UNIVERSITÄT
MANNHEIM

Fakultät für Wirtschaftsinformatik und Wirtschaftsmathematik

Improved Tracking with IEEE 802.11 and Location Fingerprinting

Inauguraldissertation

zur Erlangung des akademischen Grades
eines Doktors der Naturwissenschaften
der Universität Mannheim

vorgelegt von

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aus Heidelberg

Mannheim, 2012

Hendrik, Lemelson (Dipl.-Wirtsch.-Inf.)
Improved Tracking with IEEE 802.11
and Location Fingerprinting
Dissertation, Universität Mannheim

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Tag der mündlichen Prüfung: 15. Februar 2013

Abstract

In recent years, we have seen a proliferation of powerful mobile devices like smartphones and tablet computers. This development was accompanied by considerable improvements in the mobile communication infrastructure and resulted in an increased use of many different types of network-based services by mobile users. Among these services, the so-called Location-based Services take a special position. These services make use of knowledge about the user's whereabouts to improve their delivered service. To estimate the user's position, several different approaches can be used. Outdoors, often the Global Positioning System is the method of choice. However, as GPS cannot be used inside buildings and also often fails in urban environments where large buildings shade the mobile device from satellite signals, the position estimation with the help of IEEE 802.11 and location fingerprinting has emerged as a viable alternative. It offers a reasonably good accuracy and has the advantage that existing infrastructure can be re-used. But there are still several aspects with respect to using IEEE 802.11 for location estimation that impede a widespread use of this technique beyond an academic setting. The contribution of this thesis are solutions to these issues.

In the first part of this thesis, we identify these limiting aspects and give an overview on how other researchers have approached them in the past. The major limiting factors we identified are: a still improvable accuracy, the high effort needed to set up a positioning system based on fingerprints, and the lack of means to estimate the error inherent in a given position estimate.

Subsequently, we present our solutions to the different aspects. We first introduce each solution, followed by giving an overview of the evaluation, then present the achieved results, and discuss issues that are connected to our findings.

As a first algorithm, we present Quick Fingerprinting: An algorithm that, while considerably reducing the necessary effort, additionally increases the positioning accuracy by taking measurements from several adjacent positions into account when creating location fingerprints.

This is followed by the Region-based Location Estimation algorithm. With this algorithm, the effort necessary for setting up a location fingerprinting system with IEEE 802.11 is reduced even further to a mere walk of the area of operation at the cost of minor reductions in the achieved accuracy.

We then present four different algorithms that can be used to estimate the error that is immanent in any given position estimation with a high degree of precision: Fingerprint Clustering, Leave Out Fingerprint, Best Candidates Set, and Signal Strength Variance.

In the second part of this thesis, we analyze how a tracking approach can be used as a solution to the identified problems. We present a tracking algorithm we have developed and give an overview of our thorough evaluation of the system and the obtained results. Our algorithm makes use of different types of contextual information to improve the positioning results.

We subsequently analyze how to make sure that the best possible positioning system is always chosen from a set of available systems if the user is moving. We introduce different approaches on how to select the optimal system and analyze their performance.

Before the thesis is finally concluded, we give several application examples to allow the reader to get an impression for which scenarios our findings are especially applicable.

Zusammenfassung

In den letzten Jahren ist die Verbreitung leistungsstarker mobiler Endgeräte, wie zum Beispiel Smartphones und Tablet-Computer, stetig gewachsen. Diese Entwicklung ging einher mit der ebenfalls deutlich verbesserten Verfügbarkeit mobiler Breitbandverbindungen und hatte zur Folge, dass die Verwendung Netzwerk-basierter Dienste von unterwegs stark zugenommen hat. Als Teilmenge dieser Dienste nehmen die sogenannten ortsabhängigen Dienste eine besondere Rolle ein. Diese Dienste variieren ihre angebotene Dienstleistung abhängig vom aktuellen Aufenthaltsort des Benutzers. Um dabei die Position des Benutzers zu ermitteln, gibt es verschiedene Möglichkeiten. Im Freien wird häufig das Global Positioning System verwendet. Dieses funktioniert allerdings innerhalb von Gebäuden nicht und ist auch in innerstädtischen Umgebungen, in denen größere Gebäude die Ausbreitung der Satellitensignale behindern, nur eingeschränkt nutzbar. Als besonders geeignete Alternative zu GPS hat sich in den letzten Jahren die Positionsbestimmung mit Hilfe von IEEE 802.11 und Location Fingerprinting etabliert. Dieses Verfahren bietet eine in vielen Fällen ausreichende Genauigkeit und hat den Vorteil, dass die bestehende IEEE 802.11 Infrastruktur weiter verwendet werden kann. Allerdings gibt es trotz der Vorteile auch einige negative Aspekte, die eine weite Verbreitung dieser Technik über das akademische Umfeld hinaus bisher verhindert haben. Diese Arbeit bietet nachfolgend Lösungen zu diesen Problemen.

Im ersten Teil der Arbeit werden die einzelnen Problembereiche identifiziert, und es wird ein Überblick über Lösungsansätze anderer Wissenschaftler gegeben. Die Problembereiche sind eine weiter verbesserungswürdige Genauigkeit, ein inakzeptabel hoher Aufwand bei der Installation eines solchen Systems und das Fehlen einer Möglichkeit zur zuverlässigen Schätzung des Positionierungsfehlers.

Anschließend stellen wir unsere Lösungen zu den einzelnen Problembereichen vor. Zunächst wird jeweils der einzelne Lösungsansatz eingeführt. Darauffolgend geben wir einen Überblick über die Evaluation des Ansatzes und präsentieren dann die Ergebnisse. Schließlich gehen wir auf besondere Aspekte ein, auf die wir während unserer Arbeit gestoßen sind.

Der erste Algorithmus, denn wir präsentieren, ist Quick Fingerprinting, ein Algorithmus, der eine nennenswerte Reduktion des Aufwandes bei der Installation eines Location Fingerprinting Systems ermöglicht und gleichzeitig eine Verbesserung der Genauigkeit erreicht. Dies wird durch die Verwendung von Messungen erzielt, die an benachbarten Referenzpunkten gesammelt wurden.

Als nächstes stellen wir den Region-based Location Estimation Algorithmus vor. Dieser Algorithmus reduziert den Aufwand für das Sammeln der Trainingsdaten bei der Installation eines Location Fingerprinting Systems noch weiter. Dies wird mit leichten Einbußen bei der Genauigkeit erkauft.

Anschließend stellen wir vier verschiedene Algorithmen vor, die zur Abschätzung des zu erwartenden Fehlers bei der Positionsbestimmung verwendet werden können. Diese vier Algorithmen sind Fingerprint Clustering, Leave Out Fingerprint, Best Candidates Set und Signal Strength Variance.

Im zweiten Teil der Arbeit untersuchen wir die Verwendung eines Tracking-Ansatzes zur Verbesserung der Positionsbestimmung mit Hilfe von IEEE 802.11 und Location Fingerprinting. Wir stellen ein von uns entwickeltes System vor und bieten einen Überblick über die bei der Evaluation dieses Systems erzielten Ergebnisse. Unser System verwendet dabei verschiedene Arten von Kontextinformationen, um die Positionsbestimmung zu verbessern.

Im Anschluss daran geben wir dann einen Überblick über verschiedene Ansätze, die das Problem der Wahl des optimalen Positionierungssystems für einen mobilen Benutzer behandeln. Die einzelnen Möglichkeiten werden erklärt und ihre Leistungsfähigkeit untersucht.

Bevor wir die Arbeit abschließen, geben wir einige Beispiele, die illustrieren, in welchen Szenarien die entwickelten Techniken Vorteile im Vergleich zum aktuellen Stand der Technik bringen.

Acknowledgements

Being a member of the Lehrstuhl für Praktische Informatik IV at the University of Mannheim has always been a pleasure for me. I really had a great time there and have lots of reason to be thankful.

First of all, I want to deeply thank my supervisor Prof. Dr. Wolfang Effelsberg. His thorough reviews of my work and his well placed objections gave me the opportunity to learn a lot and to sharpen my own view for details and particular aspects that I had not seen before. Furthermore, Prof. Effelsberg always had an open ear for all my matters, regardless of whether they were research related, concerning the university's bureaucracy, or were about rather personal issues like traveling.

I also honestly thank Prof. Dr. Dr. h. c. Kurt Rothermel for being so kind to co-examine this dissertation and my former colleagues: Thomas Haenselmann, Thomas King, Sascha Schnaufer, Stephan Kopf, Benjamin Guthier, Tonio Triebel, Philipp Schaber, Philip Mildner, Johannes Kiess, Daniel Schön, and Fleming Lampi. It was a pleasure to work together with all of you and I also enjoyed our regular coffee breaks and the inspiring and also challenging discussions we had on our research topics as well as also on many other interesting issues. I will keep this time in good memory.

Honest thank also goes to Ursula Eckle and Walter Müller, the two good souls of the Lehrstuhl für Praktische Informatik IV. You always helped me out when I could not resolve problems on my own, and you have become good friends for me.

Last but not least, my deep gratitude goes to my family. I thank my parents, who during all my life supported me in any matter and helped me out both with words and deeds whenever necessary. Without you, I would not be the man I am today. Thank you. Most of all, I thank my wife Claudia. Whenever I lost track, you covered my back and motivated me to keep going. You always believed in me and never had a doubt. Thank you! You bring out the best in me!

Contents

List of Abbreviations

AOA	Angle Of Arrival
AP	Access Point
CDF	Cumulative Distribution Function
COA	Cell Of Origin
CPU	Central Processing Unit
$DGPS$	Differential GPS
DOP	Dilution Of Precision
$E911$	Enhanced 911
FAF	Floor Attenuation Factor
FCC	Federal Communications Commission
$GDOP$	Geometric Dilution Of Precision
GHz	Gigahertz
GPS	Global Positioning System
GSM	Global System for Mobile Communications
HDD	Hard Disk Drive
HMM	Hidden Markov Model
LBS	Location-based Service
LF	Location Fingerprinting
LOS	Line Of Sight

LTE	Long-Term Evolution
MAC	Medium Access Control
MHz	Megahertz
NIC	Network Interface Card
$NLOS$	No Line Of Sight
$NNSS$	Nearest Neighbor in Signal Space
OTS	Off-The-Shelf
PDA	Personal Digital Assistant
PF	Particle Filter
POI	Point Of Interest
POI	Point Of Interest
$PSAP$	Public Safety Answering Point
$RFID$	Radio-Frequency Identification
$RSSI$	Received Signal Strength Indicator
RTT	Round-Trip Time
SIR	Sampling Importance Re-sampling
SIS	Sequential Importance Sampling
SMC	Sequential Monte-Carlo Method
$TDOA$	Time Difference Of Arrival
$TDOP$	Time Dilution Of Precision
TOA	Time Of Arrival
TOF	Time Of Flight
TSS	Training Set Size
UDP	User Datagram Protocol
$UMTS$	Universal Mobile Telecommunications System

USB	Universal Serial Bus
UWB	Ultra-Wideband
$WGS-84$	World Geodetic System 1984
$WLAN$	Wireless Local Area Network

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CHAPTER 1 Introduction

In the last years, we have seen an ongoing trend of customers moving away from classical desktop computers and towards laptops and other mobile devices like tablet computers or smart phones. The reasons for this behavior were and still are mainly the fast-paced developments that are taking place in the market for mobile electronic consumer products as well as an increasing saturation of households with regard to classical desktop computers.

Furthermore, so-called mobile devices in the past were rarely portable in the literal meaning of the word or were lightweight but lacked the processing power and memory to do serious work. However, today's mobile devices offer small and light form factors, high processing power paired with lots of memory and, furthermore, long lasting batteries for untroubled and infrastructure-independent usage on the move. These days, even cellular phones offer central processing units (CPUs) in the range of one Gigahertz (GHz) and above and amounts of memory that were subject to much larger devices in the past.

This change in the type of devices used for computing and communication also fostered an impressive change in the users' behavior. Whereas users of computing devices or services in the past were mainly stationary when using their devices, this is not necessarily true nowadays. Today, users often use mobile devices like laptops or smart phones while being on the move, for example while commuting to work or when they are out in the evening. The changed user behavior also induced a change in the type of applications and services used.

In the past, services that were offered over a network connection were most often only used at home or in the office due to the lack of mobile network access or other restrictions like insufficient bandwidth and high fees. Nowadays, consumers are able to access such services almost anywhere by using modern mobile devices and fast next-generation wireless networks based on the Universal Mobile Telecommunications System (UMTS), Long-Term Evolution (LTE), or IEEE 802.11 and Wireless Local Area Networks (WLANs). For further information on these networks, please refer to [HT00] for UMTS, [DPSB08, STB09] for LTE, and, for example, [Gas05] for IEEE 802.11 and WLAN.

As a reaction to these major developments, existing services were adapted to the changing usage paradigms and new services were created to better support especially mobile users in many different ways. A good example to demonstrate these developments is *Google Maps*[1]. In its early days, Google Maps offered the possibility to view the schematic map or a bird's eye view of a city or region. This initial version soon was extended by the possibility to also supply driving or walking directions between different locations. Of course, these two features are useful, especially when using a stationary computer at home where one can eventually print the map or the directions and take them along. For a mobile scenario, though - where even the own location might be uncertain - supplying the user with an overview map or driving directions between fixed locations is not optimal. Thus, the next logical step was to extend the application by a navigation function. As such, the user's current location is now taken into account to provide up-to-date navigation information from the current location to the target.

Another example for an exiting new service that was created due to the new possibilities nomadic users nowadays have is *Foursquare*[2]. Foursquare offers its users the possibility to disclose their actual location to their friends and the foursquare community. Furthermore, users can write reviews about places, recommend them to other users and earn points and so-called badges, for instance for repeatedly visiting the same place or visiting many different places within a certain time frame. For example, considering a bar, the foursquare user who has most often logged into the systems while being at that bar is awarded a *major badge* for the location. When using such a system, it is easy for people visiting an unknown city to get an overview of sights and locations that might be worth visiting. Additionally, they can get in touch with other similar minded people that eventually are at the same location right at the same time. This allows to easily meet locals and make new friends.

The *Enhanced 911*[3] (E911) initiative of the Federal Communications Commission (FCC) of the United States of America is yet another proof for the changed usage paradigms. In the past, whenever a customer of a telephone company dialed the emergency number 911 from a fixed telephone line, the call routing system of the telephone company could – based on the customer record and the caller id – route the call to the Public Safety Answering Point (PSAP) responsible for the area from which it originated. With the increasing use of cellular phones, such an automatic routing is of course also desirable for mobile users. Thus, the E911 initiative demands from operators of mobile communication networks – like the ones that are used for cellular phones – that they, in case of an emergency call, are able to perform the same automatic call routing based on the caller's location as in wired telephone networks. Additionally, the location of the caller has to be transmitted automatically to the PSAP. This approach guarantees that, in case of an emergency, help can be dispatched in a fast end efficient manner without the need for lengthy investigations for the caller's location.

[1] `http://maps.google.com`
[2] `http://www.foursquare.com`
[3] `http://www.fcc.gov/guides/wireless-911-services`

1.1 Location-based Services

All these kinds of applications are generally subsumed under the term *location-based services* (LBSs). An LBS is defined as an application or service that uses information about a user's or device's current whereabouts to adapt the delivered service accordingly. As we have seen, LBSs can be found in almost every area where users make use of mobile devices in their everyday life.

Types of Services

But of course, not all LBSs are the same. There exist several features that are used to differentiate between different types of LBSs [SV04, Kü05]. These features also have a major influence on how we interact with an LBS and how the LBS affects us when using it. The most important aspect that can be used to divide the group of LBSs is the interaction model. We distinguish between two major groups:

- **Pull-Services:** The first part is comprised of the so-called *pull-services*. These kinds of applications only act upon a direct request from the user. As such, the user formulates a query containing her current location, and that query is sent to the application or LBS. The user then waits until the application has processed the request and the answer is sent back. This is depicted on the left in Figure 1.1. Using a location-aware search engine and performing a search for a gas station in one's own proximity is a good example for this kind of service.

- **Push-Services:** The second group of services is made up of the so-called *push-services*. These services require the user to once register or opt in for the service. This can, for example, be done by creating an account on a website or by downloading an application to a mobile device and then starting it. After the opt-in, the service is allowed to regularly or even continuously monitor the user's location. Upon the occurrence of a certain event – like the user entering a defined area or getting close to a point of interest (POI) – the service takes action. Actions can, for example, be to notify the user of special offerings of shops in her proximity. This approach is shown on the right-hand side of Figure 1.1.

In addition to the interaction model of LBSs, there exists also another way to differentiate between such services. While not as important as the first aspect, this type of differentiation should not be neglected and is therefore mentioned here for completeness.

- **Person-Oriented Services:** If a service's mode of operation is *person oriented*, this means that it operates on the user's current location and uses this location to adapt the delivered service. This is the more common way of operation for most LBSs. The just mentioned example of a shopping alert is a good example for a person-oriented LBS, too. The user's location is the relevant factor to select which shops should be considered for having their special offers sent to the user.

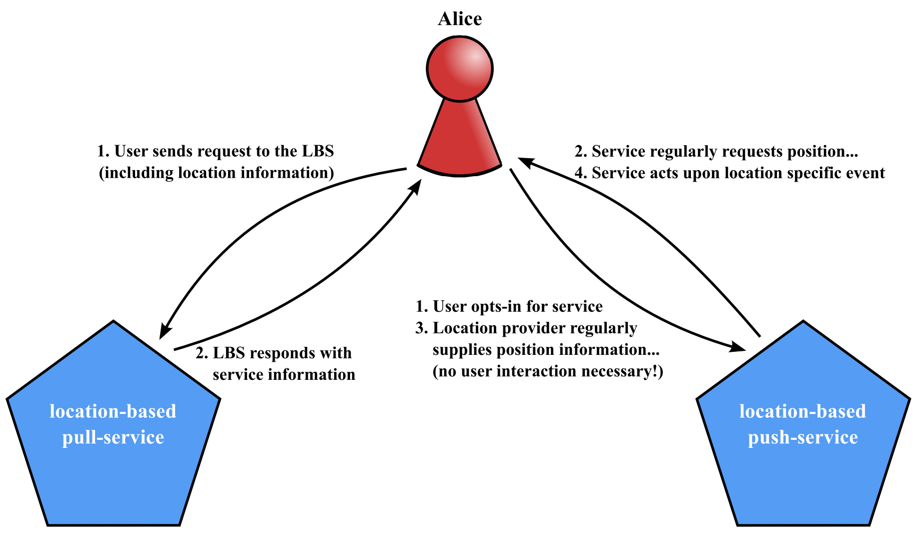

Alice
1. User sends request to the LBS (including location information)
2. LBS responds with service information
2. Service regularly requests position...
4. Service acts upon location specific event
1. User opts-in for service
3. Location provider regularly supplies position information... (no user interaction necessary!)
location-based pull-service
location-based push-service

Figure 1.1: Difference between location-based push- and pull-services.

- **Device-Oriented Services:** In contrast to this, services that follow a *device-oriented* approach consider the location of a certain device or object to adapt their delivered service. This device or object generally is under the user's control but different from the device with which the user is accessing the service. The user herself neither has to be at a certain location or even does not have to disclose her position at all. This approach is used most often for monitoring tasks like for example fleet management. In such a scenario, the user can use the system to monitor the locations of cars from her fleet. This, for instance, is very useful to detect vehicles that have technical problems and have to be replaced quickly.

1.2 Location Providers

Naturally, for any LBS to perform its tasks, the user's or device's location the service operates upon must be known to it. To provide such information about the location is generally the task of a so-called *location service* or *location provider*. The location provider provides the necessary location information to the requesting LBSs and often also handles additional requirements regarding authentication and user privacy. Generally, it is either situated on the user's device or somewhere in the infrastructure. It often cooperates with several different independent LBSs. The exact location of the location provider is a system design decision that is affected by many different factors. Whereas a placement on the user's device allows the user to perform a fine grained control over her location, a placement somewhere in the network operator's infrastructure generally offers advantages in terms of scalability and access to shared resources like for example map data.

Types of Locations

The information about the user's whereabouts provided by location providers can generally have one of two different types [BD05]:

- **Geometric Locations:** On the one hand, the location provider can provide a *geometric location* or *coordinate*. Such a location is a fixed point or area defined by coordinates in a given coordinate system. As such, the coordinate system and its properties must be known to make use of the location information. If the coordinate system is known, though, the location can be easily set into relationship with other locations in the same coordinate system. This includes the computation of distances between different locations as well as other spatial relationships. *Position* is another name that is often used in the meaning of geometric locations. A frequently used coordinate system is the *World Geodetic System 1984* (WGS-84) [WGS04] and its longitudes and latitudes that are widely used to exactly pinpoint positions on the surface of the earth.

- **Symbolic Locations:** On the other hand, a location provider can alternatively or additionally provide so-called *symbolic locations*. In comparison to the former type of geometric locations, a symbolic location is not necessarily bound to a coordinate system. Instead, it is merely a description for a certain place that – without further knowledge – does not disclose any relationship like the distance or the containment status with regard to other symbolic or geometric locations. The name of a certain restaurant is a suitable example for a symbolic location. While it quite exactly describes the whereabouts of a user to those knowing the restaurant and its address, this information is useless for others without this knowledge.

Privacy and Authentication

Of course, being able to access such sensitive information as a user's position raises privacy concerns. This is especially true for push-services that are allowed to constantly monitor the user's position. Therefore, an important task of the location service is the proper handling of the authentication of requesting services. It has to make sure that only those services to which the user has granted access are allowed to access the user's context information. In addition, also privacy is a very important issue when looking at LBS and location services. Generally, not every service needs precise information about the user's location. Sometimes, also a rough estimate is sufficient, or it may be the case that a user wants to temporarily restrict the granularity by which her position is submitted to requesting services. To provide for this issue, many solutions have been proposed in literature in the past.

The location provider can, for example, return a randomized rectangle in which the user's location is contained to a requesting service instead of returning the true geometric position. This is called spatial cloaking. The service then would try to answer the request for the given region. A good example for an application where this approach is suitable is an online weather service. In cases where spatial cloaking is not feasible, the location provider can also return a set of different locations. In this case, the LBS processes and returns the results for all the supplied locations, and the user or – depending on the system design – the location provider has to filter out the inappropriate answers. In the literature, this approach is often referred to as *k-Anonymity*, where k refers to the total number of possible locations [Swe02, SS98]. Both approaches are exemplarily depicted in Figure 1.2.

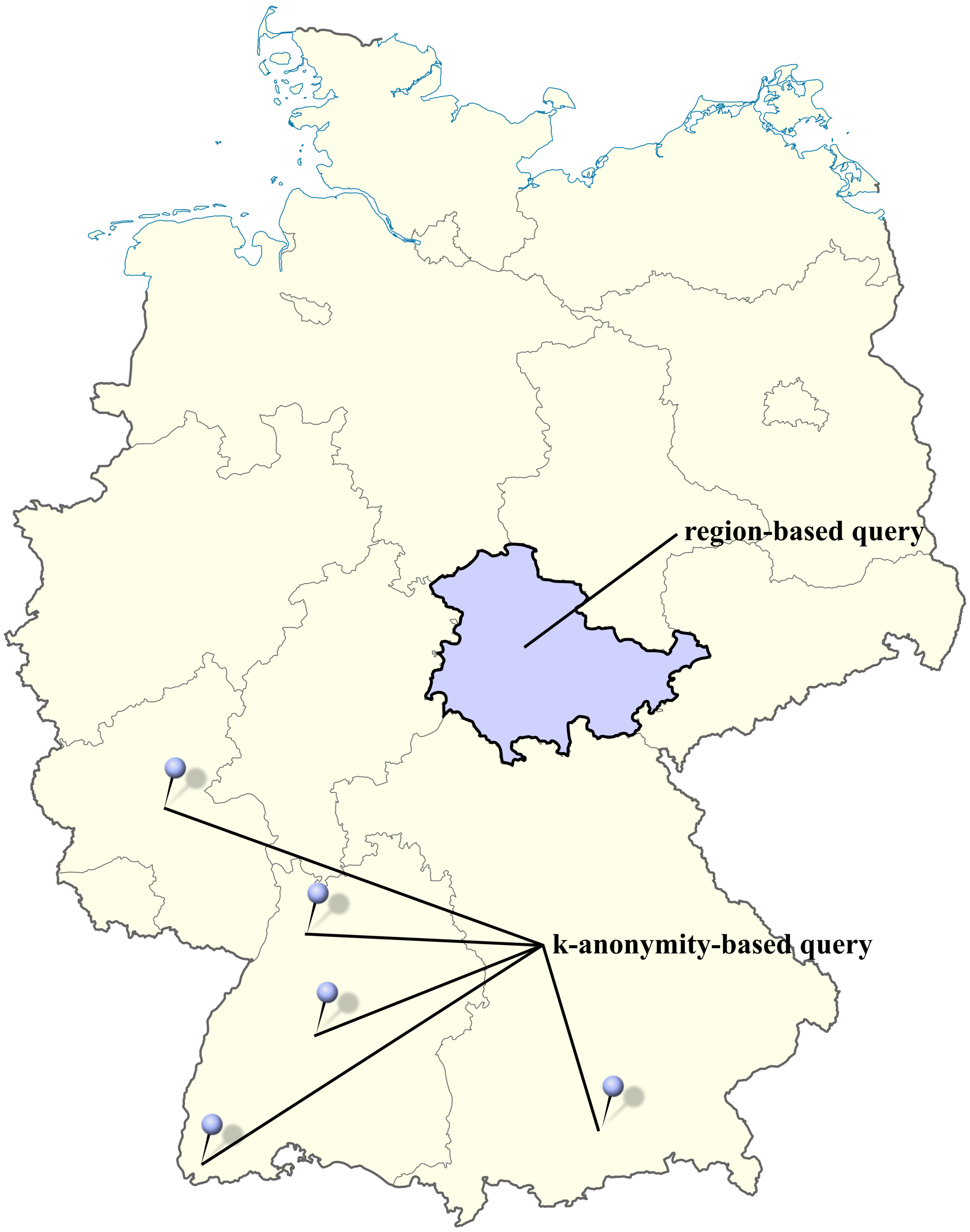


Figure 1.2: Examples how to anonymize user queries in an LBS.

