fi-based systems

Wi-Fi networks (IEEE 802.11 standard) are a popular basis for indoor positioning systems. Their popularity among the researchers can be explained by high availability of the network infrastructure, Wi-Fi-enabled mobile devices, and a good localization performance. Wireless networks are deployed in many office buildings and homes, and the positioning system can exploit already existing beacons.

One of the pioneering projects in RSSI-based Wi-Fi positioning was RADAR [20]. The authors applied both propagation modelling and fingerprinting and achieved 2.94 m median error [20]; with some enhancements, the accuracy could be increased to 2 m [38]. Ferris et al. [26] designed a Wi-Fi localization system using Gaussian processes in conjunction with graph-based tracking. They modeled users moving through the rooms on the same floor, as well as more complicated patterns of moving, such as going up and downstairs. When tested over the 3 km of test data in a three-floor building with 54 rooms, the average error was 2.12 meters. With advanced probabilistic methods, the median error of a Wi-Fi based system can reach 1.2–1.45 m [39, 40].

Brunato and Battiti [30] compared the performance of Wi-Fi fingerprinting localization for several machine learning methods, such as multi-layer

perceptron (MLP), support vector machine (SVM) and k-nearest neighbour (kNN), both weighted and unweighted. The SVM approach demonstrated the best median accuracy (2.75 m). Notably, the median performance of a simple unweighted kNN classifier was only 0.16 m less, while 95<sup>th</sup> percentile errors were almost the same (6.09 m for SVM and 6.10 m for kNN).

Chen et al. [7] investigated the dependence of the Wi-Fi positioning accuracy on such environmental factors as humidity, doors, and people presence. Door states (open or closed) and people presence in receiver's vicinity were found to have a significant impact on positioning error (236% and 86% increase, respectively), while the humidity had smaller effect (43% increase). While such degradation of performance is typical for fingerprinting based systems, the impact of each component varies with signal frequency: when the obstacles are small in comparison to wavelength, their interaction with the wave is negligible [41, p. 132]. Therefore, environmental factors could have smaller impact on lower-frequency FM radio waves. However, most indoor propagation measurements have been done for frequencies above 1 GHz [3] and there is a lack of results for lower frequencies.

The environment dynamics also create a possibility that some beacons present in calibration data are missing from the test set, or vice versa. This can be caused by rearrangements of network infrastructure; a more frequent reason, however, is the limited sensitivity of Wi-Fi modules, which cannot detect beacon presence if its signal strength is below certain threshold. An explicit consideration of such cases can significantly improve the positioning accuracy [42].

Wi-Fi based positioning systems have several advantages, such as: leveraging the existing infrastructure, wide availability in mobile devices, and good accuracy. However, there are also certain limitations:

**Limited coverage.** Despite the popularity, the coverage of Wi-Fi net-

works are mostly concentrated in office buildings and dense urban areas. Wi-Fi networks are rare in less populated cities and developing countries [43]. Broadcasting FM stations, in contrast, transmit at high power levels and cover areas with radius of up to several hundreds of kilometers [44], providing almost world-wide availability. Short-range FM transmitters, in turn, provide a cost-effective alternative to Wi-Fi access points in areas where Wi-Fi infrastructure is not readily available.

**Interference.** The 2.4 GHz industrial, scientific and medical (ISM) band used by Wi-Fi is shared by many other electronic devices, such as cordless phones [45] and microwave ovens [46], which may interfere with Wi-Fi signals and affect the positioning accuracy. The FM radio is more protected in this regard, as it operates in a dedicated frequency band with minimal interference from other devices. Moreover, Wi-Fi transmissions can be prohibited in sensitive environments, while the passive FM tuners can be safely used to receive the signals from broadcasting stations.

**Power consumption.** Another factor, rarely taken into account [22], is power efficiency of the positioning system, especially on the battery-powered mobile devices. Wi-Fi modules have a substantial power consumption (about 300 mW in idle power-saving mode [47]), which shortens the battery life of the mobile device. FM receivers are significantly simpler than Wi-Fi units, and operate in passive receiving-only mode, which results in notably longer battery life.

### 2.2.2 Cellular network-based systems

Cellular networks, such as GSM and CDMA, provide noticeably better coverage than Wi-Fi. However, for a long time they were not considered



for indoor localization due to the low accuracy demonstrated in outdoor settings [43, 48, 49].

The first results for GSM indoor positioning performance have been published by Otsason et al. [50]. They used a GSM modem to collect wide RSSI fingerprints which included information from 6 strongest base stations, extended by up to 35 channels which could report the RSSI but not the Cell-ID. The experimental results for different buildings have demonstrated a median accuracy from 3.4 to 11 m with six strongest stations, and from 2.5 to 5.4 m with wide fingerprints. In many cases the GSM accuracy with wide fingerprints was comparable to the Wi-Fi positioning performance. The authors also reported that the RSSI of GSM signals was more stable than Wi-Fi RSSI [50].

In contrast to GSM, CDMA base stations networks can dynamically adjust their transmission power according to the network load [51], which makes RSSI fingerprinting impractical. However, the CDMA stations are synchronized to a common time reference (provided by GPS), which enables application of time based localization methods. Using a CDMA scanner, ur Rehman et al. [51] were able to evaluate signal delays from nearby stations. Unlike the RSSI, signal delays were found to be rather stable in time. The median localization accuracy of a system using signal delay fingerprints reached 4.5 m (with all channels employed).

Cellular network based indoor positioning systems have three main advantages:

**Coverage** Unlike Wi-Fi, the GSM/CDMA networks are currently widely available in most countries; the size of large macrocells can reach 30 km [9].

**Low cost** While GSM/CDMA base stations are themselves very expensive (up to \$1 million [50]), the costs are covered by the cellular network op-

erator (and ultimately, the subscribers). Thus, the positioning system can exploit readily available stations and does not require installation of a dedicated indoor infrastructure as Wi-Fi does.

**Battery life** Although a cellular transceiver module is rather battery-consuming even in an idle state [52], in many scenarios it remains powered in order to provide the voice or data connectivity. Thus, the overhead introduced by a positioning system relates only to location estimation and excludes powering additional wireless module, which is often the case for Wi-Fi.

However, GSM/CDMA positioning has also several shortcomings:

**Low accuracy** The presented works rely on the use of wide fingerprints in order to provide a good accuracy. Acquisition of extended data, however, required special hardware (programmable GSM modem and CDMA scanner). With the narrow fingerprints which could be acquired with conventional hardware, the localization accuracy was rather low.

**Low reliability** Given that GSM/CDMA beacons are situated outdoors, the signal propagation conditions vary due to environmental factors, such as weather and terrain. In particular, radio signals with frequencies above 1 GHz are affected by rain scatter interference [53, p. 8] and terrain vegetation [17]; trees in leaf can cause a 20% higher attenuation than leafless trees [17, p. 3]. In theory, these factors can significantly affect the positioning performance; however, no experimental studies are available yet.

### 2.2.3 FM radio-based systems

There are only few works dedicated to FM radio based positioning. The first localization system based on FM radio signals was presented by Krumm et al. [54]. It was an outdoors-only positioning system that employed a prototype wristwatch device (with an FM receiver) to distinguish six districts of Seattle using the signals broadcast from public FM stations. The authors were able to identify the correct district in about 80% of cases. More advanced algorithms, combined with propagation modelling, enabled the system to locate the user with 8 km median accuracy [1].

Fang et al. [2] presented a comparison of FM and GSM outdoor localization within 20 reference points in an urban area of about 1 km<sup>2</sup>. Using the data collected with a professional spectrum analyzer, the authors demonstrated that with six-channel fingerprints the GSM accuracy was better than that of FM; however, when the number of FM channels was increased to 11 the situation reversed (error below 20 m in 67% of cases). In a rural area, however, GSM signals were weaker and 5-channel FM positioning outperformed the 8-channel GSM based system; the FM positioning error was within 35 m with 67% probability. Unfortunately, the reported data is not sufficient to compare FM accuracy in urban and rural areas for equal number of used channels. The authors also reported better temporal stability of FM signals in comparison to GSM.

Recently, the same group evaluated the positioning performance of multiple wireless technologies (FM, GSM, DVB, Wi-Fi) in both outdoor and indoor settings. However, FM measurements were performed only outdoors [55] and therefore FM positioning was not included into comparison of indoor localization systems.

All the systems described above utilize the differences of signal strength between different locations. The two main sources of signal attenuation (leading to spatial variation of the fingerprints) in outdoor settings are:

free-space propagation loss (in order of  $20 \log d$ , where  $d$  is travel distance) and shadowing by terrain and buildings [14, 56]. In [2], the distance between test points was about 100 m, and free-space propagation loss contributed about 40 dB to the signal strength differences between locations. At indoor scales, however, the free-space propagation loss is negligible and the main source of spatial signal variation is fast fading caused by indoor obstacles and multipath propagation [6, 14]. Thus, the discussed FM positioning systems rely on outdoor-only propagation phenomena and their results cannot be simply scaled down to indoor scenario.

In 1994, Giordano et al. [57] proposed (and patented [58–60]) an FM based outdoor localization system which leverages differences of FM stereo pilot phase (see Section 2.3.3), as received by the mobile unit and a fixed observer. The authors claimed the accuracy “on the order of 10–20 m depending on channel conditions” [57, p. 1144]. However, the origins of these numbers are questionable, since the authors have not provided any experimental proofs of the claimed performance. Moreover, there are certain indications that the pilot tone, although transmitted with a good stability, is distorted by multipath [61, 62] and non-linear effects in the receiver [63, p. 5]. For instance, typical peak-to-peak pilot phase fluctuations observed by Howe [62] were of about  $2 \mu\text{s}$ , which corresponds to about 600 m distance for a 19 kHz pilot tone. Such a low accuracy is unsuitable for indoor positioning, and the phase-difference approach is listed in this thesis only for completeness.

Broadcasting FM stations can also be employed as “illuminators of opportunity” for passive coherent location (PCL) systems [64, 65]. PCL systems exploit civilian ground-based stations such as FM radio, digital and analog TV, cellular networks as the transmitters in bistatic radar setup (spatially separated stationary transmitter and receiver). This setup is effective against stealth technology, while passive receivers make the radars

less vulnerable for electronic counter measures. By correlating the direct and target-scattered signals, a PCL system is able to estimate the distance to the target. FM-based PCL systems have a theoretical range resolution of up to 1 km [66] with the coverage of tens of kilometers [64]. PCL systems, however, are largely out of the scope of this thesis and are mentioned only for completeness.

As the literature shows, the previous works have focused only on outdoor localization using broadcast FM signals and special receivers (prototype wristwatch [1], professional spectrum analyzer [2] and special radar equipment [64, 66]). This thesis, in contrast, focuses on *indoor* positioning with consumer-grade mobile devices. This is first study of indoor localization using FM-band radio signals.

#### 2.2.4 Other systems

While Wi-Fi and cellular networks represent the prevailing infrastructures for indoor localization due to their availability, there are many other positioning technologies. This section presents a short overview of the relevant systems and an analysis of their properties.

Practically every Wi-Fi enabled mobile device, such as cellphone or computer, also has an embedded Bluetooth module. The distance range of the typical class-II devices is 10 m. Moreover, Bluetooth hardware and communication protocol have been designed with a focus on low power consumption. All of this makes Bluetooth an interesting technology for indoor positioning, and there are several works dedicated to Bluetooth based localization systems [67, 68]. However, the coverage of such systems is very limited due to the short range of Bluetooth modules, and, more importantly, the lack of *stationary* Bluetooth devices. Another drawback is that each location acquisition runs the device discovery procedure; this significantly increases both the localization latency (10–30 s) and power

consumption. Therefore, Bluetooth is commonly agreed [67] to be unsuitable for localization systems.

Ultra-wide band (UWB) systems, on contrary, demonstrate very good localization accuracy. The commercially available indoor localization system Ubisense [69] employs TDOA and AOA methods for UWB radio signals and is capable of achieving 15 cm accuracy in three dimensions. However, the system has a very high cost which severely impacts wide adoption.

Radio Frequency IDentification (RFID) technology is widely used for asset tracking and shop security systems. Due to the short communication range (dozens of centimeters), it provides a good localization accuracy. The short reading distance, however, also significantly limits its possible application areas. While RFID based systems can accurately detect proximity and are used for activity recognition [70], a wide-scale indoor localization requires a dense infrastructure of either tags (for mobile reader) or readers (for mobile tags). The limited coverage and sporadic location updates make RFID based systems unsuitable for general-purpose indoor localization.

An interesting approach to indoor positioning has been proposed by [71]. The system included two beacons which injected radio frequency (RF) signals into domestic powerline. These signals were then detected by a specialised receiver and associated with the user's location using the fingerprinting approach. An extended, wide-band version of the system achieved a room-level accuracy of 90% [72]. While only two beacons are sufficient for an entire building, the system relies on specialised hardware with limited availability.

Digital Enhanced Cordless Telecommunication (DECT) phones, despite their popularity in Europe, have received little attention with regard to their suitability for indoor localization. This can be explained by limited availability of DECT systems capable of providing signal information to external devices (such as computers or smartphones) and high cost of such

systems. However, recently, Kranz et al. [73] presented a DECT positioning system employing an open DECT stack implementation. The authors demonstrated that in all indoor scenarios DECT localization outperformed the Wi-Fi based system. This can be explained by the relatively high transmission power of DECT stations (up to 250 mW [74, p. 27]), which results in significantly higher number of DECT stations in each fingerprint, in comparison to Wi-Fi.

Contrary to indoor results, the accuracy of DECT localization in outdoor scenario was lower than Wi-Fi, despite the larger number of DECT stations. This demonstrates that the differences between indoor and outdoor environments with regard to localization accuracy vary depending on the environment, and a low accuracy outdoors is not necessarily the case indoors. Thus, the low outdoors accuracy of FM radio based systems discussed in previous section, cannot constitute a basis for assumptions about FM radio's applicability for indoor localization.

While DECT presents an interesting opportunity for localization systems, its coverage is currently limited to European urban environments; no DECT signals were detected in US [75]. DECT based localization would also require hardware modifications of the mobile devices. These reasons significantly limit the feasibility of DECT localization at the present time.

### 2.2.5 Summary

A summary of the wireless positioning technologies discussed above is presented in Table 2.2.

Table 2.2: Summary of wireless indoor localization technologies.

Technology	Accuracy	Coverage	Power consumption	Cost of infrastructure	Note
Wi-Fi	medium	low	high	low	Low cost if the infrastructure is already available; however, initial deployment is expensive.
Cellular	low	medium	high	low <sup>4</sup>	Subject to environmental influence; low accuracy with standard hardware.
Bluetooth	medium	low	high <sup>1</sup>	high <sup>5</sup>	High localization latency.
RFID	high	low	low/high <sup>2</sup>	low/high <sup>2</sup>	Sporadic location updates.
Powerline	medium	low	not reported	high	Requires specialized hardware.
DECT	medium	medium/low <sup>3</sup>	low [76]	low	Mobile device requires special (expensive) hardware.
FM (outdoor)	low	high	low [77]	low	Receivers are readily available in mobile devices.
FM (indoor)	?				

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<sup>1</sup>Bluetooth localization requires device discovery procedure, which is power-consuming.

<sup>2</sup>RFID tags are cheap and either have low power consumption or powered by readers [78]. Mobile RFID readers are more costly and have relatively low battery life [79].

<sup>3</sup>DECT coverage is high in Europe and non-existent in US. No data is available for other regions.

<sup>4</sup>While the actual costs of cellular base station hardware are high, its is typically covered by the cellular network operator. A positioning system employs the already existing cellular infrastructure rather than deploying a new one, therefore from the localization system's perspective the costs are low.

<sup>5</sup>Bluetooth infrastructure costs are high because Bluetooth devices are typically mobile; the stationary Bluetooth access points are not commonly found.



## 2.3 FM radio technology

This section provides background information about FM radio technology and its specifics. This material is necessary for complete understanding of some aspects of the proposed approach.

### 2.3.1 Overview

Despite its considerable age, FM radio is still very popular. It is widely available across the world, and most households have even more than one receiver [80, p. 7]. Car manufacturers consider FM radio as a de-facto standard feature [80]. Although currently there are global trends of substituting analog broadcasts by digital ones, the European Radio Spectrum Policy Group notes that “there is no indication of any progress anywhere to cease analogue radio in the foreseeable future” [80].

FM radio employs the frequency-division multiple access (FDMA) approach which splits the band into a number of separate frequency channels that are used by stations. FM band ranges and channel separation distances vary in different regions (Table 2.3).

Table 2.3: FM broadcast frequencies and channel spacing for different countries [81].

Country	Frequency range	Channel spacing
Europe	87.5–108.0 MHz	100 kHz
US	87.5–108.0 MHz	200 kHz
Japan	76.0–90.0 MHz	100 kHz

While the “FM” part of the “FM radio” originally refers to frequency modulation of the signals, it is now customarily used as a reference to commercial radio broadcasts occupying their dedicated frequency band (see Table 2.3). In this thesis, “FM” generally refers to the radio waves of the corresponding frequencies rather than to the modulation type, unless explicitly stated otherwise. The transmitters employed by broadcasting

FM stations are powerful: a typical radiated power is 50 kW [74, p. 11], while for large stations it may reach 250 kW [82]. High transmission powers and elevated antennas result in high availability of FM signals. Figure 2.2

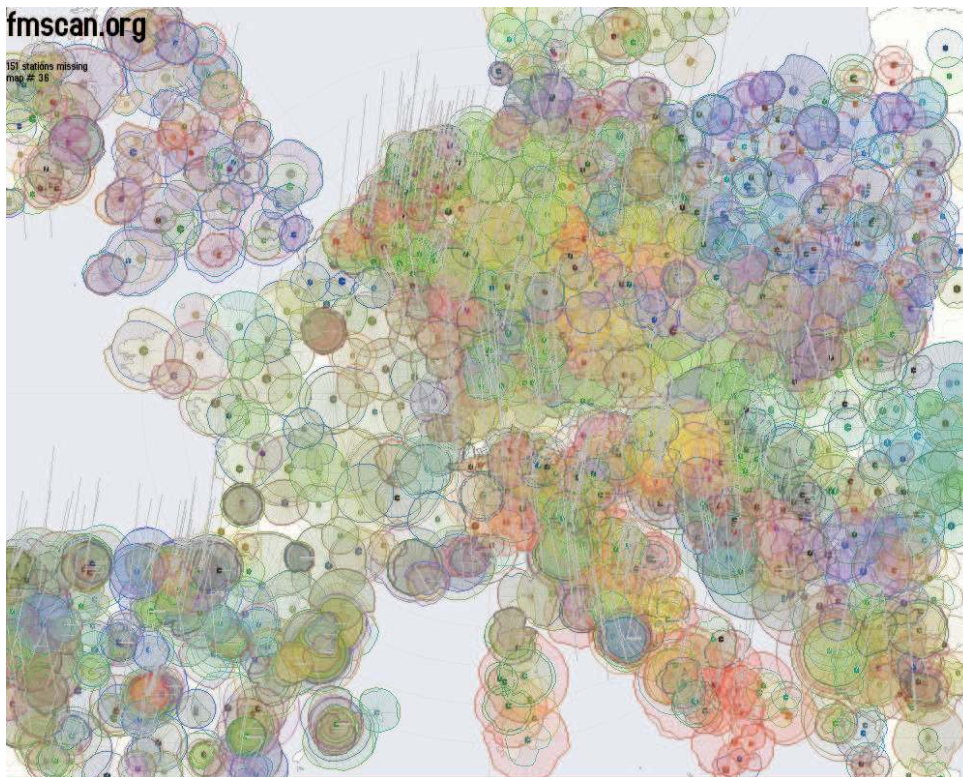


Figure 2.2: FM radio coverage in Europe (only stations with power above 5 kW are shown) [44].

demonstrates the FM coverage in Europe, provided by the stations with transmission power above 5 kW (less powerful stations are not shown to improve picture clarity).

### 2.3.2 Properties of FM radio signals

The major difference of FM radio signals from other technologies, such as Wi-Fi, GSM or DECT, is defined by the significantly (9 to 50 times) lower operational frequencies. The low frequency provides the FM localization a number of advantages described below.

Firstly, FM signals are less affected by weather conditions. The recommendations of the International Telecommunication Union suggest that rain scatter interference is negligible for frequencies below 1 GHz [53, 83, p. 8], while fog and clouds can be ignored for up to 10 GHz [16].

Secondly, low frequency radio waves are less sensitive to the terrain conditions. In particular, the specific attenuation in woodland at 100 MHz is typically about 0.04 dB/m, while for GSM frequencies (0.9/1.8 GHz) the attenuation increases to 0.1–0.3 dB/m, with additional 20% for trees in leaf [17]. The foliage movement due to wind may produce additional attenuation at higher frequencies [17]. FM signals are thus not affected by these minor influences.

Thirdly, the attenuation of radio waves by building materials increases with frequency [41, 74] and thus FM signals penetrate walls more easily than Wi-Fi or GSM. This ensures high availability of positioning signals in indoor settings.

Finally, the FM wavelength of about 3 m results in different interaction with most indoor objects, as compared to 0.12 m Wi-Fi waves. At low frequencies, when the obstacles are small compared to wavelength, they do not interact significantly with the electromagnetic fields of the wave [41, p. 132]. However, when the size of an obstacle is comparable to the wavelength, interaction is very strong and produces complex interference patterns [14, 41]. Ultimately, this means that most indoor objects are transparent for long FM radio waves, but do interact with shorter Wi-Fi and GSM signals. Clearly, this makes FM signals less perceptive to small object movements than Wi-Fi or GSM.

The described considerations suggest that FM based indoor positioning has a number of theoretical advantages over the current high-frequency systems.

### 2.3.2.1 Capture effect

For amplitude modulated signals, when two stations broadcast on the same or nearby frequencies, both of them will be heard at the receiver side. This, however, is not the case for frequency modulation, which is inherently more robust to interference. Due to the so-called *FM capture effect*, only the station with the strongest signal will be demodulated and reach the receiver's output, while the other will be attenuated to a high degree [84] (assuming that both signal levels are above the *capture threshold* [85]).

The capture effect enables situations when several FM beacons can occupy the same frequency channels without interfering with each other. The receiver will notice only the strongest beacon.

### 2.3.3 Stereo FM and RDS

Due to relatively wide channels, FM broadcasts may include more information than just monophonic audio, and transmit also stereo sound and digital data.

The currently used stereophonic multiplexing scheme has been proposed by Zenith Corp. and General Electric Company [86]. Although its stereophonic quality was somewhat lower than that of a competing system, it had smaller losses for monophonic reception and had significantly lower cost [63]. To ensure the compatibility with monophonic receivers, left ( $L$ ) and right ( $R$ ) audio channels are encoded as a summary  $L + R$  and a differential  $L - R$  signals (Figure 2.3). The  $L - R$  sub-channel modulates a 38 kHz sub-carrier, which is not transmitted but instead is restored at the receiving side from a 19 kHz *stereo pilot* tone. This design decision was motivated by the fact that higher frequencies of the baseband are subject to increased noise [61, Fig. 9 and 12]. The noise in the stereo pilot and the differential  $L - R$  sub-channel explains why mono transmissions have

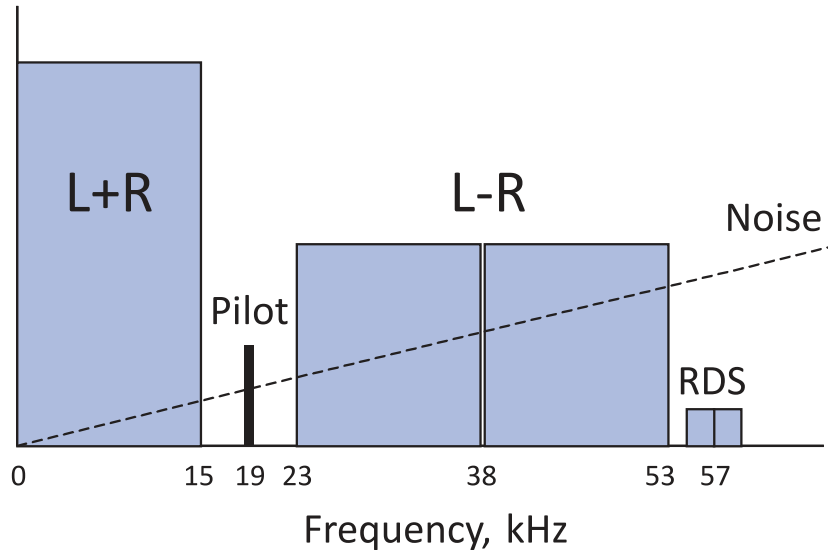


Figure 2.3: Spectrum of a multiplexed FM signal (the noise level is scaled up for clarity).

higher SNR than the stereo ones.