CHAPTER 2 Basic Techniques for Location Estimation

To estimate a user's or device's location, several different approaches can be used. We will give a brief overview of the most common ones in the following section. A more in-depth overview can, for example, be found in [HB01].

2.1 Lateration

An often used technique is called *lateration*. Here, the distances to at least three reference points for a position estimation in the plane and four reference points for a position estimation in the three-dimensional space have to be measured. With the known positions of the reference points and these distances, the own position can be computed by solving the resulting system of equations (see Equation 2.1):

$$r_i = \sqrt{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2} \qquad i = 1 \cdots 4 \tag{2.1}$$

To measure the distances, several different techniques can be used. Common is, for instance, the measurement of the time that a signal sent by the user's device needs to travel to the different receivers or vice versa. This technique is called time of flight (TOF) or sometimes also time of arrival (TOA). A measurement of the signal strength is also a possibility to draw conclusions on the distance between the sender and the receiver. When both the signal level at the sender and at the receiver and the propagation behavior of a signal is known, one can use the signal attenuation to compute the distance a signal has traveled and use that distance in a subsequent location estimation step.

2.2 Angulation

Another technique that can be used for position estimation is *angulation*. Similar to lateration, with angulation a set of at least two reference points with known positions is needed to estimate a user's position in the plain. By measuring the angle of arrival (AOA) between a signal received from the user at each of the reference points and a known reference vector, the user's position can be calculated. For a position estimation in the three-dimensional space, an additional angle between the incoming signals and a common plain has to be measured at one of the reference spots. Figure 2.1 exemplarily depicts this approach. In the Figure, R_1 and R_2 are the reference spots at which the angles α_1 and α_2 on the plain and the angle β_1 between the plain and the incoming signals are measured to estimate the position of P.

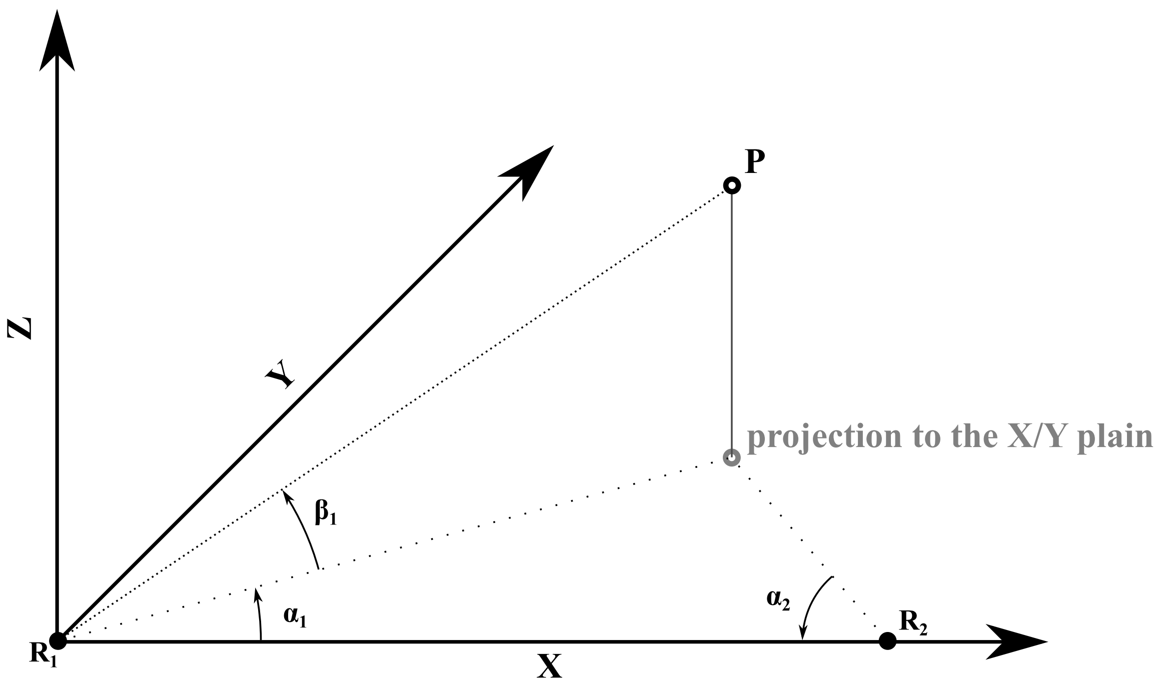


Figure 2.1: Example for a position estimation with the help of angulation.

To measure the AOA, an antenna array at each receiver can be used. In this case, the time difference of arrival (TDOA) of the signal arriving at each of the different antennas in the array is measured and used to calculate the angle.

2.3 Proximity

Basic information about a user's position can also be drawn from about how close a user is to which other objects. A good example for this approach is the position estimation with radio-frequency identification (RFID) technology. RFID uses small unique tags and readers with a limited reading range to read the information stored on the tags. While the targeted application field for RFID mainly is logistics and the replacement of the bar codes used to identify products, it can also be used for position estimation [NLLP04]. When a user who has been tagged with an RFID tag passes by an RFID reader, she can be identified by the unique information stored on the tag. Her position is then close to the known position of the specific reader. In a broader scale, the same effect can also be achieved when using WLAN. The most common mode of operation that WLANs are operated in is the so-called *infrastructure mode*. In this mode, clients using the network do *not* communicate with each other directly (*ad-hoc*). Instead, all messages are forwarded by an infrastructure formed by a set of access points (APs). These APs typically have a radio range of roughly $300\ m$ in a completely open environment and outdoors, $150\ m$ in semi-open environments like open-plan offices, and up to $50\ m$ in closed indoor environments. Given these numbers, the known position of the AP a user is currently connected to thus can be used as a good indication of where she approximately is currently located.

2.4 Dead Reckoning

Using *dead reckoning* is another possible technique to estimate a user's position. Based on a known start position and local sensor measurements from, e.g., accelerometers, one tries to draw conclusions about the user's motion speed and motion direction and thus her current and upcoming positions. This technique is often used by navigation systems in cases where their normally used techniques are temporarily not available. If, for example, a car equipped with an in-car navigation system enters a tunnel or otherwise loses the connection to the normally used satellite-based positioning system, the available data from the speedometer, wheel-mounted sensors, and sensors that measure the steering angle can be used to extrapolate the car's position by dead reckoning. Also, some approaches exist that try to transfer this technique to the domain of human-centered indoor applications. Here, generally highly precise accelerometers and gyroscopes are, for example, mounted on the user's shoe or leg. Based on the data from these devices, the positioning system at first tries to draw conclusions on the step number, step length, and direction of a user and then uses this information to extrapolate the path a user takes from a given start position [Fox05, CSG05, SFL05].

2.5 Scene Analysis

A further method that can be used to estimate a user's position is called *scene analysis*. Relying on local observations, too, scene analysis also takes further knowledge into account for position estimation. *Easy Living* is a system designed by Microsoft Research that follows this [BMK^{+}00].

In the *statical scene analysis*, an analysis of only current local measurements is performed to estimate the user's position. This can be done by, for instance, matching the data to an available knowledge base. As an example, a system might try to identify a user on the image of a surveillance camera. Based on the known position of the camera and the field of view, the system is then able to conclude on the current whereabouts of the user. Opposed to this, in the *differential scene analysis*, the *differences* between several consecutive local measurements are used. Once more considering a system based on camera images, it would, for example, be possible to draw information about the user's motion from changes like pans in subsequent camera image frames.

2.6 Location Fingerprinting

The last possibility mentioned here to estimate a user's position is the so-called *location fingerprinting* (LF) technique. Closely related to scene analysis, location fingerprinting also relies on local measurements at the time of the position estimation and on a knowledge base with additional information.

Fingerprinting algorithms are split into two phases. In a first phase, called *training phase*, a set of fingerprints is collected throughout the area the positioning system shall cover. A fingerprint may contain any type of data that is characteristic for a certain position. The fingerprints then are stored in a *fingerprint database* together with the positions where they were collected.

In the second, so-called *position determination phase*, another fingerprint is collected at the user's yet unknown position. This fingerprint again contains the same type of data and measurements as those collected during the training phase. The fingerprint, sometimes also referred to as *online fingerprint* or *live data*, is then compared to all the fingerprints stored in the fingerprint database. The position of the best matching fingerprint from the database is returned as the position estimate for the user. As especially location fingerprinting with the help of WLAN signals is a key concept used in this thesis, we will look into that topic in more detail in Chapter 4.

CHAPTER 3 A Brief History of Location Estimation

Most of the just presented techniques to estimate a position date back to ancient times. Angulation was, for instance, already used by sailors in ancient times to estimate their position and is still a valid approach today. However, besides the basic positioning techniques, also the idea of estimating a user's position and using it to enhance *services* offered to the user is already quite old – at least in terms of information technology. In its history, many different techniques and systems to estimate a user's position have been developed and tested by the scientific community and by industry. In the following, a brief overview of some positioning systems that were developed in the past is given without intending to be exhaustive. The main goal of this overview is to give the reader an idea of what systems have been used for location estimation in the past, how they worked, and what their main drawbacks were.

3.1 Active Badge

Even as early as 1990, the *Active Badge* system was developed at the Olivetti Research Laboratories in Cambridge [WHFaG92]. Its main purpose was to allow for an efficient automatic call forwarding, and it was one of the first LBSs at all. The system uses badges attached to the users that regularly emit a unique infrared light signal. This signal is received by receivers placed in each room. The receivers then transmit the received signals to a central system where a mapping of which badge – and thus which user – is located within the proximity of which receiver and therefore located in which room can be created. Subsequently, phone calls for that user can be forwarded to the room she is currently in.

Due to the technological solutions used for Active Badge, the system suffers from some major problems. Generally, systems using infrared light often are very sensitive to sunlight. This is also true for Active Badge. Thus, sunny days and large window panes severely affect the operation of the system in such a way that the signals from the transmitters can no longer be received. Furthermore, Active Badge needs a dedicated infrastructure made up of at least one receiver in every room together with the necessary installation. Additionally, it requires the personnel to carry the transmitters just for the purpose of location estimation. Finally, having only an accuracy at room granularity is probably not sufficient for many types of LBSs.

3.2 Active Bats

Active Bats is another positioning system that was developed in Cambridge around the year 2000 [HHS$^+$99]. Instead of infrared light, it uses ultrasonic sound signals and additionally a 433 Megahertz (MHz) radio as a control channel. Small units attached to the user regularly emit sound pulses. At the same time, a reset signal is sent to receivers placed in a grid fashion on the ceiling of each room via the radio channel. Upon the reception of the reset signal, the receivers start a high precision timer and measure the time till the reception of the sound pulse. Based on these TOF measurements, the known locations of the receivers, and lateration, the position of the user can be computed very accurately. Active Bats achieves an average positioning accuracy in the range of a few centimeters.

However, similar to the Active Badge system, also the Active Bats system has some drawbacks. Again, a dedicated infrastructure is necessary and, in the case of Active Bats, this infrastructure even has much higher installation requirements than the one needed for Active Badge. Additionally, the use of ultra sonic sound pulses is controversial as this kind of noise can severely distract both people sensitive to high frequencies and also animals that are nearby. These problems were reasons why the system was not adopted by the community at a large scale.

3.3 Ubisense

Another quite new system used for position estimation is offered by a company called Ubisense[1]. It relies on a combination of lateration and angulation and uses ultra-wideband (UWB) radio pulses to estimate a user's position. The user carries a small badge that is triggered by receivers placed in the corners of each room to emit UWB pulses. The receivers are connected to a central instance by a dedicated infrastructure and communicate the reception of the pulse together with further information, like the reception angle, to the central unit. There, based on knowledge about the time that messages need to travel from each of the receivers to the central instance, the TDOA between the different receivers is measured. Together with the known positions of the receivers and the reception angles, this information is used to compute the exact location of the user's badge. The accuracy that can be achieved with this approach is similar to the one achieved by Active Bats and is close to $15\ cm$. Compared to other systems that use signals bound to a small frequency range, the use of UWB signals offers several advantages. Especially in indoor scenarios, radio signals often suffer from a bad propagation behavior. This includes diffraction, scattering, multi-path propagation, and attenuation of the signals [Rap01]. While

[1] `http://www.ubisense.net`

these restrictions are also true for UWB signals, due to the wide range of frequencies used, a UWB signal is only partially affected by them. If, for example, an obstacle attenuates the signal in a certain frequency range, the remaining parts of the UWB signal stay mainly unaffected. Considering the problem of multi-path propagation and small-scale fading, the system offered by Ubisense further has the advantage that it uses very short pulses. These pulses have a physical dimension of only roughly $30\ cm$ and as such avoid the problem of interfering with themselves if the signal takes several different paths to the receiver.

Similar to the other systems mentioned earlier, the most limiting problem for the system offered by Ubisense is the very high effort in terms of costly infrastructure, cabling, and initial calibration that is needed to set it up. Furthermore, our own experiences with the system have shown a high sensitivity to metal objects in the proximity of both the transmitter carried by the user as well as the receivers mounted on the walls. In our own offices that are separated by metal walls, we did not even manage to get the system working for position estimation at all.

3.4 The Global Positioning System

The Global Positioning System (GPS) is a satellite-based system for position estimation that was developed under the guidance of the American Department of Defense starting as early as 1970. It uses at least 24 satellites placed in a medium earth orbit of about $20,200\ km$ height. Each satellite constantly sends out data transmissions containing a precise time stamp of the time the transmission is sent, precise orbital information about the sending satellite, and an almanac containing rough information about the system health and the orbits of all other GPS satellites. To avoid interference between the signals of different satellites at the receiver, GPS uses a spread spectrum approach and different chipping sequences for each satellite. Once a receiver receives the signals of at least four satellites, it can compute its own position including longitude, latitude, and elevation. Although it would be possible to compute this information with the signals from only three satellites (as one estimated position would generally be somewhere in space), GPS uses a fourth one to handle the imprecise local time as another unknown in the equation to solve (also refer to Equation 3.1). When available, GPS offers a good positioning accuracy of up to ten meters on average.

$$R_i = \sqrt{(x_r - x_i)^2 + (y_r - y_i)^2 + (z_r - z_i)^2} + \Delta t * c \tag{3.1}$$

To further improve the positioning accuracy of GPS, different additions to the system exist. For instance, the accuracy can be improved up to a few centimeters by using additional local transmitters as reference data sources. However, as the local transmitters are very expensive, this approach is only feasible for a limited set of applications.

Another possibility is the use of *Differential GPS* (DGPS). DGPS used stationary local receivers that, due to their fixed location, can compute a very precise estimate of their own position over time. This knowledge together with the currently estimated position is used to identify the error immanent in the currently received satellite signals. After the local DGPS station has estimated the error, correction information is broadcasted to all DGPS-enabled devices in the surrounding which in the following can use it to correct their own received signals and, thus, improve their positioning accuracy.

The major problem GPS faces is that it is hardly available inside buildings and that it often fails in situations where obstacles like buildings block the line of sight (LOS) between the receiver and the satellites. Unfortunately, this is quite often the case, especially indoors and in urban and suburban areas. In these situations, the position estimation with GPS is either imprecise or even impossible. While the complete failure is caused by the satellite signals not reaching the receiver at all, the – from a user's perspective – even worse case is caused by the signals reaching the receiver on indirect paths. Due to the incorrect estimation of the TOF for these signals, this leads to large errors in the position estimation.

CHAPTER 4

Location Estimation with IEEE 802.11

This chapter gives an overview of related work in the area of position estimation with the help of IEEE 802.11. The first section begins by presenting systems that use this networking technology for position estimation without using location fingerprinting. This is followed by a section that introduces several systems in the area of location fingerprinting with the help of IEEE 802.11 that are directly related to the topics of this thesis. In the third section, the research questions for which this thesis provides solutions are stated. Finally, Section 5.2 introduces our research methodology.

4.1 Location Estimation without Fingerprints

In the past, several approaches were made to reuse the existing infrastructure of WLANs for the purpose of location estimation and positioning. Of these, some use other techniques than fingerprinting to estimate a user's position. In the following, we give an introduction to some of these systems and point out what their advantages and disadvantages are compared to systems that follow a fingerprinting approach.

In the year 2000, an early system using existing WLAN infrastructure for position estimation was introduced. It was part of the GUIDE project [CDMF00]. The overall system was designed as a mobile, context-aware tourist guide. It uses a built-in IEEE 802.11 network interface card to communicate with content servers and also to determine the proximity of nearby APs. As such, it is one of the first IEEE 802.11-based positioning systems. Of course, using the proximity to a single AP for location estimation can only offer a coarse accuracy. Furthermore, depending on environmental factors like the weather, the shape of the region in which an AP can be received might change. Thus, following this approach is only suitable for a limited set of applications where the just mentioned drawbacks do not prohibit its use.

Another common approach for location estimation is, as shown in Chapter 1, lateration. This technique has also been used to estimate positions with IEEE 802.11 in the past. For example, in [PBM$^+$09a], Prieto et al. describe a system that measures the round-trip times (RTT) of signals from a mobile station to at least three APs. Based on the propagation speed of the signals and these times, the authors then calculate the distances between the station and the APs and use them and the known coordinates of the APs to estimate the user's position.

This kind of system has several disadvantages, though. One major disadvantage is the problem of the signals taking many and unpredictable paths within an indoor environment. Especially in no line of sight (NLOS) scenarios, this multipath propagation leads to signals needing a longer time to propagate from the sender to the receiver and thus to wrong distance estimations. Prieto et al. deal with this problem in a follow-up paper by modeling the NLOS component of the signals with a probability distribution and dynamically estimated parameters [PBM$^+$09b]. While they are able to improve the accuracy with their addition, it also highly increases the system's complexity.

Furthermore, their approach has a second major disadvantage. Special hardware or at least modifications to the used standard hardware is needed. The protocol that is used on the data link layer of WLANs defines several random backoff times. The network interface card waits such a random backoff time frame if, for instance, a collision occurred while sending a data frame. If no special hardware or drivers are used, then the length of this time is not easily accessible from user-space and thus cannot be separately considered upon the estimation of the RTT. This induces a high inaccuracy in the position estimation.

4.2 Location Estimation with Fingerprints

Both the systems mentioned in Chapter 1 as well as the ones just introduced fulfill their task of estimating a user's position. However, all of them also have major drawbacks. They require specialized hardware or *dedicated* infrastructure, are very costly and hard to set up, or only offer a coarse positioning accuracy except for special conditions.

In many regards, estimating a user's position with the help of location fingerprinting and IEEE 802.11 can overcome these issues. WLAN infrastructure is already available almost everywhere where people live or work in the developed countries these days [LCC$^+$05, BHM$^+$06]. And, as commodity or off-the-shelf (OTS) hardware can be used, the hardware cost when extending an existing positioning system based on IEEE 802.11 is moderate. Furthermore, the accuracy that is achievable with IEEE 802.11-LF is sufficient for many types of LBSs. Current IEEE 802.11-LF systems achieve an average accuracy of about three meters.

But of course, location estimation with IEEE 802.11-LF is not perfect either. The achieved accuracy and precision can still hardly compete with systems like Active Bats or UWB positioning where the accuracy is in the range of few decimeters. These systems need an expensive infrastructure for the sole purpose of location estimation, though. An IEEE 802.11-LF system can reuse the existing WLAN infrastructure that is already in place for communication purposes. Additionally, most mobile devices ranging from cellular phones over laptops to tablet computers these days are already equipped with IEEE 802.11 interfaces. So, to use an IEEE 802.11-LF system, there is no need to attach or carry additional hardware. Compared to GPS functionality that is also built into many modern mobile devices, IEEE 802.11-LF has the major advantage that it can be used both indoors and outdoors to estimate a user's position where APs are nearby. GPS and IEEE 802.11 thus complement each other very well.

4.2.1 RADAR

At the same time as Active Bats, another interesting system called *RADAR* was developed at Microsoft Research in Redmond by Paramvir Bahl and Venkata Padmanabhan [BP00]. The authors used a mobile device equipped with an IEEE 802.11 interface card and three fixed base stations to demonstrate the feasibility of using IEEE 802.11 and LF for position estimation. They collected signal strength measurements at 70 reference spots distributed over the hallways of an office building. Their testbed had a dimension of $43.5\ m$ by $22.5\ m$. To collect the measurements, the authors programmed the mobile device to regularly broadcast UDP packets to the three base stations. At each base station, the *received signal strength indicator* (RSSIs) was measured and stored together with a globally synchronized time stamp and a base station identifier for later reference. To have a ground truth available for the later evaluation of the system, the operator marked his true position on a map, and this information was stored together with time information. As the authors also made the observation that the user's orientation has a remarkable influence on the RSSI at the base stations, the operator's orientation (one of north, south, east, or west) was recorded together with the time stamp and position. At each position and for each of the orientations, at least 20 measurements were recorded.

After the collection of the training data, the authors merged the data from the three base stations and the mobile host into one dataset containing tuples of the form x, y, d, ss_i, snr_i, where x and y represent the position within the testbed, d represents the orientation, and ss_i and snr_i represent the RSSI and signal to noise ratio for base station i. Additionally, for each position, the mean, standard deviation, and median of the RSSI values were computed for each base station. The latter processed data was used by the authors for most of the experiments instead of the raw dataset. Such kind of data used to represent the unique properties of the signal space at a certain location is what we call a *location fingerprint* for the remainder of this thesis.

For the later position determination, the authors evaluated two different approaches. One was the use of what they call an *empirical method* based on the collected training data. The other one was based on a *signal propagation* model. For both approaches, the Euclidean distance in signal space was used to compare different measurements with each other. This kind of metric for comparing measurements is called *deterministic*. Equation 4.1 gives an example of how the distance would be computed for an online measurement *o* and a training measurement *t* in case of three APs $i = 1, 2, 3$.

$$\delta(f_o, f_t) = \sqrt{\sum_{i=1}^{i=3} (x_{oi} - x_{ti})^2} \tag{4.1}$$

For the evaluation of the empirical approach, the authors randomly selected one of the 70 reference positions and one orientation and used the processed data to find the best matching counterpart among the remaining 69 positions with regard to the distance in signal space. They call this the *Nearest Neighbor in Signal Space* (NNSS). As a benchmark, the authors used an algorithm that uses the position of the strongest base station as a position estimate as well as an algorithm that randomly picked one of the 70 possible positions.

Their results show that using such an approach can well be used to estimate a user's position and is superior to both other algorithms described above. The authors report an accuracy of $2.94\ m$ in more than 50% of all cases opposed to, e.g., $8.16\ m$ for the strongest base station approach.

The results were even further improved by using not only the best match from the training data but by selecting the k best matches and averaging their positions. This is advantageous, as the error vectors of the different matches in physical space often point in different directions. Thus, averaging the coordinates leads to a better overall estimate. In their experiments, by using a k of five, the authors improved their results by 9% for the 50%-percentile compared to only using the best match.

Another improvement was made by mitigating the influence of the user's body. The authors created another processed dataset that, for each position, contained only the strongest RSSI values for each AP. Using this dataset, the results were further improved by 9% for the 50%-percentile.