The 57 kHz sub-carrier of the multiplexed FM signal is reserved for the Radio Data System (RDS) [87], which delivers a differentially-coded 1187.5 bit/s datastream to the RDS-enabled receivers. The data carried over the RDS contains various information, such as station identifier, programme name, alternative transmission frequencies; some data slots are available for Open Data Applications which allow the broadcasters to deliver customized data [87]. However, due to the position of the RDS carrier in the multiplexed spectrum, the RDS is very sensitive to noise.

#### 2.3.4 Short-range FM transmitters

Apart from the broadcasting FM stations, there also are short-range FM transmitters available for private use. These devices, available at a low cost in conventional electronics markets, are commonly used to deliver high-fidelity sound from various sources to home or car audio system. Approximately 3.4 million devices were sold in US in 2005 [88].

In most countries the usage of radio 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 [89]. 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 [90, Section 15.239b]. The device can be used only with the antenna furnished with it [90, Section 15.203] (European regulations do not include this requirement). 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 [90, Section 15.23a].

## 2.4 Summary

The analysis of the state of the art demonstrates that at the moment there are no perfect indoor localization systems reported in the literature. The major problems are limited coverage (Wi-Fi, Bluetooth, RFID, powerline, DECT), high power consumption (Wi-Fi, cellular, mobile RFID readers), low accuracy (GSM) and high hardware costs (Bluetooth access points, powerline, RFID readers, specialized DECT receivers).

FM radio stations, in contrast, provide worldwide coverage; FM receivers are already embedded in many mobile devices and have small power consumption. However, in the current literature the accuracy of FM based positioning has been evaluated in outdoor settings only and there are no

results for its indoor performance. This gap is addressed by the present thesis.





# Chapter 3

## Indoor positioning using FM radio signals

This chapter introduces the FM radio based positioning system, analyze the features it relies upon and provide an in-depth description of the used methods and techniques.

### 3.1 Proposed approach

The indoor positioning system proposed in this thesis is based on fingerprinting of FM radio signals. As stated in Section 2.1.4.2, the fingerprinting approach is well-suited for indoor conditions, characterized by multipath and non-line-of-sight (NLOS) propagation, refraction and attenuation by internal obstacles, such as walls, furniture and smaller objects [3]. Despite the complex conditions, fingerprinting provides a good accuracy with minimal infrastructure costs [21, 91]. Clearly, while the proximity-based systems are easy to implement, their accuracy directly depends on the spatial density of the beacons. Better accuracy requires more beacons and increases both hardware and deployment costs. The systems based on the direction of signal arrival require sophisticated antenna arrays which are expensive and can be too large for some environments. Time-based systems,

as mentioned in Section 2.1.3, can provide high positioning accuracy, but require precise synchronisation of beacon clocks and suffer from multipath and NLOS propagation typical for indoors. The systems based on fingerprinting are well-suited for complex environments and demonstrate good performance with relatively small number of beacons (Section 2.1.4.2).

In this work, two types of FM radio transmitters (*beacons*) are considered:

- *local beacons*, such as short-range transmitters deployed in the indoor environment (referenced as  $FM_L$  hereinafter);
- *external beacons*, such as broadcasting FM stations (referenced as  $FM_B$ ).

Local beacons can be installed at arbitrary locations, where the positioning system is to be used. Additional beacons improve the accuracy of the system (which depends on the spatial density of the beacons), but increase the infrastructure costs. An FM positioning system with local beacons has substantially lower cost than an equivalent Wi-Fi based system, yet demonstrates comparable or better performance (see Chapter 4).

In the case of broadcasting stations, it is impossible to set the position of the beacons, their number or the transmitted signals. Thus, it is difficult to predict the accuracy of the system in different areas without actual measurements. However, this kind of system does not require any additional infrastructure, which can be a significant advantage over other indoor positioning systems. An experimental evaluation of this approach (Chapter 5) demonstrates that accuracy of an  $FM_B$  positioning system is comparable with that of other systems.

This thesis focuses mainly on self-positioning paradigm [91], whereby the mobile device estimates its location using the signals received from the beacons. An inverse approach, where a number of interconnected station-

ary receivers estimate the location of a mobile transmitter, could also be possible. However, this approach has a number of disadvantages in comparison to self-positioning using FM radio signals. A radio transmission from the mobile device would significantly impact its battery life. Moreover, it could also possibly affect user's privacy, as in a network-based positioning system the user has no control over processing of the location information. In the FM-based self-positioning approach, in contrast, the mobile unit is merely a receiver, invisible to the beacons, and sensitive location data can be processed locally by the mobile device, thus ensuring user's privacy. Due to the described reasons, the proposed FM localization system employs the self-positioning approach.

In any positioning system, there are two core components:

- a method for distinguishing different reference points (beacons), and
- a measure of distance or angle between the mobile unit and the beacons.

Beacon identity is usually encoded in the signal it transmits. While in many systems this information is easily available from the hardware layer (MAC address for Wi-Fi and Bluetooth, Cell-ID for GSM, tag number for RFID), FM radio has not been initially designed to deliver machine-understandable station ID. This thesis proposes several ways to identify a beacon within an FM positioning system, such as: by radio channel, using audio-encoded message, and using RDS data. An analysis of these methods, their features and limitations, will be presented in Section 3.3.

The literature review in Section 2.1 suggests a variety of distance-dependent features of radio signals. The most prominent and widely used feature is the strength of the received radio signal (RSS), or its representation by the receiver's hardware, called the *received signal strength indicator* (*RSSI*). An FM radio signal, however, also carries a lower-frequency audio

component which could provide distance information. This thesis identified four distance-dependent features suitable for FM-based localization:

- received signal strength indicator (RSSI),
- audio signal-to-noise ratio (SNR),
- stereo channel separation (SCS), and
- phase of the stereo pilot tone.

Although the last feature has been found to be unsuitable for indoor positioning, it is included for completeness. The audio-based methods (SNR and SCS) demonstrated limited dependence on the transmitter-to-receiver distance. The main focus of this thesis is dedicated to the RSSI, which yielded the best positioning performance. A detailed analysis of distance-dependent features is presented in the following section.

## 3.2 Distance-dependent features of FM radio signal

The relative position of the user with regard to a beacon can be characterised by the angle between directed antennas, signal propagation time and certain properties of the received signal. For the FM radio, a set of four distance-dependent feature candidates have been identified within this thesis, namely: received signal strength, audio signal quality (represented by signal-to-noise ratio), separation of stereo channels, and pilot tone phase. The following sections discuss each feature in detail.

### 3.2.1 Received signal strength

Received signal strength indicator (RSSI) is one of the most popular feature used for positioning (see Section 2.1.4.2). The RSSI corresponds to the amplitude of the received radio-frequency signal. It can be expressed in

decibels or in abstract units, such as percents or even categorical values like “excellent” or “poor”. Most of the current FM receivers employ the RSSI to provide seek tuning functionality [77]; some of them also provide the RSSI value to the software layer.

Theoretically, received signal strength is inversely proportional to the square of travel distance (see Section 2.1.4.1). In practice, however, the RSSI dependence on distance is subject to multiple factors, such as environment properties, transmitter and receiver characteristics (power, sensitivity, signal processing methods).

In order to evaluate the applicability of the RSSI for FM positioning, two tests with local short-range FM transmitters [92] were performed. The receiver employed in both tests was Nokia N800, which distinguishes 16 RSSI levels (see Appendix B.1).

The first test evaluated the RSSI dependence on the distance from the transmitter. To avoid any interference from furniture, this test was performed outdoors. The results are presented in Figure 3.1. The RSSI dependence on distance is relatively smooth and monotone starting from 0.5 m, and proves the RSSI to be a suitable feature for positioning<sup>1</sup>. The plateau-looking areas can be explained by the limited number of RSSI levels recognized by the receiver used in the test.

In the second test, the measurements were performed indoors. Figure 3.2a shows the RSSI from three transmitters (represented by antenna signs in Figure 3.2b) while the user was moving from Transmitter 1 to Transmitter 3 along the dashed line in the floorplan. Although the dependencies are not very smooth, which is caused by the distortions from the furniture and multipath propagation, the general trends, nevertheless, are clearly observable.

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<sup>1</sup>The RSSI values at distance “0” have been measured in the close vicinity of the transmitter’s antenna, which constitutes the near-field region of the radiation, where reactive component dominates the distance one [74, p. 46]. Therefore the RSSI near the antenna does not follow the general trend.

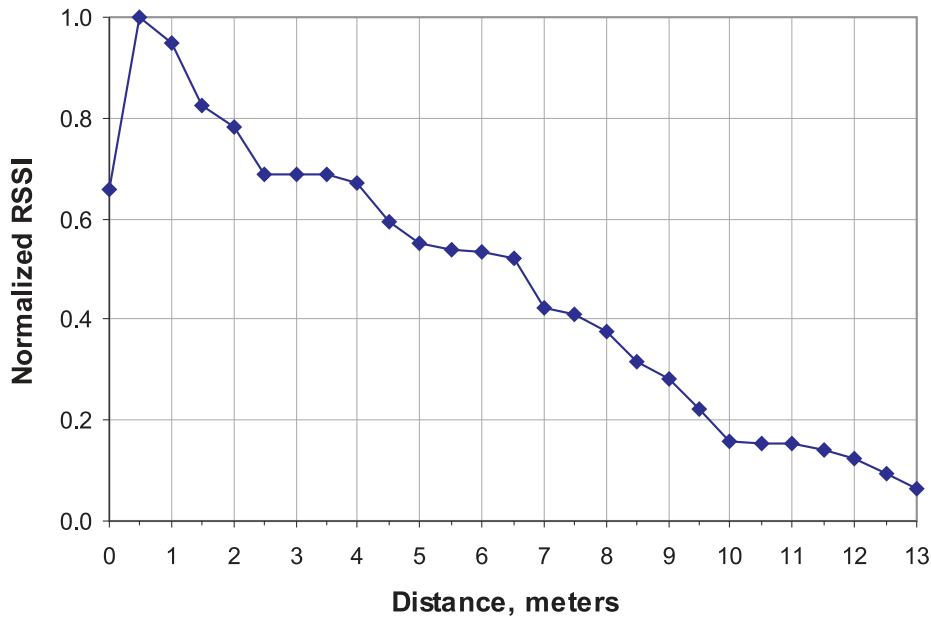


Figure 3.1: RSSI dependence on distance.

The results of the tests prove that the RSSI, commonly used by other localization technologies, is a suitable feature for FM positioning. The RSSI value monotonically decreases from its maximum to zero; the dependence is observable within the whole coverage area of the beacon. Due to these characteristics, the RSSI has been chosen as a candidate feature for positioning experiments (see Chapter 4).

### 3.2.2 Audio signal-to-noise ratio

The primary purpose of FM radio is to deliver sound. The audio information is encoded into the RF signal by means of modulation, and the quality of extracted audio depends on the quality of the received RF signal, which degrades with the distance due to path losses. Thus, it is reasonable to assume that audio signal quality depends on the distance between receiver and transmitter: as the signal strength decreases with the distance, the signal-to-noise ratio (SNR) for the RF signal drops, and the demodulated

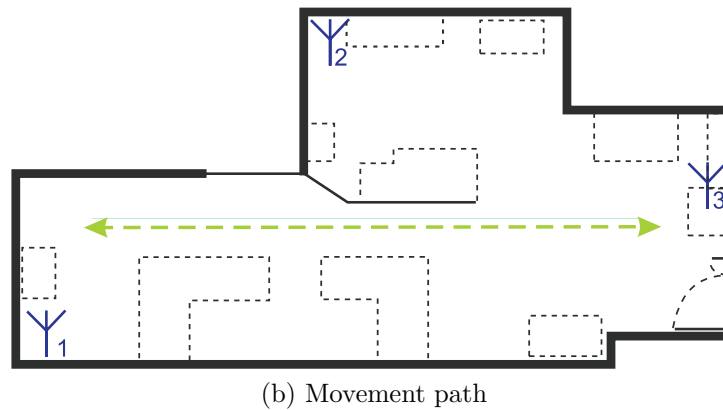
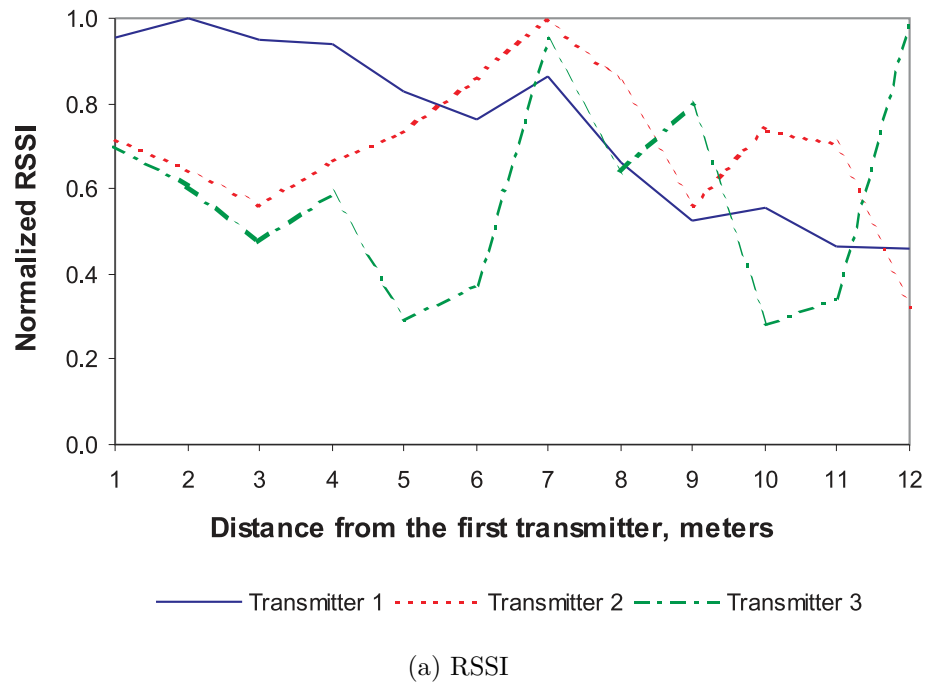


Figure 3.2: RSSI variation while moving along the room.

noise passes through to the audio part, thus decreasing the SNR of the audio signal. Therefore, the audio SNR can be used as a distance-dependent feature of an FM radio signal.

Previously, the SNR method has been successfully used as a measure of receiver-transmitter distance in a positioning system based on amplitude-modulated (AM) signals [71]. Frequency modulation, however, is more robust to noise than the AM [93], therefore a separate experiment has

been performed to evaluate the relationship between distance and audio SNR of FM radio.

To test the applicability of audio SNR method for FM positioning, a short-range FM transmitter has been set to broadcast a continuous dual tone multi-frequency (DTMF) signal for digit “1”, compose of 1209 Hz and 697 Hz sine waves. At the client side, the signal was received by a conventional FM radio (Creative MuVo TX FM). The audio signal was sampled by a laptop sound card at 8 kHz sampling frequency and transformed to the frequency domain using 1024-band FFT. For each distance, 32 spectra were recorded and then averaged. The SNR was then calculated as follows:

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

The experiment discovered no clear dependency of audio SNR from the distance to the transmitter (see Figure 3.3). The distances from 0 to about

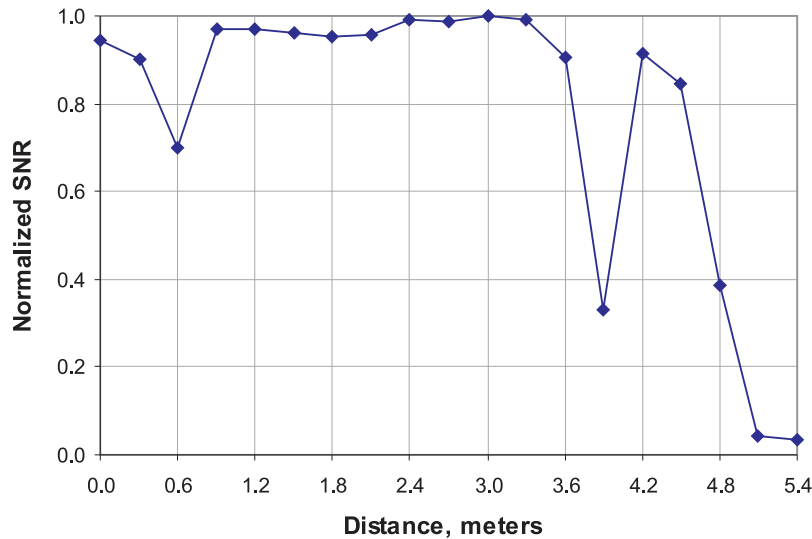


Figure 3.3: Audio SNR dependence on distance.

0.6 m correspond to near field of the antenna[74, p. 46] and are not relevant for positioning. In range from 0.9 m to 3.6 m the mean SNR value remained



almost constant (varied within 5%), 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 FM capture effect which improves the post-detection SNR for non-linear modulations (such as FM) when the pre-detection SNR is above a certain level, called “*capture threshold*”; below this threshold the SNR drops dramatically [85].

However, the observed behavior can also be attributed to the receiver’s noise-reduction circuitry which automatically mutes the audio output if the received signal is too weak [94]. To verify this hypothesis, a separate experiment has been performed with a programmable FM tuner with auto-mute feature disabled.

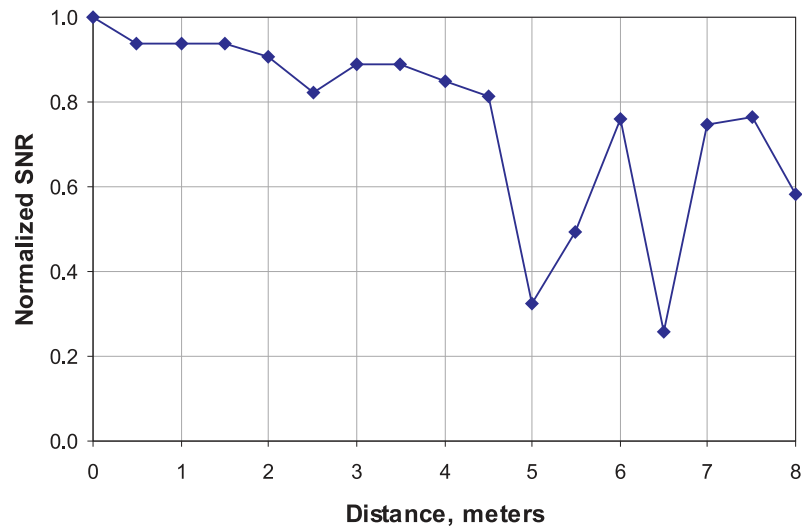


Figure 3.4: Audio SNR dependence on distance (auto-mute off).

The results in Figure 3.4 confirm the assumption, and demonstrate that audio SNR does in fact reflect the distance from the signal source, even though the dependence is less smooth than in the case of RSSI (see Figure 3.1). At short distances, the reception quality is almost perfect, and SNR is limited by the SNR characteristics of the transmitter and receiver.

As the distance increases, the SNR declines.

Thus, audio SNR can be utilized as a distance-dependent feature, provided that audio quality augmentation features of the receiver are switched off. The positioning performance of the SNR approach is evaluated in Section 4.1.3.

### 3.2.3 Stereo channel separation

The FCC rules [95] define “*stereophonic separation*” as

The ratio of the electrical signal caused in sound channel A to the signal caused in sound channel B by the transmission of only a channel B signal. Channels A and B may be any two channels of a stereophonic sound broadcast transmission system.

The motivation for considering the stereo channel separation (SCS) as a measure of distance is two-fold. Firstly, the stereophonic signal is more sensitive to noise than the monophonic one [63]. At the same RSS level, the SNR difference between the two modes can reach 20 dB [61, Fig. 12]. The inherent white noise of the RF signal transforms after the detection to a noise linearly increasing with the frequency [61, Fig. 9]. As described in Section 2.3.3, this noise mostly affects the pilot subcarrier and the differential  $L - R$  part of the stereo signal, where  $L$  and  $R$  denote the left and the right audio channels, respectively. The summary  $L + R$  signal, however, is less affected. Secondly, the quality of the stereo signal strongly depends on the quality of the received pilot subcarrier and distortions in the pilot affect the quality of the stereo signal. When the distance to the beacon increases and the RF signal quality degrades, the differential  $L - R$  part of the audio signal is affected the most, and the receiver gradually combines the stereo channels to maintain the sound quality [77, p. 17].

Consequently, the  $L + R$  part will dominate in the output of the receiver, which results in the reduction of stereo channel separation.

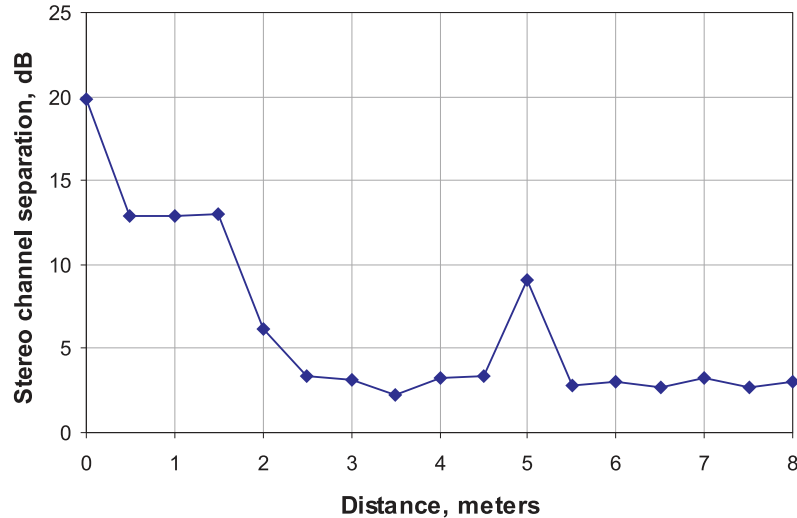


Figure 3.5: Stereo channel separation (SCS) dependence on distance.

Figure 3.5 shows the experimental results for SCS dependence on distance to the beacon (the experimental setup is described in Appendix B.2). As the distance increases, the SCS quickly deteriorates, reaches its minimum and remains constant while the distance grows further. The minimum of the SCS corresponds to no channel separation, or monophonic mode.

The use of stereo channel separation as a measure of distance is unique for FM positioning and, according to the literature, has never been evaluated before. However, it has certain limitations. First of all, the beacons must transmit a known stereo signal, so that the client can estimate the cross-talk between the channels. This limits the SCS approach to local beacons only, as the signal of broadcasting FM stations (voice, music) changes dynamically and is generally unknown. Secondly, the SCS method is usable in a smaller range of distances than the RSSI one, as when the distance — and hence the noise — increases, it becomes impossible to maintain the stereo decoding, and the receiver switches to monophonic mode, ef-

fectively converging the channel separation to zero. The RSSI, however, remains non-zero and sufficient to keep mono reception. The experimental evaluation of the FM positioning system based on the SCS approach is presented in Section 4.1.3

### 3.2.4 Stereo pilot phase

All stereophonic FM transmissions contain a special signal, known as *pilot tone*, which is required to decode the multiplexed audio signal (Section 2.3.3). The stability of this 19 KHz pilot defines the quality of the output stereo signal and therefore the accuracy of the pilot tone is guaranteed by the corresponding standards [96].

Provided that the pilot signal is very stable, it might be possible to use the phase difference of pilot tones from multiple stations to estimate the client position. This idea is presented in [57] and a number of patents [60, 97]. For example, US patent #5689270 [60] proposes to estimate distance between the client and a reference point using the the phase difference of the pilot measured at these two locations. To acquire the position of the client, multiple FM signals (pilot tones) must be collected.

However, this approach is unsuitable for indoor positioning. Despite the pilot stability at the transmitting side, in real world its phase at the receiver is subject to distortions caused by RF channel conditions, receiver noise [63, p. 5], and multipath propagation [61, 62, Fig. 17], which is typical for indoor environments. The experiments conducted by Howe [62] show that a typical jitter of the pilot tone phase is about  $2 \mu\text{s}$ ; given the pilot frequency of 19 kHz and thus the wavelength of about 15 km, the jitter would result in about 600 m positioning error. Clearly, such a high error is insufficient for an indoor positioning system.

### 3.2.5 Summary

A summary of distance-dependent features is presented in Table 3.1.

Table 3.1: Summary of distance-dependent features of FM radio signal.

Method	Working range	Computation complexity	Note
RSSI	all	low	<ul style="list-style-type: none"> <li>• Directly provided by radio hardware.</li> </ul>
SNR	far	high	<ul style="list-style-type: none"> <li>• Beacons must transmit a specific or known signal (inapplicable to broadcasting stations).</li> <li>• Audio sample acquisition takes some time.</li> <li>• Requires noise-reduction functions to be switched off (impossible for some receivers).</li> </ul>
SCS	near	medium	<ul style="list-style-type: none"> <li>• Beacons must transmit a specific or known signal (inapplicable to broadcasting stations).</li> <li>• Effective algorithms exist for extracting separate frequency components [98].</li> <li>• Audio sample acquisition takes some time.</li> <li>• Requires stereo-capable hardware.</li> <li>• Highly sensitive to noise.</li> </ul>
Stereo pilot phase	—	high	<ul style="list-style-type: none"> <li>• Too low potential accuracy for indoors.</li> <li>• Highly sensitive to noise.</li> <li>• Pilot phase has large fluctuations [62].</li> </ul>

As the table shows, the RSSI approach is the best candidate for FM positioning system. The audio-signal based methods, SNR and SCS, have a number of limitations, but can also be used for localization. The estimated minimal accuracy of the pilot phase method is about 600 m, which is far larger than most of indoor dimensions; therefore, this method was not considered any further.

The experimental evaluation of the positioning performance of the RSSI, SNR and SCS methods will be presented in Chapter 4.

## 3.3 Beacon identification methods

### 3.3.1 Radio channels

FM radio broadcast utilizes the frequency division multiple access (FDMA) model, where each transmitting station occupies one or more radio channels. The number of channels and their frequencies are defined by the corresponding standards; in Europe this results in 205 RF channels (from 87.5 to 108.0 MHz, with 100 KHz spacing [77]).

In this approach, each beacon transmits FM radio signals on its own predefined frequency channel and the mobile unit can identify the beacon by simply checking the current frequency of the FM receiver. Essentially, the primary purpose of this method is beacon selection; the identification comes as side effect, subject to the “one beacon — one channel” condition.

While this method is very simple and has minimal computational requirements, there are several limitations that should be taken into account.

Firstly, the number of RF channels is limited, therefore a careful network planning is required to ensure that nearby beacons do not interfere with each other. In this case, the RF channels of  $N$  nearest (strongest) beacons heard by the receiver at any location should constitute a unique set. This would allow reuse of frequency channels by more distant beacons, and thus improve the scalability of this beacon identification approach.

Secondly, with the the RF channel identification method the mobile unit only *assumes* that there is an active beacon transmitting on the selected channel. This, however, might not always be the case, as there can be a hardware failure of the beacon, or its signal could be suppressed by a more powerful interfering transmitter. The mobile unit has no means of detecting such cases and thus it will unwarily rely on the parameters extracted from the interfering signal or noise, instead of those from the positioning beacon. Obviously, such events might significantly affect the localization

accuracy. The robustness of the system to such errors can be improved by increasing the number of beacons scanned by the mobile unit. In this case, individual channel failures would have less impact on the positioning. A further stability improvement can be achieved by combining the RF channel approach with other beacon identification methods discussed below.

Apart from the already mentioned simplicity, this method is very fast, as the current frequency is immediately available from the receiver's hardware, in contrast to other beacon identification methods, which require relatively long data acquisition step. Another advantage of this approach is that it can be used with either local or broadcasting beacons in a uniform manner and even work transparently with a mix of different beacons. Due to the described advantages and low computational requirements, the beacon identification by RF channel has been selected as the main approach for this thesis.

### 3.3.2 Audio signals

Apart from the transmission frequency, positioning beacons can be identified by the information they deliver in the sound part of the FM radio signal. The information can be embedded into the audio in several ways, from continuous pilot tones with specific frequencies, to advanced modulation schemes [93]. It is important, however, to take into account the following consideration.

Firstly, audio processing requires acquisition of a sound sample. Given that during the localization step the mobile device typically has to query multiple beacons, it is important to keep the length of the identification sound sample minimal (but sufficient for reliable analysis).

The second factor, complimenting the previous one, is that an erroneous recognition of the beacon ID may severely affect the positioning accuracy.

Therefore, when the received sound is noisy and the ID recognition is ambiguous, the processing algorithm should discard the result rather than return the most probable result. The validity of the ID can be verified by a checksum attached to the transmitted data packet. If the mobile unit is unable to recognize the beacon ID, or the received signal is too noisy so that the checksum verification fails, the corresponding beacon will be considered as “out of range” (which is often the case for noisy reception) and will not be used for positioning. Thus, in contrast to RF channel approach, failed or unreliable beacons do not introduce any additional positioning error.

In comparison to the RF channel method, the audio ID approach is more demanding to the mobile device resources due to the need to decode the beacon sound signal. It also takes some time to acquire the sound sample and analyze it, while in the RF channel approach the beacon ID is known immediately. Also, as the beacons must emit a specific signal, the audio-based beacon ID approach is limited only to local beacons and cannot be used with broadcasting FM stations.

On the other hand, the audio approach has a number of advantages as compared to identification using RF channel.

- The client is able to detect a beacon failure (no ID transmitted) and to ignore the missing beacon during localization. In case of identification based only on RF channel, the mobile unit is unable to distinguish a failed local beacon from a distant same-channel station, and will rely on the latter for position estimation.
- The audio beacon identification can be easily combined with the audio-based distance estimation methods like SNR or SCS (Section 3.2), as both identification and distance-dependent feature extraction methods can use the same sound sample and share some audio processing steps, thus reducing resource requirements and overall processing time.



In the combined approach, each beacon uses one of the stereo channels to transmit several sound tones with non-interfering harmonics. The client calculated the spectrum of the received sound signal and recognizes the pilot frequencies, which identify the beacon. The ratio of their magnitudes to the rest of spectrum bands is the SNR. That ratio calculated on the other (silent) stereo channel provides the value of channel cross-talk (reciprocal of channel separation).

- The audio ID method does not rely on specific RF channels, so the positioning system has more flexibility with regard to network planning.
- Multiple beacons can be used on one RF channel. Due to the FM capture effect (see Section 2.3.2.1), only the sound from the strongest beacon will be heard by the mobile client, while the signal from other beacons will be attenuated. The possible number of beacons is no longer limited by the available radio channels, as in case of RF-channel approach. With appropriate network planning, it is possible to cover an arbitrarily large areas using only three RF channels (Figure 3.6).

### 3.3.3 RDS data

The Radio Data System (RDS) [87] is a standard way of transferring digital data over conventional FM radio channels (see Section 2.3.3). The RDS is widely used to deliver additional information about the radio station, such as station name, alternative frequencies, current playing title, or local traffic information. The RDS format is extensible with open data applications (ODA) which enable the stations to deliver arbitrary custom data.

There are two approaches for beacon identification using RDS. In the first approach, the beacon transmits its ID directly, either as an 8-character Programme Station (PS) name RDS field, or as ODA data. This method,

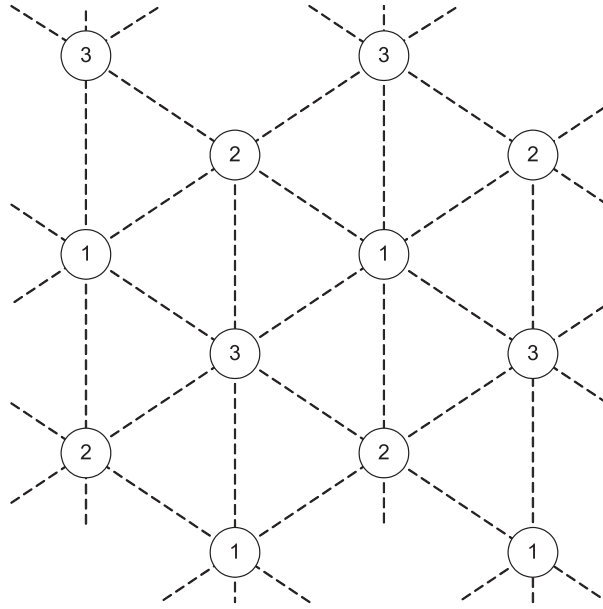


Figure 3.6: A possible beacon network structure utilizing only three RF channels. Circles represent beacons, digits represent channel numbers.

however, is suitable only for local beacons that are programmable. The second approach combines beacon selection using RF-channel approach (Section 3.3.1) and validation of the beacon by its PS name. This approach is suitable for broadcasting stations.

The RDS approach has a number of advantages. Firstly, the RDS processing is done in the receiver hardware, and the decoded data is readily available for the client device, which saves computational and battery resources. Secondly, the RDS envisages error-correcting encoding of all data. Finally, the RDS specification suggests that the program station name should be invariant for the channel [87, Section 6.1.5], which provides a reliable way of identification of broadcasting FM stations.

However, the RDS employs 57 kHz subcarrier, which is subject to increased noise (see Section 2.3.3). The reception and decoding of PS name takes at least 470 ms (RDS synchronization takes about 120 ms [99], after this, the PS name is transmitted in four 104-bit groups with duration

87.6 ms each [87]). Moreover, the acquisition time may significantly increase in case of noisy reception. Nevertheless, the RDS approach is the only method of validating the identity of a broadcasting beacon.

### 3.3.4 Summary

A summary of the beacons identification methods discussed above is presented in Table 3.2.

Table 3.2: Summary of beacon identification methods for FM radio.

Method	Beacon selection	Beacon ID check	Beacon type	Acquisition time	Sensitivity to noise	Resources required
RF channel	yes	no	local, broadcasting	short	n/a	low
Audio	no	yes	local only	medium	medium	high
RDS	no	yes	local, broadcasting	high	high	low

Although audio and RDS based methods provide a reliable recognition of beacon ID and are capable of detecting beacon failures, they have long acquisition times, high computational complexity (audio) and require specific hardware support (RDS). The RF-channel approach, in contrast, provides almost instantaneous results with minimal resource requirements; the beacon failure detection feature was irrelevant for controlled tests. Therefore, this thesis employed the RF channel approach for the performance evaluation experiments.

## 3.4 Data analysis methods for positioning

In a positioning system based on fingerprinting, the data analysis methods solve the problem of associating acquired fingerprints with locations, using the data collected during calibration phase. There are two groups of machine learning methods applicable for this task: classification and regression.

The classification approach considers each calibration point as a discrete class. Given a fingerprint, a classifier returns the class to which this fingerprint most likely belongs. This method considers all locations as independent and is most suitable for symbolic positioning, as it immediately returns the location name or ID. Nevertheless, the classification approach can be easily extended to coordinate-based positioning by including point coordinates into class labels and parsing them later from the classifier output.

The regression approach, in turn, is best suited to work with continuous values. The calibration data is used to train a model (or fit a curve) which associates fingerprints with floating-point values, such as coordinates. At the positioning stage, the acquired fingerprint is fed into the model, which subsequently produces the corresponding coordinate values as its output. Due to the continuous nature of the regression method, it is not suitable for symbolic localization.

The difference between classification and regression is defined by the difference of their output formats: categorical class labels for the first one and continuous values for the second. A classifier can produce only those class labels that were present in the training data. Thus, the positioning accuracy of the classification approach is limited by the granularity of the calibration data, that is the spatial density of the calibration points. If the calibration dataset has been collected for points forming a 1-m grid,

a classifier can either recognize the location correctly, or make at least 1-meter error. With leave-one-out evaluation (see Section 3.4.3), correct recognition is not possible and thus the classification error is always larger or equal to the grid step.

The regression approach is free from this limitation, as the regression model effectively interpolates the data between training points. Thus, the positioning error for a regression can be smaller than the calibration points spacing. However, the accuracy of the regression approach heavily depends on the choice of the fitting model. If the chosen model does not correspond to data, the positioning accuracy remains low, regardless the amount or the spatial density of the calibration data.

The following sections describe the classification and regression methods employed in this thesis.

### 3.4.1 K-nearest neighbour classifier

There are various classifiers that have been successfully used for positioning, such as: neural networks [22, 30], support vector machines [30], Bayesian models [1, 29]. However, as the literature shows, the k-nearest neighbour (kNN) classifier provides very good [30] or best localization accuracy [22].

KNN is a simple yet powerful classification method, widely used in indoor localization systems based on fingerprinting approach [20, 22, 50]. Given a fingerprint to classify, the algorithm evaluates the distances in signal space from this fingerprint to the fingerprints in the training set, and selects  $k$  nearest ones. From the corresponding  $k$  labels, the most frequent one is returned as the classification result [28]. The algorithm works with any suitable distance measure. The commonly utilized Euclidean distance

measure has been used in this thesis:

$$d(\vec{a}, \vec{b}) = \sqrt{\sum_i (a_i - b_i)^2} \quad (3.1)$$

The method has one parameter,  $k$ , the number of considered neighbors. The optimal value of  $k$  is task-specific. The optimal values of  $k$  are found using leave-one-out cross-validation (see Section 4.1.2).

While the kNN method is computationally intensive and does not scale well, it does have a number of advantages, such as very simple and fast training phase (which comprises only storing the training data) and often the best positioning performance [22, 27, 100]. Moreover, kNN demonstrates superior performance in obstructed areas [25] (such as indoors). The described reasons have motivated the application of kNN as the main classification approach in this thesis.

### 3.4.2 Gaussian processes regression

The Gaussian process (GP) regression [101] is widely used for location estimation [26, 27, 102]. Ferris et al. [26] specifically emphasize the GP regression method for RSSI-based localization, because GP is suitable for approximation of a wide range of non-linear functions; moreover, the GP provides uncertainty estimates for its predictions; finally, the algorithm's parameters can be learned from training data via well-know algorithms. This motivated the use of the GP regression algorithm in some experiments (see Chapter 4).

For fingerprint-based localization, the output values of a localization algorithm (that is, coordinates) can be represented as  $y_i = f(x) + \epsilon$ , where  $x$  are input fingerprints, and  $\epsilon$  is a Gaussian noise with zero mean and variance  $\sigma_n^2$ , since in practice only noisy observations of the dependence are available. These observed outputs are jointly Gaussian:

$$y \sim N(0, K + \sigma_n^2 I) \quad (3.2)$$

where  $K$  is a matrix of covariance functions. A covariance function, or *kernel*, reflects the underlying idea of the GP that the function values at different points are correlated. While there are many different covariance functions, the most commonly used one is the squared exponential covariance function:

$$k(x_p, x_q) = \sigma_f^2 \exp\left(-\frac{1}{2l^2}|x_p - x_q|^2\right) \quad (3.3)$$

where  $l$  is the length-scale and  $\sigma_f^2$  is signal variance. The free parameters  $l$ ,  $\sigma_f^2$  and  $\sigma_n^2$  are called hyper-parameters and have a strong influence on the smoothness of the estimated functions [101].

Taking into account training data  $(X, y)$ , one can write the joint distribution of the target values  $y$  and the function values  $f_*$  for a new input vector  $x_*$  as:

$$\begin{bmatrix} y \\ f_* \end{bmatrix} \sim N\left(0, \begin{bmatrix} K(X, X) + \sigma_n^2 I & k(X, x_*) \\ k(x_*, X) & k(x_*, x_*) \end{bmatrix}\right) \quad (3.4)$$

The optimal hyper-parameter values are estimated by log likelihood maximization [101]. Training of the GP model (that is, estimation of hyper-parameters) is a computationally intensive process, and its complexity rapidly grows with the dimensionality of the input data. As the  $FM_B$  fingerprints are rather wide (dozens of stations), the GP regression has been used only in  $FM_L$  localization experiments with few beacons (Chapter 4).

### 3.4.3 Performance evaluation

Supervised machine learning methods (such as kNN and GP) typically require two datasets: for training and for testing. However, collecting

two separate datasets can be rather laborious and time-consuming process in fingerprinting-based systems, due to the number of locations and the measurement time.

A possible solution is to collect a single extensive dataset and split it to the training and testing sets. However, if signal fingerprints are relatively stable (or acquisition time is short), this approach may result in the same data being present in both datasets, which would significantly boost the recognition accuracy (up to 100%), but provide little information about the real localization accuracy of the system.

Therefore, the positioning performance of localization systems is commonly evaluated with leave-one-out approach [20, 30, 50, 51]. From a single dataset, this method at each step extracts one point to be used for testing, while all the other points are used for training. When all the points are processed, the resulting set of recognized coordinates is processed in order to build the cumulative distribution function (CDF) of localization error. It should be noted, however, that leave-one-out approach provides a pessimistic estimate of the real localization accuracy when used with a classifier, since the classifier cannot return a point which was not present in the training set, and thus the best achievable accuracy is defined by the grid step [20].

### 3.5 Fingerprint stability and accuracy degradation

An FM positioning system, similarly to other localization systems based on fingerprinting approach, depends on the assumption that the signal properties measured during the calibration phase do not drift over time. Unfortunately, this assumption holds only for short intervals of time, while in longer-term perspective fingerprints are prone to fluctuations caused by various external factors (Section 2.1.4.2). Such fluctuations inevitably



affect the positioning accuracy and consequently require a periodic re-acquisition of the calibration data, thus increasing the maintenance costs of the system. It has been demonstrated, that many current fingerprinting-based systems are affected by the signal stability problems [72, 103].

A number of factors that may cause fluctuations of fingerprints for a system using local beacons (Wi-Fi or  $FM_L$ ), such as:

- Furniture layout in the room of interest;
- Furniture layout in nearby rooms;
- Air temperature and humidity;
- Temperature of the beacons' components (Wi-Fi access points may warm up under a heavy load);
- Presence of people.

The systems employing external beacons, such as GSM or  $FM_B$  stations, have additional sources of uncertainty:

- Buildings and other large structures (especially RF-reflective);
- Weather conditions (rain, clouds, thunderstorms);
- Vegetation, season of the year [104].

It is worth noting, however, that FM, Wi-Fi and GSM operate at significantly different frequencies (87.5–108 MHz, 2.4/5 GHz and 0.9/1.8 GHz, respectively) and the above factors may have different impact on these systems. In particular, it has been shown that for nearby FM stations with high RSS levels the long-term variations are relatively small [104, Figure 5]. Thus, an important step for ensuring the temporal stability of the  $FM_B$  positioning system is careful selection of beacon stations. The empirical

results of FM RSSI statistics over several hours and days, as well as the influence of people's presence, are presented in Section 5.3.

The problem of maintaining the accuracy of a fingerprinting-based positioning system is addressed by the spontaneous recalibration approach described in the following section.

### 3.5.1 Spontaneous recalibration

An effective, although rather naïve, approach of countering the accuracy degradation is to perform a complete calibration for the whole environment. Acquiring a new set of fingerprints, however, is a labor-intensive process which requires expert knowledge. Thus, full periodic recalibration results in high maintenance costs. To address this issue, a number of projects rely on additional hardware (e.g. RFID or dedicated robot) to obtain new measurements from well-known points [19, 37, 105]. However, these auxiliary devices increase the installation and maintenance costs. In contrast, the method proposed by this thesis does not rely on additional hardware and is transparent for the users.

The spontaneous recalibration approach is based on the observation that in indoor environments there are predefined locations where the position of the mobile device can be derived from context sensors other than the positioning system. Examples of such locations include mobile phone cradle, wall charger, night stand, inductive charging pad, or other places where the device typically remains stationary for prolonged periods of time (hours). These locations can often be easily identified (for example, when the mobile device is placed into a cradle or being charged on a night stand during night time). When the location is known, the device initiates acquisition of updated fingerprints for this location. In contrast to other solutions, the proposed method is capable of updating the signal fingerprints without any additional hardware.

The spontaneous recalibration counters the accuracy degradation by exploiting well-known locations and updating the corresponding points in the calibration dataset. The known locations can be recognized based on certain events detected by the mobile device, such as start of battery charging, or inferred from time, or from their combination. Whenever the mobile device recognizes one of such places, it acquires a stable signal fingerprint  $F$  and compares it with the fingerprint  $F_0$  from the training set. If their difference  $\delta F$  is above a threshold, the calibration data is updated with the new values.

Updating only the current location, however, is insufficient to obtain a noticeable accuracy improvement, because in a typical indoor environment there can be only few reference places with known locations, which constitute only a small fraction of all the calibration points. Thus, updating only few points would not result in a visible improvement of the real positioning performance; an evaluation with leave-one-out method would not demonstrate any changes at all.

This problem can be solved using the following observations. First of all, the reference locations often have a number of unobstructed calibration points nearby. An example can be a nightstand, which is likely to have a passage to it and a bed nearby. Secondly, the RSSI fingerprints of two nearby points with no obstacles around them fluctuate in a correlated manner, as the RF channel changes are insignificant over short distances [3, p. 954], and the signal strengths in nearby points can thus be described by the signal propagation model [20]:

$$P(d)[dBm] = P(d_0)[dBm] - 10n \log \frac{d}{d_0} - WAF \quad (3.5)$$

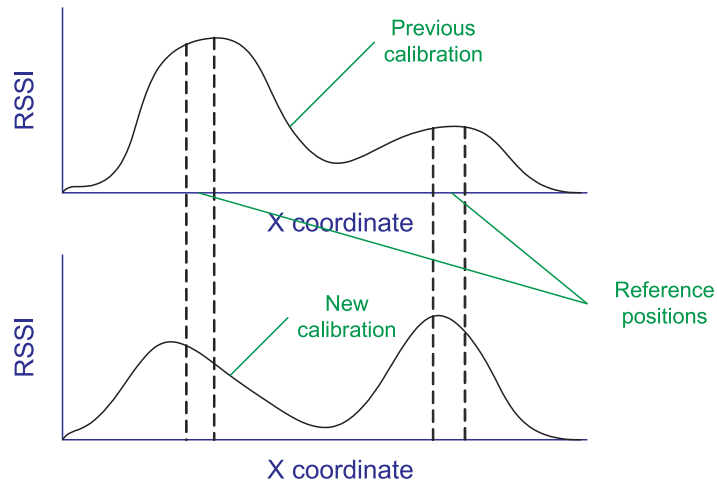
where  $n$  is path loss change rate,  $P(d_0)$  is the signal power at a reference distance  $d_0$  and  $P(d)$  is the signal power at the location at distance  $d$  from the transmitter; WAF is a wall attenuation factor, which accounts

for losses incurred by walls between transmitter and receiver. For two nearby locations with no obstacles,  $WAF$  and  $P(d_0)$  are constant, and  $P(d)$  depends only on the distance  $d$  between the location and the transmitter.

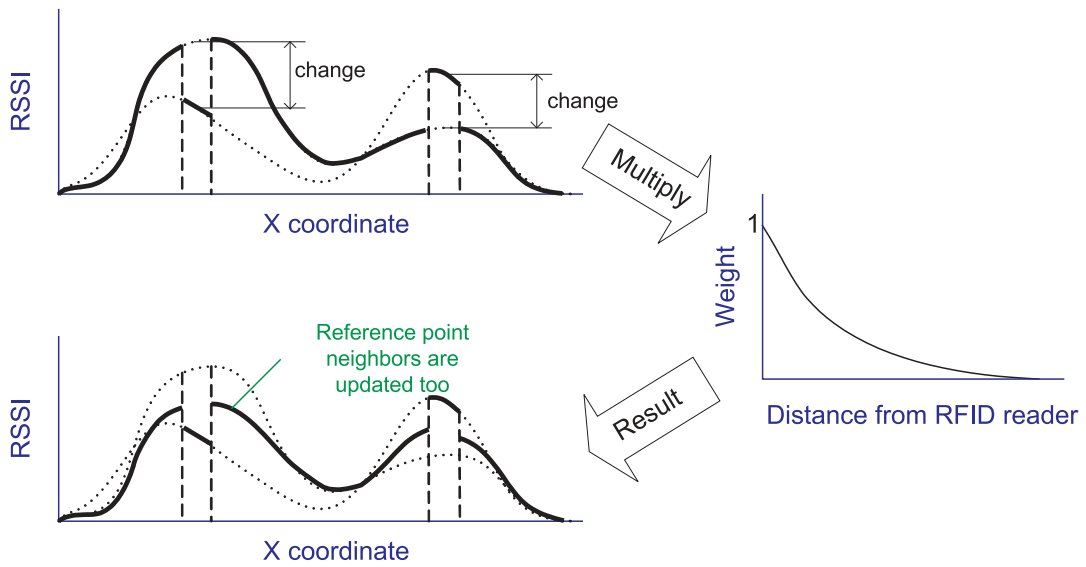
As the signal fingerprints of a reference location and its immediate neighbours change in a correlated manner, an increase of signal strength in the reference point is reflected by the proportional increase in the adjacent points, and vice versa. Unfortunately, as the distance between a calibration point and the reference location increases, so does the chance of finding an obstacle. Therefore, when the calibration set is updated, the fingerprint difference  $\delta F$  is added to the training points with a weighting coefficient  $f(d)$ , where  $d$  is the distance between the reference point and the point being updated. An exponential weight function  $f(d) = e^{-1.5d}$  led to the best experimental results (Section 4.3).

A schematic one-dimensional representation of the spontaneous recalibration approach is presented in Figure 3.7. Figure 3.7a shows a possible change of RSSI distribution over some line in the environment; the positions of the reference points are indicated by dashed lines. Figure 3.7b, in turn, explains how the RSSI changes in reference positions are applied to update the neighbouring points.