Regarding their approach with a radio propagation model, the authors used the *Floor Attenuation Factor* (FAF) propagation model by Seidel and Rappaport [SRF$^+$92] and modified it to suit their needs. They replaced the original FAF by a wall attenuation factor to compensate for walls and other obstructions in the signal path. Using that model, they then *computationally* created a training dataset containing fingerprints for a grid of positions on the floor and used that set as a search space for the NNSS algorithm. While being significantly better than the strongest base station algorithm, this approach cannot compete with the results of the fingerprinting-based system.

4.2.2 Rice

Another system – we are going to call it *Rice* from now on – that uses location fingerprinting and IEEE 802.11 was introduced by Haeberlen et al. in the year 2004 [HFL$^+$04]. Compared to RADAR, this system introduced a new type of metric to match the online measurements with the fingerprints stored in the database. Instead of using the *deterministic* Euclidean distance, the new system uses a Bayesian inference algorithm to model the state space of possible user positions and the emission probabilities for a certain measurement. In the model, each position and thus each fingerprint stored in the fingerprint database corresponds to a possible state the user can be in. During the position determination phase, for each online measurement and fingerprint in the database, a probability of the user being at the position of the fingerprint is computed. This is done by, for each position, combining the emission probabilities for the measured signal strengths of each AP. The probabilities are computed from the measured signal strength histograms stored in the fingerprints. After the computation of the probabilities for all states, the state with the highest overall probability is selected as a position estimate. This type of metric is called *probabilistic*, and it has even been shown by Youssef and Agrawala that this type of metric generally offers a better accuracy than deterministic metrics [YA04].

In order to verify the use of their system when tracking a mobile user, the authors furthermore implemented what they call a sensor fusion approach by using a Hidden Markov Model (HMM) to handle transitions between different states. Following this approach, the state space and thus the probability distribution over it is transferred between subsequent position estimations. This increased the accuracy by 8%.

In a subsequent step, the authors of RICE furthermore modified their system to use Gaussian signal strength distributions instead of signal strength histograms. This was done because the Gaussian distribution allows the system to perform more robustly in case of suboptimal signal conditions. They also extended their testbed from some floors on a single story to an entire three-story building and changed the collection of the fingerprints: Instead of using a grid of reference spots where to collect the training data, the authors switched to a cell-based approach with manually defined cells for each single fingerprint. The typical size of a cell was approximately $15\ m^2$. They furthermore extended their system by a topological map of the regions. This map was used in a later step to increase the system's performance during the tracking operation.

While this probabilistic approach – especially when using Gaussian distributions – is more complex than the deterministic one taken by RADAR, it offers several advantages. First, it is more robust to variations in the RSSI that are inherent when working with IEEE 802.11. When using a normal distribution, even values that did not occur during the training data collection are covered by the distribution. Thus, if such values occur during the position determination phase, they still can be used. Second, the algorithm is more easily able to handle the case where the signals of access points are missing in the collected online measurement. In such a case, the probability of the user being at the position of the fingerprint is multiplied with a small penalty value and is thereby reduced to indicate the missing AP.

Using their second approach, the authors were able to achieve good results with regard to both the positioning accuracy as well as the reliability. When using the Bayesian inference algorithm together with the signal strength histograms, the system achieved an accuracy of less than $1.5\ m$ in 77% of all cases within the – admittedly – limited scenario of eleven reference spots and two orientations used. Incorporating the last two online measurements increased this value to 83%. A further experiment with the HMM showed additional improvements in some situations but decreased the accuracy in others, especially in areas with large open spaces. The authors explain this result with the dilution of the signal due to the open spaces and a suboptimal placement of the base stations.

Another important aspect covered by Haeberlen et al. is the problem of different device characteristics. As different devices generally have different antenna designs and chipsets, the measured signal strengths at one position may vary between devices. The authors identified this problem and found that a linear model can be used to create a mapping between different devices. These results were used by Kjaergaard et al. in a subsequent work on signal strength normalization over different devices [Kjæ06]. There, they could be confirmed, and an even better normalization method was introduced [KM08] later.

CHAPTER 5 Improvements for IEEE 802.11-LF

As we have seen in Chapter 4, position estimation with IEEE 802.11-LF is a viable alternative to other techniques. It is accurate enough for most types of LBSs, it can be used indoors as well as outdoors, and an additional installation of dedicated infrastructure is not necessary in most cases. Thus, it seems like this is an ideal solution to all positioning tasks. Unfortunately, most approaches that use IEEE 802.11-LF still suffer from several drawbacks. The following section gives an overview of the three major problems from which IEEE 802.11-LF systems suffer. After presenting our research methodology, we then present our own solutions to each of these single challenges in the subsequent sections.

5.1 Research Questions

As shown, in the past, the position estimation with IEEE 802.11 has already been an extensively studied field of research. Nevertheless, there are still many open problems that need to be solved before positioning systems based on IEEE 802.11-LF become conveniently usable products.

In order to give an overview to the reader, we, in this Chapter, will show some urgent fields for the improvement of IEEE 802.11-LF in general and also approaches targeting these issues. The problems are:

- A still improvable accuracy.
- The huge effort needed to initially set up a WLAN-LF system and to maintain the fingerprint database.
- The lack of an error estimation for WLAN-LF.

In the following, our own developments to deal with these issues are presented. This includes what we call *Quick Fingerprinting*, an approach that, at the same time, can deliver both an increased accuracy and a largely reduced amount of time needed for the collection of the training data. We then present and evaluate a system that goes even further by replacing the fixed reference spots and uses pre-defined trajectories instead. This allows for the fast and efficient collection of training data at the cost of only minor degradations in accuracy. And, finally, several different algorithms to estimate the error for a given position estimate are introduced and thoroughly evaluated.

All these systems deal with a static scenario. But of course, in reality, a user will be moving around most of the time. Therefore, in the second half of this thesis, we deal with the question how the position estimation could be further improved for tracking. While the simple reuse of existing techniques for static position estimation does not yet yield major improvements, tracking – the continuous estimation of a user's position – offers several advantages over the independent estimation of subsequent positions. Firstly, a new position estimate can incorporate information from a history of former position estimates. Secondly, information about the current motion state of the user can be used. And thirdly, also information about other context, like for instance an available building map, can be used to verify position estimates and an estimated movement.

5.2 Research Methodology

Several different ways exist to evaluate the performance of positioning algorithms. Of course, the best one is to perform a large number of position measurements in the true environment where the system will be used. However, this unfortunately is not manageable for many settings due to the high amount of time and effort needed for such an evaluation.

Another possibility to evaluate positioning algorithms is by *simulation*. Here, the algorithm is provided with artificially created information and uses this information to estimate a position. This approach stands or falls with the quality of the created input. If it reflects the true environment well, then also the achieved results for the positioning algorithm are valuable. In the case of position estimation with IEEE 802.11-LF, though, the latter approach is not usable, either. The reason is once more the complex propagation behavior of the radio signals in indoor environments. As these cannot be precisely modeled, it is also not possible to predict what signals a mobile station would measure at a specific position.

Thus, to evaluate positioning algorithms that use the signals of IEEE 802.11 APs, the common approach is *emulation*. Emulation is a combination of the former two techniques. At first, the data that the system would normally use to estimate a position are collected for the evaluation environment. Then, instead of using artificially created input, this collected data is provided to the positioning algorithms in simulation runs.

For the evaluation of our own algorithms, we used emulation for the just mentioned reasons. We have collected several different datasets at the premises of our department at the University of Mannheim. The collection of different datasets became necessary for several reasons. Our first dataset covers a single floor with a high density of reference spots. The dimensions of this dataset were limited by the effort needed to collect it, and it was used to analyze, for instance, the influence of the distance between different reference spots on several aspects of the position estimation. Over time, we realized that for our novel algorithms, like the region-based position estimation, a larger dataset containing both the floor from the first dataset and another less cluttered floor would allow for a better evaluation of the algorithm in different settings. We therefore collected another dataset covering a much larger area with different characteristics. This dataset was also used to evaluate the error estimation for IEEE 802.11-LF. To estimate the performance of our tracking approach, we once more extended the area covered by the large dataset to also include several offices and lecture halls. This was necessary to be able to also consider the influence of available building information on the positioning results. In addition to the dimensions, the third dataset is also special considering the mode of data collection: Whereas the first two datasets were collected over a period during the weekend when the building was almost empty to assure a very high quality of the collected data, the third dataset was collected during normal office hours over a longer timespan. This results in a poorer data quality but gives an even more realistic impression of what an IEEE 802.11-LF-based positioning system can provide.

As a result of using these different datasets, our single results for the different algorithms are only partly comparable. To compensate for this, we – when needed – also performed performance evaluations of the RICE system with the corresponding datasets. These can serve as a common baseline between the different systems.

5.3 Areas for Improvements

The first aspect we take a look at is the overall positioning accuracy. These days, IEEE 802.11-LF systems offer an *average* positioning accuracy of less than three meters. Compared to RADAR, this is already an improvement, and it is sufficiently accurate for many applications and types of LBSs. But still, there exist cases in which a higher accuracy would be desirable or is even necessary. Just consider a museum guide application for an art museum: In such a scenario, a positioning accuracy better than half the spacing between the exhibited images or objects would be necessary for the guide to function optimally.

Another even more important aspect that still is a problem for IEEE 802.11-LF systems is the following: Even though especially IEEE 802.11-LF systems that are based on probabilistic algorithms offer a competitive average positioning accuracy, a remaining major problem is the uncertainty that is inherent in the position estimation most of the time. Besides their good average accuracy, there are situations where the conditions are suboptimal. In these situations, the accuracy decreases rapidly. However, as most IEEE 802.11-LF systems do not offer any means to estimate the error that has to be expected, in these cases, the user or subsequent systems are not notified that the currently estimated position might be far from the real whereabouts. Thus, a major improvement for these systems are means to estimate the error that has to be expected for a given position estimation.

Finally, the third and maybe most urgent drawback IEEE 802.11-LF systems suffer from is the need for the very time consuming creation of the fingerprint database. To achieve a satisfactory positioning accuracy, a small-spaced grid of reference spots has to be laid out over the area of operation and, at each of these spots, a high number of training measurements have to be made [KHE07]. This is – at least in our opinion – one of the main reasons why IEEE 802.11-LF-based positioning systems have not been widely adopted for general use yet.

Figure 5.1 gives an overview of existing possibilities to improve the positioning accuracy of IEEE 802.11-LF systems and to estimate the positioning error that has to be expected. These two aspects are important issues especially from a user's perspective. The Figure furthermore shows systems that deal with the – from a system operator side – most important aspect of IEEE 802.11-LF systems, namely the effort needed for setup.

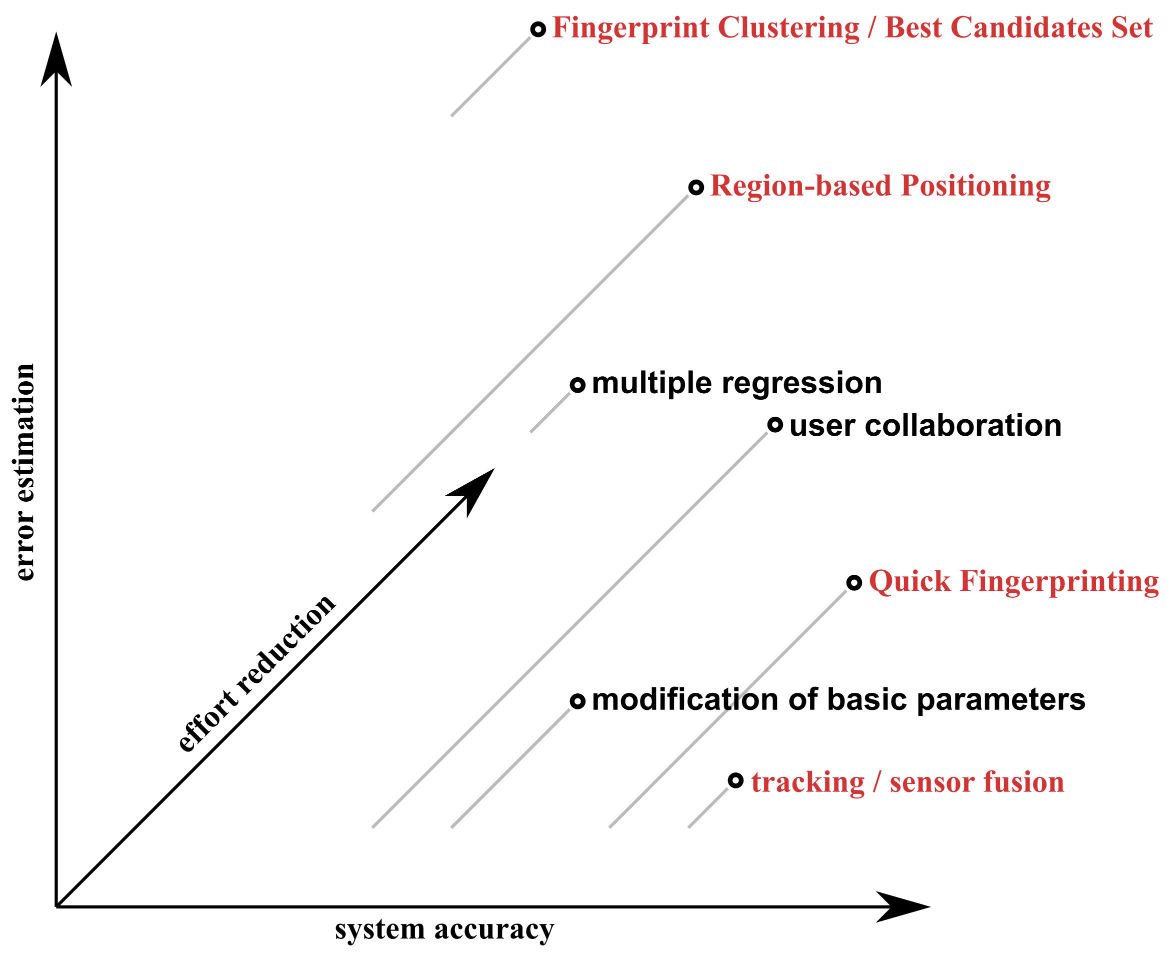


Figure 5.1: Classification of different IEEE 802.11-LF-based systems with respect to the identified problems. Systems depicted in red are dealt with in more detail later in this thesis.

Even though the concepts presented here are mostly universal, we will mainly stick to systems that use IEEE 802.11 as the underlying radio infrastructure. The reason is that nowadays

IEEE 802.11 is the most ubiquitous radio technology that offers the possibility of a positioning accuracy sufficient for most indoor scenarios, a sufficient coverage, and that is easy to use. Extending our approaches to other radio systems (for example Zigbee) should be straightforward.

At first, Section 5.3.1 introduces current methods from other researchers as well as from ourselves to improve the positioning accuracy. This is followed by Section 5.3.2 where we present techniques to estimate the error of common IEEE 802.11-LF systems. Subsequently, Section 5.3.3 introduces new approaches to reduce the effort for creating the fingerprint database. In Section 5.3.4, we discuss the presented solutions from a more general perspective before we, in Section 5.3.5, finally conclude this section.

5.3.1 Increasing the Positioning Accuracy

There are many different aspects that affect the performance of a positioning system with regard to the positioning accuracy. As stated before, the class of systems that use a probabilistic metric generally offers a better positioning accuracy in most cases [YA04]. The Rice system introduced by Haeberlen et al. [HFL$^+$04] is a typical representative of this class. However, besides a variation of the metric, several other aspects exist that can be used to improve the positioning accuracy of LF systems based on IEEE 802.11. The possibilities range from advanced pre- or post-processing steps of the sensor data over the consideration of the position or measurement history to the use of sensor fusion techniques.

Basic System Parameters

The easiest way to improve the positioning accuracy of LF systems is to modify basic setup parameters. As shown in [KHE07], a reduction of the grid spacing between the reference spots – in case a grid is used – has a major influence on the achievable accuracy. When, for example, the grid spacing is reduced form $4\ m$ to $2\ m$, the average accuracy of the studied system increases from roughly $3\ m$ to $2.5\ m$. In addition, both the number of measurements used to create each single fingerprint during the training phase as well as the number of measurements used during the position determination phase have a large impact on the positioning accuracy. If the number of the latter is increased from one to three, the achieved accuracy increases by 11%. Finally, also the number of APs which can be received throughout the coverage area matters for the achievable accuracy.

Measurement Processing

Inspired by fundamental research on this topic, other systems have been proposed that extend the basic IEEE 802.11-LF approach by measurement pre- or post-processing steps to increase the accuracy. An example for such an advanced system is Horus [YA05]. Horus uses an algorithm to detect and eliminate small-scale signal variations as they often occur when measuring the signal strength of an IEEE 802.11 access point at a fixed position.

Another often suggested possibility to improve the position accuracy of IEEE 802.11-based LF systems is the use of advanced machine learning algorithms. In [WKB08], for instance, a *particle filter* approach is chosen to estimate the position of a user based on signal strength measurements. Particle filters are part of the sequential Monte-Carlo methods and quite similar to Kalman filters. They are very well suited to deal with data and measurements that do not adhere to standardized distributions, like e.g., Gaussian distributions, as it is the case for indoor signal strength measurements. Also, particle filters are computationally less expensive than many other methods. This makes them especially suitable for the use on mobile devices, being less powerful compared to stationary computers. Widyawan et al. use a variation of the general particle filter approach called *backtracking particle filter* to increase the positioning accuracy of the underlying IEEE 802.11-LF system.

Feature Selection

Another approach is used by a system called SkyLoc [VLHdL07]. SkyLoc is a localization system designed to run on cellular phones and is used to reliably determine the floor on which a user is located in tall multi-story buildings. It uses the radio signals from base stations – or so-called cell towers – of the *Global System for Mobile Communications* (GSM) and location fingerprints created for each floor of a building. To find the best-matching fingerprint in the database, SkyLoc relies on a deterministic approach – namely the Euclidean distance in signal space. To additionally improve the estimation accuracy, SkyLoc incorporates a method called *feature selection*. Instead of using data for all GSM cells from which a signal was received at the user's current position, only a subset of these is used for matching against each of the fingerprints in the database. To identify the subset that offers the highest position accuracy in advance of the deployment, the authors of [VLHdL07] suggest three different methods: The first one is called *Forward Selection*. Starting with an empty set, the feature that offers the highest increase in average position accuracy is added to the set of used features until it has reached its final size. The second alternative is *Backward Elimination*. It proceeds in the opposite way. From the full set of all available features, those features are removed successively from the set of which their removal offers the highest increase in the average position accuracy. Finally, the third method, namely *Per-Floor Feature Selection*, tries to find not one optimal feature set to be used for the whole database but optimizes the set for each story separately. Additionally, the third method also uses weights for the single features to further increase the performance. Transferring this approach to IEEE 802.11-LF would, for instance, suggest to only use an optimized subset of the APs available at each reference position for an optimized positioning performance.

Sensor Fusion

Sensor fusion is another possibility to improve the accuracy of IEEE 802.11-LF systems. Sensor fusion means to not only use the readings from a single data source, in our case for instance from an IEEE 802.11 network interface card (NIC), but also to consider data from other sources. This can be built-in cameras, other radio devices like a Bluetooth radio interface, audio sensors, or even accelerometers like the ones used for shock protection systems of computer hard disk drives (HDDs). A good example for a system that follows this approach is Compass [KKH+06]. Compass is based on LF with IEEE 802.11 and exploits the fact that the human body attenuates radio waves in the 2.4 GHz band that pass through it (also see Figure 5.2). As already identified by Bahl and Padmanabhan in [BP00], this effect can highly deteriorate the positioning accuracy of an IEEE 802.11-LF system if the user is standing in an unsuitable position.

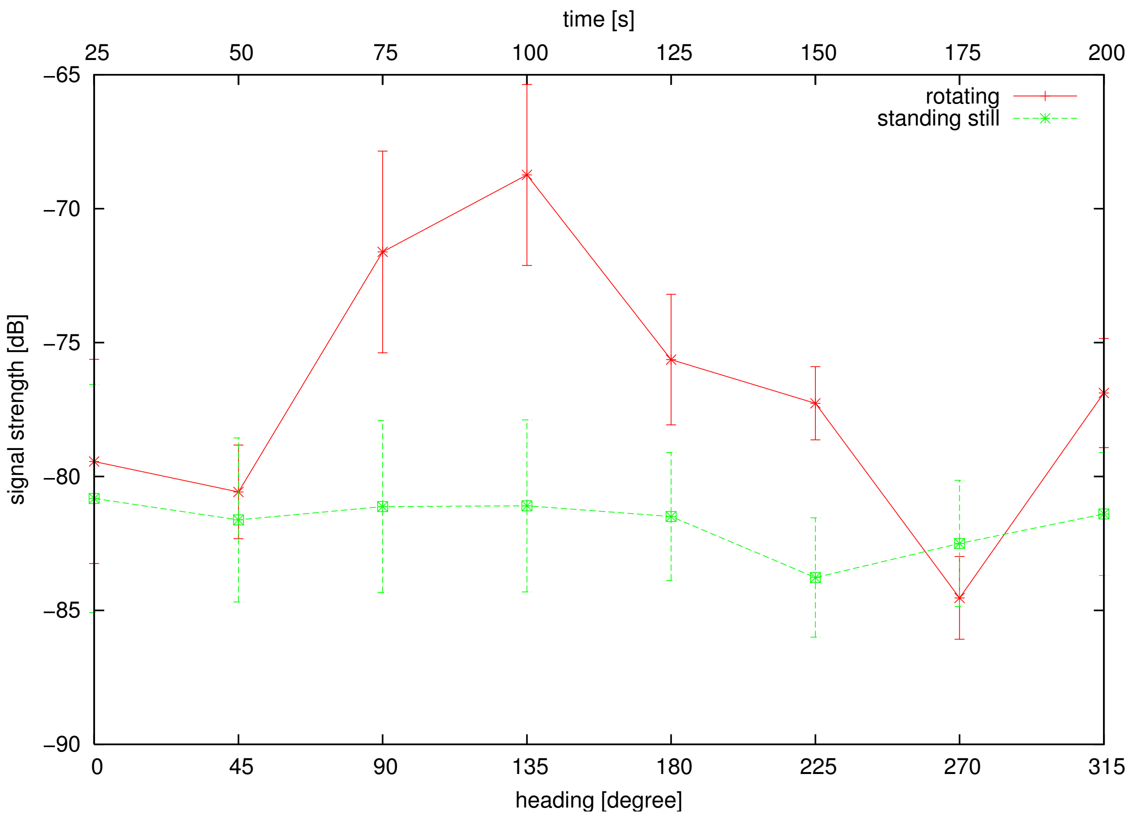


Figure 5.2: Influence of the user's orientation on the received signal strength [KKH+06].

To mitigate this effect, the Compass system creates not only one fingerprint for each reference spot but a set of fingerprints with the operator facing in different directions. The directions are predefined, and the adjustment is made using a digital compass built into or attached to the mobile device. In the position determination phase, the user's mobile device – as well equipped with a digital compass – creates a fingerprint of the current radio environment, as usual. This fingerprint, however, is not matched against all fingerprints in the database. Instead, it is only matched against those fingerprints that were collected having a similar orientation as the user (see Figure 5.3). In the Figure, the arrows represent fingerprints taken while facing in a certain direction. The black dot represents the user and the arrow points in the direction she is currently facing. Finally, the shaded area represents the interval used to select appropriate fingerprints

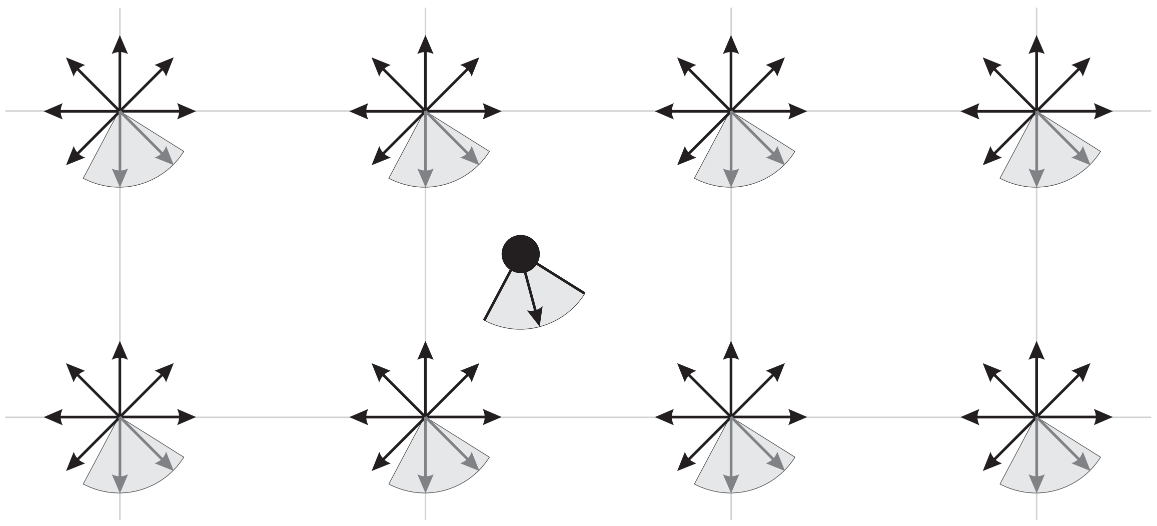


Figure 5.3: Selection of the fingerprints based on the user's orientation [KKH+06].

from the database for the position estimation. Using this sensor fusion approach, a significant accuracy improvement of approximately 20% is achieved.

Sampling Frequency

While it does not completely fit into the category of improving the accuracy, at this point, also the Composcan system [KK08] should be mentioned. Composcan is a system that, based on the variance of subsequent measurements taken during the position determination phase, can estimate whether a user is moving or standing still. The reasons why such an approach can be used to increase the positioning accuracy are twofold. First, when the user is detected as being stationary, several consecutive measurements taken at the same position can be combined before comparing them to the fingerprints in the database. As stated in Section 5.3.1, increasing the number of measurements used for the position estimation considerably increases the positioning accuracy. Second, it is well known that the sampling of measurements with IEEE 802.11 network cards interferes with ongoing data communication. Therefore, the sampling frequency as well as the sampling scheme can be adapted for a stationary user to reduce the impact on concurrent data communication. If the user is moving, the sampling frequency can be raised again. This helps to maintain an acceptable position accuracy at the cost of decreased data throughput for moving users.

5.3.2 Estimating the Error

Even though reducing the overall error and thus increasing the accuracy of IEEE 802.11-LF systems is a desirable goal, the achievable accuracy will probably always leave room for improvements. Additionally, when considering the average accuracy of current systems which is typically between $2.5\ m$ and $3\ m$, errors in this order of magnitude are acceptable for most applications. However, one of the remaining problems with the position estimation is the so-called *long-tail error*: the quite unlike but still existing occurrence of a very large error. An estimation of the positioning error would be of high value to both the user and the system operator. In this section, we therefore introduce different approaches that deal with the error of IEEE 802.11-LF systems.

Error Distribution

The most basic approach of error estimation is to supply the user with general information about the positioning error that has to be expected when using a certain positioning system. This can be achieved by, for instance, supplying her with a *cumulative distribution function* (CDF) for the error of the positioning system. Figure 5.4 gives an example for such a CDF. Here, for instance, the error is smaller than $3\ m$ in 80% of all cases. In this case, the user herself has to estimate the probability of a certain error to happen, and to adapt her behavior accordingly.

Even this very simple way of dealing with error information already has a remarkable impact on the user perception of an LBS. As a study by Dearman et al. [DVDLT07] has shown, even this situation-unspecific knowledge of the error distribution helps users of an LBS to perform better when solving location-specific tasks. The main drawback of this approach is that it only offers a general and not a situation-specific error estimation and as such might reduce the overall trust a user has in her positioning system.

Multiple Regression

The authors of [DVDLT07] also introduced the use of *multiple regression* to estimate the positioning error. Using the training data and a small number of test measurements for the reference spots, the system operator computes a linear model of the error that is expected based on a defined set of signal features. This set can contain the receivable APs or GSM cells, the signal strengths, properties of the noise floor or other information available in the measurements. During the position determination phase, the user then can apply the linear model to his currently collected data and compute an appropriate error estimate. Even though this approach still uses quite basic features to estimate the error, it already offers promising results. Therefore, we will introduce several techniques using more advanced features to estimate the error in Section 5.6.

5.3.3 Reducing the Effort

The major reason why IEEE 802.11-LF is still only rarely adopted for position estimation beyond academic settings is the need for the very time-consuming setup of the system. As analyzed in [KK08], a fine-grained grid of reference spots has to be used, and at least 20 measurements have to be collected at each reference spot to achieve a sufficient accuracy for most LBSs. The following sections will present techniques on how this cumbersome process can be circumvented and how the overall effort can be reduced.

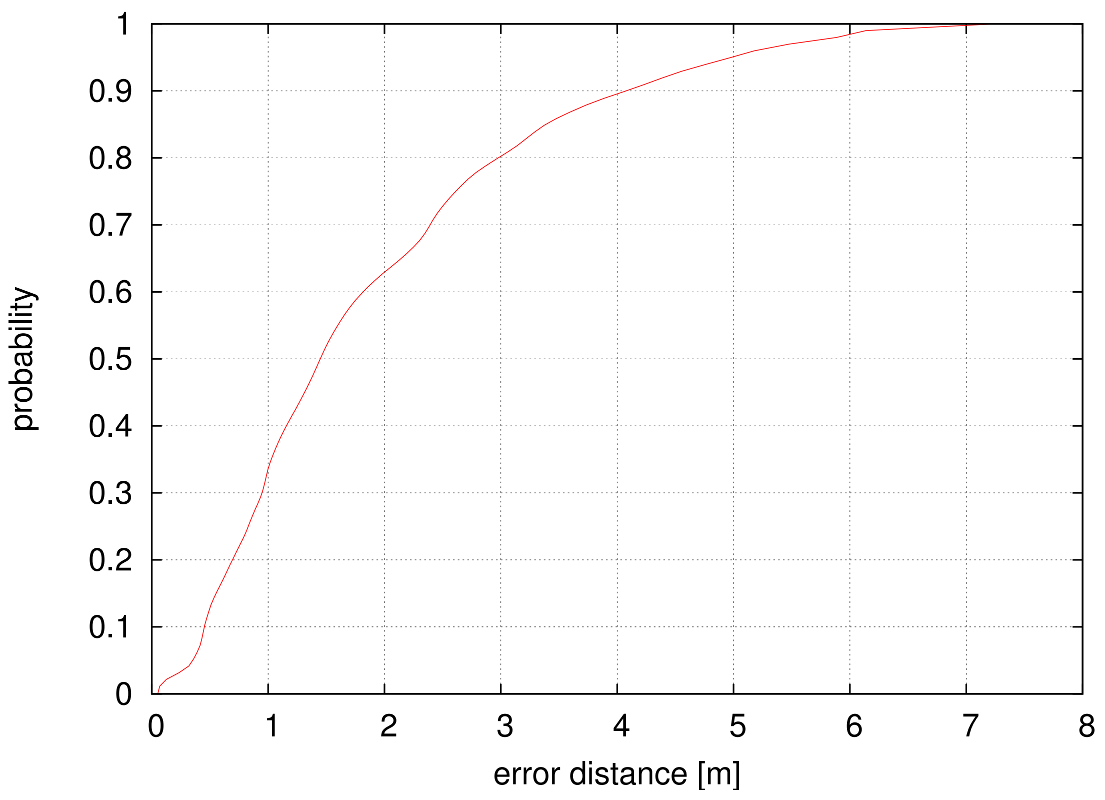


Figure 5.4: Example for a cumulative error distribution of an LF system.

User Collaboration

The probably most effort-saving way to setup an LF system is to let the user provide the training data for the fingerprint database on the fly. While, with this approach, the system operator loses control over the training data collection, he gains the possibility to continuously improve the coverage and to keep the database updated.

A good example for an LF system that follows this approach is Redpin [Bol08]. It uses a software that runs on the mobile device to collect signal measurements from GSM cells, IEEE 802.11 APs, and nearby Bluetooth-enabled devices. Besides the normal operation where a fingerprint created from live measurements is matched against the fingerprints in the database, the software offers the possibility to store a fingerprint for the user's current location in the database in case that no matching fingerprint was found and therefore no position estimation was possible. Thus, different users can collaborate with the system operator to extend the system to new areas and to keep the available data up to date. This reduces the training effort of the system operator to a minimum.

Another example for a system that uses user-supplied data was introduced by Chai and Yang in 2005 [CY05]. In contrast to Redpin, this system does not completely rely on user-supplied data but requires an initial fingerprint database to be set up by the system operator. During the position determination phase, so-called unlabeled traces – sequences of user measurements of which the positions are unknown – are used to refine the data in the fingerprint database. To identify the corresponding fingerprints, the authors apply an algorithm introduced by Dempster et al. [DLR77] called *Expectation Maximization* algorithm. This algorithm iteratively computes maximum likelihood estimates from a given set of incomplete observations. It is split into two steps, an expectation step and a maximization step. The advantage of using unlabeled traces compared to Redpin is that the operator can offer a guaranteed basic coverage of the area the initial fingerprint database covers. However, this also shows the limits of this approach as the unlabeled traces can only be used to refine existing data. Thus, the users cannot extend the coverage area of the system on their own. An optimized solution could therefore use a combination of both approaches.

Generated Fingerprints

It is also possible to create the fingerprint database computationally. This approach reduces the effort to set up an LF system very effectively. Most common here is the use of a radio propagation model in combination with a few or even only one reference measurement. Based on the measurement and the model, a radio map for the area to cover is computed. With values taken from this computed radio map, fingerprints are created for each reference spot in the area, and are then stored in the fingerprint database. For example, the system introduced by Ji et al. [JBPA06] follows this concept.

Whereas such an approach reduces the effort effectively, it is questionable how usable such a system really is in practice. Considering the unpredictable behavior that radio signals show inside buildings, the performance of such a system strongly depends on the quality of the radio model in use. For instance, it has to incorporate factors like building materials or furniture at a high level of detail. If the model does not reflect the real radio propagation correctly, the entire system is unusable.

5.3.4 Discussion

As we have shown in the previous sections, several different solutions exist to mitigate the drawbacks of 802.11-based LF systems. Each of these solutions fulfills its purpose when considering its specific area. However, a look at the complete picture shows that not all solutions are equally well suited for a real-world deployment.

Positioning Accuracy

For example, if we consider the Compass system mentioned in Section 5.3.1, we can see that it offers a very competitive accuracy. But because one fingerprint has to be created for each considered direction, the effort to set up the system would be even larger than it already is for a basic LF system.

Exactly the opposite is true for the feature selection system presented in Section 5.3.1. As this system relies on data that is available anyway, and as its usage should have no negative influence on other system parameters like the effort needed for setup, it can well be adopted for widespread usage in LF systems.

Error Estimation

As mentioned in Section 5.3.2, the estimation of the expected error is mainly desirable to be able to provide the user with information in case of possibly large errors. This helps to increase the user's trust in the system. Because this is only possible with situation-specific knowledge, using only a distribution function like the one presented in Section 5.3.2 seems inappropriate. Algorithms that are able to use situation-specific information are better suited. This can either be the training data, the online measurements, or even a combination of both. Such algorithms were developed by us, and will be presented in Section 5.6.

Effort Reduction

Regarding the algorithms presented in Section 5.3.3, they have both advantages and disadvantages. Whereas the system presented in Section 5.3.3 that uses generated fingerprints very consequently reduces the effort necessary to set up the system, this comes at the cost of a heavily degraded accuracy if the selected radio model is not realistic. The system Redpin described in Section 5.3.3 seems to be much better suited. The effort is effectively reduced while the accuracy of the system is only influenced in terms of missing coverage. This comes at the cost of lost control over the coverage area and the quality of the fingerprints, though.

Application-specific Requirements

As we have seen, not all presented solutions are equally well-suited to solve their corresponding problems and also the combination of different approaches is not always easily possible. Therefore, for a real deployment, the application requirements have to be considered as well in order to identify features that need special consideration.

Let us think of, for instance, a friend finder application that is used on a university campus. On the one hand, the accuracy requirement could very well be reduced to room level as friends would easily recognize each other if they were inside the same room. The same is true for the error estimation where only errors beyond the size of a room would matter to the user. On the other hand, as the campus of a university generally covers a large area, a reduction of the effort to set up the system and to maintain the fingerprint database is a very important factor for this scenario.

In contrast, when considering a warehouse navigation system, the situation is different. To locate items on the storage shelves, a high accuracy is necessary. Also the estimation of the positioning error is of a higher importance in such a case: If the system is unsure about the current estimate, it should inform the user in order to avoid the frustrating search for a stored item that might have been placed somewhere else. Therefore, such a system should obviously only consider position estimates with a very low estimated error to avoid giving false directions to the user. Compared to the first two properties, however, the effort necessary for setup and operation is generally only of secondary importance in such a limited scenario.

5.3.5 Conclusions

Up to now, we gave a brief overview of techniques used to address the major issues that still are obstacles to the wide adoption of IEEE 802.11-LF as a pervasive localization technology. Firstly, we have presented different techniques that can be used to increase the positioning accuracy of 802.11-based LF systems. Increasing the accuracy is a prerequisite to be able to also allow the use of advanced LBSs. Secondly, several possibilities to handle the problem of error estimation for IEEE 802.11-LF systems have been introduced. While this field of research is still quite new, it nevertheless is of high importance – especially to the users of LBSs. Finally, we have presented techniques that system operators can use to reduce the effort that is necessary to set up a location fingerprinting database. This can help system operators to deploy and maintain IEEE 802.11-LF systems at a reasonable cost and, thus, to make their usage more feasible. During our discussion, we have shown that, while suitable solutions exist for the single problems, a combination of these is neither always possible nor always necessary. Which of the different parameters should be optimized is highly dependent on the targeted application. We will now introduce our own contributions in the three mentioned fields.

5.4 Quick Fingerprinting

The time-consuming training phase is one of the major reasons why IEEE 802.11-based positioning systems are still struggling to make their step from a scientific prototype to a convenience product. In this section, we therefore propose novel algorithms to set up a fingerprinting system. Our algorithms reduce the time needed to collect the necessary data during the training phase considerably without losing positioning accuracy. To accomplish this task, our algorithms pre-process the data that has been collected during the training phase. To create a fingerprint, not only the samples that have been collected at a single reference position are considered. Instead, also samples that have been collected at positions adjacent to the position we create the fingerprint for are taken into account. With this approach, we can reduce both the amount of data that needs to be collected at each reference position and the time needed to collect the data by about 80% without losing positioning accuracy. In fact, our algorithms even increase the positioning accuracy in most cases.

5.4.1 Algorithms

In this section, we introduce the techniques used by our algorithms as well as by the algorithm which was taken as a benchmark during our evaluation.

Probabilistic Fingerprinting

When the Rice system is used, samples of the signal strengths of all receivable access points are collected at each reference position during the training phase. For each access point contained in the samples of one reference position, the average and the standard deviation of the signal strength measurements are computed. These values are stored in the fingerprint of the corresponding reference position. As a result, each fingerprint contains a pair of average signal strength and standard deviation for each access point of which signals have been received at the reference position. During the position determination phase, samples of the signal strength of each receivable access point are collected. These samples are compared to the values stored in each of the fingerprints. By computing a normalized probability for each reference position and selecting the position with the highest probability, the system comes up with a position estimate.

In the following, we describe the computation of the probabilities in a more detailed fashion.

For each fingerprint and each access point ap contained in the live samples, we compute a probability $P(s_{ap})$. This probability states how probable it is to receive a signal of access point ap with a signal strength s_{ap} at the reference position r to which the fingerprint belongs.

To compute the probability, the live measured signal strength for access point ap is matched with the density function of a normal distribution with the parameters for access point ap taken from the current fingerprint. As the probability for a single value and a given continuous probability distribution is zero per definition, the probability for an interval of $s \pm 0.5$ is computed instead (also refer to Equation 5.1).

While another value could also be used for the width of the interval, we decided to use the value introduced in [HFL+04] to map the discrete signal strength values the hardware delivers ($-102\ dB$ to $0\ dB$) to the continuous number space of the normal distribution.

$$P_{r,ap}(s_{ap}) = \int_{s-0.5}^{s+0.5} df(\mu_{r,ap}, \sigma_{r,ap}) \tag{5.1}$$

For access point ap, df is the density function of the normal distribution with an average of $\mu_{r,ap}$ and a standard deviation of $\sigma_{r,ap}$. These values are taken from the fingerprint of reference position r (see Figure 5.5).

The latter step is repeated for all access points contained in the live samples. This, finally, leads to one overall value P_r per reference spot (see Equation 5.2) which – after a normalization step considering the sum of the values for all reference spots – can be interpreted as the probability of the user being at reference position r.

$$P_r(s) = \Pi_{i=1}^{n} P_{r,ap_i}(s_{ap_i}) \tag{5.2}$$

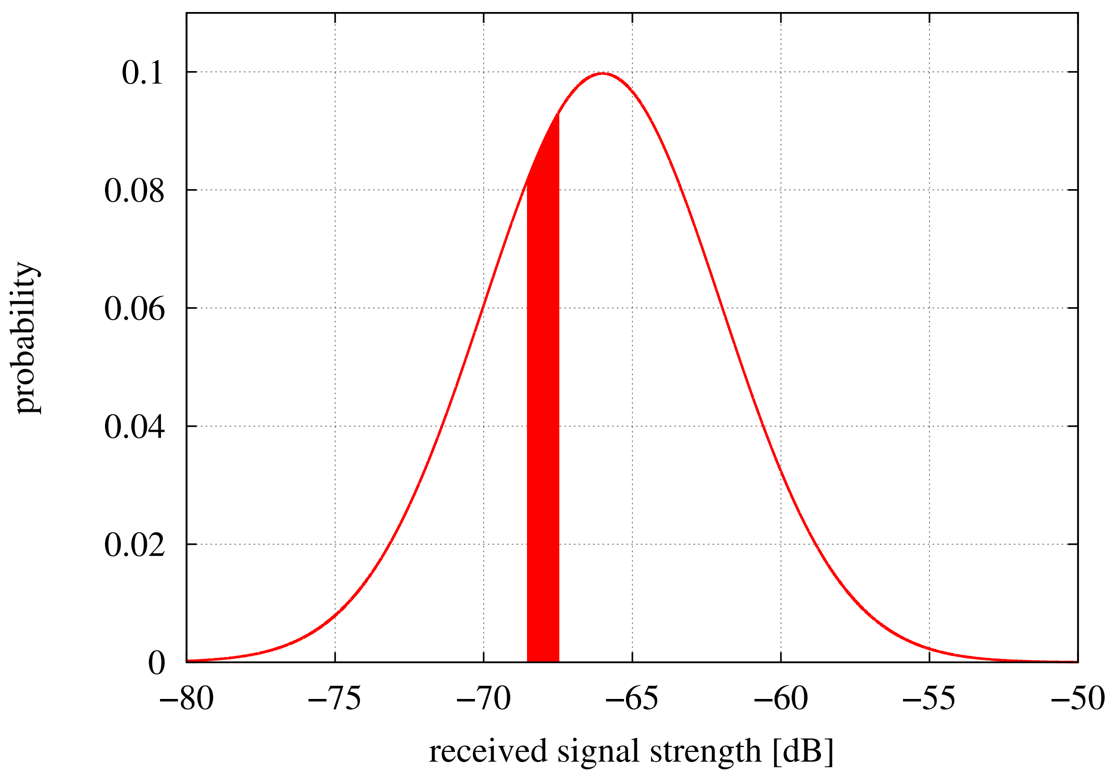


Figure 5.5: Visualized probability for a signal strength of $-71dB$ and a $\phi(-69.47, 2.5)$-distributed normal distribution.

Here, n is the number of access points that are found in the collected live samples, s_{ap_i} is the average signal strength collected for the access point ap_i, and r is the reference position for which the overall probability is currently computed.

After the calculations are completed for all fingerprints, the algorithm selects the reference position with the highest overall probability as a position estimate.

Neighbor Considerations

During earlier research (e.g., [KHE07]), it has been shown that several important factors exist that have an influence on the positioning results of probabilistic fingerprinting algorithms. For example, the number of received access points and the quality of the hardware have a major influence on how well a fingerprinting algorithm performs in terms of the average positioning error. The same is true for the number of samples collected to create a fingerprint and the distances between the reference positions. Earlier publications (e.g., [HFL$^+$04, KHE07]) indicate that at least about 20 to 30 training samples need to be collected for each fingerprint to achieve satisfying results during a later positioning with common fingerprinting algorithms.

The reason for this high number is that, for a fixed position, the collected signal strength samples have a natural variation we are not able to overcome. This variation is caused by the adverse propagation behavior of radio signals in indoor environments where we have to face signal attenuation, signal diffraction, scattering, and multi-path propagation. To compensate for these variations, a sufficiently large number of samples is generally needed to allow the average signal strength value to stabilize when creating a fingerprint. Having in mind the time-consuming task of collecting these samples for each single reference spot, the goal of our work is to reduce the required effort in a transparent and easy implementable way.

Furthermore, from a user's perspective, a user who is located somewhere in a building during the position determination phase generally does not remain still while waiting for the collection of enough samples to let the measurement values stabilize. As a result, even fewer signal strength measurements will be taken during the position determination phase and, thus, the measured values will scatter around the values stored in the fingerprints that were collected at the reference positions close to the user's current whereabouts.

Additionally, the user will almost never be located exactly at a reference position. Instead, she will stand or move somewhere between several reference positions in most cases. Therefore, often more than one fingerprint of adjacent reference spots around the user will give a suitable match to the live data collected at the user's real position.

Considering that the user will be located in between several reference spots most of the time and that the signal strength of an access point at a given position has an inevitable fluctuation indoors, we propose new algorithms that take these insights into account in order to increase the positioning accuracy on the one hand, while reducing the amount of needed samples to be collected at each reference position on the other hand.

Equal Weighting

At first, we present an algorithm that not only considers the samples that have been collected at a certain reference position itself but also the samples that have been collected at all adjacent reference spots in order to create the fingerprint. If the current reference position has m adjacent reference positions and n samples are available for each position, this leads to $m * n$ samples used to compute the fingerprint for the current position. The samples in this case are *equally weighted* in the created fingerprint, which means that all the samples from the reference position itself as well as those from the adjacent positions have an equal influence on the resulting fingerprint. This leads to a fingerprint that no longer represents only a single reference position but instead represents an area that is defined by the adjacent reference positions. Figure 5.6 depicts this. The area C is – amongst others – covered by both the fingerprints for reference positions A and B.

At this point, we want to point out that, even though we use more samples to create a single fingerprint, we do not need to collect more samples. The essence of what we do is to re-use the existing samples several times for different fingerprints.

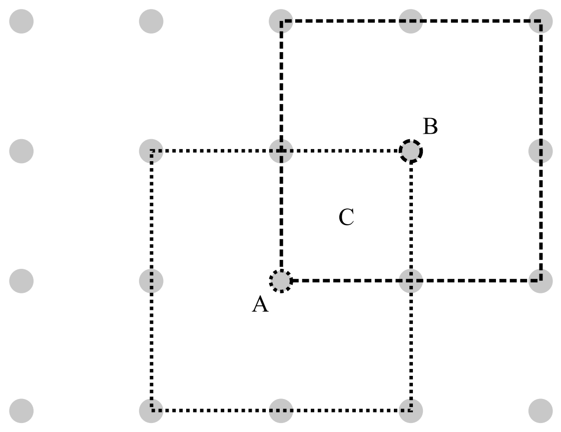


Figure 5.6: Combination of measurements from different reference spots.

Unequal Weighting

The equal weighting algorithm works quite well for smaller distances between the single reference positions. Nevertheless, we have to face a decrease in the positioning accuracy of the algorithm if we increase the distance between the reference spots. Investigating this behavior, we realized that the samples collected at adjacent positions blur the resulting fingerprint increasingly if the distances between the reference positions get too large. To overcome this, we extended our equal weighting algorithm by adding a weight factor w. This factor defines the influence ratio that samples of adjacent positions shall have on the final fingerprint. Our idea is to combine the samples from the reference position itself with those of the adjacent positions in such a way that the influence of the latter set of samples can be adjusted by varying w. To accomplish this, for each set, we at first compute the representing normal distributions for all the access points that are contained in the samples. This gives us two temporal fingerprints. One represents the reference position itself, the other represents the surrounding area. Afterwards, for each access point contained in at least one of the two temporal fingerprints, we compute a new distribution based on w and the two distributions from the temporal fingerprints. The computation is carried out using the following formulas (Equations 5.3 and 5.4) common for the combination of normal distributions:

$$\mu_{new} = w * \mu_{adj} + (1-w) * \mu_r \tag{5.3}$$

$$\sigma_{new} = \sqrt{w^2 * \sigma_{adj}^2 + (1-w)^2 * \sigma_r^2} \tag{5.4}$$

The information about the resulting distribution for that access point is then stored in the new fingerprint for use during the position determination phase. Even though we lose information by reducing the samples to only these values, we consider this approach as being valid. It is essentially the same procedure as the one used in other probabilistic algorithms (e.g., those that we use as benchmark) when creating the fingerprints. After the calculation is finished for the current reference position, the newly computed fingerprint embodies two values (μ_{new} and σ_{new}) for each access point that was contained in the original set of samples for that position.