As shown in this section, the spontaneous recalibration approach counters the accuracy degradation by employing a number of fixed locations with known positions. It recalibrates the system regularly, with no additional hardware or user effort. The experimental evaluation of the spontaneous recalibration approach, presented in Section 4.3, proves method's capability to maintain the positioning accuracy over time.



(a) RSSI fluctuation along a coordinate axis.



(b) Propagation of the new calibration data to the reference point neighbours.

Figure 3.7: Spontaneous recalibration approach.



# Chapter 4

## Evaluation of FM positioning using local transmitters ( $\text{FM}_L$ )

This chapter presents the results of performance evaluation of  $\text{FM}_L$  positioning system, its dependence on user orientation and its comparison to Wi-Fi positioning. The experimental evaluation of the positioning accuracy decay and the spontaneous recalibration approach is also provided. Finally, a comparison of battery life in FM and Wi-Fi fingerprinting modes is presented.

### 4.1 $\text{FM}_L$ positioning system performance

#### 4.1.1 Experimental setup

The experimental evaluation of an FM indoor positioning system using local short-range transmitters has been performed in a room with dimensions  $12 \times 6$  m; its shape, the beacon locations and the furniture setting are shown in Figure 4.1.

Three short-range FM transmitters (König [92]) and three collocated Wi-Fi stations (Cisco Aironet 1300) shown in Figure 4.2 served as the localization beacons. An initial scan of the FM band has been performed to identify the frequency channels free from broadcast. The FM transmit-

ters were then tuned to these free channels; two-meter wires were used as transmitters' antennas<sup>1</sup>.

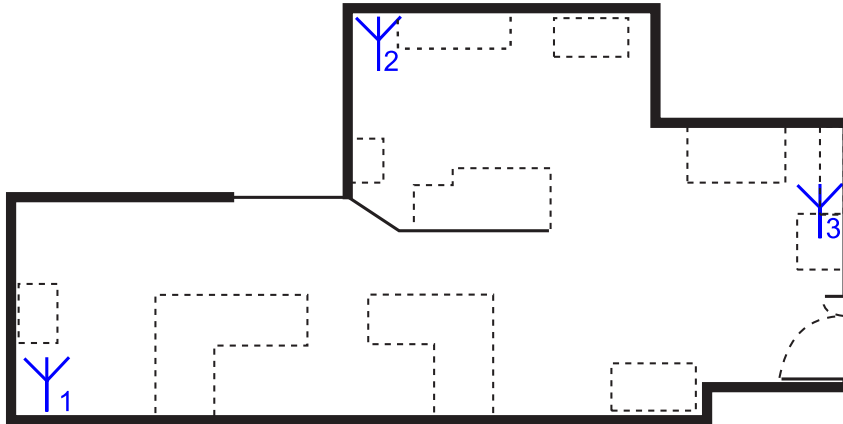


Figure 4.1: Experimental testbed layout (UBiNT lab [106]).



Figure 4.2: FM transmitter and Wi-Fi access point.

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<sup>1</sup>The use of short-range FM transmitters with third-party antennas is allowed in EU (where this experiment was performed), but forbidden in US (see Section 2.3.4). The compliance with the US regulations might have limited the coverage of the transmitters and possibly vary the experimental results, but would not affect the concepts presented in this chapter.



### 4.1.2 $FM_L$ positioning using RSSI

The first experiment explored the accuracy of a system leveraging the RSSI as a distance-dependent signal feature.

In this experiment, an HTC Artemis smartphone (see Appendix B.1) has been used for data collection. The device features an embedded FM receiver and a Wi-Fi module. The data acquisition software has been written in C# using .NET Compact Framework. The FM tuner was controlled through a custom, low-level library written in C++, while the Wi-Fi RSSI values were provided by the OpenNetCF SDF library [27]. A standard HTC headset has been used as an FM antenna.

Due to the firmware design, the mobile device used in the experiment reported the Wi-Fi signal strength as one of six different levels. The FM RSSI, in turn, is represented with 63 levels; the maximum RSSI values, observed in the proximity of the transmitters, were below 45. In order to ensure a fair comparison of FM and Wi-Fi, the precision of acquired FM RSSI samples were reduced to 6 levels as shown in Table 4.1. Note that this

Table 4.1: Mapping of FM and Wi-Fi RSSI (HTC Artemis).

Original FM RSSI	6-level FM RSSI	Wi-Fi RSSI
40 to 49	-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

conversion has an adverse effect on FM positioning accuracy and has been applied only for comparison with Wi-Fi. While FM transmitters were distinguished by their radio frequency, the different Wi-Fi access points were recognized by their MAC addresses. The RSSI values received from different access points were assumed to be independent since the interference does not have an important influence on the system [107].

There are no guidelines for choosing the size of the grid which defines the data collection points. Kaemarungsi and Krishnamurthy [108] demonstrated that with smaller grid size the probability of exact location recognition drops. The issue, however, should be analyzed from a wider perspective: it might be acceptable to sacrifice some “exact match” accuracy for better median precision or 95<sup>th</sup> percentile precision. Several works [42, 100] showed that using a smaller grid spacing does improve the overall localization performance; however, after a certain threshold the accuracy starts to level off or even degrade [100].

Taking this into account, both Wi-Fi and FM signal measurements were carried out in each accessible point in the room (see Figure 4.1) initially following a grid of 1.0 m and then switching to 0.5 m grid (which resulted in 30 cm lower median error). Since not all points were accessible in the room, these datasets contained 40 and 140 points, respectively. The person performing the experiment was always facing the same direction. (The experiments which considered four different orientations will be presented in Section 4.2.)

The location recognition has been performed by kNN classifier and GP regression (see Section 3.4). For the kNN,  $k = 1$  provided the best results. The positioning accuracy was evaluated using the leave-one-out approach of sequentially selecting one point from the dataset as a test point while excluding the rest of the measurements that correspond to this point from the training set (see Section 3.4.3). This procedure was then repeated for the entire set and the errors were calculated as a Euclidian distance between the location estimation and the ground truth. The cumulative distribution function (CDF) of the error distances was then plotted and used as the indicator of the system’s performance.

Initially, the system accuracy was tested using all the 100 signal samples collected at each point. However, the results with only 20 samples per point

yielded no notable degradation, thus suggesting that both FM and Wi-Fi signal exhibit relatively stable behavior and 20 signal samples sufficed without performance degradation.

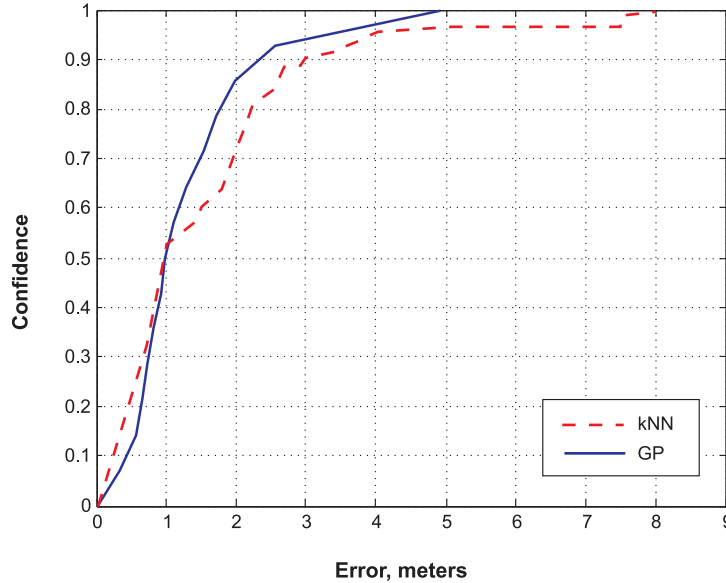


Figure 4.3:  $FM_L$  positioning system performance.

Figure 4.3 shows the cumulative distribution function of the distance error when kNN and GP methods are applied, using the training set with a grid of 0.5 m. The median estimation error (50<sup>th</sup> percentile) of the RSSI-based system is 0.97 m for GP and 0.93 m for kNN while 95<sup>th</sup> percentile error is 2.65 m for GP and 3.88 m for kNN. The next section will present the experimental results for the FM localization system based on audio signal features.

### 4.1.3 $FM_L$ positioning using audio signal features

As it has been mentioned in Section 3.2, there are several distance-dependent features of FM signal, apart from RSSI. These features, namely audio signal-to-noise ratio (SNR) and stereo channel separation (SCS), are correlated with the RSSI, but their effect on positioning accuracy cannot be

directly inferred. This section provides an experimental evaluation of the positioning accuracy of an  $FM_L$  positioning system based on audio SNR and stereo channel separation.

The experiment has been conducted in the testbed described in the previous section. The beacons were set to transmit a stereophonic audio signal; each stereo channel contained a sinusoidal signal of specific frequency. The frequencies were selected so that the sine waves from different channels, nor their harmonics, did not overlap. This has been achieved by employing a DTMF signal [109]: 1209 Hz for the left channel, and 697 Hz for the right one (these correspond to DTMF signal for “1”). At the client side, there was a laptop computer equipped with a Brando USB FM Radio receiver [110]. For each accessible point of a 1 m grid in the testbed, the client recorded a 5 s long audio sample from each beacon (44100 Hz sampling frequency, stereo) and simultaneously acquired the RSSI values for the beacon being recorded (the RSSI was sampled every 100 ms).

The recorded audio samples were processed to estimate the SNR and channel separation values. The procedure was the following. Firstly, the right channel data was discarded and only left channel data has been used for processing. Then, the spectrum of left channel signal was evaluated by fast fourier transform (FFT) with Hanning window of length 8192. The signal magnitude was the magnitude of 1209 Hz band, as 1209 Hz signal was the one actually transmitted in the left channel. The 697 Hz band, in turn, represented the magnitude of the right-channel signal leaked into the left one due to channel cross-talk. Thus, the stereo channel separation was evaluated as the difference between 1209 Hz and 697 Hz band magnitudes. The SNR was evaluated as the ratio of 1209 Hz band magnitude to the average magnitude of all the other bands. Finally, the SNR, RSSI and channel separation measurements for each point were averaged.

The evaluation of the positioning accuracy for each method has been

performed using a kNN classifier ( $k = 1$ ) and leave-one-out approach, implemented in R language [111]. The results are presented in Figure 4.4.

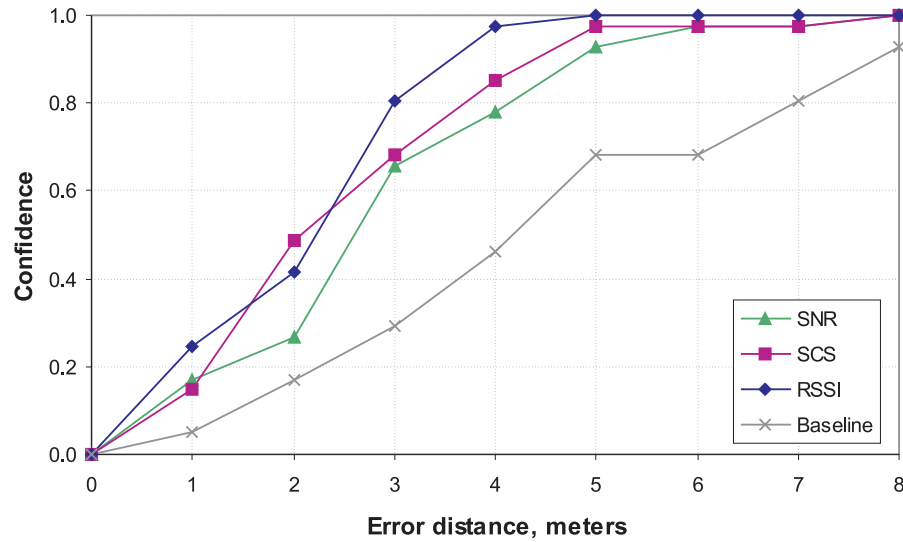


Figure 4.4: Accuracy of FM positioning system using audio signal features.

The results confirm the feasibility of FM positioning based on audio signal properties, as all methods perform better than the baseline (where the system returned a random training point for any input fingerprint). The SCS approach demonstrates a slightly better performance than the SNR one, and provides the best median accuracy of 2.1 m over all competitors. However, the best overall accuracy is demonstrated by the RSSI approach.

In order to understand the reasons behind the inferior performance of audio-based approaches, let us analyze the dependencies between the collected SNR, SCS and RSSI values, presented in Figure 4.5.

Figure 4.5a shows the relationship between SNR and RSSI. As one can see, for low RSSI values the SNR increases linearly or quasi-linearly. At a certain point, however, the SNR reaches its maximum of about 50 dB and saturates. This means that the SNR approach is usable for positioning only

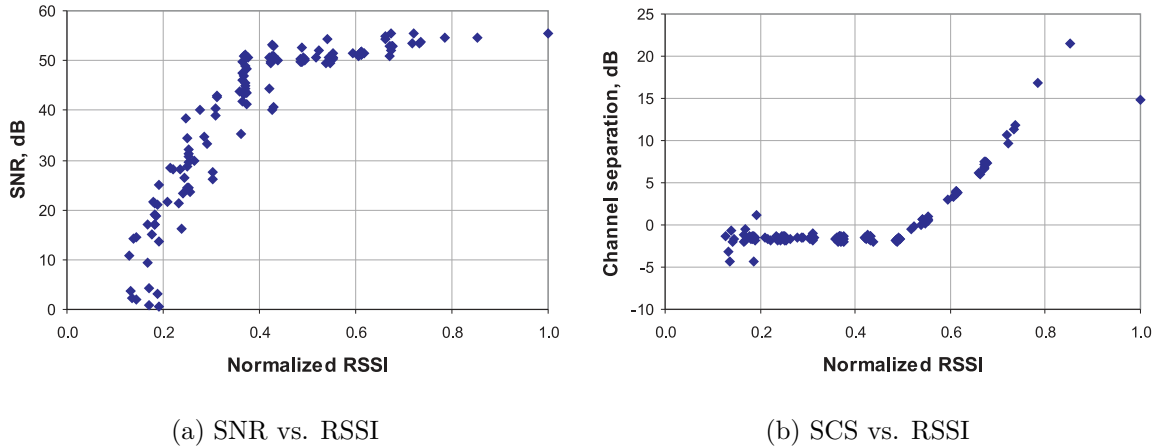


Figure 4.5: Relationship between SNR, SCS and RSSI.

at relatively long distances. At shorter range, when the signal strength is high, the SNR's dependence on distance is weak. This explains why SNR demonstrated lower positioning accuracy than SCS: the power of the used transmitters was sufficient to provide the good audio quality in most parts of the test environment.

Figure 4.5b demonstrates the dependence of channel separation from RSSI. When the signal is weak, the reception is monophonic and the channel separation is low. As the RSSI increases, the receiver eventually picks up the stereo pilot tone and switches to stereophonic mode; the channel separation improves with the further growth of the RSSI.

The experimental results demonstrate that SNR and SCS approaches are more limited than the RSSI one. SCS works at shorter distances with high RSSI values, while the SNR approach is more suitable at longer ranges with low RSSI values. While SNR and SCS methods can be used for positioning, the RSSI is applicable for all ranges and provides better accuracy. Therefore, all further experiments focus on the RSSI approach.

#### 4.1.4 Comparison of $FM_L$ and Wi-Fi positioning accuracy

In order to understand how FM performance relates to other techniques, and to ensure a fair comparison, another set of experiments has been performed to evaluate the FM and Wi-Fi positioning systems performance in the same testbed. As previously mentioned in Chapter 2, Wi-Fi localization systems have gained a notable popularity due to the availability of Wi-Fi infrastructure in many office buildings. This motivated the choice of Wi-Fi as the localization technology to compare FM with.

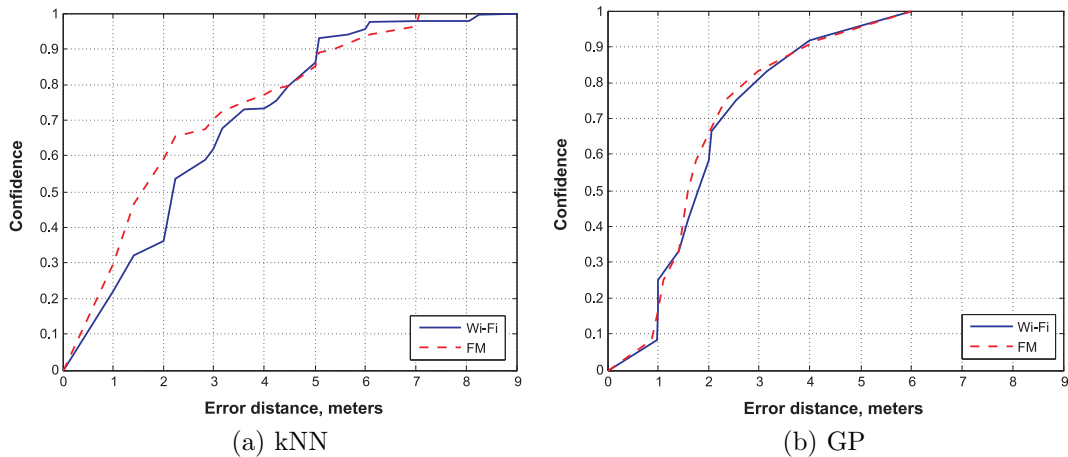


Figure 4.6: FM versus Wi-Fi positioning system.

Figure 4.6 demonstrates the error distance CDFs for Wi-Fi and FM positioning systems utilizing two machine learning algorithms, namely kNN and GP. As mentioned in Section 4.1.2, the test device (HTC Artemis) reported Wi-Fi RSSI in a coarse-grained manner due to firmware limitations. To ensure fair comparison of the two methods, the FM signal strengths were mapped to a scale similar to Wi-Fi (see Table 4.1). Under these conditions, Wi-Fi and FM systems demonstrate very similar performance (Figure 4.6).

From the comparison of the two graphs, one can note that the classification approach provides slightly better median accuracy, but it is more prone to distant outliers, which increase the error for high confidence levels.

The regression approach, in contrast, is more suitable for applications that require high reliability of position information. Also, it should be noted that the nature of classification method makes it impossible for kNN to provide any estimation with an error smaller than the dimension of used grid (in this experiment it was 1 m) while this is not the case for GP regression.

#### 4.1.5 Performance of a combined $FM_L$ and Wi-Fi system

In the literature, there are a number of reports demonstrating that the positioning systems which perform a fusion of different localization technologies usually provide better accuracy than any of these technologies in isolation [10, 43, 112]. This section presents the performance results of a system combining FM and Wi-Fi fingerprinting.

The data fusion has been done by merging the FM and Wi-Fi fingerprints into wider FM+Wi-Fi fingerprints. Despite the simplicity of such data fusion approach, it has been previously demonstrated as being capable to provide an improved localization performance [50, 51, 72]. In this experiment, each wide fingerprint included 6 RSSI values: 3 for FM and 3 for Wi-Fi. The FM RSSI values were of full precision, without conversion to the 6-level values.

The localization accuracy of the combined FM+Wi-Fi system is presented in Figure 4.7. For both data processing methods, the combined system outperforms each of the underlying technologies alone. While for GP the difference is minor, in the case of kNN even low-precision Wi-Fi fingerprints can significantly improve the positioning accuracy of pure-FM approach. The fusion of FM and Wi-Fi positioning technologies improved the positioning accuracy by up to 22% (0.85 m at 95<sup>th</sup> percentile for kNN).

Combining Wi-Fi and FM positioning systems also has a number of other advantages. In the environments with existing Wi-Fi infrastruc-



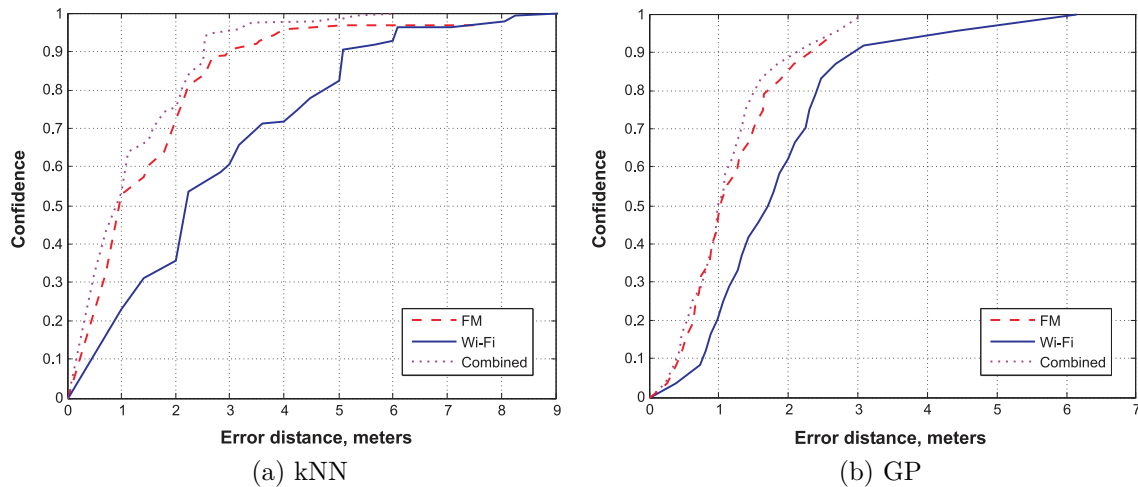


Figure 4.7: Performance of a combined FM and Wi-Fi positioning system.

ture, the positioning accuracy can be improved by installing additional FM transmitters, which are more cost-effective than Wi-Fi access points. FM can also be employed to provide positioning in areas not well covered by Wi-Fi (such as passages and hallways). In sensitive or mixed environments, the mobile devices can switch between Wi-Fi + FM, Wi-Fi-only (when no FM available), and FM-only positioning (where Wi-Fi is banned or non-existent) transparently for the user. Finally, switching between precise Wi-Fi + FM positioning and power-effective FM technology enables smart power management and enhances battery life, due to FM’s lower power requirements (see Section 4.4).

All the experiments presented so far have assumed that the user always faces the same direction. The next section presents an experimental evaluation of the FM localization system which takes into account the user orientation.

## 4.2 Recognition of orientation

The orientation of a user might have a significant impact on the observed signal strength and consequently on the localization accuracy. The reasons for that lie in the direction of mobile unit's antenna, reflections of the radio signals and the fact that components of the mobile unit can partly shield signals from certain directions [113]. For Wi-Fi signals, the user body has a noticeable effect on the signal strength variations [20, 107]. This is explained by the fact that a human body is 70% composed of water and that the resonant frequency of water is 2.4 GHz (similar to Wi-Fi frequencies), which ultimately results in the attenuation of Wi-Fi radio signals by up to 9 dB [107] due to human body. Thus, changing the direction of the mobile device will result in the change of the RSS, even if the position remains fixed. The RADAR project [20] investigated the case in which the training set points were acquired while facing a single direction, while the test samples corresponded to the other three directions. In this case, their results showed a significant (up to 67%) degradation of the localization accuracy.

However, the frequencies of FM radio signals are by orders of magnitude less than the resonant frequency of water, and the effect of user body orientation on the positioning accuracy can be different from Wi-Fi results. The following sections will examine the accuracy of the  $FM_L$  positioning system considering the orientation, and test whether the orientation-induced changes in RSS can provide means for detecting user's facing direction.

### 4.2.1 Impact of orientation on positioning accuracy

This section considers two possible solutions for overcoming the problem of user orientation affecting the RSS fingerprints.

- The first solution consists of having four different training sets (one

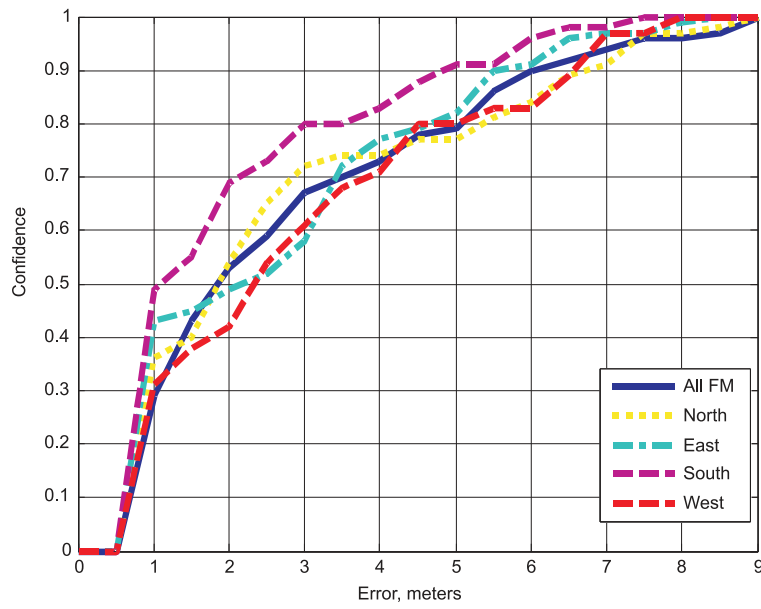
for each orientation). To estimate the location, one of these sets would be used depending on the user's orientation at any given time. The current orientation would be detected using an additional sensor, such as a compass.

- The second solution is based on using one extensive training set that is composed of signal strengths from the three FM beacons for all four orientations in each physical point.

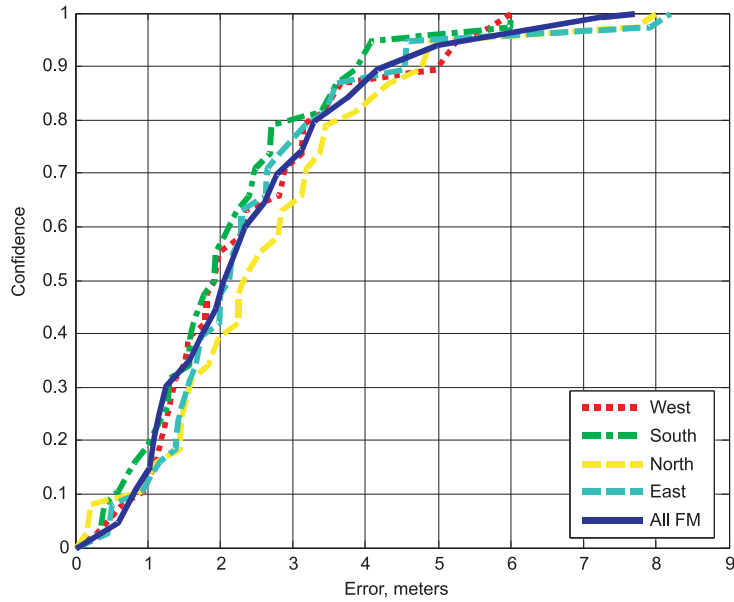
These two approaches have been tested experimentally in order to verify whether having an additional sensor for orientation is an acceptable trade-off in terms of localization accuracy.

The RSSI measurements have been performed in 40 physically accessible points in the testbed, following a 1-meter grid (Figure 4.1). In each point, 20 samples were taken for all four directions: facing North, South, East and West. This resulted in four training sets, one for each direction. The first approach assumes that the orientation is known, so to estimate the user's position one of the four training sets is used accordingly. The accuracy for each orientation has been evaluated by applying the leave-one-out method on four training datasets separately (North, South, East and West graphs in Figure 4.8). Note that the mobile device may be oriented in between of two orientations, such as between North and West for example. In this case, the closest of the four orientations should be taken as the actual user's orientation and the corresponding training set should be used. This means that  $45^\circ$  is the maximal error, which, according to the experimental results, does not significantly affect the RSSI.

In order to compare this approach with the second solution, a leave-one-out evaluation has been performed on the dataset composed of previously used four datasets containing North, South, East and West orientations, all merged together. For each physical point, the leave-one-out method



(a) kNN



(b) GP

Figure 4.8: Positioning accuracy depending on orientation.

excludes from the training set all the measurements (for all orientations) that belong to the current point, and assigns all the other samples (for all four orientations) to the training set. The results are presented in Figure 4.8 for both kNN and GP localization methods.

From the obtained results it can be seen that one extensive training set containing measurements for all four orientations provides a similar localization accuracy to the case when the orientation is known and the corresponding training set is used. In particular, the graphs show that the localization accuracy of using the merged training set with four orientations is very similar to the result of fixed orientation training sets West and East for kNN and North and West for GP (Figure 4.8).

Intuitively, a number of different fingerprints associated to one physical point would result in decreased localization accuracy, since the probability of having similar fingerprints in two or more physical points is higher (for example, facing North in one point may produce the same fingerprint as facing West in another point). Despite this intuition, however, the accuracy of the FM localization system degrades negligibly even if the calibration set includes fingerprints for all orientations. This may be attributed to relatively small interaction of human body with the FM-band radio waves, in comparison to higher-frequency Wi-Fi signals.

Thus, the experimental results demonstrate that the impact of the user body orientation on the FM localization accuracy is minimal, which provides a good basis for a real-life localization system.

### 4.2.2 Analysis of user's orientation

Although the user body orientation has been shown to have a minor impact on the localization accuracy, the RSSI readings are nevertheless affected by the orientation. This motivated the investigation of whether it is possible to recognize the user facing direction from the RSSI readings.

To investigate whether the correlation between signal strengths and orientation is sufficient to estimate user's direction, two datasets were acquired by two different people. Out of these datasets, one was used as the training set and the other as the test set. Both sets were composed of RSSI fingerprints for 40 physical points following a grid of 1 m and including four orientations. As in the previous experiments, the kNN and GP algorithms were used for location recognition. For the kNN classifier, there were four classes, one for each direction. For the GP regression, which has a continuous output, the different directions were annotated with angles ( $0^\circ$  for North,  $90^\circ$  for East,  $180^\circ$  for South and  $270^\circ$  for West). The angle estimation provided by the GP algorithm fell into one of the ranges:  $0^\circ \pm 45^\circ$ ,  $90^\circ \pm 45^\circ$ ,  $180^\circ \pm 45^\circ$ ,  $270^\circ \pm 45^\circ$ , which were subsequently labelled as one of the four orientations, North, East, South and West, respectively.

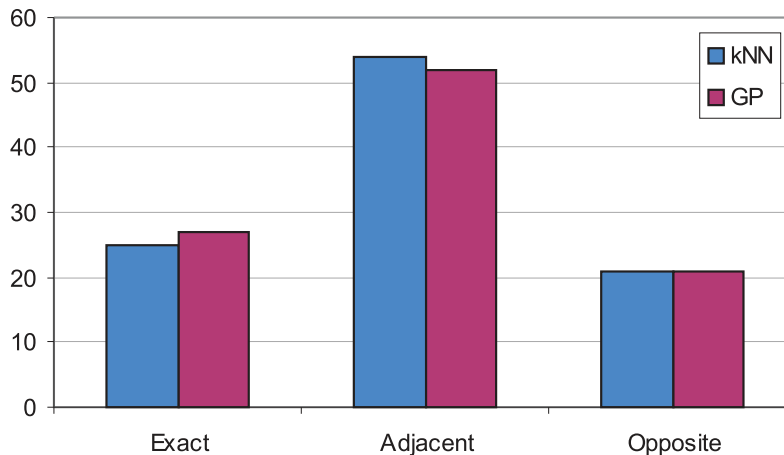


Figure 4.9: User orientation detection results.

The obtained results are shown in Figure 4.9. The bars in the graph have the following meaning:

**Exact** describes the results when the estimated orientation matches the ground truth;

**Adjacent** corresponds to the cases when the estimated and real orientation are adjacent (for example, when the system recognizes the true West orientation as North);

**Opposite** depicts the cases when the estimated and real orientation have opposite directions.

It can be seen that the results are similar to a random prediction: around 25% for the accurate estimation, around 50% for one of two adjacent orientations and almost 25% for the opposite directions.

Therefore, the correlation between signal strengths and orientations proved to be insufficient for detection of user body orientation in an FM localization system. These results are in line with the literature reports for Wi-Fi signals. Saha et al. [114] found that while the variation of Wi-Fi signal due to user direction were within 3–4 dB, this value was less than RSSI variation across different locations and even below the RSSI fluctuations within a fixed location (5–7 dB) [114]. Thus, both FM and Wi-Fi systems cannot recognize user body orientation from localization RSSI fingerprints.

### 4.3 Accuracy degradation

Radio signal propagation in an indoor environment is affected by a number of factors, both dynamic (people movement) and long-lasting (furniture layout changes, atmosphere conditions). These factors can change the propagation conditions so that the previously collected fingerprints differ from the current ones, which might significantly decrease the localization accuracy [103].

To evaluate the long-term stability of the FM localization, a number of fingerprint datasets have been collected over the period of seven months, from December 2008 till July 2009. Unexpectedly, the test that was performed in July using the set of fingerprints measured in June showed more

degradation in comparison to the tests in June and July using the training set acquired in December. Such results point to a conclusion that fingerprint fluctuations are derived from a random process and are difficult to predict. The following experiments consider the datasets with the highest accuracy degradation (June and July 2009).

### 4.3.1 Lessening the causes of degradation

The first step of addressing the performance degradation is to lessen the causes of degradation through preprocessing the input data. Some environmental factors, such as air humidity, simultaneously affect the RSSI from all beacons. To compensate for such changes, the RSSI readings from the three FM transmitters have been represented as a matrix with columns  $ss1$ ,  $ss2$ , and  $ss3$  and preprocessed in the following way. Firstly, the absolute RSSI values were converted to their pairwise differences ( $ss1 - ss2$ ,  $ss2 - ss3$ ,  $ss1 - ss3$ ). Then, each column was divided by its maximum value and finally the resulting values were centered around zero by subtracting each column's mean value. The idea behind this procedure was to mitigate the RSSI changes over time and to make new inputs less dependent on their absolute values.

The described preprocessing has improved the performance of the GP regression (even for the same dataset, see Figure 4.10), but had an adverse impact on kNN results and therefore was used only with GP.

Applying the GP regression to the preprocessed data proved the assumption that all transmitters generally follow the same pattern of change or exhibit same degradation levels and that the described preprocessing procedure can mitigate the system degradation to a certain extent. As a result, the median accuracy of the system trained on the June dataset and tested on the July one, improved from 2 m to 1.45 m only due to preprocessing (Figure 4.10).



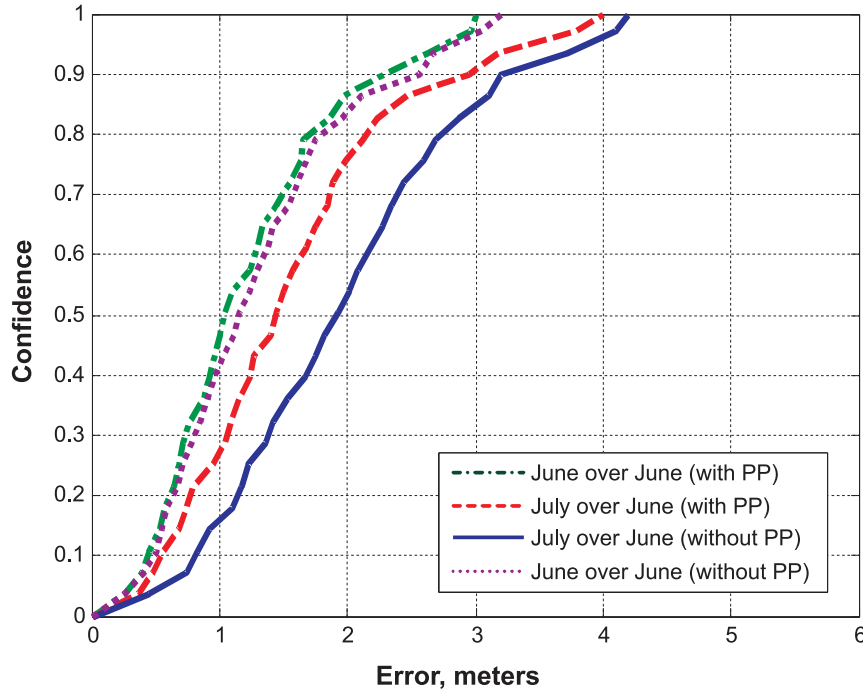


Figure 4.10: Effect of preprocessing (PP) on the positioning accuracy.

### 4.3.2 Spontaneous recalibration approach

The second step of countering accuracy degradation is the spontaneous recalibration method introduced in Section 3.5.1. The method leverages the existence of predefined locations where the position of the mobile device is known or can be inferred. These locations may be associated with mobile phone cradle, wall charger, night stand and other locations where a mobile phone typically remains stationary. When the location is known, the system starts fingerprint acquisition at that location and compares the current fingerprints with those in the calibration dataset. If the fingerprints are different, the calibration data will be updated with the new fingerprints.

In this experiment, five known locations have been defined (Figure 4.11), and these points were sufficient to observe the effect of spontaneous recalibration.

In order to spread the changes from the reference location to its closest

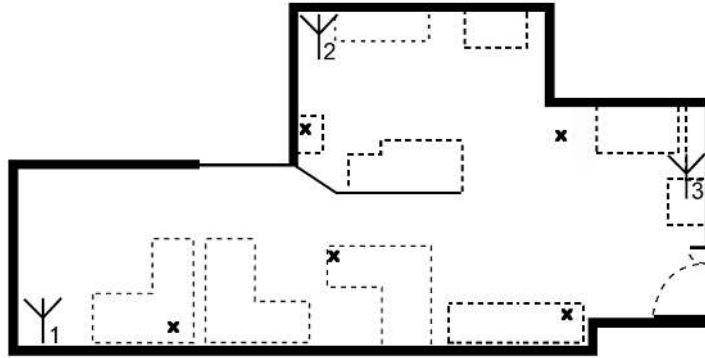


Figure 4.11: Positions of the points used for spontaneous recalibration.

neighboring points, a propagation model has been employed (Formula 3.5 in Section 3.5.1). The parameters of the model have been found empirically from the initial training set. The best suited value for the path loss change rate  $n$  was 2, while the wall attenuation factor was set to zero, as there were no walls between adjacent points. For each reference point, eight neighboring points have been adjusted using the propagation model. Thus, 45 out of 140 points were updated (5 reference locations plus  $5 \times 8$  neighboring points). As a result, the spontaneous recalibration further improved the median localization accuracy from 1.45 m to 1.2 m (Figure 4.12a).

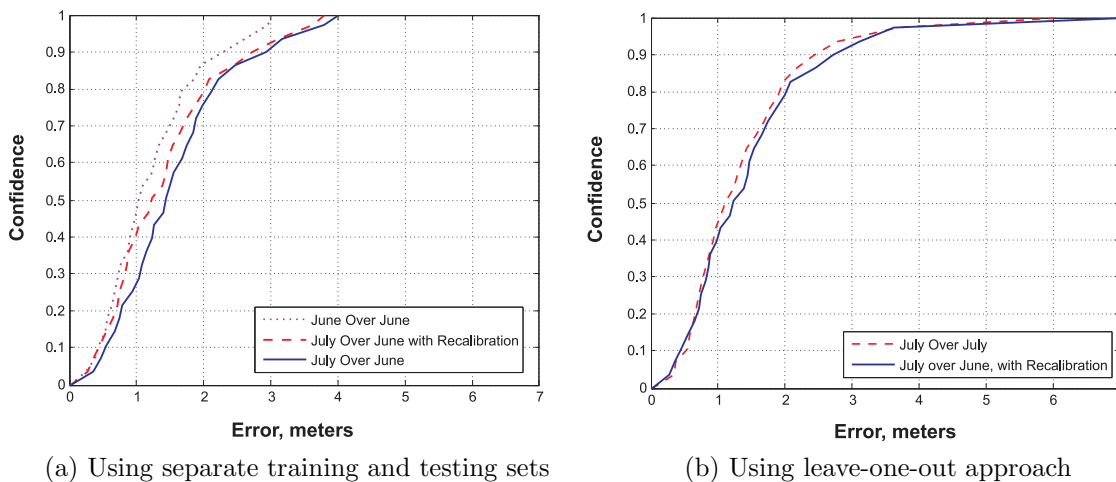


Figure 4.12: Effect of the spontaneous recalibration on system performance.

To evaluate how spontaneous recalibration compares to the complete recalibration scenario (“July over July”), the acquired results were compared using the leave-one-out method (Figure 4.12b). The results depicted in Figure 4.12b show a very similar performance of the spontaneous and complete recalibration (only 12 cm difference in the median error). Thus, using only 5 reference locations out of the complete set of 140 points, the system can be regularly calibrated with no effort from the user and without any additional hardware.

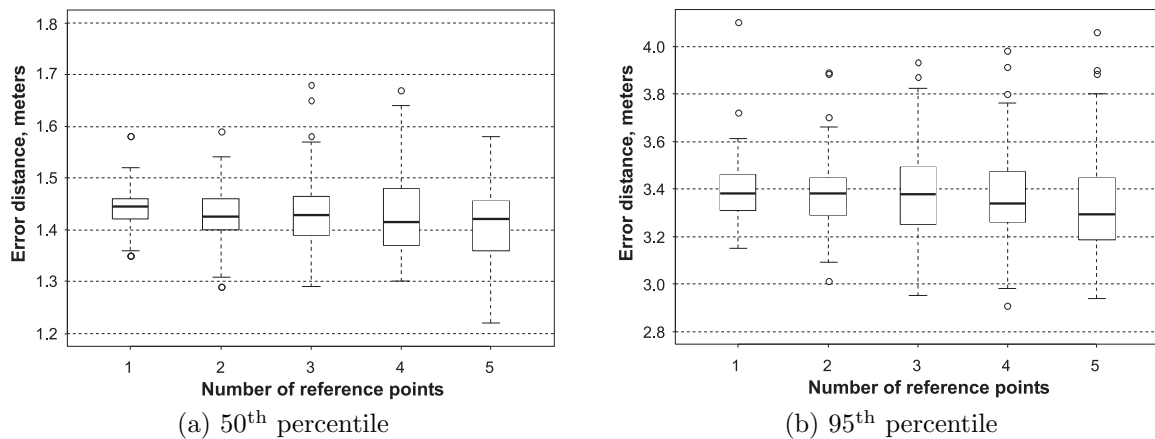


Figure 4.13: Recalibrated accuracy vs. number of reference points.

In order to estimate how the effect of the spontaneous recalibration depends on the number of reference points and their locations, the recalibration procedure has been performed 100 times for randomly selected sets of points. The box-and-whisker diagrams in Figure 4.13 demonstrate the distribution of the median and 95<sup>th</sup> percentile error for the corresponding number of reference points. In the diagram, the thick horizontal lines correspond to median values; bottom and top of each box correspond to the first and third quartiles of distribution, and the whiskers extend up to 1.5 times the interquartile range; small circles represent outliers.

It can be seen that as the number of reference points increases, so does the variance of the positioning error. This demonstrates that some sets

of reference positions are more effective than the others, and by carefully selecting the reference points it is possible to significantly reduce the accuracy degradation. The graphs also show that the accuracy of a recalibrated system generally improves as the number of reference points grows. As explained above, the accuracy gain can be further increased by careful selection of the reference locations.

## 4.4 Analysis of FM and Wi-Fi power consumption

This section provides a theoretical and experimental comparison of FM and Wi-Fi power consumption.

Unlike Wi-Fi modules, the FM tuners are designed for receiving signals and cannot transmit them. Moreover, Wi-Fi requires complicated data processing, while FM demodulation is rather straight-forward process. Due to these two facts, FM receivers have considerably lower power consumption than Wi-Fi modules. Depending on the complexity of its circuitry, an FM receiver can consume from about 15 mW (TDA7088 [94], analog-only) to about 50 mW (Si4703 [77] with RDS enabled). In contrast, Anand et al. [47] have reported idle-state Wi-Fi power consumption varying from 190–390 mW in power-saving mode to 1200 mW in constantly-active mode. Evidently, FM tuners are significantly more power-effective than Wi-Fi network modules. However, the runtime of a mobile device also depends on other components (such as CPU and display) and CPU load. Therefore, it is more appropriate to measure the total battery life of the device, rather than the consumption of separate components.

The battery life tests were carried out using a Samsung Omnia 2 smartphone running My Experience tool [115] with FM and Wi-Fi fingerprinting sensors. My Experience is a popular platform for acquisition of user experience data, which often includes location. Thus, the experiment simulated

one of the real applications for a positioning system. During the tests, My Experience periodically acquired location fingerprint and stored it in a database; the device was kept in the “unattended” power state [116], with screen and backlight turned off. All tests started with a completely charged battery and continued until the device run out of power and switched off. The running time was then extracted from My Experience logs.

Two groups of tests have been performed, separately for Wi-Fi and FM. In order to minimize the influence of other components, all unused wireless modules were switched off (GSM and Bluetooth — for all tests, Wi-Fi — during FM tests, and FM — during Wi-Fi tests). The modules were configured for localization purposes in the following way. For FM tests, a standard headset was connected to the device to serve as an FM antenna; Wi-Fi module was switched off; sound volume was set to zero. During Wi-Fi tests, FM was switched off; Wi-Fi network card was not associated with any nearby access points, to ensure that there are no background data transfers. Both modules used the available power saving routines.

The FM-related tests took into account the number of beacons in fingerprint. While for Wi-Fi the fingerprint acquisition time of 1 s was relatively constant and independent on the number of beacons, an FM receiver needed to switch from one beacon to another explicitly. Thus, wider FM fingerprints imply longer duty cycles due to increased channel switching and longer sample acquisition times; this potentially leads to higher power consumption. FM sample acquisition times are presented in Table 4.2.

Table 4.2: FM RSSI sample acquisition time for different fingerprint width.

Beacons in fingerprint	Acquisition time, s
3	0.4
10	1.5
45	9.0
205	36

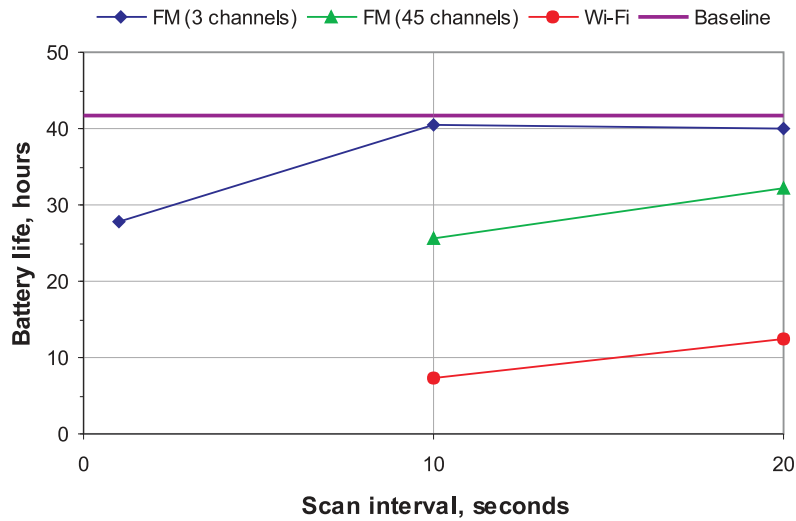


Figure 4.14: Battery life in FM and Wi-Fi fingerprinting modes. The baseline corresponds to all wireless modules switched off.

Figure 4.14 presents the results of battery life measurements in FM and Wi-Fi fingerprinting modes for different scan intervals. As expected, the run time of the device grows as the time interval between scans increases. Unfortunately, it was impossible to evaluate Wi-Fi performance with 1 s update period, as the Wi-Fi driver was unstable at high sampling rates and quickly crashed. From the general trend, however, it is evident that the result would have been less than 7.4 h, which is still significantly below the 27.9 h demonstrated by FM with 3 beacons. Overall, FM demonstrates superior power efficiency, providing 2.6 to 5.5 times longer battery life than Wi-Fi and closely approaching the baseline maximum.

## 4.5 Summary

The evaluation presented in this chapter demonstrated the possibility of indoor localization using signals of local short-range FM transmitters. Both RF signal strength and audio signal characteristics, such as signal-to-noise ratio (SNR) and stereo channel separation (SCS) can be used for positioning. It has been found, however, that SCS method works only at short distances from transmitters while the SNR one — only at longer distances. The RSSI, in turn, covers the whole range and provides superior positioning accuracy.

$FM_L$  provided similar accuracy to the Wi-Fi localization system installed in the same environment; the median error for  $FM_L$  was 0.9 m in a  $50\text{ m}^2$  room. It has been demonstrated that combination with  $FM_L$  can improve performance of an existing Wi-Fi positioning system. The two data analysis approaches used, classification (kNN) and regression (Gaussian processes), demonstrated better median accuracy for classification, but regression has faster convergence and excelled at high confidence levels. The experiments on direction recognition have shown that RSSI is affected by the user orientation. However, the accuracy of direction recognition using RSSI fingerprints was indistinguishable from random. The positive result was that user orientation had only minimal impact on localization accuracy.

This chapter also demonstrated that the gradual degradation of accuracy, which is inherent to any fingerprinting based system, can be countered by fingerprint preprocessing and spontaneous recalibration. The latter is capable of periodical updating the calibration dataset transparently to the user and without any additional hardware.

Finally, the power consumption tests have shown that FM fingerprinting is significantly more power-efficient than Wi-Fi. Depending on sampling

rate and number of scanned beacons, the mobile device with FM positioning client provides 2.6 to 5.5 times longer battery life than in the case of Wi-Fi localization, closely approaching the device's maximum run time.