5.4.2 Evaluation Setup

The following section briefly describes the environment in which we collected the data for our evaluation. Additionally, an overview is given of the data themselves as well as the hard- and software used for collecting them.

Evaluation Environment

The environment where we conducted the data collection for the evaluation of our algorithms is the second floor of the building A5-B at the University of Mannheim in Germany, where the offices of our group are located. The story is split up into two hallways, several offices, and three smaller rooms in the middle of the larger hallway (see Figure 5.7). The two hallways measure $30\ m$ times $6\ m$ and $15\ m$ times $4\ m$ respectively, covering an area of approximately $240\ m^2$.

Data Collection

To get a sufficient amount of data for the evaluation, 612 reference positions were laid out in the evaluation environment using a grid of $0.5\ m$ side length (see the blue dots in Figure 5.7). The samples collected at these positions are the foundation for the fingerprint databases used during our evaluation.

Additionally, 70 points were spread randomly over the hallways (the pink dots in Figure 5.7) to which we will refer to as *live positions* or *live spots* from now on. The samples collected at these positions are used to emulate a user requesting a position estimation during the following emulation of the position determination phase.

110 samples were collected at each reference position and each live position during the data collection process. The collected samples contain a time stamp, the medium access control (MAC) address of the collecting IEEE 802.11 interface card, the current position, and, for each received access point, the MAC address, the channel, and the RSSI. All samples were logged to a file for easy reference during the following evaluation.

Hard- and Software

To collect the samples, we used an IBM Thinkpad R51 laptop computer running Suse Linux 10.1. The laptop computer was equipped with a plug-in Lucent Silver PCMCIA card.

On the software side, the samples were collected with the LocEva framework [KBH07]. The application to collect the samples uses the Java Native Interface and a wrapper written in C to interact with the operating system kernel's wireless extensions interface. This makes it possible

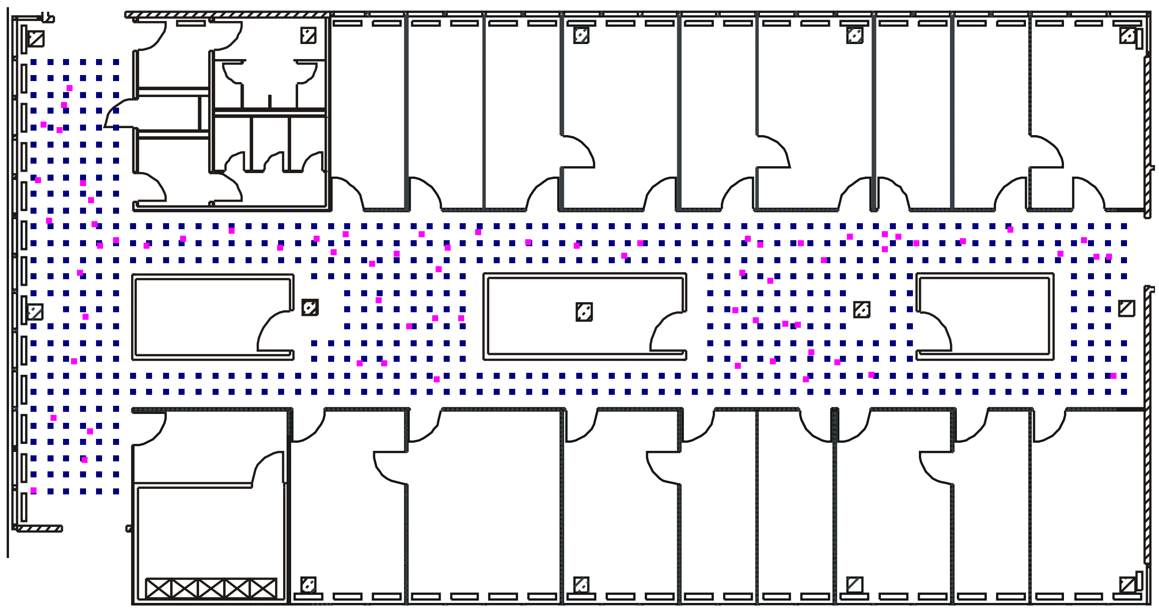


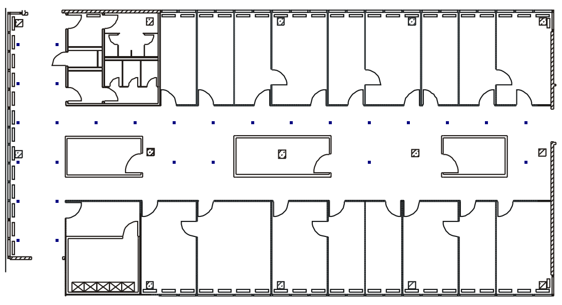
Figure 5.7: Overview of the reference and live spots at which we collected data to evaluate our Quick Fingerprinting algorithms.

to request the communication parameters and connection information directly from the driver module of the IEEE 802.11 interface card.

5.4.3 Evaluation

With the large amount of collected data, we performed a comprehensive evaluation of our algorithms. Using our own set of emulation tools, each algorithm had to perform 250 runs per setting, and the average positioning accuracy as well as the standard deviation of the error and a cumulative error distribution for the runs were recorded. During each run, the algorithm for each *reference position* was given a number of randomly selected training samples to create the fingerprint. Then, for each *live position*, we emulated a user in the position determination phase requesting a position estimation. This was done by supplying the algorithm with samples randomly selected from the set of in advance collected live samples for the current live position. Subsequently, we compared the position estimated by the algorithm to the real position and computed the physical error distance between those two. The procedure was conducted with the original Rice algorithm and with our Equal and Unequal Weighting algorithms using different sets of reference positions. The sets were built by selecting grids of reference positions with grid distances ranging from $0.5\ m$ to $4.5\ m$. We will call this inter-position distance *grid size* in the following.

Especially for larger grid sizes, the layout and the origin of the reference grid have a major influence on the positioning accuracy. We therefore varied the grid origin for the different grid sizes and selected offsets that maximize the number of available reference positions (e.g., see Figure 5.8).


Without offset: 28 ref. spots.

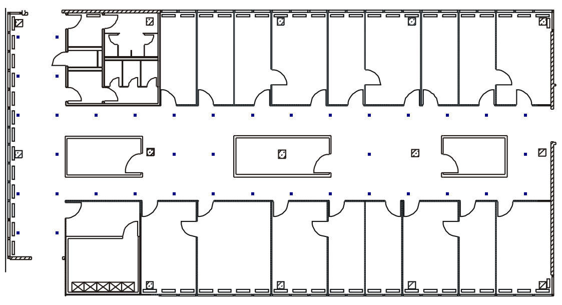

With offset: 39 ref. spots.

Figure 5.8: Selection of a proper offset for a grid size of $2.5\ m$.

In addition to varying the grid size, we also evaluated the use of different numbers of training samples. All algorithms had to perform runs with 20 and four training samples given per reference position to create the fingerprints. This parameter will be referred to as *training set size* (TSS) for the remainder of this section. The value 20 was selected based on the results of earlier research (see [KHE07]). Above a TSS of 20, the gain in positioning accuracy starts to saturate when using the Rice algorithm. The value four was selected based on preliminary experiments with our own novel algorithms, for which the average increase of the positioning accuracy already starts to saturate at a value of four training samples. This is depicted in Figure 5.9.

Equal Weighting

Our equal weighting algorithm performs quite well as long as the distance between adjacent reference positions is not too large. For grid sizes between $0.5\ m$ and $2.0\ m$, our equal weighting algorithm always outperforms the Rice algorithm (see Figure 5.10). With a training set size of 20 samples, the gain of positioning accuracy by our algorithm is about 20% or in absolute numbers about $35\ cm$. If we reduce the training set size to only four samples, the supremacy of our new algorithm is even higher, and we have an average increase of about $67\ cm$ compared to the Rice algorithm. Another interesting insight is that, while the accuracy of the Rice algorithm decreases noticeably when reducing the training set size to four samples, our equal weighting algorithm still delivers results which are almost as good as with a training set size of 20 samples (also refer to Figure 5.10).

The fluctuations in the positioning accuracy of the Rice positioning algorithm especially for the larger grid sizes are caused by our selection of the reference positions. Due to the layout of our testbed, for certain grid sizes, the positions used to emulate a user in the position determination phase are farther away from the positions selected for the reference grid than for other grid sizes. This results in a worse positioning accuracy. Even though we tried to minimize

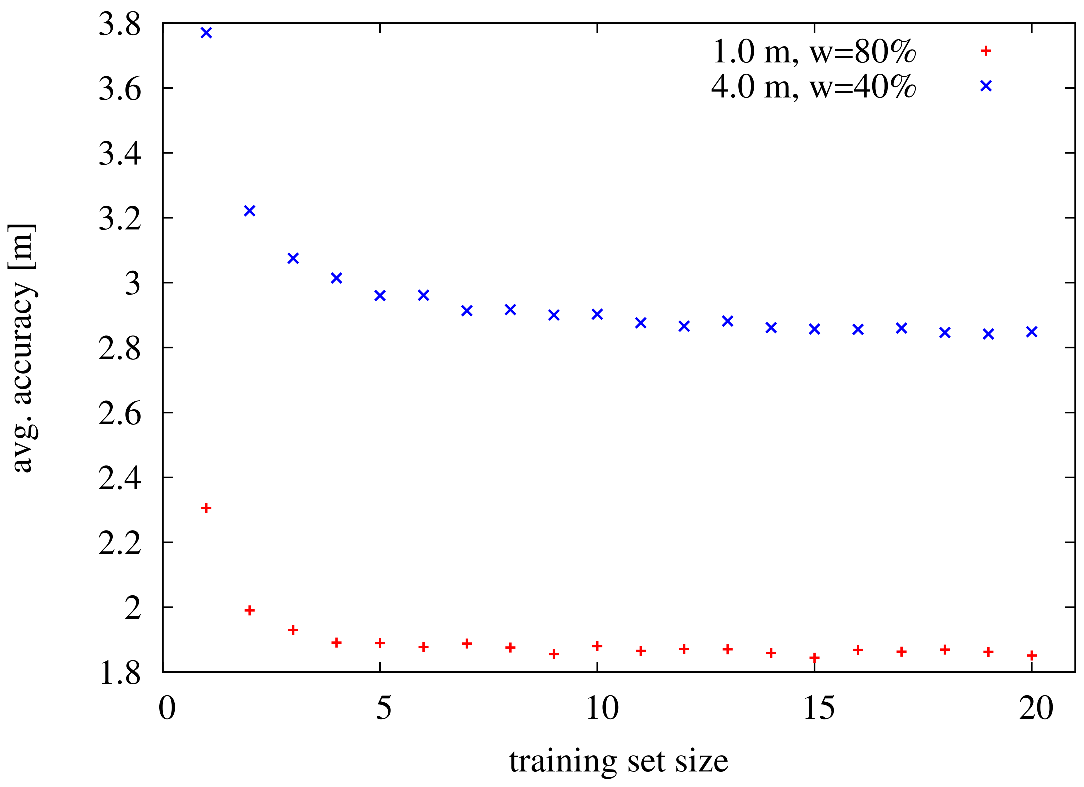


Figure 5.9: The avg. positioning error of our Unequal Weighting algorithm for different training set sizes and grid sizes.

this effect by adapting the grid origin to maximize the number of available reference positions for each grid size, we still could not completely eliminate this effect for our local testbed.

Unequal Weighting

Due to the fact that our Equal Weighting algorithm was not able to outperform the Rice Gaussian algorithm for larger grid sizes, we studied the reason for this issue. If, for a certain grid size, the average error of the Rice algorithm is smaller than the grid size itself, then our algorithm is no longer able to deliver satisfying results. In such a case, the samples for the adjacent reference positions – regarding the metric of the algorithm – vary sufficiently for the Rice algorithm to properly distinguish between them and to make proper position estimations. For our equal weighting algorithm, though, the samples are already too different to get an advantage by taking them into consideration. For larger grid sizes, the merging of the samples even decreases the positioning accuracy below that of the Rice algorithm.

To evaluate the unequal weighting algorithm, we therefore chose to vary the weight in 10%-steps from 0% to 100% during our evaluation and computed the fingerprints for each reference position according to Section 5.4.1. We then checked which value performed best for the different grid sizes. The result of these experiments can be seen in Figure 5.11. They indicate that

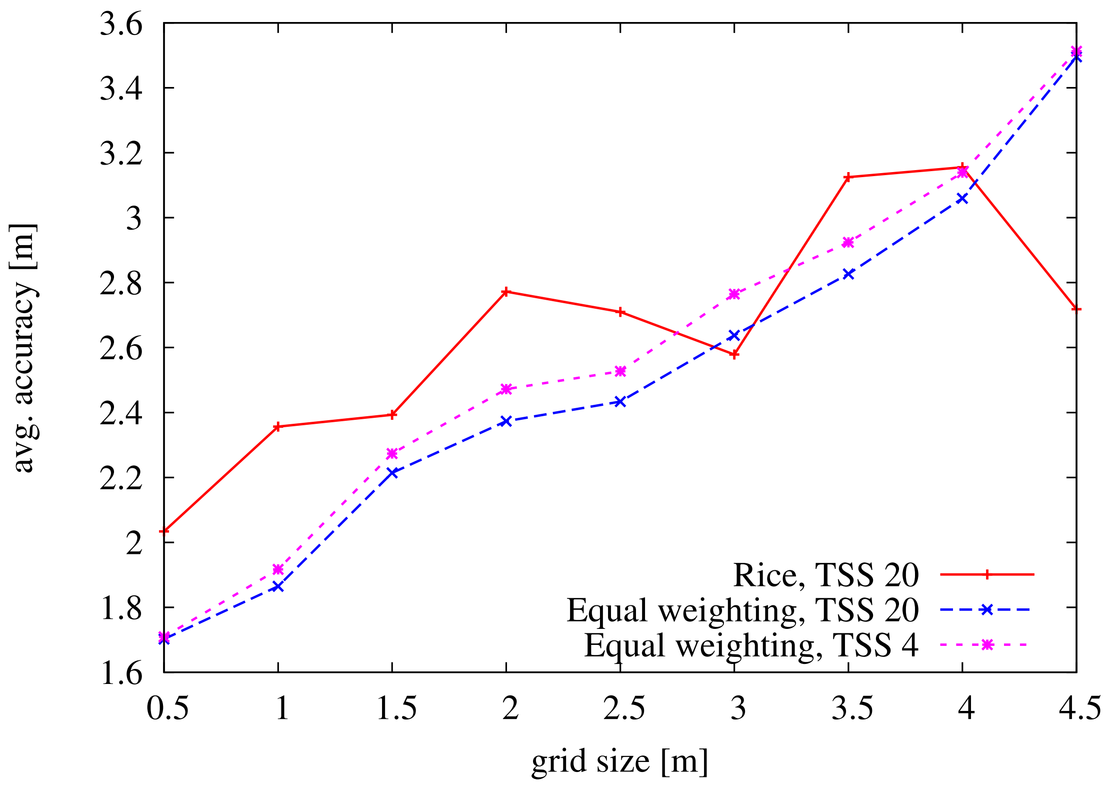


Figure 5.10: The Equal Weighting algorithm compared to the Rice algorithm.

the more the grid size increases, the smaller should the influence of the surrounding samples be to achieve satisfying results.

If we - for each grid size - compare the result of the unequal weighting algorithm using the best suited percentage for the current grid size to those of the Rice and the equal weighting algorithms, the concept of adapting the influence the data from adjacent positions has on the fingerprint clearly shows its advantages. As we can see from Figure 5.12, for smaller grid sizes, the unequal weighting algorithm delivers results as good as those of the equal weighting one. For grid sizes larger than $3.5\ m$ though, the former algorithm clearly performs better than both the Rice algorithm and the equal weighting algorithm.

Even for grid sizes larger than $4\ m$, where the Rice algorithm outperforms our equal weighting algorithm, the unequal weighting algorithm still delivers the best results of the three algorithms.

If we continue to increase the grid size even beyond the values shown in Figure 5.12, the results of the Rice Gaussian and the unequal weighting algorithms finally converge. For these large grid sizes, the weight factor w approaches the value zero. This means that, for a value of zero for w, both the unequal weighting and the Rice Gaussian algorithm perform essentially the same steps to compute a position estimate and therefore deliver identical results.

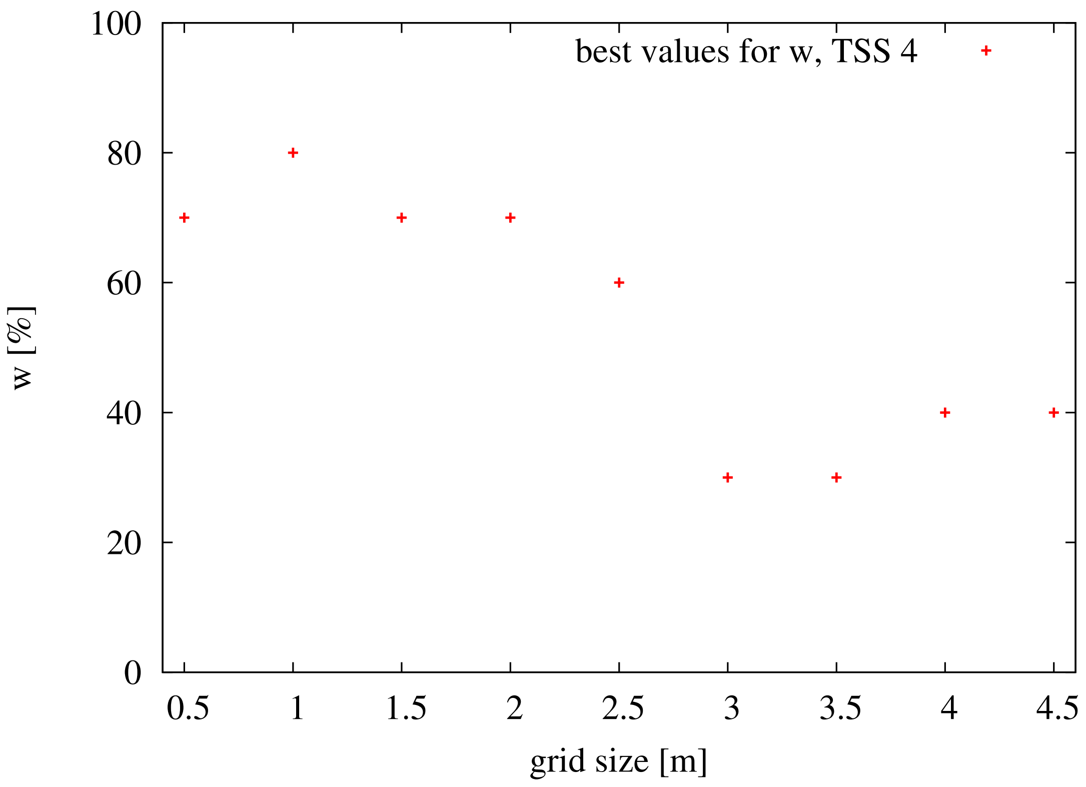


Figure 5.11: Optimal weights for different grid sizes.

Taking a look at the cumulative error distributions of the Rice algorithm and our unequal weighting algorithm, we can see even more advantages of our novel algorithm. In Figure 5.13, the error distributions of the two algorithms for a typical grid size of two meters are depicted. As we can see, the unequal weighting algorithm has a positioning error of less than $5.18\ m$ in 95% of all cases. For the Rice Gaussian algorithm, this value is $6.18\ m$, which means a difference of about 15% or $100\ cm$.

While these improvements do not look too exciting at first glance, it is very important to understand that our novel unequal weighting algorithm achieves its results using only four training measurements per reference position. In comparison, the Rice Gaussian algorithm needs 20 training measurements. Taking the time needed to collect these samples into consideration, our algorithm allows to decrease the required time by about 80%.

5.4.4 Conclusions

In this section, we presented two novel IEEE 802.11-based LF algorithms. Our algorithms pre-process the available data used to create the fingerprints, and by doing so, increase the positioning accuracy. At the same time, they decrease the amount of time needed to collect the training data. This is achieved by reducing the number of required samples per reference

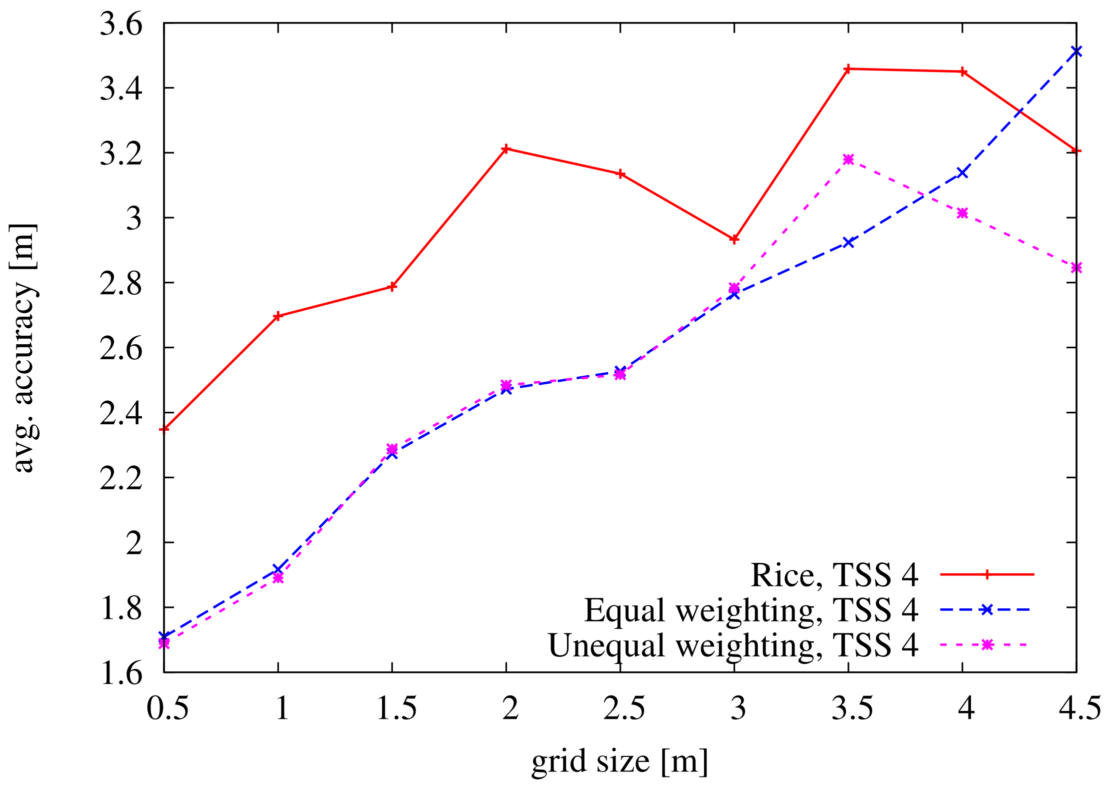


Figure 5.12: The Unequal Weighting algorithm compared to the Equal Weighting algorithm and the Rice algorithm.

position from 20 to four. Taking the time needed to collect the samples into consideration, this is an improvement of 80%.

During the pre-processing, the samples collected at adjacent reference positions are combined into one fingerprint for each reference spot. Such a fingerprint no longer represents one single position but rather an area surrounded by the adjacent reference positions. This accounts for the fact that the user of an indoor positioning system based on fingerprints typically is located between reference positions most of the time. By additionally re-using the samples collected at one reference position several times, we can reduce the overall amount of samples needed per reference position tremendously.

5.5 Region-based Location Estimation

As we have seen, positioning systems based on location fingerprinting offer a viable alternative to other positioning techniques. But to achieve an accuracy beyond a coarse proximity estimation, a dense grid of reference spots is needed, and a high number of measurements has to be collected at each reference spot [KHE07]. As a result, a high effort is necessary to set up such a positioning system, as well as to keep it up-to-date.