# Chapter 5

## Evaluation of FM positioning using broadcasting stations ( $\text{FM}_B$ )

This chapter presents the results of experimental evaluation of indoor positioning based on broadcasting FM stations ( $\text{FM}_B$ ), the comparison with other positioning systems, such as Wi-Fi and GSM. Also, an experimental evaluation of  $\text{FM}_B$  RSSI stability and its dependence on people's presence is provided.

### 5.1 Detection of active broadcasting stations

In Europe, the FM band spans from 87.5 to 108.0 MHz with 100 kHz channel spacing. This results in 205 FM channels. While there are many FM stations, usually not all of the available channels are utilized. Clearly, it makes little sense for FM positioning to consider inactive channels without transmission, as they introduce additional noise into fingerprints, increase scanning time and storage requirements. Therefore, there is a need for a method capable of detecting the channels with active transmission.

The common method of finding active broadcasting stations during seek tuning, employed by virtually all FM receivers, is RSSI thresholding, where the receiver registers a broadcasting station at a specific channel if its RSSI

level is above the predefined threshold [77, 94, 117]. While this approach is widely used due to its simplicity, it is not very robust, as setting the threshold too low would increase the number of false-positive detections. On the other hand, with a too high threshold the receiver may not recognize less powerful stations. The manufacturers of FM receiver solutions address this problem by introducing additional channel validation criteria, such as peak noise detectors [77] and SNR estimates [117, 118], intermediate frequency checks [119, 120]. These measures significantly decrease the number of false channel detections. Unfortunately, in some cases the additional seek tuning qualifiers are not available, either due to hardware limitations or when the channel activity data has not been recorded.

In order to evaluate the possibility of detecting active FM channels using only RSSI data, the following experiment has been performed. Initially, the list of active channels has been acquired using the receiver's hardware seek tuning functionality. The receiver was Brando USB FM radio (based on Si4700 chip [121]), the channel spacing was set to 100 kHz and the RSSI threshold was set to 15/63. The procedure was repeated three times and the channels detected in all three cases were listed. Totally, 54 channels have been detected; 7 of them had very high level of audio noise. At the next step, the whole FM band was scanned three times and mean RSSI values for each channel were recorded. The acquired data is presented in Figure 5.1.

According to the results, the assumption that active stations correspond to peaks on RSSI graph, is not valid. Instead, the active stations usually appear within 100 kHz from the peaks, which are produced by additive interference of adjacent channels (see, for example, 91.6 MHz in Figure 5.1). Such cases are usually associated with a sharp increase of the RSSI. If there was no sharp increase of the RSSI, then the station is probably associated with the peak. Finally, all the active stations found by seek tuning have

RSSI above the threshold (15/63 in this experiment) and are separated by at least 200 kHz. The algorithm implementing these considerations in R language [111] is presented in Listing 5.1.

```

#Identifies active FM channels using RSSI sweep data
#Input:
# rssi - vector of stations' mean RSSI values
# rssiThreshold - minimum level of active channels
#Output:
# boolean vector indicating whether the channel is active
getActiveFMChannels <- function(rssi , rssiThreshold = 15) {
  nChannels <- length(rssi); # number of FM channels in the RSSI data

  #boolean vector marking local RSSI peaks with TRUE values
  isPeak = peaks(rssi , span = 3);

  result <- rep(FALSE, nChannels);

  #band bounds are always considered active
  result[1] = (rssi[1] >= rssiThreshold);
  result[nChannels] = (rssi[nChannels] >= rssiThreshold);

  for (i in 2:(nChannels-1)) {
    result[i] =
      (rssi[i] > rssiThreshold) && # RSSI must be above the threshold
      (
        #it is a sharp increase (by at least 25%) just before the peak
         #(25% parameter value provides best precision/recall values)
        (isPeak[i+1] && ((rssi[i+1] - rssi[i])/rssi[i] < 0.25)) ||
        #if no station detected at the peak slope, it is on the peak itself
        (isPeak[i] && !result[i-1])
      );
  }
  return (result);
}

```

Listing 5.1: Active station detection algorithm.

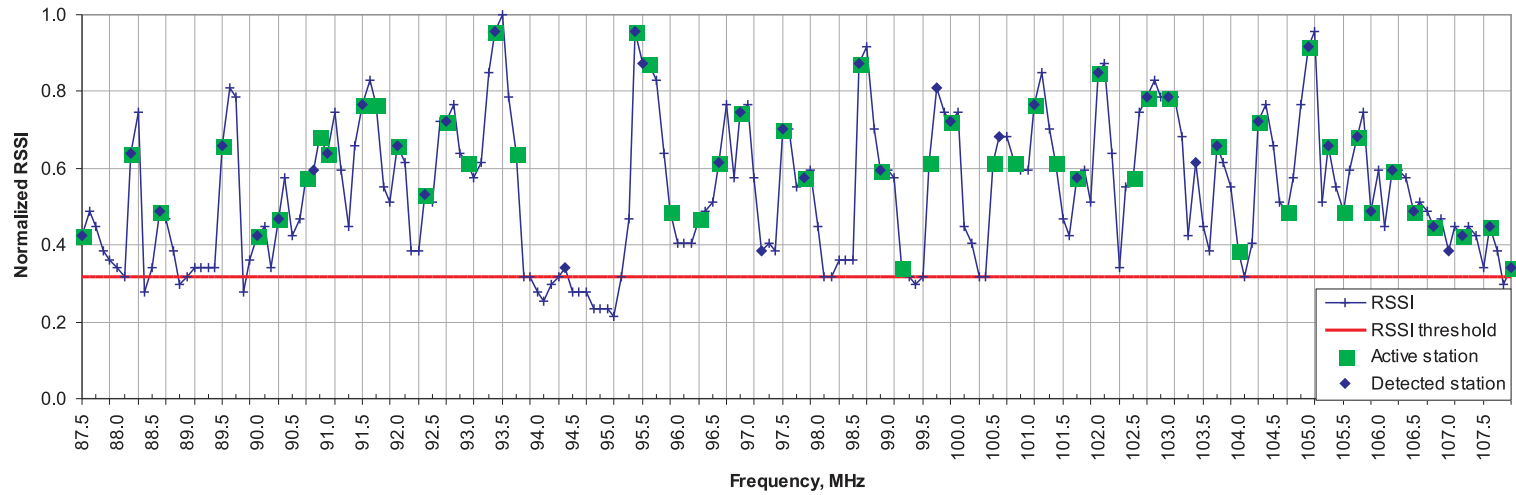


Figure 5.1: Detection of active FM channels using RSSI data.

The results of active channel detection using RSSI data are presented in Figure 5.1. The algorithm found 45 active channels, with 80% precision and 67% recall with regard to the 54 channels found by seek tuning. For the FM positioning, it is more important to minimize the number of false positive detections rather than false negatives; in other words, it is better to miss some active stations rather than rely on high-power noise. The 80% precision demonstrated by the presented algorithm provides a suitable basis for identification of active FM channels using only RSSI data.

## 5.2 $FM_B$ positioning system performance

This section provides performance evaluation results of the positioning system using RSSI fingerprints of broadcasting FM stations.

The experimental environment was the same as in the  $FM_L$  positioning experiments (Figure 4.1 in Chapter 4). The furniture layout, however, has changed since then, which changed the spatial distribution of RSSI and also influenced the positioning accuracy results. Due to these changes, the  $FM_L$  results presented in this section are different from the  $FM_L$  results previously reported in Section 4.1.2.

Before the measurements, the list of active FM channels was acquired at several parts of the room using Brando USB FM receiver’s “seek tuning” capability (RSSI threshold was set to 15/63). All detected channels were combined into a single list of 76 active FM stations. Three local FM transmitters were installed at the locations shown in Figure 4.1 and tuned to transmit DTMF “1” signal at frequencies not occupied by broadcasting stations.

FM fingerprints were acquired by Samsung Omnia 2 smartphone. The RSSI values were collected at the points defined by a 1 m grid; due to the furniture, totally 40 points have been measured in the  $12 \times 6$  m room. The

experimenter was always facing the same direction. Each FM fingerprint included 10 RSSI samples of each of 79 channels (76 broadcasting stations and 3 local transmitters).

The preprocessing step comprised normalization of the fingerprints' RSSI values to 0..1 range in accordance with the characteristics of the corresponding receivers (Appendix B.1). To recognize locations by fingerprints, a  $k$ -nearest neighbour classifier ( $k = 1$ ) has been used (see Section 3.4). The positioning performance was evaluated using leave-one-out approach (Section 3.4.3).

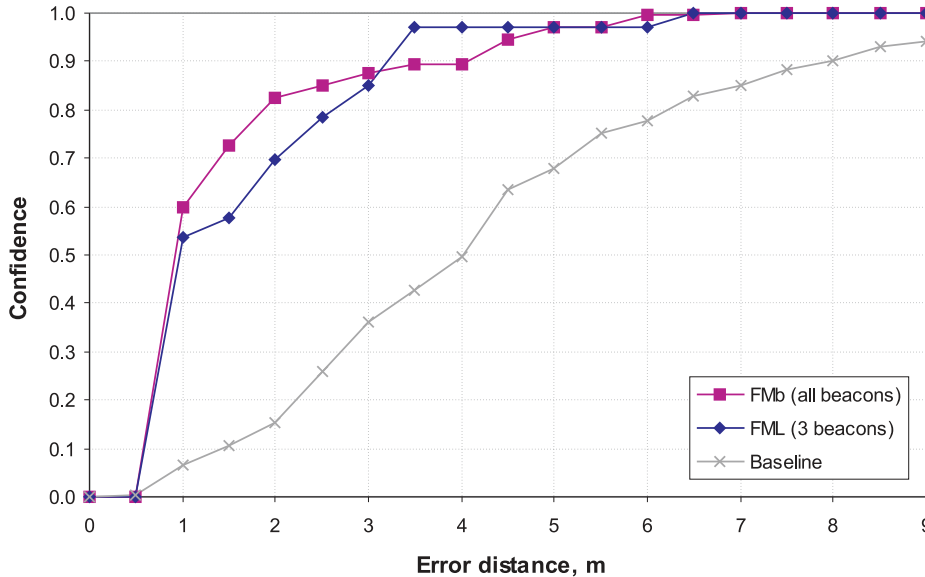


Figure 5.2:  $FM_B$  and  $FM_L$  positioning accuracy.

The performance results of the  $FM_B$  positioning system using all broadcasting FM stations are presented in Figure 5.2 (local beacons are excluded). The median positioning error of the system is 0.91 m, the 95<sup>th</sup> percentile error is 4.71 m. For confidence levels of up to 90%,  $FM_B$  outperforms the  $FM_L$  positioning based on three local beacons. Evidently, such a high  $FM_B$  performance should be attributed to the high number of

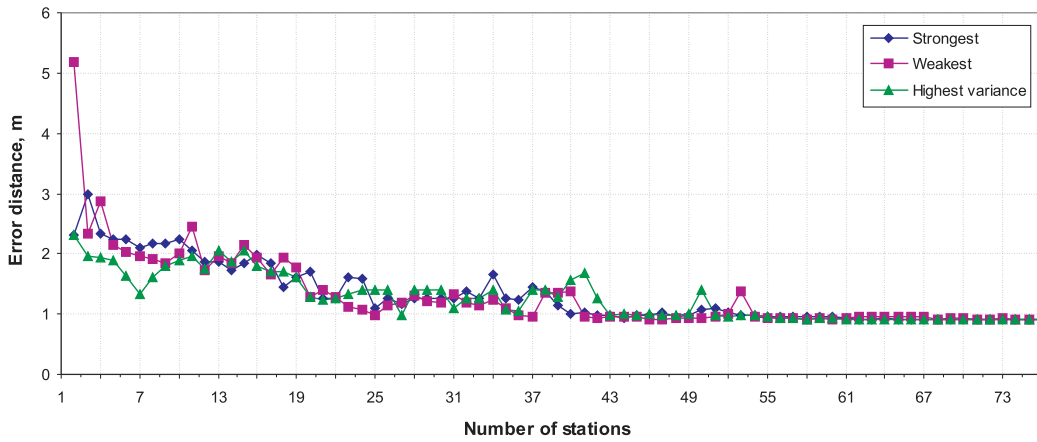
used beacons: there is evidence in the literature that suggests that wider fingerprints result in better positioning performance [2, 50, 51, 72].

### 5.2.1 Accuracy vs. number of beacons

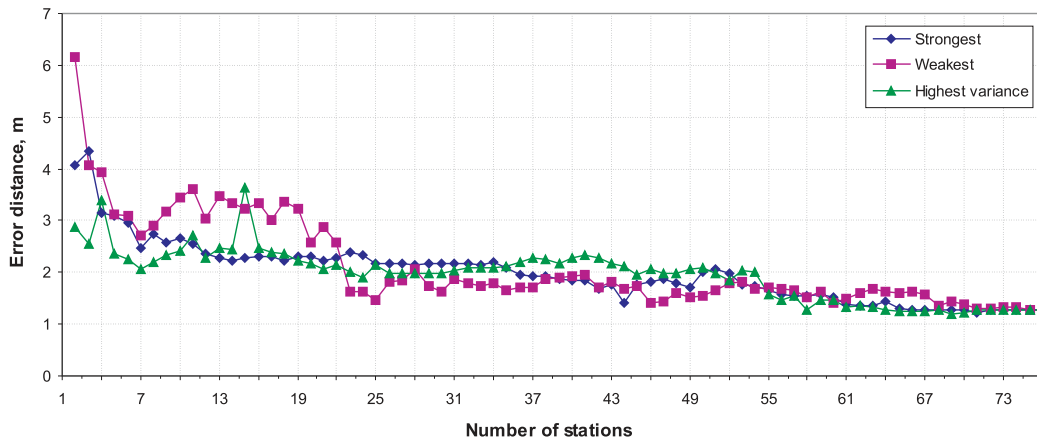
In the previous section, all the beacons have been used for positioning. However, wide fingerprints take more time to acquire and increase the dimensionality of the classification task, thus increasing the computational requirements of the positioning system. Therefore, it would be beneficial to find a trade-off between the fingerprint width and localization accuracy, assuming that not all of the beacons contribute to positioning equally. Indeed, if the character of obstacles between the test environment and certain broadcasting stations is the same for the majority of test points, the signal properties from such station are likely to remain the same for the large part of the environment and such a station can be safely excluded. This section describes a number of  $FM_B$  beacon selection approaches and evaluates how number of beacons (fingerprint width) affects the positioning accuracy.

One of the most obvious, although rather naïve, methods is to select the stations with highest signal strength, which comes along with the inverse approach of preferring the stations with low RSSI values. The results for these approaches are presented in Figure 5.3. As one can see, the two methods have similar performance in terms of median error (Figure 5.3a). For higher confidence levels, the results are inconsistent: sometimes weaker stations perform worse (at 67%), sometimes better (at 95%). The unstable performance of strong stations at 95% confidence (Figure 5.3c) can be explained by increased variation of the high RSSI levels, which results in few points with high positioning error, which, in turn, significantly affect the high-confidence positioning performance.

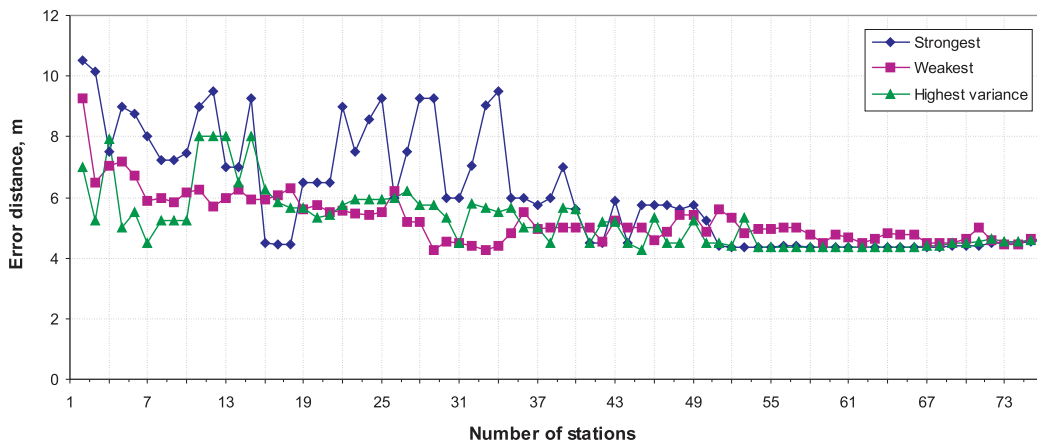
The presented findings are in contradiction with the results previously



(a) 50<sup>th</sup> percentile (median) error



(b) 67<sup>th</sup> percentile error



(c) 95<sup>th</sup> percentile error

Figure 5.3: FM positioning accuracy vs. number of beacons (for different beacon selection methods).



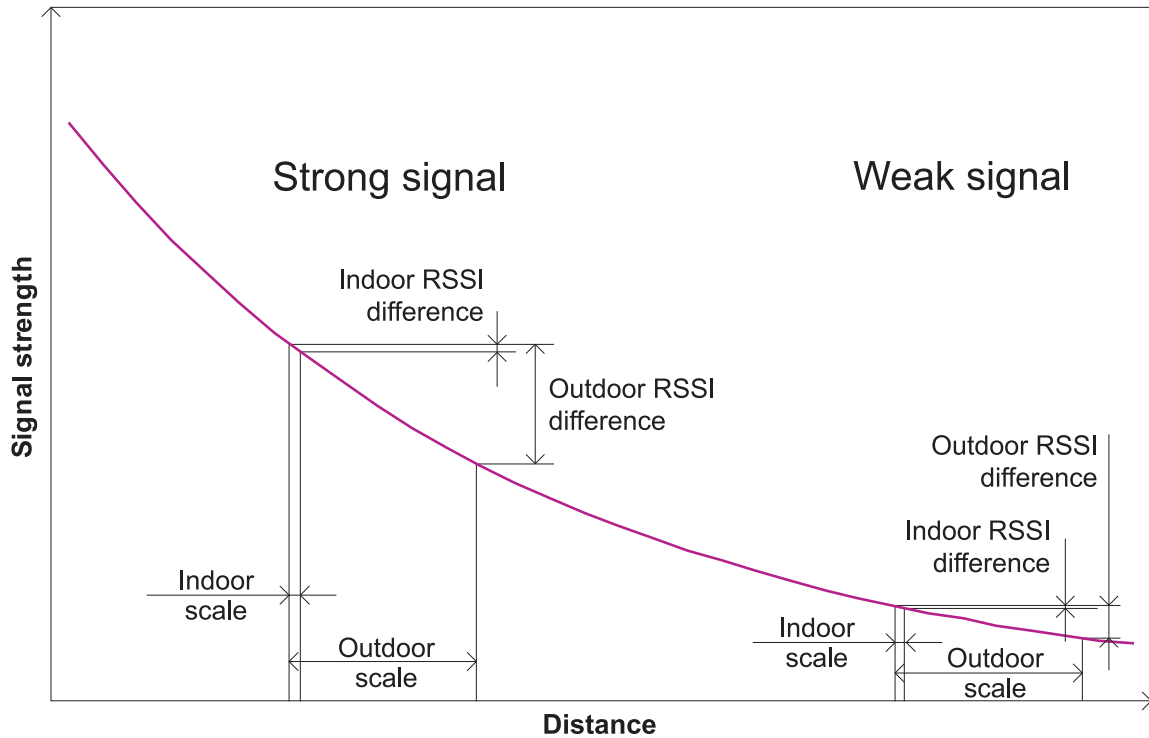


Figure 5.4: RSSI difference caused by path loss at indoor and outdoor scales.

demonstrated for outdoors. Fang et al. [2] have found that in outdoor scenarios selecting stations with stronger signals leads to better positioning accuracy than for weak-signal stations [2, Fig. 4]. To understand the reasons of this inconsistency, let us consider the difference between indoor and outdoor positioning using broadcasting beacons. In outdoor scenario, the distances between test points are relatively large (100–150 m in [2]). At such distances, the signals of nearby (strong-signal) stations are subject to significant path loss (see Section 2.1.4.1). In indoor environments, the distances between test points are by orders of magnitude smaller (1 m in Section 5.2), and path loss has minimal effect on signal propagation (see Figure 5.4). In this case, the FM signal RSSI varies between indoor locations mainly due to walls and other obstacles, which equally affect all beacons transmitting from the same direction, despite their signal strengths.

Therefore, in indoor scenarios stronger stations have no advantage over weaker ones in terms of positioning performance.

As the results suggest, the averaged signal strengths of individual stations are not a good indication of their contribution to positioning performance. Instead, the suitability of each station should be estimated by taking into account the properties of the test environment. The third approach considers this by selecting the stations with the most diverse signals across the test points. In particular, it evaluates the standard deviation of signals from a beacon using averaged fingerprints of every test point. It can be argued, that a high signal diversity might be caused by external interfering factors rather than by the location of test points. Nevertheless, the described approach outperforms the strongest/weakest station methods for small number of beacons (see Figure 5.3). As the number of beacons increases, the accuracy of this approach becomes similar to the others, possibly due to the external interference mentioned above.

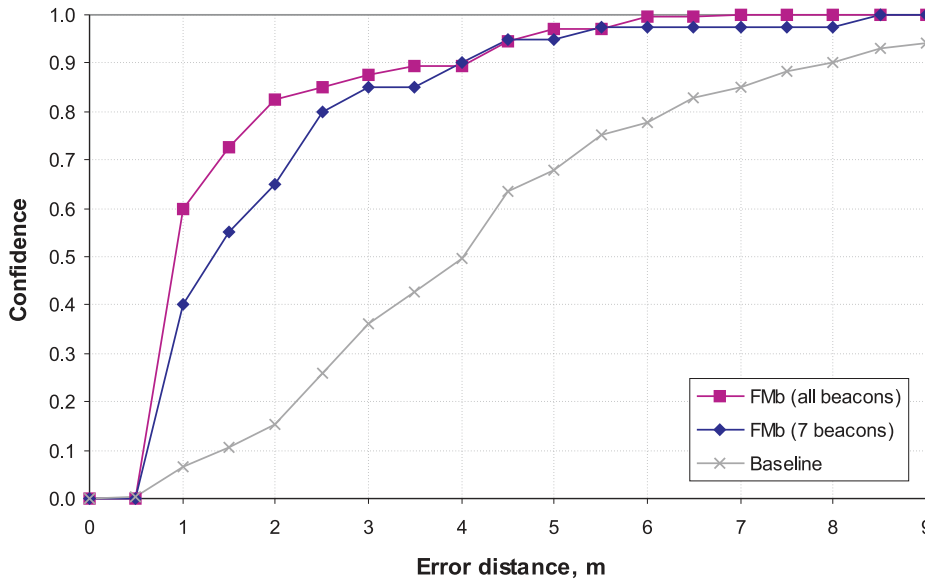


Figure 5.5:  $FM_B$  positioning using 7 beacons with highest signal diversity.

The “highest diversity” graphs in Figure 5.3 have an evident local min-

imum at 7 stations, for which the accuracy of the system is only slightly inferior to that with all 76 beacons. Figure 5.5 confirms that the median error of a system using only 10% of all beacons is 1.3 m, or only 0.4 m worse than that of the full-scale system.

The presented results confirm that careful selection of broadcasting FM beacons can reduce the fingerprint width by 90% with only minor degradation of positioning accuracy.

### 5.2.2 Comparison of $FM_B$ and Wi-Fi positioning accuracy

This section provides a comparison of experimental results of  $FM_B$  positioning performance and that of Wi-Fi, which is the current de-facto standard of indoor localization.

The Wi-Fi fingerprints were collected with Samsung Omnia 2 device, simultaneously with the FM data, as described in Section 5.2. 10 Wi-Fi samples were acquired at each point with 1 s interval. Totally, there were 17 different Wi-Fi beacons in the dataset (many of them only at certain points). The collected RSSI values were normalized to 0..1 range according to the device specifications (Appendix B.1).

For classification was used the same kNN ( $k = 1$ ) method as in the  $FM_B$  case. The beacons missing in particular fingerprints, were marked by not-a-number (NaN) RSSI values and were ignored by the kNN. So, the distance between fingerprints was evaluated using information only about the beacons present in the test fingerprint. The classification accuracy was evaluated using leave-one-out method.