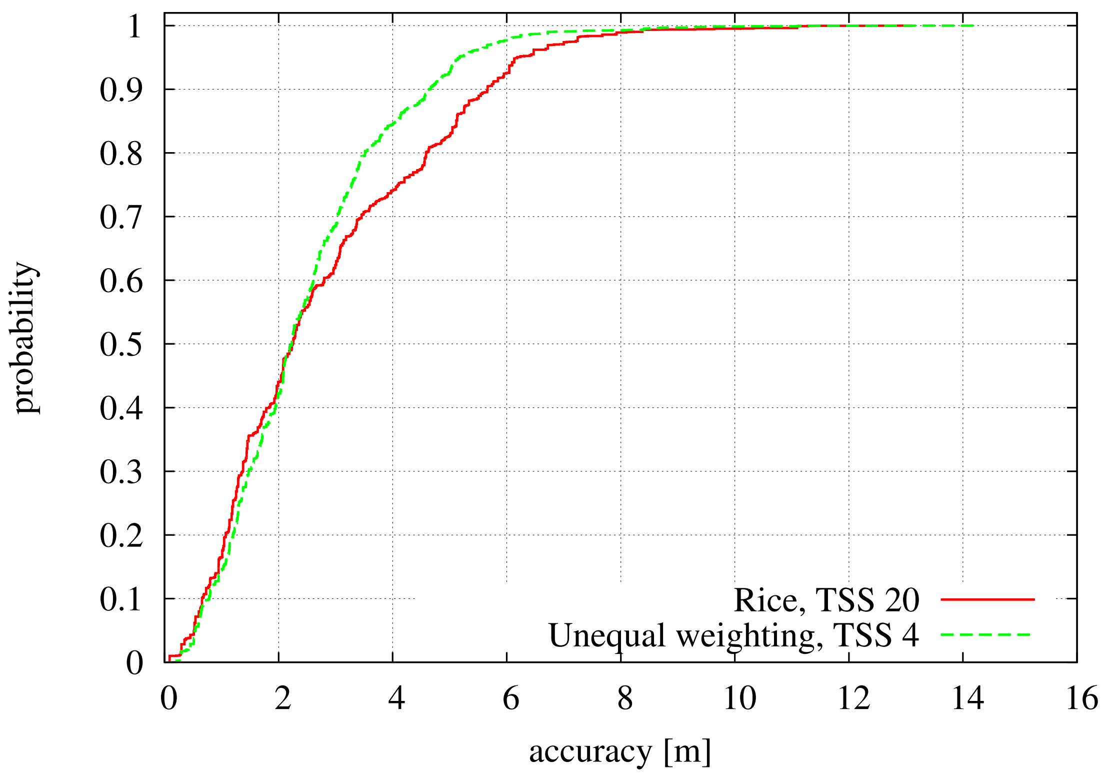


Figure 5.13: Cumulative error distribution for the Rice algorithm compared to that of our novel unequal weighting algorithm.

In this section, we introduce a second novel location fingerprinting algorithm that aims at an even further reduction of the effort needed for setup and operation while retaining a good positioning accuracy and reliability. The algorithm identifies regions of similar signal properties and uses these regions for location estimation. With our approach, the training data no longer has to be collected at pre-defined reference spots. Instead, it can be collected while moving through the area of operation at walking speed. This is a great improvement over grid-based systems. In addition, with our approach, only one fingerprint is created per region. When computing a position estimate, this reduces the computational load as the search database is much smaller compared to a grid-based approach. By identifying regions of similar signal properties, our algorithm achieves a high reliability of the location estimates.

We furthermore provide an extensive evaluation of this novel LF algorithm by means of emulation with real-world data collected in our testbed and show that, with our algorithm, we can achieve an accuracy sufficient for most LBSs while reducing the effort to set up the system to a mere walk through the covered area.

We are aware of the fact that the user's body has an influence on the signal strength of signals received from APs, which, in turn, affects the performance of positioning systems that use this information. For our evaluation, however, we did not further consider this. During the collection of the static data the operator generally was facing the same direction both for reference and live spots where possible. The in-motion data, however, was collected with the operator facing in the direction he was currently walking. This decision was made with the algorithm's goal of reducing the effort in mind. As stated earlier, considering different user directions requires the collection of multiple sets of training data and, thus, multiplies the effort as well.

5.5.1 Positioning Algorithm

We at first introduce our clustering technique and explain our special similarity measure used during the clustering process.

Measurement Clustering

During our own research, we have made the observation that in structurally limited areas the signals received from IEEE 802.11 APs tend to stay within a limited range of all possible values. For instance, when looking at measurements taken at different positions inside an office room, the measurements tend to have similar characteristics despite effects such as small-scale fading, diffraction, scattering, or multi-path propagation. This makes it hard for fingerprinting algorithms to estimate the correct position within the room as the fingerprints for such a structurally limited area are all similar.

Our algorithm exploits this effect by automatically identifying these regions of similar signal properties and by using them for a more reliable position estimation. As inside one region a further distinction between the single cells the region is made up of is hard to achieve because of the similar signal properties, the whole region is returned as a location estimate. After the collection of the training data, our algorithm performs the following steps:

- First, the area covered by the positioning system is divided into a grid of quadratic cells. In the beginning, each cell is a single cluster comprising the measurements that were made in the cell.

- Next, for each cluster, the similarity to all its neighbors is computed. This is done using our novel similarity measure.We then select the pair of neighboring clusters with the highest similarity value and – if that value lies above the given similarity threshold – merge the two clusters.

- The second step is repeated with the remaining set of clusters until, for all clusters, no more merges take place.

- Each remaining cluster now represents a physically connected region of similar signal properties. The size and shape of the region are defined by the grid cells that the cluster is comprised of.

An example for such a set of regions computed from real-world data is given in Figure 5.14. For each region, one fingerprint is created from all the measurements that were made in the area the region covers. This fingerprint is then stored in the fingerprint database for later reference during the position determination phase.

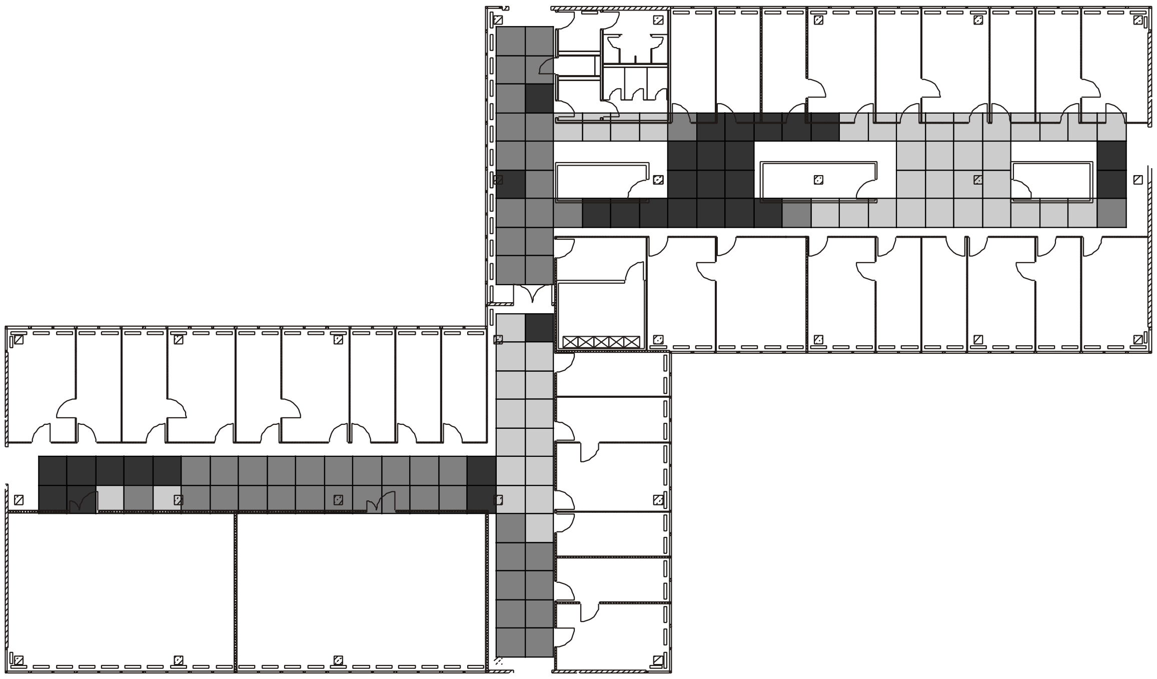


Figure 5.14: Example for a set of regions automatically identified by our algorithm.

In the position determination phase, the user's mobile device measures the signal properties at its current position and matches them against the fingerprints in the database. As we only have one fingerprint per region, our algorithm does not return a position estimate but rather a region as a location estimate to the user.

Similarity Measure

To estimate the similarity of two clusters A and B during the merging process, we use a newly developed similarity measure. The computation of the measure consists of several steps:

- For each access point i of which signal strength measurements are contained in both currently considered clusters, we independently compute the average signal strength and standard deviation of the signal strength measurements on a per-cluster basis.
- These values are used to create two normal distributions (ρ_{A_i}, ρ_{B_i}). Each distribution represents the approximate signal strength density for the access point i and one of the two clusters A or B.

- We then compute the intersection area of the two density distributions (see Equation 5.5). Examples for the result of this computation are depicted in Figure 5.15.

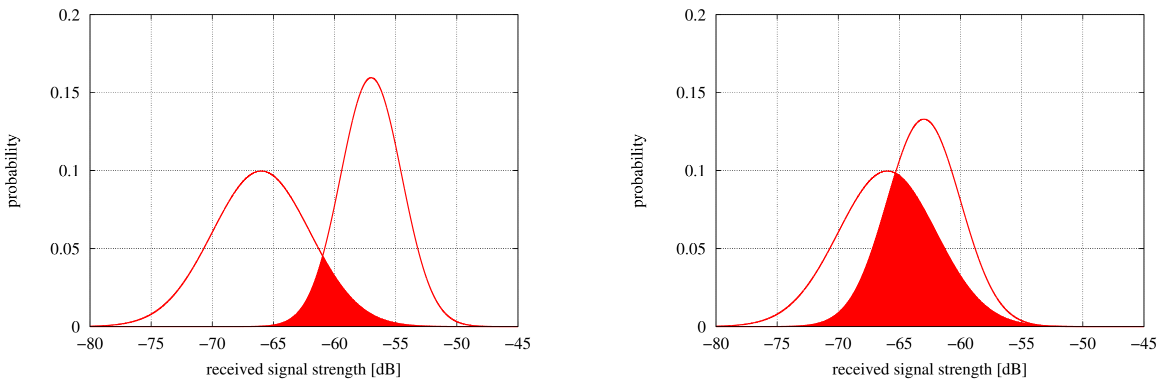
$$area(A_i, B_i) = \int_{-\infty}^{+\infty} \left(min \left\{ \begin{array}{l} \rho_{A_i}(x) \\ \rho_{B_i}(x) \end{array} \right. \right) \tag{5.5}$$

  Looking at Equation 5.5, $\rho_{A_i}(x)$ is the density distribution for access point i and cluster A whereas $\rho_{B_i}(x)$ is the density distribution for access point i and cluster B.

- The sum of the intersection areas for all common access points divided by the number of all access points contained in either one of the clusters is finally taken as the similarity measure for the two clusters (see Equation 5.6).

$$similarity(A, B) = \frac{\sum_n area(A_n, B_n)}{m} \tag{5.6}$$

  In Equation 5.6, n is the set of common access points and m is the number of all access points contained in either one of the fingerprints for the clusters A and B. Considering not only the common but all access points ensures that clusters having only a few access points in common are not falsely rated as similar.



(a) Example for a bad match. (b) Example for a good match.

Figure 5.15: Example for the calculation of the similarity measure. The size of the shaded area represents the similarity of the two clusters with regard to one specific access point.

While it would also be possible to use other statistical approaches, we decided to use this method to compare the distributions as it very well reflects the way the positioning algorithm itself – during the position determination phase – performs the matching of the fingerprints.

5.5.2 Experimental Setup

This section describes the hard- and software as well as the environment in which we performed the evaluation of our algorithm. Additionally, the metric applied and our experimental methodology are introduced, and we give an overview of how we collected the data used for the evaluation.

Hardware and Software

For the data collection, we again used a Lucent Orinoco Silver PCMCIA network card supporting the IEEE 802.11b standard. The card was plugged into an IBM Thinkpad R51 laptop computer. On the software side, we reused our own set of tools [KBH07] to collect the signal strength measurements.

Local Test Environment

This time, we deployed our IEEE 802.11-based positioning system on the entire second floor of the office building A5-B on the campus of the University of Mannheim. The deployment area consists of many offices and three long hallways (see Figure 5.16). It is nearly $57\ m$ long and about $32\ m$ wide. Compared to the evaluation of the quick fingerprinting system introduced in Section 5.4, the size of the evaluation area was more than doubled. We did this to get an impression of the behavior of our algorithm in less cluttered areas like they are offered by the long hallway in the lower left part of our evaluation testbed.

In the test environment, 34 access points were installed at the time of the data collection. Of these, twelve were administered by the computer center of the university, eleven were installed by us, and the remaining eleven were located in nearby offices and buildings and were as such beyond our control. Our data shows that most of the APs cover only parts of the operation area. In fact, some APs can only be received at very few spots and only two APs cover the operation area completely.

Data Collection

To evaluate our algorithm, we collected different sets of training data. For the first set, we applied a grid of reference spots with a grid spacing of $1.5\ m$. These spots are marked by the blue dots in Figure 5.16a. At each spot, while standing still, we collected 110 signal strength measurements to which we will refer to as *static training measurements* from now on.

The second and the third set contain signal strength measurements which were collected while in motion. We initially defined trajectories within our area of operation. For each path, we then continuously collected signal strength measurements while walking along the path at pedestrian walking speed. Based on the time that passed while moving from the beginning of the path to its end and the measurements' timestamps, we interpolated the physical coordinates where each measurement was collected. An example for the result of this procedure is shown in Figure 5.16b.

We repeated the collection ten times per path moving at normal walking speed ($\approx 1.0\ \frac{m}{s}$) and ten times moving quite slowly ($\approx 0.5\ \frac{m}{s}$). We call these two kinds of measurements *in-motion training measurements*.

We selected the normal walking speed because we consider it to be the most intuitive speed for in-motion data collection. After the collection, we realized a fairly low density of measurements at this speed and thus collected a second set of in-motion training data at a lower speed.

For the evaluation, we furthermore randomly selected 46 more spots in the area of operation (marked as pink dots in Figure 5.16a) and collected 110 signal strength measurements – or *position determination measurements* – at each of these spots. This data is used to emulate a user requesting a position estimate during the position determination phase.

Metric

The use of a region as a location estimate for a user is settled between position estimation and location estimation. The difference between these two is that for position estimation a coordinate in a known coordinate system is returned as the result of the position estimation process. For location estimation, on the other hand, the result is a logical description like *"cafeteria"* or *"office 221"* (also refer to [Kjæ07]).

As our algorithm is a combination of both positioning and locating, neither using the *accuracy* (the distance between real and estimated position) – as it is usually done for positioning systems – nor the *reliability* (the rate of correct location estimations) – as it is often done for location estimation systems – alone would serve as a suitable performance metric.

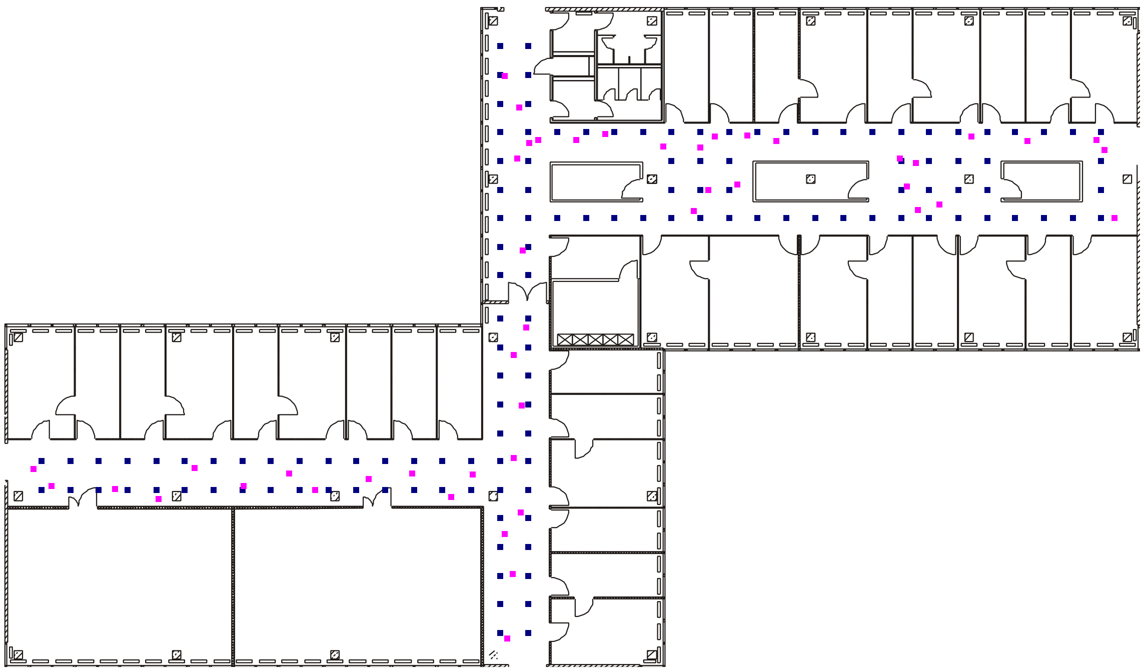
So, besides looking at the reliability, we decided to combine these two metrics and to form a new one: Whenever our algorithm returns an estimated region, we check whether the real position lies within that region. If this is the case, the error is counted as 0. If the real position is outside, we use the distance between the real position and the border of the estimated region as the error value. Thereby we can get an impression of how distant our estimated regions are from the user's real position.

Methodology

To analyze the properties of our algorithm, we again reused our suite of positioning-related tools [KBH07] and extended it to suit our needs.

Our basic experiment consists of the following steps:

- At first, the positioning algorithm is initialized with either 20 or four randomly selected static training measurements per reference spot or one set of in-motion training measurements per path to create the regions and to build up the fingerprint database. Remember, we refer to the number of measurements, respectively sets, as *training set size* (TSS).


(a) Layout of the reference and position determination spots.

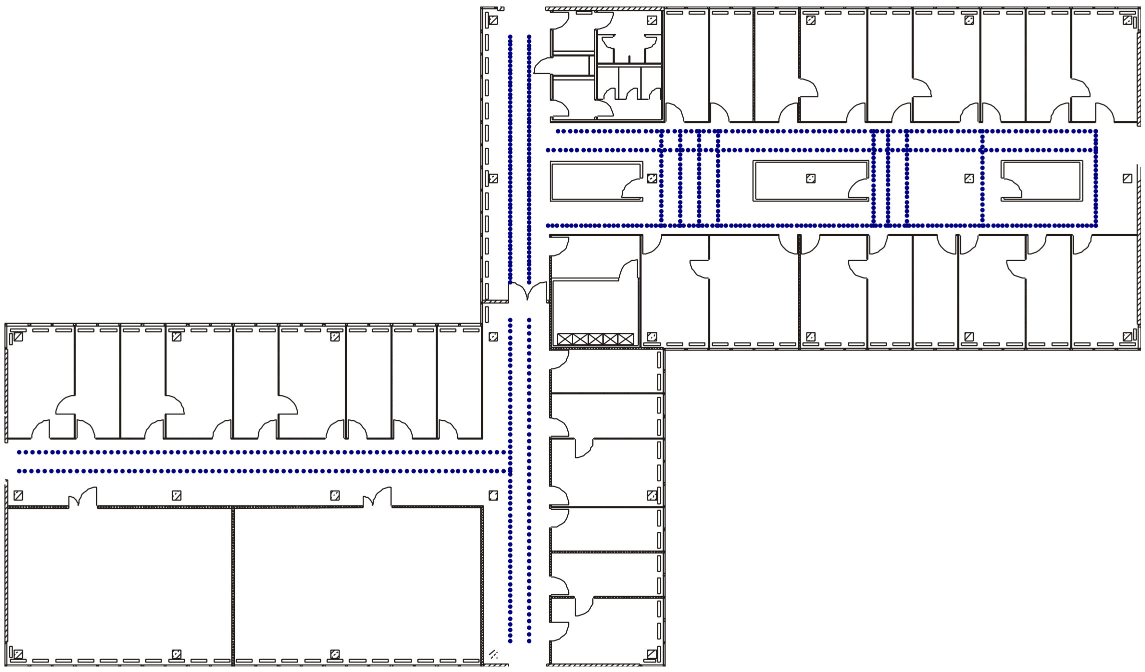

(b) Layout of the in-motion measurements.

Figure 5.16: Reference and position determination spots (Figure 5.16a) and moving paths (Figure 5.16b) within the area of operation.

- This is followed by providing the algorithm – for each test position – with three position determination measurements randomly selected from the samples collected for that position. For the subsequently estimated region, the error is computed according to our metric and stored for later reference.

For the performance evaluation of our algorithm, we used our different sets of training data. Thus, we were able to compare the performance of the algorithm when using training data that was collected while moving to it's performance when using statically collected training data. The number of training and position determination measurements were – as far as applicable – chosen according to King et al. [KHE07]. We furthermore varied the similarity threshold in 0.01 steps from 0.01 to 0.99. To achieve statistically stable results, we repeated our basic experiment 250 times for each setup.

5.5.3 Experimental Results

In this section, we describe our experimental results. We explain the influence that the similarity threshold has on the performance of our algorithm and show the effects of smaller or larger regions on the position determination. Afterwards, we look at the consequences of using training data that was collected while moving, and the clustering process.

Similarity Threshold and Region Size

The factor that has the largest influence on our algorithm is the similarity threshold that is used to determine whether two adjacent clusters should be merged. By varying this factor, we can adjust the overall rate of correct region estimates and the average error.

As shown in Figure 5.17, a very low threshold results in few but large regions. This also increases the rate of correct region estimations (see Figure 5.19). If we, for instance, set the similarity threshold to a value of 0.40, our algorithm – being given the training data that was collected at slow walking speed – estimates the correct region in about 82% of all cases. This comes at the cost of a decreasing *absolute* accuracy, though. Absolute accuracy in this case means that even if the system estimates the correct region, it has no further information where inside this region – the average region size is roughly $22\ m^2$ in our example – the user is located.

In contrast, if a high value is selected, the regions stay small and ultimately only comprise single cells. In this case, the positioning results of our region-based algorithm are similar to those of a fingerprinting-based positioning algorithm that uses a grid of reference spots. Each region or cell then corresponds to one of the reference spots inside the grid.

The density as well as the quality of the training data have a high influence on the clustering process during the training phase. Whereas there is only little difference between the use of the statically-collected and in-motion training data for the case of a high density of training measurements, we can see that the higher quality of the statically collected training measurements in the low-density case leads to much larger clusters compared to the in-motion training data that was collected at a speed of $\approx 1.0\ \frac{m}{s}$. In that case, the average region size is well below $60\ m^2$. This tendency is confirmed when looking at higher values for the similarity threshold,

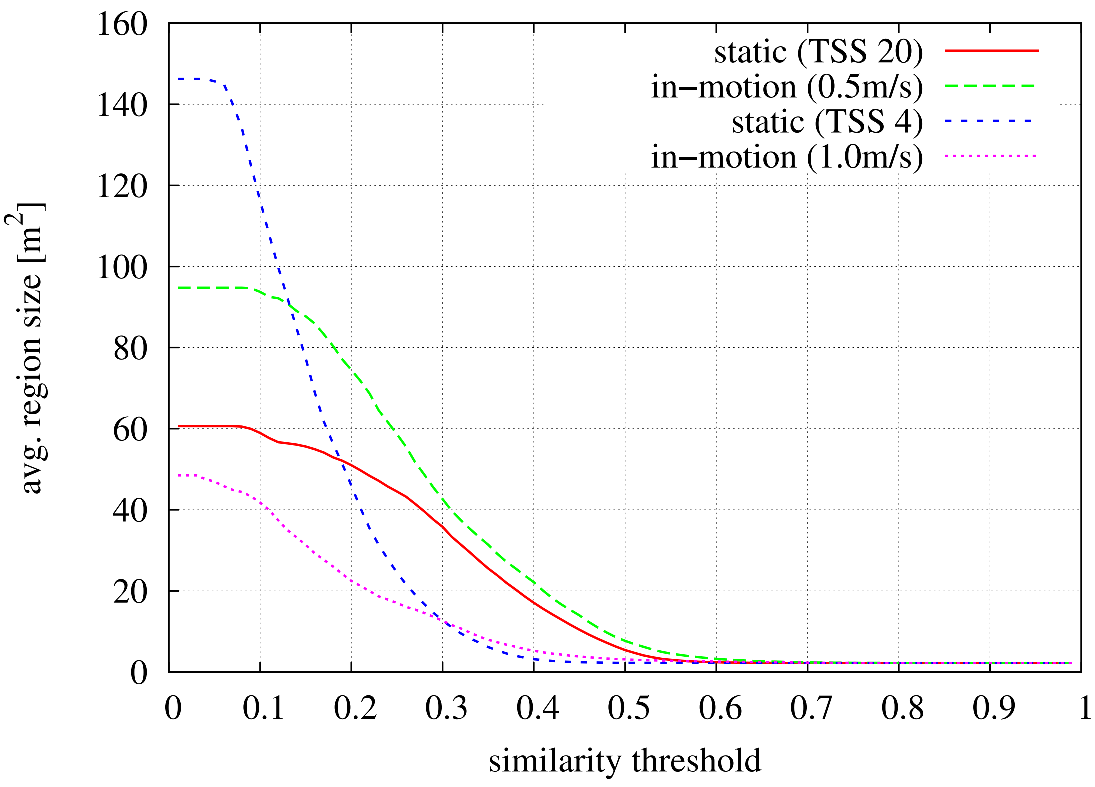


Figure 5.17: Influence of the similarity threshold on the region size.

where the average region size reaches its minimum of $2.25\ m^2$ – the size of one cell – much earlier when using the training data that offers a lower measurement density. An example for such a set of regions is depicted in Figure 5.18.

On the other hand, if the similarity threshold is decreased, the size of the computed regions increases. This also increases the rate of correct region estimations (see Figure 5.19).

At the same time, it decreases the *absolute* accuracy. The reason for this effect is that, even if the algorithm estimates the correct region, we cannot say where exactly inside the region the user is located. As a result, the absolute accuracy is worse for large regions.

Additionally, in the Figure, we can see the influence of the number and quality of the training measurements used: Whereas for the high-density case we achieve a near to perfect reliability, the lower region size in the case of a lower training measurement density also leads to a reduced reliability.

Motion and Motion Speed

Another important factor for the performance of our algorithm is the way the training measurements are collected. It influences both the density of and also the signal variation between consecutively collected samples.

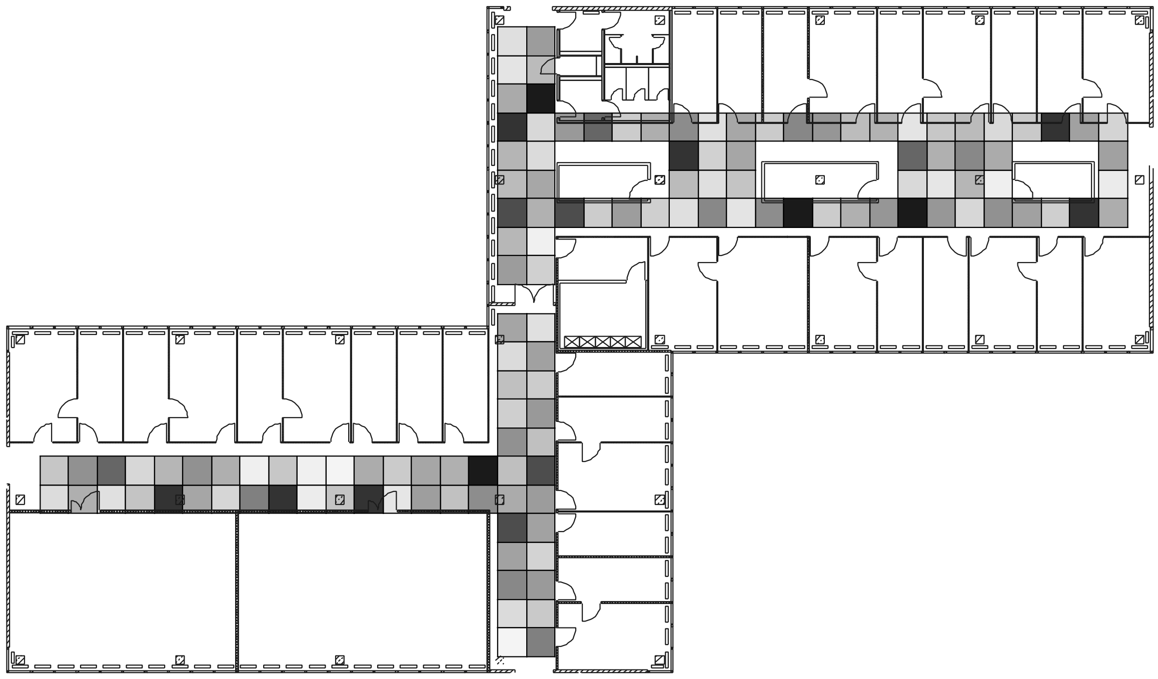


Figure 5.18: An example for the result of the clustering process using a high threshold for the similarity.

When using the set of static training measurements and a training set size of 20 or four, we obviously have a density of 20 respectively four measurements per grid cell as each grid cell contains exactly one reference spot. For the training data collected while moving, the density depends on the time the collecting device spends within the area of each cell. In our case, with a cell size of $1.5\ m \times 1.5\ m$, the density of the measurements collected while moving at a speed of about $0.5\ \frac{m}{s}$ is seven measurements per grid cell. When moving faster, at $1.0\ \frac{m}{s}$, this value drops to roughly three measurements per grid cell.

Compared to the static training data, our in-motion training data also has an inherently higher signal variance. This in combination with the sample density results in a varying number of APs that were received in the different grid cells. On the average, ten access points are contained in each fingerprint for the $1.0\ \frac{m}{s}$ in-motion training measurements, about twelve access points for the $0.5\ \frac{m}{s}$ in-motion training measurements, 14 for the static training measurements when using a TSS of four, and about 16 access points in each fingerprint when using a TSS of 20.

For the sets of measurements used for position estimation during the position determination phase, the average number of contained APs is ten for the measurements from the static dataset and eight for the measurements from the in-motion dataset.

Looking at the actual positioning performance of our algorithm when being given training measurements that were collected while standing still and those that were collected while in motion, we can see that our algorithm handles both almost equally well. Only for higher values of the similarity threshold – and therefore when the regions become small – we achieve better results when using statically collected training data (see Figure 5.20). The reason for this be-

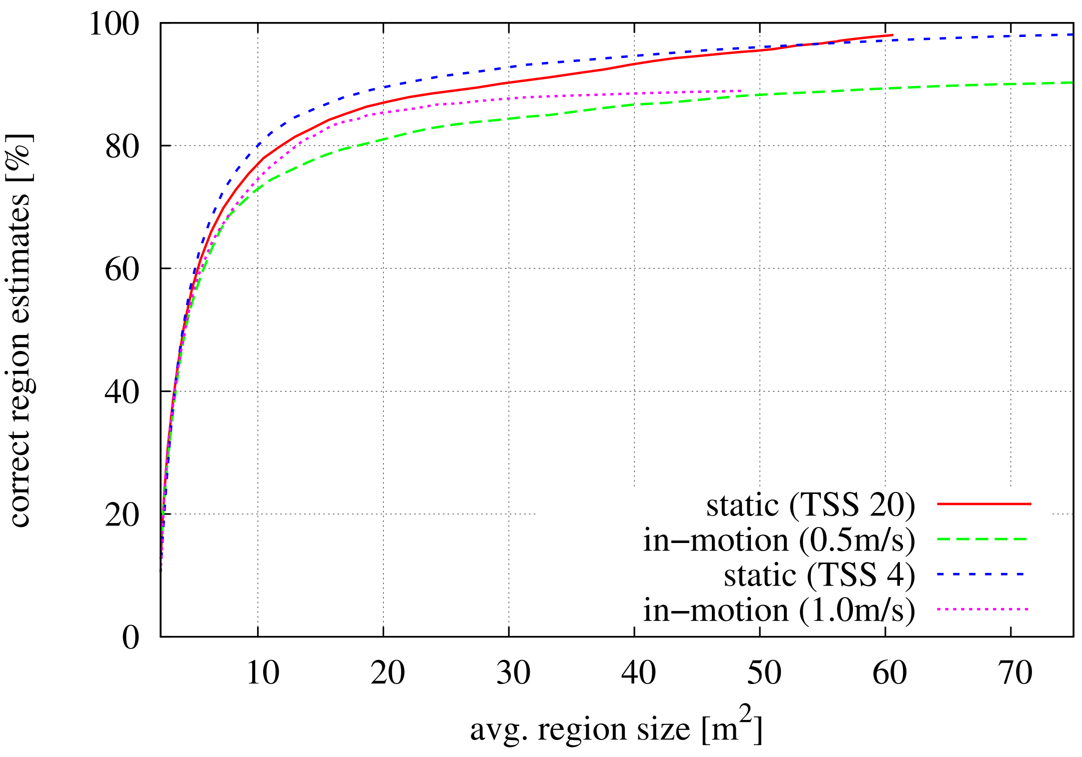


Figure 5.19: Influence of the region size on the rate of correct region estimates.

havior is the low number of measurements per grid cell in combination with the higher signal variation. Especially for small regions, the overall number of measurements per region is not sufficient to create stable distributions for the fingerprints (also refer to [KHE07]). If the data has additionally been collected while moving, this further decreases the distribution quality.

This higher variance in the signals is also the reason why the maximum average region size (see Figure 5.19) is lower for the two cases where we used the training data with a TSS of four, respectively the one that was collected at normal walking speed. For the latter case, for instance, the maximum average size of the regions was only about $50\ m^2$.

Clustering

As a further benchmark for our own algorithm, we used our implementation of the original LF algorithm from Haeberlen et al. [HFL+04]. During each run of the emulation, we fed the same training data to our own clustering algorithm to let it create the set of regions and also to the algorithm from Haeberlen et al. to create its fingerprint database. During the position determination phase, we then checked in which region the position estimated by the algorithm from Haeberlen et al. lay and used our metric to compute the error. As the algorithm from Haeberlen et al. cannot handle training data that was collected while moving, we only used the statically collected data in this case. The results of this comparison can be seen in Figure 5.20

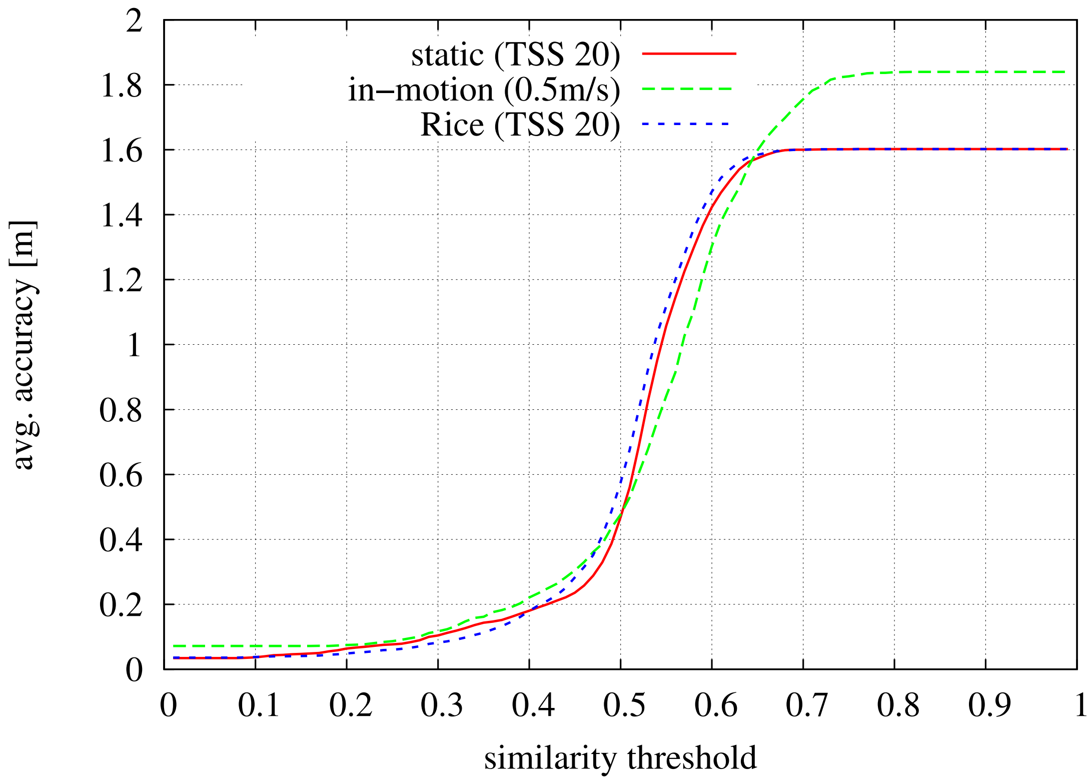


Figure 5.20: Comparison of the performance of our algorithm being given training measurements that were collected when standing still or when moving.

and 5.21. As shown there, using one fingerprint per region – as our algorithm does – results in a slightly higher amount of correct region estimates most of the time, whereas the approach of using the algorithm from Haeberlen et al. to estimate the position and matching it afterwards to the regions is slightly inferior in our case.

The reason for this result is that our algorithm better reflects the overall situation with regard to the signal space. While small variations in the received signals might cause the Rice algorithm to select a position far off and beyond the actual region, our algorithm mitigates small variations especially with regard to the fingerprints and as such avoids such large errors.

5.5.4 Discussion

This section briefly discusses the implications of our findings for IEEE 802.11 LF systems and LBSs. We consider both the standpoint of the service provider as well as the standpoint of the service user and also some other aspects of our system.

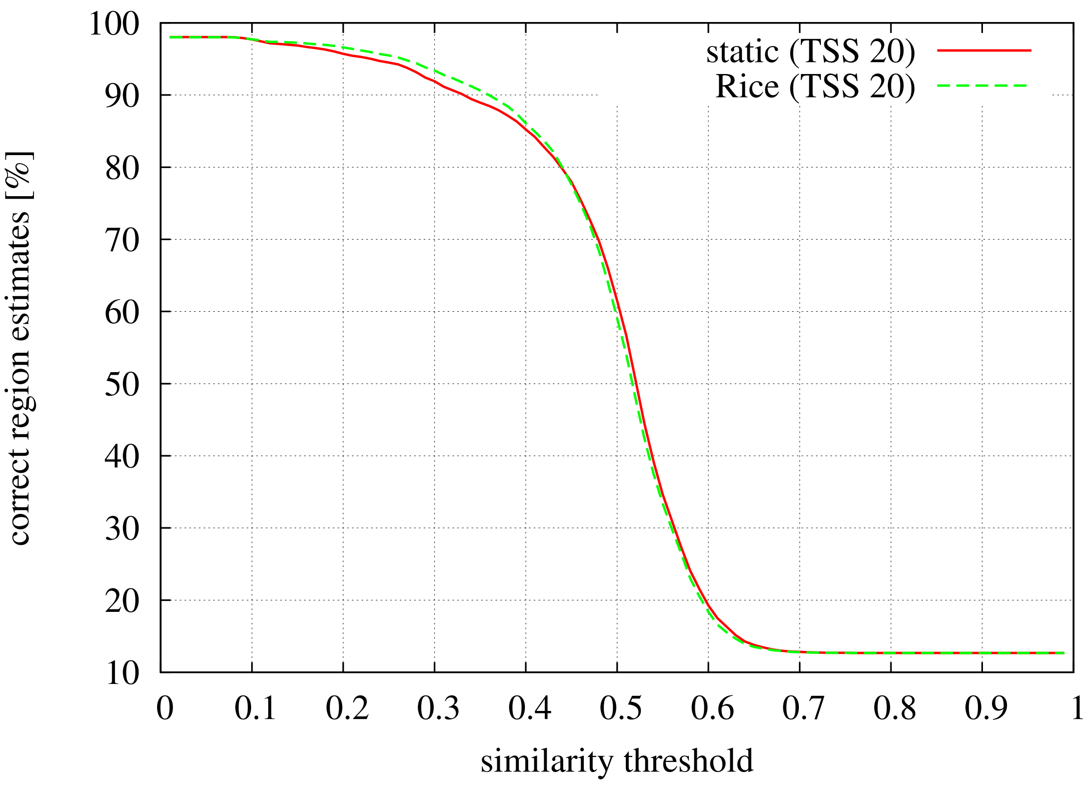


Figure 5.21: The results of our own algorithm compared to those of the algorithm from Haeberlen et al.

Accuracy and Reliability

Different applications have different requirements regarding the accuracy of the delivered position estimates and their reliability. Our algorithm accounts for these differences by offering the similarity threshold as a parameter to adapt the algorithm's performance to the application's requirements (see Figure 5.19).

By reducing the similarity that is required for two clusters to be merged during the training phase, we can directly influence the average size of the clusters and thus adapt the coverage area of the single fingerprints to the required accuracy of the application.

Increasing the size of the clusters also increases the reliability of our algorithm. This comes at the cost of a decreased absolute accuracy. When, for instance, the similarity threshold is set to a very low value, the regions finally cover full floors. The system, in this case, estimates the correct region with a reliability of almost 100% but we have no further information about where the user is exactly located in the estimated region. Thus, for applications that require a high reliability, a lower similarity threshold would be a better setting.

Position Refinement

To overcome the loss of accuracy for larger regions, we tried to further refine the position estimation by introducing a second position determination step: After the estimation of the region the user is located in, we created a second fingerprint database with one fingerprint for each cell in the estimated region. We then matched the collected live data against the fingerprints in that second, limited database and selected the cell with the best matching fingerprint as an estimate for the position inside the cluster.

Especially for higher values used for the similarity threshold, this did not improve the positioning accuracy, though. The reason for this is that, when the signal strength properties from within the region are similar anyway, such a refinement step performs hardly better than a random selection of a cell from within the region.

Motion and Motion Speed

We can influence the performance of the algorithm directly by changing the similarity threshold. However, also the way how the training data is collected has a major influence. In cases where static measurements are used to create the regions, mainly the number of measurements per reference spot has an influence on the algorithm's performance.

In comparison, when the training measurements are taken while in motion, each measurement is collected at a different position. In this case, mainly the speed of motion while collecting the data is the factor that influences the algorithm's performance. At a higher speed, fewer measurements can be collected in each cell and thus fewer measurements can be used later when creating the regions. Especially when the regions are small, the latter case has a negative effect on the performance of the algorithm, as there are only few measurements available to create the fingerprint for each region. This observation is also confirmed by earlier research [KHE07] that has shown that the number of training measurements per reference spot has a remarkable influence on the positioning accuracy for the static case.

The lower density of measurements at higher speeds also has another effect. As Figure 5.17 shows, collecting the data while moving leads to smaller-sized regions. Whereas for a similarity threshold of 0.20, the average region size for the training data collected at slow speed is about $130\ m^2$, the same value is only about $60\ m^2$ for the training data collected at normal walking speed. The reason for this behavior is the generally higher signal variance that incurs in this case and that causes adjacent clusters to not be merged, even if they probably were in case that there would be more measurements available from within each cluster.

Compared to this behavior, the better data quality of the measurements collected while standing still leads to slightly larger regions and an overall better performance when using this kind of data (see Figure 5.22).

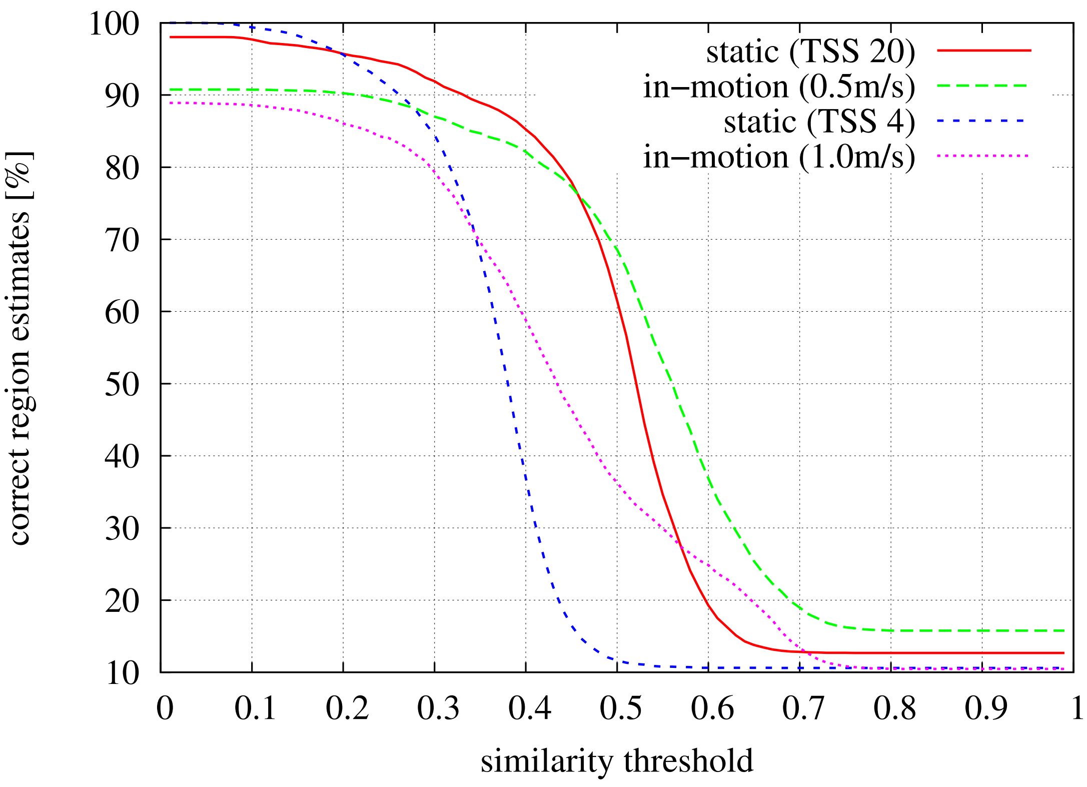


Figure 5.22: Overview of the influence of the similarity threshold on the estimation of the correct region.

Usability

In terms of usability, our algorithm is a considerable improvement. It delivers an accuracy and reliability that is sufficient for most LBSs. At the same time, it offers the possibility to reduce the amount of time that needs to be spent for setup and maintenance of the fingerprint database to a fraction of what other systems need. The main reason for this is that the training data no longer needs to be collected while standing still but can be collected by simply walking through the area of operation that the positioning system shall cover.

Table 5.1 gives an overview of the measurement collection times for our different datasets. It should be noted that, for the in-motion approach, these numbers reflect the real effort quite well. For the grid-based approach, though, the time needed to exactly position the measuring device on each reference spot is not included in the numbers. If we take an average time of only $10\ s$ to reposition the collecting device on each reference spot, an additional amount of $1300\ s$ would have to be added to reflect the real effort.

Furthermore, compared to systems where fingerprints are only created for symbolic locations, our approach offers the possibility to cover the complete area of operation, as it is generally done when using a grid-based approach. By automatically detecting regions of similar signal properties, we avoid the error-prone process of letting the operator manually define regions or

Table 5.1: Time needed for measuring the training data for the area of operation.

	static (TSS 20)	static (TSS 4)	$0.5\ \frac{m}{s}$	$1.0\ \frac{m}{s}$
time [sec]	2150	430	465	280

locations himself. This prevents the definition of regions that are connected in physical space but might not be consistent in signal space.

Considering the often mentioned problem of keeping the fingerprint database up to date once the positioning system is operational, our algorithm has several advantages, too. Firstly, the operator can – in the case of environmental changes like added or removed access points – identify the affected regions and recreate the fingerprint database only for these regions in the same effort-saving manner as when initially setting up the system. Secondly, as it can handle in-motion training data, our system could also be extended to take advantage of user supplied training data as proposed by, e.g., Chai et al. [CY05].

Finally, depending on the requirements of the application, the performance of our algorithm can be adjusted for accuracy or reliability by simply varying the similarity threshold.

Computational Requirements

Taking a look at the computational requirements, our approach is advantageous as well. It combines similar cells into regions and creates only one fingerprint per region. Therefore, the overall number of fingerprints for an area to cover decreases compared to a classical grid-based approach where each cell or reference spot would have its own fingerprint. Whereas the creation of the region map is an additional effort that has to be performed once during the training phase, the system can take advantage of the lower number of fingerprints and the thereby decreased computational effort for every following position estimation during the position determination phase. For instance, using a similarity threshold of 0.53 results in a set of 19 regions and thus 19 fingerprints. Covering the same area with a grid of reference spots using a grid size of $1.5\ m$ results in a total of 130 fingerprints. As the collected data has to be matched against all fingerprints for each position estimation during the position determination phase, this means a reduction of the necessary computational effort by more than 80% when using our algorithm.

Table 5.2 exemplarily shows the measured average computation times for the above described setup on one of the systems we used for emulation. The offline time is the average time the algorithm needed to compute its fingerprint database and, in the case of our algorithm, to create the region map in advance. The online time is the average time that was needed to compute one round of position estimations for the set of position determination spots (46 spots).