The results are presented in Figure 5.6. The median error for the Wi-Fi system is 1.6 m (versus 0.9 m for  $FM_B$ ) and in all cases the positioning accuracy is within 4.5 m (6.0 m for  $FM_B$ ). As shown in the graph,  $FM_B$  outperforms Wi-Fi system for confidence levels of up to 90%. This can be explained by the significantly higher number of  $FM_B$  beacons (76 versus

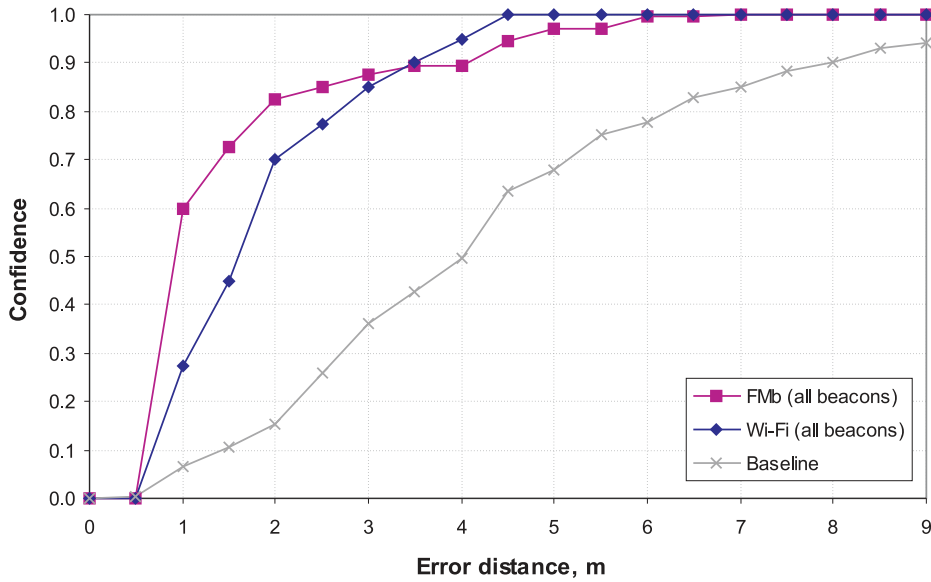


Figure 5.6:  $FM_B$  and Wi-Fi positioning accuracy using all beacons (76 and 17, respectively).

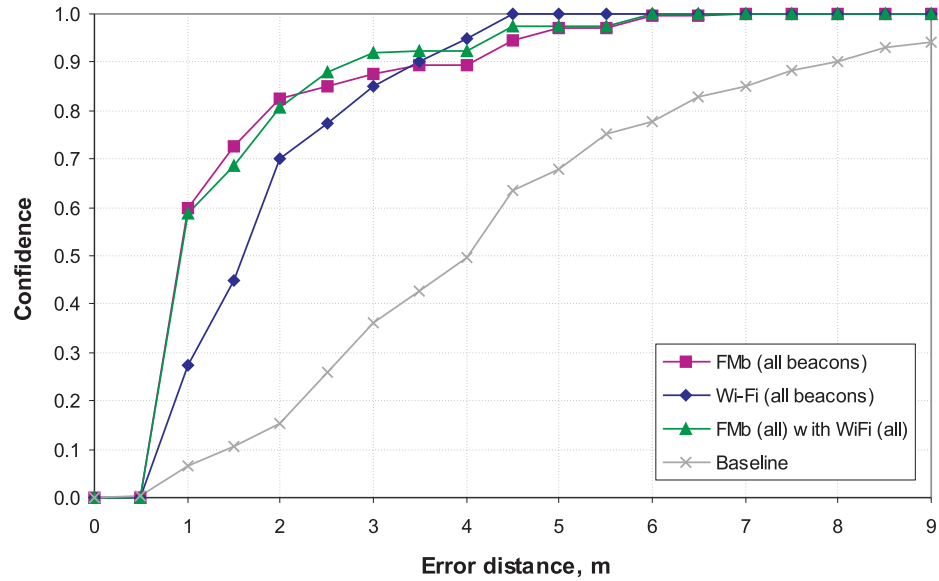
17 of Wi-Fi). On the other hand, all Wi-Fi beacons are installed in the same building and are less affected by external interference sources.

### 5.2.3 Performance of a combined $FM_B$ and Wi-Fi system

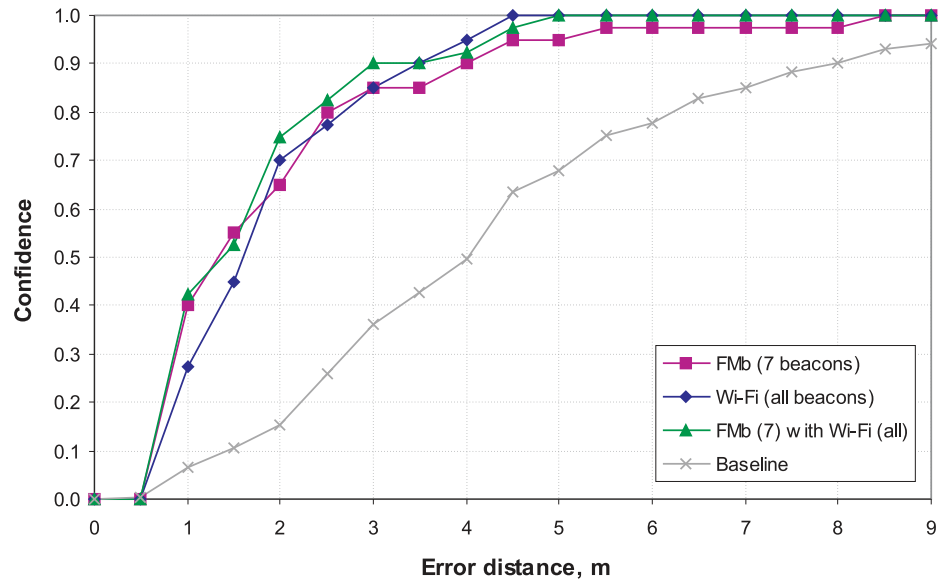
In the related work, it has been demonstrated that a fusion of different positioning methods can result in better positioning performance [43, 112, 122]. This section evaluates the performance of a combined  $FM_B$  and Wi-Fi positioning system.

A simple data fusion approach has been used to combine the two systems, where the  $FM_B$  fingerprints acquired in previously described experiments were widened with Wi-Fi fingerprints. A normalization of the RSSI values according to specifications of the appropriate wireless module has been performed to ensure balanced contribution of both technologies. It should be noted, however, that the imbalance caused by different width of the original fingerprints was not addressed, and the system with wider

fingerprints influenced the similarity evaluation to a larger extent.



(a) Using all 76  $FM_B$  and all 17 Wi-Fi beacons



(b) Using 7 best  $FM_B$  and all 17 Wi-Fi beacons

Figure 5.7: Combined  $FM_B$  and Wi-Fi positioning accuracy .

Figure 5.7 provides the comparison of standalone and combined system for the case when all  $FM_B$  beacons are used and a more practical

option, when only a subset of beacons is employed (the selection criteria are described in Section 5.2). In both cases, the combined system slightly outperforms the standalone ones, except for the 100% confidence level, where Wi-Fi dominates. In practical use, when absolute accuracy is not required, the combined  $FM_B$ +Wi-Fi system employing all the beacons provides 2.8 m accuracy (with 90% confidence), which is better than for any of the systems used alone.

#### 5.2.4 Comparison of $FM_B$ and GSM positioning accuracy

Some promising results have been previously demonstrated for indoor GSM localization (see Section 2.2.2). GSM networks are similar to  $FM_B$  in the sense that the beacons are external to the test environment and in most cases provide zero-cost infrastructure for an indoor positioning system. This section compares the performance of  $FM_B$  and GSM indoor positioning systems.

The GSM data were collected simultaneously with the FM and Wi-Fi fingerprints, as described in previous sections. An HTC Artemis smartphone was used to collect the RSSI fingerprints for 7 nearby GSM base stations. For each test point, 6 GSM samples were recorded with 5 s interval, which is the smartphone’s internal update rate of GSM information. Totally, there were 15 different cell IDs in the dataset. The RSSI values were normalized to 0..1 range; the values for beacons not detected in a particular fingerprint were set to “not a number” (NaN) value.

As in the previous cases, the association between fingerprints and locations was performed by a kNN ( $k = 1$ ) classifier and evaluated by the leave-one-out approach (Section 3.4.3). Similarly to the Wi-Fi evaluation, missing GSM beacons (labelled by “NaN” RSSI values) were ignored by the kNN distance evaluation.

The results presented in Figure 5.8 are consistent with GSM position-

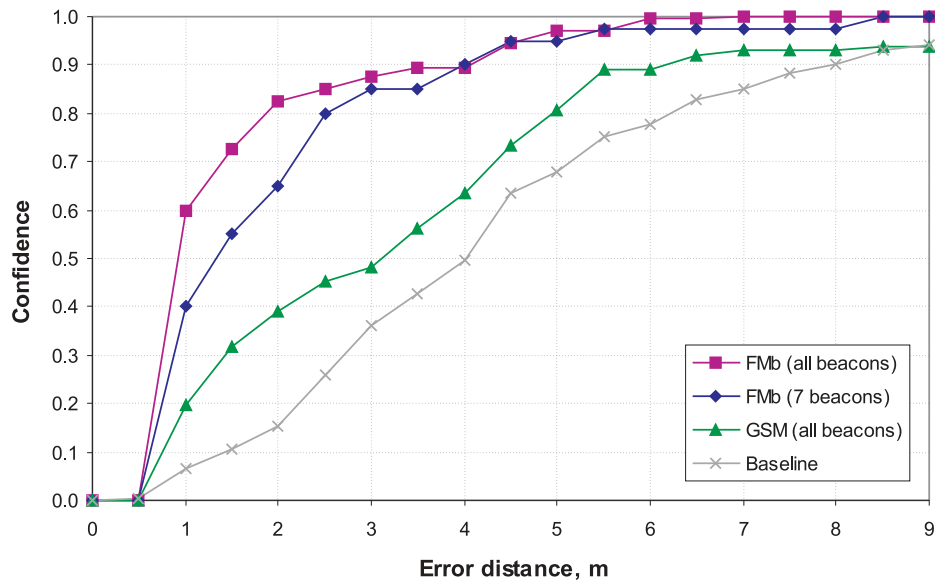


Figure 5.8:  $FM_B$  and GSM positioning performance.

ing results for other environments (3.4 m median error in a residential house [50, Table 5]). Unsurprisingly, with 76 beacons  $FM_B$  easily outperforms GSM. However,  $FM_B$  also demonstrates superior performance even when only 7 selected beacons are used (see Section 5.2.1 for the selection method).

### 5.3 RSSI stability and people’s presence

From the radio waves perspective, people are complex-form objects consisting primarily of water. As such, they can reflect and attenuate radio waves and thus influence the signal distribution in the environment, just like other indoor obstacles. Unlike other objects, however, people perform such actions as moving, rotating, crouching, — and thus represent a highly dynamic and hard-to-predict interfering factor that complicates signal distribution map even further.

Unfortunately, there are few experimental results on how people pres-

ence and movement influence radio-based positioning system performance. Moreover, the existing results are contradictory. Zemek et al. [35] performed experiments in a shopping center and found that presence of moving people has little impact on positioning accuracy. In contrast, several works evaluated Wi-Fi based positioning systems, and found that the positioning accuracy drops dramatically when the mobile client is surrounded by people [7, 36].

In order to evaluate the RSSI dependence on people presence, two experiments have been conducted in indoor environments with different crowd intensity.

### 5.3.1 Experiment 1 (medium activity levels)

The first experiment took place in a university mensa (canteen). The environment was a square-shaped room of about  $30 \times 30$  meters; the maximum capacity was 150 people. Two datasets of 50 minutes each have been collected at canteen peak hours (13–14 o’clock) and at the evening (18–19 o’clock) when the room was empty. During the lunch-time phase of the experiment, the canteen occupation varied from 70% in the beginning to 90% in the peak time and to about 20% near the closing time (Figure 5.9).

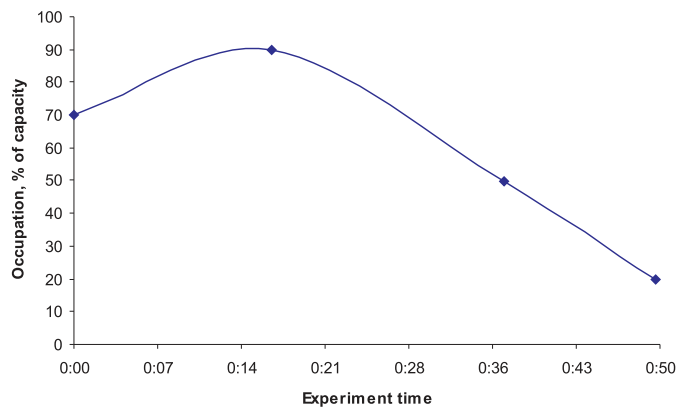


Figure 5.9: Canteen occupation profile during the “crowded” phase of the first experiment.

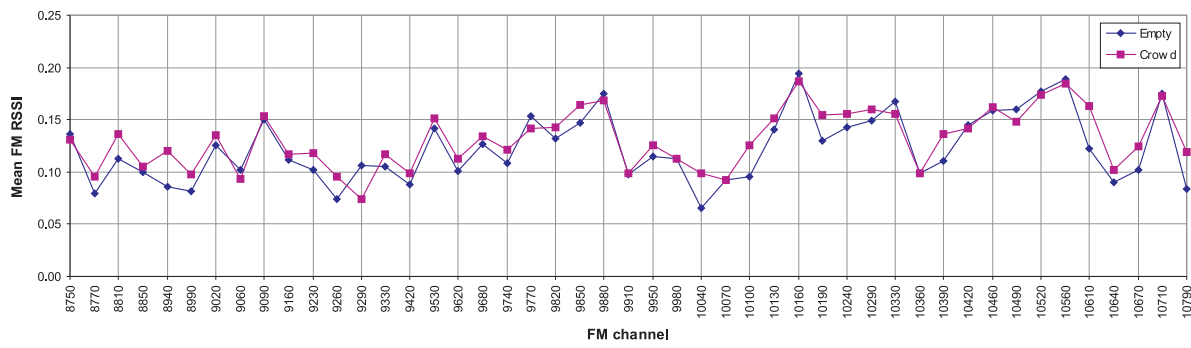


The environment was highly dynamic: people were arriving, searching for places, and eventually leaving. A Samsung Omnia 2 smartphone placed in the middle of the room collected complete Wi-Fi RSSI fingerprints every 5 s, and complete FM fingerprints every 35 s (this corresponds to continuous scanning of all of 205 FM channels, from 87.5 to 107.9 MHz with 0.1 MHz step). The second dataset has been collected about 4 hours later, at the same conditions, but the room was empty.

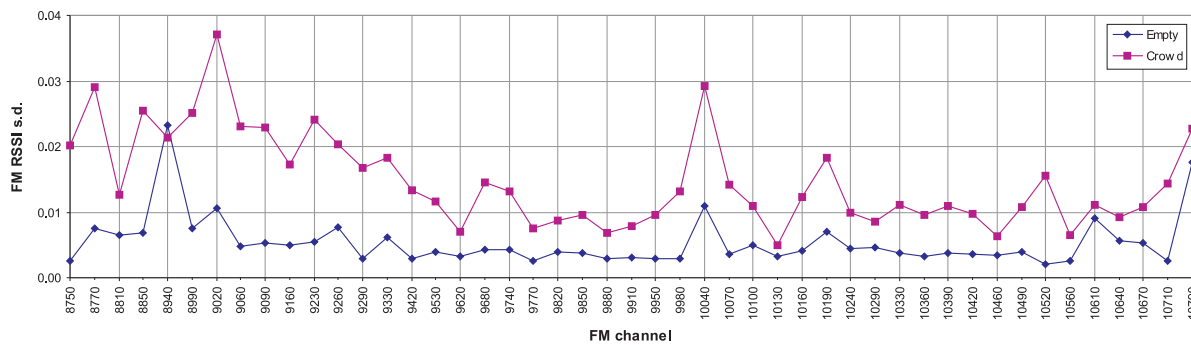
At the preprocessing stage, 26 FM beacons were selected from 205 scanned channels using the procedure described in Section 5.1. For Wi-Fi, some weak beacons were detected only few times and it was impossible to calculate their statistics. Therefore, the beacons observed for less than 10% of the dataset duration were excluded from analysis. To adjust the 6-fold difference between Wi-Fi and FM sampling rates, only every sixth of the preprocessed Wi-Fi samples was left in the dataset. After preprocessing, each dataset contained 84 fingerprints both for FM and Wi-Fi. All RSSI values were normalized to the 0..1 range, using the raw FM and Wi-Fi RSSI ranges from device specifications (see Appendix B.1).

Figures 5.10 and 5.11 demonstrate the effect of people’s presence and movement on the RSSI distribution for each of FM and Wi-Fi beacons. The mean values represent the static influence of crowd presence, as any dynamic changes get averaged out. The standard deviation (s.d.), in turn, reflects the influence of dynamic component of the crowd, such as people arriving, leaving and moving around.

It is easy to see that the mean RSSI values for most of the Wi-Fi beacons in an empty room are about 20% higher than within a crowd (Figure 5.11a). However, the change is not that obvious for the FM measurements (Figure 5.10a). To clarify the dependence, Figure 5.12a provides a graph of relative change of mean RSSI for “empty” over “crowded” rooms. The histogram in Figure 5.12a is relatively symmetric and centered around

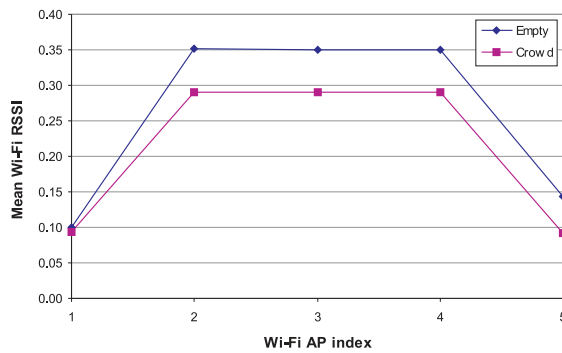


(a) Mean FM RSSI

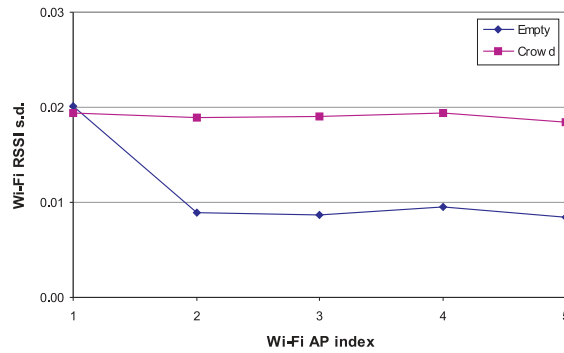


(b) FM RSSI standard deviation

Figure 5.10: FM RSSI statistics for empty and crowded environment.



(a) Mean Wi-Fi RSSI



(b) Wi-Fi RSSI standard deviation

Figure 5.11: Wi-Fi RSSI statistics for empty and crowded environment.

0.9–1.0, which means that the FM RSSI changes were random and did not follow a specific trend, as in case of Wi-Fi; the number of FM stations with increased RSSI is almost the same as those with decreased RSSI.

Thus, it is possible to conclude that in the presence of people Wi-Fi signal gets attenuated by bodies, while FM signals are generally not affected.

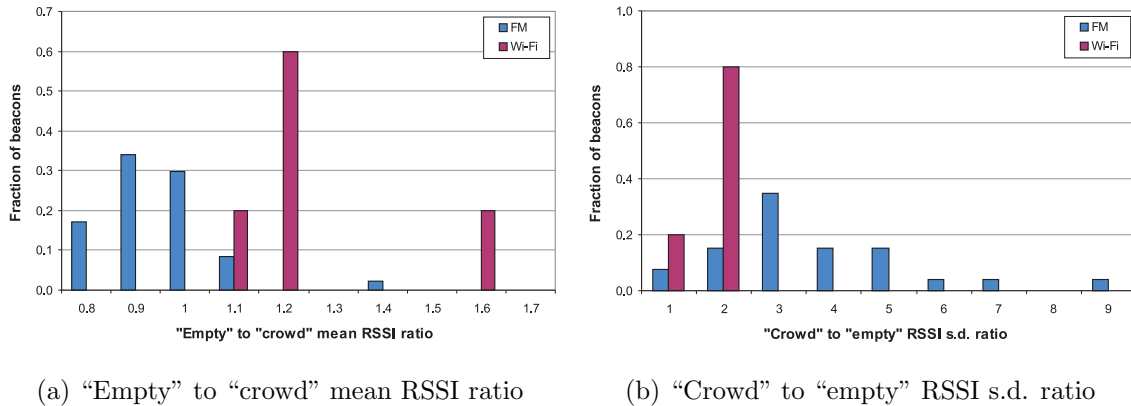


Figure 5.12: Relative changes of RSSI characteristics.

The picture changes, however, when the dynamic behaviour of the signals, represented by their standard deviations, is considered (Figures 5.10b and 5.11b). Both FM and Wi-Fi signals fluctuate significantly more within a crowded environment than in an empty room. But while standard deviation of the Wi-Fi fingerprints doubles, the FM signal fluctuations increase manifold (Figure 5.12b). A possible explanation for this fact is that radio waves of FM band (about 100 MHz) are scattered by human bodies, while Wi-Fi waves with much higher frequency (2.4 GHz) are mostly absorbed due to increased conductivity of biological tissue at high frequencies [41, p. 71].

The scatter plots in Figure 5.13b provide an alternative view of the results, and Table 5.1 summarizes the signal statistics over all beacons. It should be noted, that while the variance of FM signals significantly increases in a dynamic crowded environment, it still remains below the

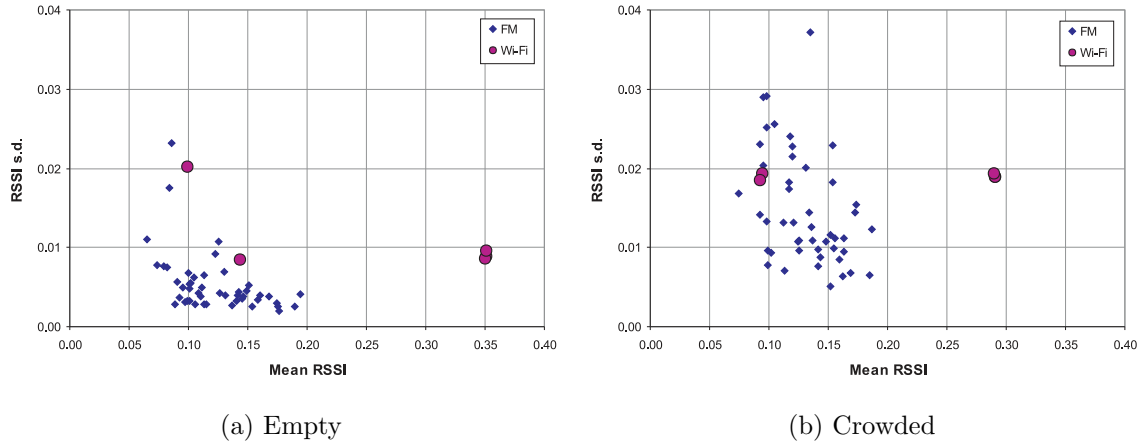


Figure 5.13: Mean vs. s.d. of FM and Wi-Fi RSSI in the empty and crowded canteen.

Table 5.1: RSSI statistics over all beacons (student canteen).

	FM		Wi-Fi	
	Mean	SD	Mean	SD
Empty	0.147	$4.60 \cdot 10^{-3}$	0.259	$1.12 \cdot 10^{-2}$
Crowd	0.150	$1.43 \cdot 10^{-2}$	0.211	$1.90 \cdot 10^{-2}$

level of Wi-Fi’s fluctuations. Thus, FM fingerprints are more stable than Wi-Fi ones in less populated environments; in crowded environments both technologies are prone to similar amount of noise.

### 5.3.2 Experiment 2 (low activity levels)

The second experiment considered a less dynamic environment and focused on the distortions of FM and Wi-Fi signals caused by people performing conventional office activities. Signal characteristics have been compared for three scenarios: empty room in daytime, populated room in normal office hours, and empty room in nighttime. The two empty-room scenarios (daytime and nighttime) have been considered in order to recognize  $FM_B$  signal distortions that could be introduced by external noise sources, such as city traffic and activities in adjacent rooms. Such noises are generally

attributed to human activities, which are minimal in the nighttime.

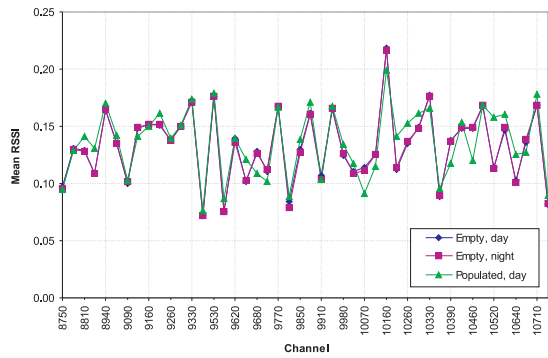
A Samsung Omnia 2 smartphone has been placed on a desk in the middle of the office (Figure 4.1) and recorded FM and Wi-Fi RSSI fingerprints for 3 full days, Saturday to Monday. From the recorded data, three 6-hour datasets have been extracted:

1. Sunday, 12 to 18 o'clock ("empty room, daytime");
2. Monday, 0 to 6 o'clock ("empty room, nighttime"); and
3. Monday, 12 to 18 o'clock ("populated room").

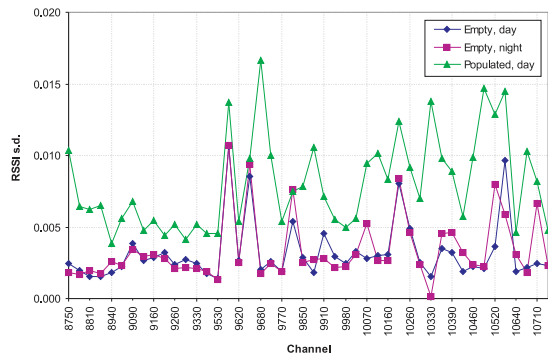
On Monday, two people were present in the room; the desk with the smartphone remained unattended for the whole period. The collected FM fingerprints included 205 channels and repeated every 36 s (this value corresponds to the maximum FM scanning speed of the device). Wi-Fi fingerprints were acquired every 6 s.

The preprocessing phase included normalization of raw RSSI values to the range 0..1, using the minimum and maximum RSSI values reported in device specification (see Appendix B.1). In order to accommodate for different sampling rates of FM and Wi-Fi, only every sixth Wi-Fi sample has been considered. Some weak Wi-Fi beacons were detected only few times during the experiment. In order to ensure a fair comparison, the beacons present in less than 10% of fingerprints, were excluded. For the FM data, the 205-channel fingerprints were narrowed to 23 active stations, using the approach described in Section 5.1. After preprocessing, each dataset contained 592 samples with 23 FM and 13 Wi-Fi beacons.

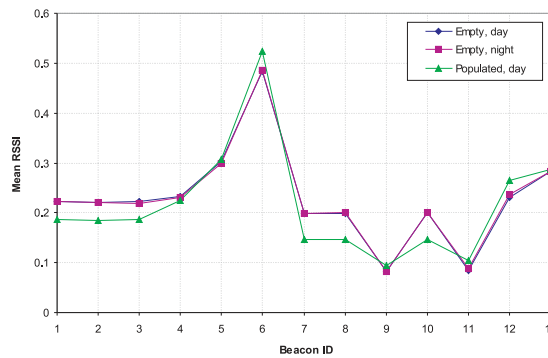
Figures 5.14 present a per-beacon comparison of RSSI statistics for each scenario. Evidently, both FM and Wi-Fi signal characteristics in an empty room remained virtually the same, irrespective of time. During the work hours, however, the situation changes; both wireless modules detect increased fluctuations of the received signals, reflected by significantly higher



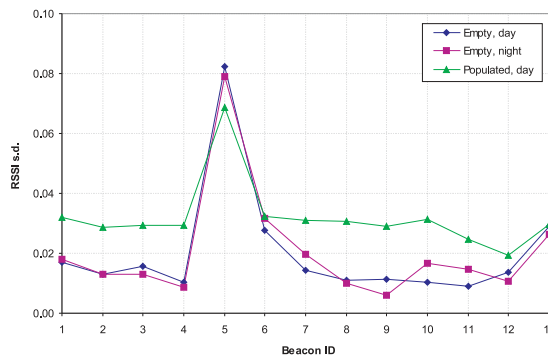
(a) Mean FM RSSI



(b) Standard deviation of FM RSSI



(c) Mean Wi-Fi RSSI



(d) Standard deviation of Wi-Fi RSSI

Figure 5.14: FM and Wi-Fi RSSI statistics for an office environment.

standard deviation of RSSI values. Although the increase is larger for the FM, the FM RSSI deviation still remains well below that of Wi-Fi, partly due to weaker signals. Remarkably, mean FM RSSI was not affected by people's presence. Average Wi-Fi readings, however, slightly decreased. An integral view of mean values and their deviations is presented in Figure 5.15.

The results presented in Table 5.2 are in a good agreement with the previous experiment (Section 5.3.1). Mean  $FM_B$  RSSI values are indifferent to the presence of people, while Wi-Fi values slightly decrease. Both technologies demonstrate stronger fluctuations of signals in populated environments; moreover, the mean Wi-Fi RSS slightly decreases. This behavior

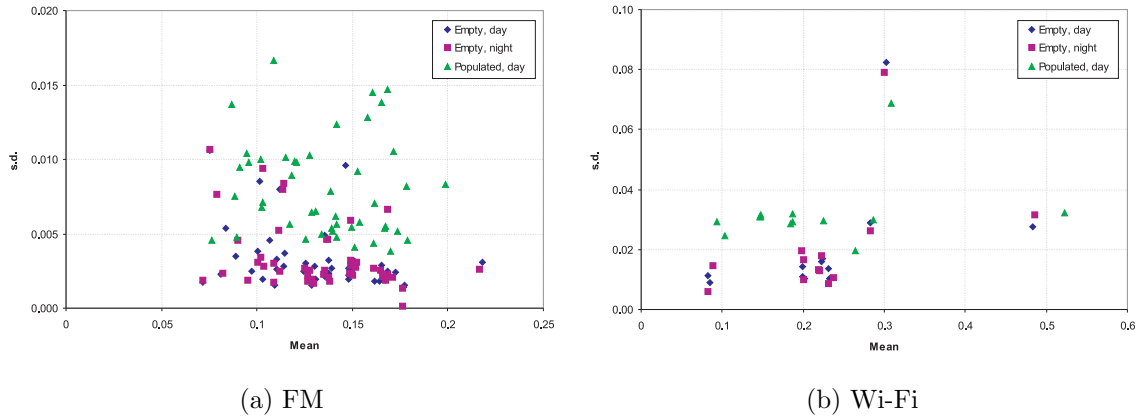


Figure 5.15: Mean vs. s.d. of FM and Wi-Fi RSSI. Note the different scales of the axes.

Table 5.2: RSSI statistics over all beacons (office).

	FM		Wi-Fi	
	mean	s.d.	mean	s.d.
Empty (day)	0.133	$3.20 \cdot 10^{-3}$	0.228	$2.03 \cdot 10^{-2}$
Empty (night)	0.132	$3.40 \cdot 10^{-3}$	0.228	$2.06 \cdot 10^{-2}$
Populated	0.136	$8.01 \cdot 10^{-3}$	0.216	$3.20 \cdot 10^{-2}$

is well-correlated with other reports about Wi-Fi RSS distribution [107]. In all cases, however, the FM jitter was less or equal to that of Wi-Fi. From the above, it can be concluded that in comparison to Wi-Fi, FM radio signals are more robust to people’s presence and movement in low and medium crowd density.

## 5.4 Summary

This chapter presented the experimental results proving the feasibility of indoor positioning with broadcasting FM stations ( $FM_B$ ). At the client side, the system employs the FM radio hardware, already present in many mobile devices. The passive receiver allows the utilization of the  $FM_B$  positioning in sensitive environments where other radio technologies, such as Wi-Fi or GSM, are prohibited for safety reasons.

Table 5.3: Summary of  $FM_B$ , Wi-Fi and GSM indoor positioning accuracy.

Confidence	$FM_B$	Wi-Fi	GSM	$FM_B$ (10% of beacons)
50%	0.9	1.6	3.1	1.3
67%	1.3	1.9	4.2	2.1
90%	3.4	3.5	6.2	4.0
95%	4.7	4.0	9.1	4.9

The summary of  $FM_B$ , Wi-Fi and GSM positioning accuracy measured in same environment is presented in Table 5.3. In comparison to Wi-Fi,  $FM_B$  provides superior accuracy at confidence levels of up to 90% in same-environment tests. Using only 10% of stations,  $FM_B$  performed similar to Wi-Fi. In contrast to Wi-Fi systems, however, the  $FM_B$  localization does not require any in-building infrastructure and consequently has minimal hardware costs. The GSM, which also uses external beacons, demonstrated far inferior accuracy than either  $FM_B$  or Wi-Fi.

This chapter also evaluated how the presence of small and medium numbers of people influences FM and Wi-Fi signal strengths. It has been found that the average Wi-Fi RSSI consistently decreased in the presence of people: by 20% in student canteen at peak hours and by 5% in a typical office with few people. For FM, the mean RSSI changed differently across stations; for most (80%) of the stations the shift was within 10%. The standard deviation of the signal strengths for both technologies significantly increased in populated environments: by 50–70% for Wi-Fi and by 135–170% for FM. Despite the higher increase, the standard deviation of FM RSS was in all cases lower or equal to that of Wi-Fi.



# Chapter 6

## Application scenario

The FM positioning system described in previous chapters has been successfully used within a research project which studied variations of psychological state in office workers [123, 124].

The hypothesis of the project was that people who spend most time sitting at their desks would have worse mood at the end of the day than those who make regular pauses, such as coffee breaks or socialization with colleagues. Another hypothesis was that some working activities may have higher impact and induce more negative mood than others (for example, missed lunch or repetitive meetings with a boss).

In this respect, the potential working activities and socialization events were associated with the locations where they typically occur: office (working), conference room (being at a meeting), coffee room or balcony (having a break), canteen or cafeteria (having lunch). Apart from the location, a number of psychophysiological parameters were recorded to monitor the mood state. The parameters were identified from clinical studies and included body movements level, heart rate and its variability, sleep quality and a number of mood characteristics. The monitoring platform consisted of a Samsung Omnia 2 smartphone running MyExperience tool [115] customized for the project, and an external Bluetooth-connected sensor from

Shimmer Research [125], which combined an accelerometer and an ECG sensor. The ground truth about psychological state has been collected via self-rating questionnaire.

As the data recording sessions lasted for the whole working day (8 hours), it was critically important that the smartphone had a sufficient memory capacity and battery life. While memory is not an issue for current devices, the battery life could be seriously affected by wireless modules used for localization and connectivity with the external sensor.

The FM positioning was well suited to the localization task due to the high power efficiency of FM receivers (see Section 4.4). A 5-minute long recording of calibration fingerprints have been performed in five predefined key locations (an office, a students' lab, a meeting room, a coffee room, and a balcony shared by the office and the lab). Initially, only broadcasting FM stations were considered; however, preliminary tests showed that the meeting and coffee rooms had similar fingerprints and thus were often mixed up by the FM<sub>B</sub>-only positioning. The issue was resolved by installing two local FM transmitters in the coffee room and the lab.

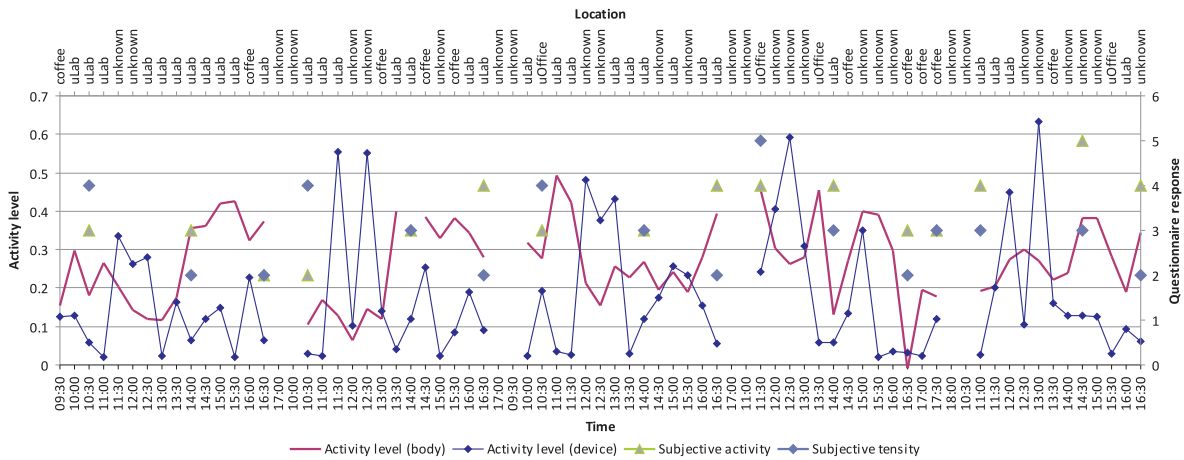


Figure 6.1: 5-day log of user location, objective and perceived activity levels.

Figure 6.1 presents a 5-day-long sample recording of one participant.

The displayed values are averaged over 30-minute intervals and include location and activity levels, both subjective (from questionnaires) and objective (from accelerometers in the phone and the on-body sensor). As the graph shows, the FM localization system provided a good recognition of known places. Moreover, it could also detect the cases when the person left the building during lunch time: the FM fingerprints collected in canteen were clearly dissimilar from the training samples in terms of signal space distance (Figure 6.2).

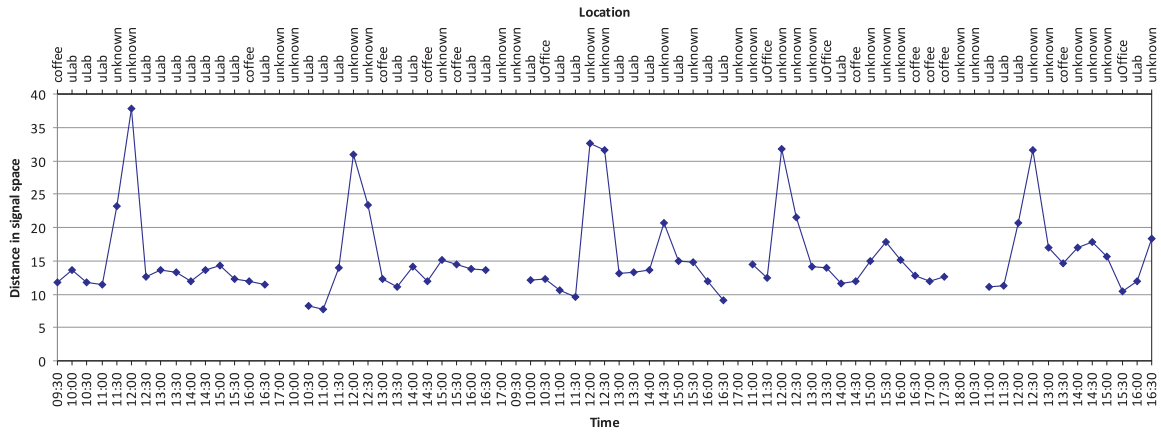


Figure 6.2: Average signal-space distance between training FM fingerprints and those acquired during experiments. Periodical peaks occurring at lunch time correspond to the canteen building which has not been included in the training set.

The results of the study demonstrated a noticeable correlation between mood changes and some activities [124]. In particular, the project provided an experimental proof that coffee breaks during the work are linked with improving mood state, while the absence of any breaks is associated with negative changes. The application of the power-efficient FM positioning has enabled a full-day uninterrupted data acquisition, with good accuracy and minimal distraction of the users.



# Chapter 7

## Conclusion

The current de-facto standard of indoor positioning, Wi-Fi based localization, has a number of constraints, such as limited coverage and low battery life. The solution proposed in this thesis leverages FM radio signals for indoor positioning; the system was proven to provide an accuracy comparable to Wi-Fi, with significantly higher coverage and battery life. Two types of signal sources have been considered: local FM transmitters and broadcasting FM stations.

The first approach,  $FM_L$ , employed local short-range FM transmitters, the consumer-grade devices which do not require licensing.  $FM_L$  localization demonstrated the performance similar to Wi-Fi (see Figure 7.1 below). A combination of  $FM_L$  and Wi-Fi provided a better positioning accuracy than either of the systems used alone.

The second approach leveraged radio signals from broadcasting FM stations ( $FM_B$ ).  $FM_B$  localization does not require any in-building infrastructure and thus has zero hardware costs. Moreover, the coverage of FM broadcasts is much wider than that of Wi-Fi or cellular networks. Finally, due to the high number of available stations, in the laboratory tests the  $FM_B$  system provided better accuracy than Wi-Fi in 90% of the cases (Figure 7.1). The performance of GSM positioning, which also employs

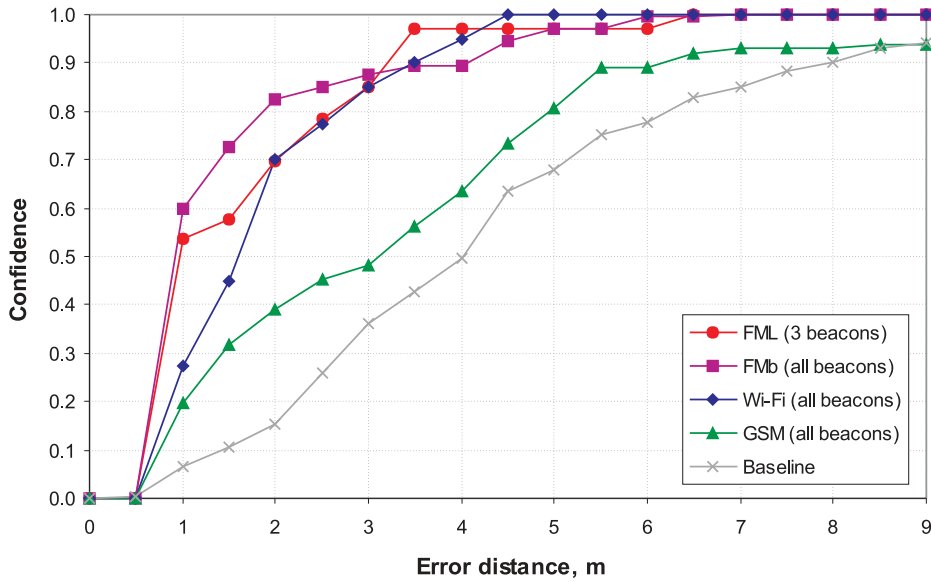


Figure 7.1: Accuracy of  $FM_L$ ,  $FM_B$ , Wi-Fi and GSM indoor positioning systems.

external beacons, was notably inferior to  $FM_B$  or Wi-Fi.

To counter the degradation of positioning accuracy, inherent to all fingerprinting based positioning systems (including FM), this thesis has proposed the spontaneous recalibration approach, which utilizes periods when device’s location is known, to update calibration data of the positioning system. Unlike other recalibration methods, spontaneous recalibration does not require additional hardware nor special efforts from the user.

A considerable part of the thesis has been dedicated to the study of influence of human presence on FM and Wi-Fi signal strength. Both FM and Wi-Fi signals were found to be sensitive to the presence of people and exhibited increased variations in such cases; the deviation of FM, however, was lower than that of Wi-Fi, except for a medium-density crowd where they were equal. Wi-Fi signal strength in populated environments decreased by up to 20% in comparison to empty-room case; FM changes were incoherent among stations. It has also been found that the  $FM_L$  RSSI depends on user orientation, however, the dependence has minor effect on

positioning accuracy and cannot be utilized to recognize user direction from signal fingerprints.

The main contributions of this thesis are:

- demonstration of feasibility of accurate indoor localization using local short-range FM transmitters, with accuracy comparable to Wi-Fi based systems;
- demonstration of feasibility of accurate indoor positioning using signals of broadcasting FM stations, with accuracy superior to Wi-Fi and GSM based systems (for confidence of up to 90% and in all cases, respectively);
- an analysis and quantitative evaluation of the influence of human presence on the stability of FM and Wi-Fi signal strengths;
- a method for countering the accuracy degradation of fingerprinting-based positioning systems.

The main advantage of the presented concepts is that they can be readily deployed: FM receivers are available in many mobile devices. In comparison to Wi-Fi, FM tuner has lower power consumption and as a result provides 2.6 to 5.5 times longer battery life in localization mode. The client-side FM radio is a passive receiver — thus, FM positioning may be used in sensitive areas where radio transmission, such as Wi-Fi or GSM, is prohibited for safety or security reasons. At the moment,  $FM_B$  is the only wireless indoor positioning technology capable to work in a completely passive manner, without introducing any additional signals into the environment. Other systems either require an infrastructure of transmitting beacons (Wi-Fi,  $FM_L$ , Bluetooth, RFID, UWB, ultrasound, infrared) or employ a transmitting mobile device (cellular networks).

## 7.1 Future work

The FM positioning tests in this thesis comprised two separate phases: fingerprints collection for the whole environment, followed by their analysis. However, in real life people move along trajectories, so that the next location depends on the previous one. Taking into account this information could significantly improve the confidence of position estimates.

Another concern regarding real-time FM localization is the time required to collect a wide FM fingerprint. Scanning several dozens of FM channels may take a considerable time; in the meanwhile, the location can change. Constraining the scans to only a subset of channels would impact the accuracy. A smart channel selection algorithm could be a more appropriate solution. Due to the heterogeneity of indoor environments, different points require different number of beacons for localization. From the calibration data, the mobile device can calculate a policy which specifies the beacon to be scanned next in order to minimize the ambiguity of location estimation. Thus, the beacons can be scanned in the optimal order, depending on the already acquired data. This will result in faster convergence of location estimates and, consequently, fast yet accurate localization.

At the moment, it is unclear if or how often the broadcasting FM stations change their transmission site, so that the signal starts to arrive from a different direction. Such changes would obviously affect the positioning performance. It might be possible to detect such cases by clustering the channels which fluctuate in a correlated manner as the client moves — this would mean that these stations are broadcasted from the same site. A station which changed its location would stand out from the correlation.

Finally, while FM radio waves are theoretically insensitive to atmospheric conditions, the influence of outdoor factors (such as weather, vehicles) on the  $FM_B$  performance requires further experimental evaluation.



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# Appendix A

## Relevant publications

1. Andrei Popleteev, Venet Osmani and Oscar Mayora. *Indoor Positioning Using FM Radio*. International Journal of Handheld Computing Research, Volume 1, Issue 3, 2010. PP. 19–31.
2. Aleksandar Matic, Andrei Popleteev, Venet Osmani, Oscar Mayora-Ibarra. *FM Radio for Indoor Localisation with Spontaneous Recalibration*. Journal of Pervasive and Mobile Computing, Volume 6, Issue 6, 2010. PP. 642–656.
3. Andrei Papliatseyeu<sup>1</sup>, Aleksandar Matic, Venet Osmani, Oscar Mayora-Ibarra. *Indoor Positioning Using off-the-shelf FM Radio Devices*. Abstracts volume of IPIN–2010. Zurich, Switzerland, 2010. PP. 41–42.
4. Aleksandar Matic, Andrei Papliatseyeu, Venet Osmani and Oscar Mayora-Ibarra. *Tuning to Your Position: FM-radio based Indoor Localization with Spontaneous Recalibration*. Proceedings of PerCom–2010. Mannheim, Germany, April 2010. PP. 153–161.
5. Andrei Papliatseyeu, Niko Kotilainen, Oscar Mayora-Ibarra, and Venet Osmani. *FINDR: Low-cost indoor positioning using FM radio*. Proceedings of MobilWare–2009, Berlin, Germany, April 2009. PP. 15–26.

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<sup>1</sup>In 2010 the author changed his name from “Papliatseyeu” to “Popleteev”.



# Appendix B

## Experimental details

### B.1 Characteristics of experimental devices

The characteristics of the FM and Wi-Fi receivers used in the experiments are presented in Table B.1.

Table B.1: Characteristics of the mobile devices.

Model	FM RSSI range	Wi-Fi RSSI range
Nokia N800	0–15	(not used)
HTC Artemis (P3300)	0–63	–50 to –90 dB (with 10 dB step)
Brando USB FM Radio	0–63	n/a
Samsung Omnia 2 (i8000)	0–255	0 to –100 dB

While the actual Wi-Fi RSSI range of the Samsung i8000 is not specified in its manual, the value of –100 dB has been assumed for the lower limit; the typical sensitivity of most Wi-Fi adapters is –95 dB [126]. The upper limit of 0 dB was assumed with a great reserve, as the typical values for other devices are –10 to –50 dB [126]. Note, that normalizing the Wi-Fi RSSI using the upper limit of –10...–50 dB would have only increased the mean and standard deviation of normalized Wi-Fi RSSI values in Section 5.3

## **B.2 Experimental setup of stereo channel separation measurements**

The experiment has been performed outdoors, outside of UBiNT lab. A König MP3 player with an embedded FM transmitter [92] was used as beacon. A 2 m wire has been used as the antenna. The beacon transmitted a stereo sound represented by the components of DTMF “1” signal (sine wave of 1209 Hz on the left channel, and 697 Hz on the right one). The receiver was Brando USB FM radio [110] connected to a laptop. A 10 s long audio sample (44100 Hz sampling frequency) was recorded at every 0.5 m distance step.

Stereo channel separation was measured as a difference of magnitudes of the corresponding bands of a spectrum acquired using FFT with Hanning window with length 8192.