Table 5.2: Computation times

	offline [ms]	online [ms]
Haeberlen et al.	22	2655
Fingerprint Clustering	270	114

5.5.5 Conclusion

We have introduced a novel algorithm to estimate the location of a user with the help of IEEE 802.11 and location fingerprinting. Our approach has the major advantage that it clusters the collected training measurements into regions of similar signal properties by using a new similarity measure and thereby needs significantly less training data to achieve satisfying results. The clustering furthermore allows us to collect the training data by simply walking through the area of operation on defined trajectories. This would not be possible without clustering due to the prohibiting low measurement density and is a major improvement over other systems that need measurements at fixed reference spots.

As our algorithm uses one fingerprint for each region instead of creating one fingerprint for each reference spot, the overall computational load – one of the limiting factors, especially when operating on mobile devices or with large amounts of parallel users – can be reduced significantly. Compared to other approaches that also use only one fingerprint, for instance, for a single office room or floor, our approach has the major advantage that it identifies the regions based on the collected training measurements. Thus, errors made during the manual definition of regions and resulting inconsistencies between the regions in physical and signal space can be avoided.

Our algorithm delivers an accuracy that is sufficient for most types of LBSs and, at the same time, maintains a high reliability. It offers the possibility to adjust its output for either higher reliability or higher accuracy by varying the similarity threshold, and it can thus be adjusted to the requirements of different applications.

5.6 Error Estimation for IEEE 802.11-LF

Positioning with the help of IEEE 802.11 and LF offers a viable alternative to other proposed techniques to estimate a user's location. However, as with GPS, IEEE 802.11-based positioning systems comprise an inherent positioning error that is caused by radio propagation effects (e.g., reflection, diffraction, and scattering) and limits of the hardware (e.g., the measurement accuracy of sensors). Even worse, under sub-optimal conditions such as sparse coverage by access points or many moving obstacles that cause radio signals to further fluctuate, the accuracy of IEEE 802.11-based positioning systems tends to decrease. This results in the estimated position being far off of the user's actual whereabouts. It sometimes even happens that the position accuracy degrades so far that LBSs which rely on reliable positioning misbehave. If we, for instance, consider a user who uses an indoor navigation system to find her way to a meeting room, the system might lead her to a wrong room without her realizing it. If, however, the system also displays information about the error that is immanent in the position estimation, the user can pay more attention in case of suboptimal positioning system performance. So we summarize that the failure to notify the user about the possible loss of precision will impede the user's trust in the system as well as in the offered services.

GPS handles variations in the positioning accuracy by offering a measure called *Dilution Of Precision* (DOP). Calculated from several different system parameters, the DOP value indicates the level of positioning error that has to be expected for a given estimated position. Positioning error estimation is mainly valuable in three ways (see Figure 5.23):

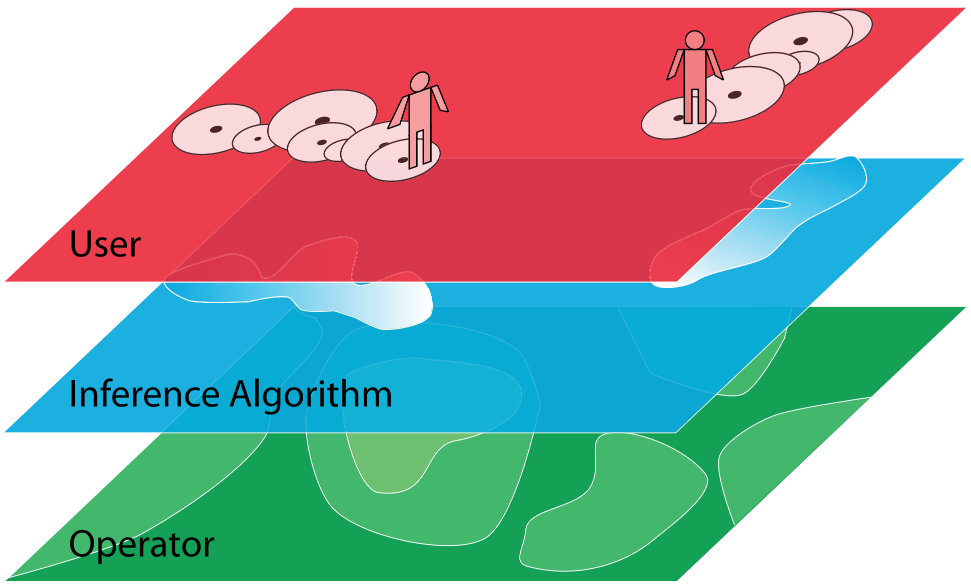


Figure 5.23: The use of information about expected errors by users, inference algorithms, and operators.

Firstly, the *user* can be notified that the estimated position might contain a certain positioning error. This helps her to make better use of the LBS [DVDLT07] and also avoids her becoming frustrated because of many unexpected wrong positioning results. For instance, if a friend-finder service not only shows the estimated position of a friend but also the estimated positioning error (e.g., as a circle around the friend's position), a user can look around in the area indicated by the positioning error estimate in case she is not able to find her friend at the place where the service estimated her to be.

Secondly, so-called *inference algorithms* utilize position estimates to derive additional information (e.g., activities or routes). Positioning error estimates allow the inference algorithms to assess the level of trust that these position estimates contain. As a result, the algorithms can give a higher priority to estimates with a low estimated error. This helps to deliver an overall higher service quality.

Thirdly, *operators* of 802.11-based positioning systems can utilize positioning error estimates to optimize their system to the precision required by the application. For instance, an operator might add additional APs to those parts of the operation area that show positioning error estimates above a certain threshold.

In this section, we propose several algorithms to estimate the expected positioning error of 802.11-based positioning systems. We focus on the static case of position estimation without any knowledge of spatial or temporal history. We have selected two well-studied systems proposed by Bahl et al. [BP00] and Haeberlen et al. [HFL$^+$04] as our positioning systems. We selected these two systems because they represent the two main types of location fingerprinting algorithms, i.e., a probabilistic and a deterministic approach. Our setup and both algorithms are sufficiently easy to understand and therefore – with their own complexity – do not blur the view for the mechanisms used by our own error prediction algorithms.

We propose positioning error estimation algorithms that are able to predict the expected positioning error in advance, using only the collected training data as well as algorithms that infer the expected positioning error from live measurements in the position determination phase. This information can then be used to inform the user in an appropriate way (also see [LKE08]) and to allow dependent services to adapt their decisions.

5.6.1 Error Estimation

In this section, we propose our four novel algorithms for positioning error estimation. The following two algorithms can predict the expected positioning error in advance, using only the data collected in the training phase:

A. Fingerprint Clustering

B. Leave Out Fingerprint

The other two algorithms infer the expected positioning error from live measurements in the position determination phase:

C. Best Candidates Set

D. Signal Strength Variance

A. Fingerprint Clustering

The *Fingerprint Clustering* algorithm uses the idea that, inside structurally limited areas, the signals received from an access point – despite inevitable small-scale fading effects – tend to be within a certain range. For instance, the signal strength measurements collected in one single office room often cover only a quite limited range of the generally possible values. As in such a case all the fingerprints collected in this office room are very similar, a positioning algorithm will hardly be able to estimate the position precisely. Instead, it will probably select one of the other fingerprints collected somewhere else in the room.

If such an area of similar signal properties has large physical dimensions, we expect the positioning error to be larger because, generally, the number of similar fingerprints is higher and also their physical distribution space is larger. We exploit this behavior in the following way. Our novel algorithm lays out a grid of cells over the complete covered area of operation of the IEEE 802.11-based positioning system. Then, the following steps are performed in order to find regions of similar signal properties:

1. Initially, each grid cell represents a single cluster containing all the training samples collected inside the physical area of the cell.
2. After that, the algorithm randomly selects a cluster. By using a similarity measure, the algorithm then checks whether the similarity to adjacent clusters lies above a given threshold. If this is the case for any adjacent cluster, the two clusters are merged into one.
3. The previous step is repeated until, for all remaining clusters, no further clusters can be merged.
4. As a next step, the set of clusters is checked for clusters that only comprise one single cell. If such a cluster is found, it is merged with its most similar adjacent cluster disregarding the threshold. The reason for this procedure is that the single cell clusters most often are a result of time and space constrained disturbances during the collection phase of the training data. If the fingerprints at these positions are selected by the positioning system during the position determination phase, this quite frequently results in large errors that would not be reflected by the small size of a single-cell cluster. Thus, eliminating these clusters helps the error estimation algorithm to deliver better and more stable results.
5. In the end, each remaining cluster represents a region of similar signal properties in the area of operation. The size and shape of the region is defined by the grid cells the cluster is comprised of. The estimated error for an estimated position is deduced from the size of the region that the estimated position is located in.

An example for a region map resulting from the Fingerprint Clustering algorithm is shown in Figure 5.24.

The similarity measure for a pair of clusters is calculated by comparing the distributions of signal strengths in the clusters using a similar function to the one used for the region-based position estimation in Section 5.5.1. For each access point of which signal strength measurements are contained in the samples of both clusters, and for each of the two clusters, the mean and the standard deviation of the measured signal strengths are computed. These values are then used to create two normal distributions, each one representing the signal strength distribution of the specific access point and cluster. Afterwards, the intersection area of these two normal distributions is calculated. This step is repeated for all access points until, finally, the average size of all intersection areas is computed and interpreted as the similarity of the two clusters. Access points of which signal strength measurements are only contained in the samples of one

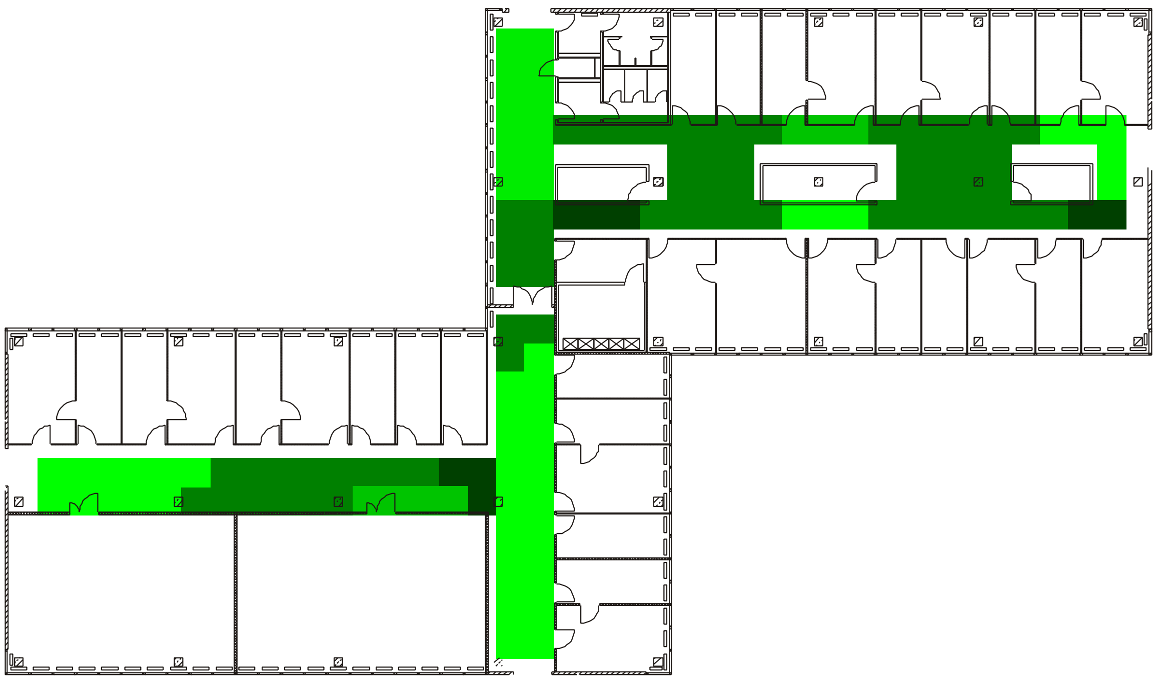


Figure 5.24: Example for a region map created for the Mannheim test bed.

cluster are not considered. Due to the spatial neighbor property of the clusters that are considered pairwise, the case where there are major differences in the set of contained access points is generally very rare and thus omitted here.

To figure out the influence of the similarity threshold on the performance of the algorithm, we conducted a pre-evaluation with varying settings for the threshold. In general, a higher similarity threshold results in the regions staying smaller. This helps to decrease the discrepancy between estimated and true error in cases where the correct region is chosen. However, it also increases the rate of wrong region selections (also refer to Section 5.6.3). From the evaluated values, for our scenarios, 0.51 performs best in terms of quantitative error estimation. Using this similarity threshold, the real and the estimated position are in the same region in 90% of all cases. Additionally, in half of the remaining cases, the real position is located in a cell directly adjacent to the selected region. Only in 5% of all cases, the real position is somewhere else. Therefore, we have selected the value 0.51 as the similarity threshold for all further experiments. As this value performs best for both of our scenarios, we assume that it is valid for other scenarios as well.

B. Leave Out Fingerprint

The *Leave Out Fingerprint* algorithm estimates errors by evaluating positioning performance using only the data collected during the training phase.

The performance evaluation uses an $(n-1)$ cross evaluation, meaning that a positioning algorithm itself, for one current fingerprint, determines the closest match amongst all other fingerprints (the other $(n-1)$ folds). The result is a good indicator of the error that can occur if the data collected during the position determination phase is noisy.

The positioning error result from this evaluation is used to compute an error map where each fingerprinted position is assigned an error estimate. In the position determination phase, the position estimated by the positioning algorithm is looked up in the error map, and the error estimate stored for the corresponding position is returned. For each fingerprinted position p, the error map contains an error estimate that is created by the following four steps:

1. Create a radio map using all fingerprints except the one for position p.
2. Run an emulation using m samples as test data taken randomly from the fingerprint for position p.
3. Calculate the observed errors for the position estimates from the emulation.
4. Calculate the error estimate for position p as the average plus two times the standard deviation of all the observed m errors. This method for computing the error estimate was selected because initial experiments showed that this type of conservative estimate gives the best results.

As a final step, when all error estimates have been calculated, the error map is averaged to filter out local variations. This is performed by assigning a new estimate to each position. The new estimate is calculated as 66% of the original estimate and 33% as the average of the estimates for all neighboring fingerprints. We chose these parameters for the weights because they provide a good balance between the error estimates for the different fingerprint positions. In our evaluation, this interpolation step increases the accuracy of the algorithm by almost five percent.

C. Best Candidates Set

When an IEEE 802.11-based positioning algorithm estimates a position, it generally returns only the position of the fingerprint that offers the best match to the data collected in the position determination phase. However, the Best Candidates Set algorithm exploits the fact that positioning algorithms can return information about the second, third etc. best matches. The Best Candidates Set algorithm uses the n best estimates returned from a positioning algorithm to estimate the expected positioning error. The rationale for using the n best estimates is based on the observation that positioning algorithms will often estimate a user to be at any of the nearby positions to his actual position. This is a result of the fact that adjacent fingerprinted positions will often exhibit overlapping signal strength properties while online samples similarly have sufficient signal strength variance to choose at random between close locations.

The Best Candidates Set algorithm deduces an error estimate by computing the average distance between the best estimate and the next $(n-1)$ best estimates. The algorithm contains the following steps:

1. Form the set of the n best estimates as outputted from an IEEE 802.11-based positioning algorithm.

2. Compute the distance between the position of the best estimate and all the other $(n-1)$ best estimates.

3. Return the average distance as the estimated error.

In addition to using the average distance between the best and the $(n-1)$ next best estimates, we also tried two other options to compute an error estimate from the Best Candidates Set. The first option was to use the maximum distance between the best estimate and any of the $(n-1)$ next best estimates. The second option was to compute the maximum distance between any two of the n best estimates. Both options led to more conservative error estimates but they were also more sensitive to large errors and to an increased n. In effect, both options produced a higher proportion of large over-estimations when the performance of the positioning algorithm degraded or when the size of the Best Candidates Set was increased. In contrast, the average-distance approach handled these situations better. Using the average distance, it was found that n set to three gave the best overall performance, although the performance was only marginally better than with n set anywhere between four and seven. Higher values of n made the error estimates more conservative while gradually decreasing performance due to the inclusion of more faraway positions.

D. Signal Strength Variance

Like most IEEE 802.11-based positioning systems, the systems selected for this paper are error-prone to signal strength variations because the position estimation process depends on probabilities or average values calculated on the signal strength samples.

The reasons for the variation of signal strength samples are two fold: Firstly, small-scale effects and multi-path radio propagation cause signal strength values to vary significantly if the mobile device moves within the wavelength (for IEEE 802.11b, the wavelength is ≈ 12.5 centimeters). So, both during the training phase as well as during the position determination phase, even if the mobile device is supposed to be static, small movements can have a big impact on the measured signal strength. Secondly, movements in the surrounding of the mobile device in question (e.g., persons moving around or doors being opened or closed) cause radio signals to travel over different paths which in consequence causes the signal strength to fluctuate.

If the variance between different signal strength samples is high, the probability that the actual closest fingerprint is selected is rather small, as a fingerprint far away might reach a higher probability. The same is true for the average calculation because the average value might differ if the variance between different signal strength samples is high. Therefore, an increase in variance also increases the probability of positioning errors.

The idea of the Signal Strength Variance algorithm is to estimate the positioning error based on the signal strength variance of the samples that are used in the position determination phase to compute a position estimate. The algorithm can be described as follows:

1. For each access point that is part of the signal strength samples, find the largest signal strength value (in dB).
2. Based on the largest signal strength value that is specific for a certain access point, subtract this value from all signal strength samples that are available for this given access point.
3. For each access point, calculate the signal strength variance for the calculated values.
4. Average the signal strength variance values calculated for each access point to get an overall variance value. This variance value can be perceived as an indicator of the expected positioning error similar to the DOP measure used by GPS.

We also tried several other ways to calculate an overall signal strength variance value. However, this did not lead to an algorithm with better results than those achieved with the algorithm presented above.

Random Value

As a baseline and to give the reader a better understanding of our results, we also implemented a simple random error estimation algorithm. This algorithm returns uniformly distributed random error estimates between 0 and ten meters independent of the supplied data.

5.6.2 Experimental Setup and Methodology

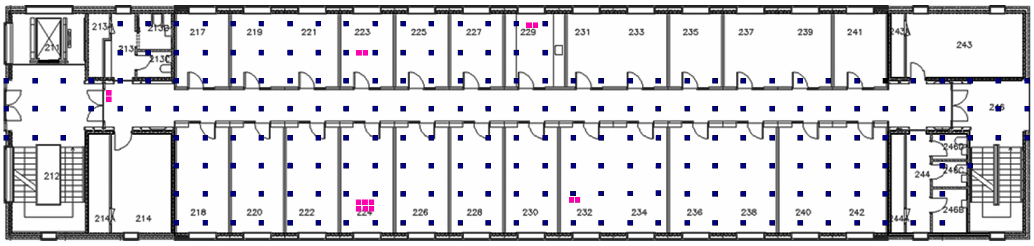
In this section, we describe the experimental setup and the measurement methodology used to evaluate the proposed algorithms.

Local Test Environments

We deployed our IEEE 802.11-based positioning systems in two different environments: On the second floor of the Hopper building on the campus of the University of Aarhus and on the second floor of the office building A5-B on the campus of the University of Mannheim.

The former one is a newly built office building consisting of many offices and a long hall (see Figure 5.25a). The area is covered by 23 access points from different vendors; only five of these access points can be detected in at least half of the measurements. Nine far-off access points are even only detectable in less than ten percent of all measurements. The average number of access points contained in the fingerprints for this environment is 6.9, while the average number contained in the samples used for positioning is 4.8. The IEEE 802.11-based positioning system covers an area of about $56\ m$ times $13\ m$.

The latter environment is also situated in an office building and consists of many offices and three longer hallways (see Figure 5.25b). The area is covered by 25 access points in total, although our data shows that most of the access points only cover parts of the operation area. In fact, only two access points cover the operation area completely. On the average, 14.7 access points are contained in each fingerprint for this environment and 10.5 access points are contained in each set of measurements used for positioning during the position determination phase. The operation area is nearly $57\ m$ wide and $32\ m$ long.



(a) The second floor of the Hopper building.

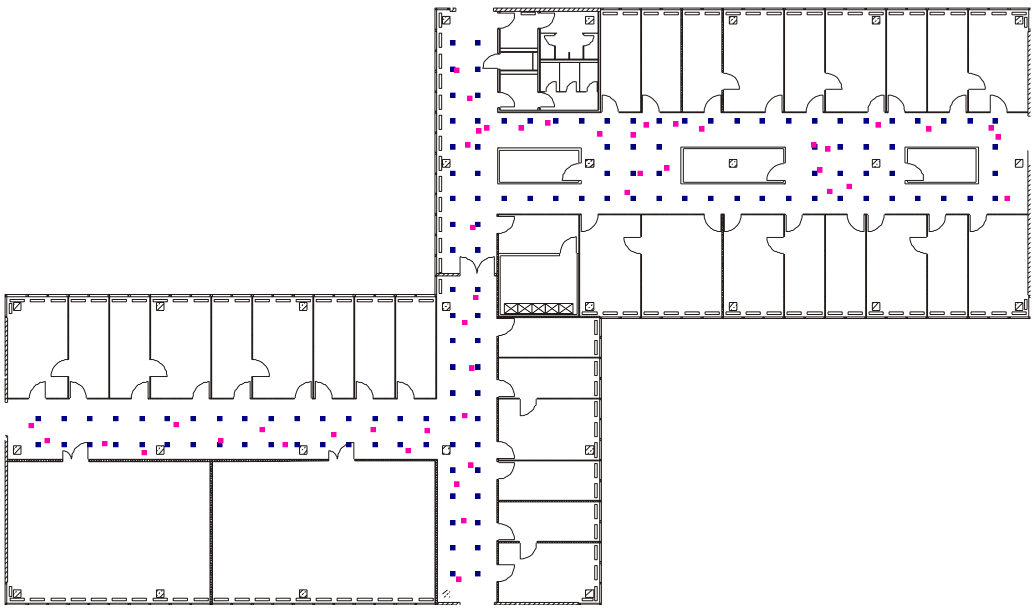

(b) The second floor of the A5-B building.

Figure 5.25: The two test environments. The reference spots are marked in blue and the test spots are depicted in pink.

Hardware and Software Setup

As a client, we used a Lucent Orinoco Silver PCMCIA network card supporting 802.11b. This card was plugged into an IBM Thinkpad R51 laptop computer. To collect signal strength samples, we used our own set of tools [KBH07].

Data Collection

For both environments, we applied a grid of reference spots with a spacing of $1.5\ m$ to the operation areas. For the Hopper building, this resulted in 225 reference spots, while the Mannheim environment comprised 130 reference spots (see the blue markers in Figures 5.25a and 5.25b). For the former environment, 120 signal strength measurements and, for the latter one, 110 signal strength measurements were subsequently collected at each reference spot. The reason for the difference in the number of measurements per spot is, that we were able to use datasets that had been collected independently of each other in advance.

For the position determination phase, we then selected 14 spots in the Hopper building and 46 spots in the A5-B building. At each of these spots, we collected 110 signal strength samples as well. In Figure 5.25a and Figure 5.25b, these spots are marked by pink dots.

Metrics

Regarding the metric used to compare our error estimation algorithms, we use the *error difference*. For each position estimate, we compute the physical distance between the real and the estimated position (*the real error*) and then subtract the result from the value that our error estimation algorithms return as the expected error. By using the error difference, it is, for instance, easy for us to analyze whether our algorithms tend to estimate the positioning error too high or too low.

Experimental Methodology

We performed an evaluation of our four error estimation algorithms. To keep the results comparable, we examined the four algorithms in parallel. To achieve this, we used our suite of positioning-related tools [KBH07] and extended them to suit our special needs.

The basic experiment consisted of the following steps: At first, one of the two used positioning algorithms is initialized with 25 randomly selected samples per reference spot to build up its fingerprint database. Subsequently, our four different error estimation algorithms are initialized as well. Those that make use of the training data are additionally provided with exactly the same data as the positioning algorithm itself. The same is then done with the data for the position determination phase. At first, the positioning algorithm – for each test position – is given five online samples to estimate a position. Afterwards, the same samples used for the position determination as well as the estimated position are provided to our error estimation algorithms.

Each of the algorithms then solely computes an error estimate which is recorded and stored for later reference.

The values used for the number of training and position determination samples were chosen according to [KHE07]. To achieve statistically stable results, we repeated our basic experiment 100 times. We ran our basic experiment using the positioning algorithm proposed by Bahl et al. [BP00] and the one proposed by Haeberlen at el. [HFL$^+$04] on data collected from both of our test environments.

As listed in Table 5.3, the position accuracy of the positioning algorithms by Bahl et al. [BP00] and Haeberlen at el. [HFL$^+$04] is quite different when considering the data for each of our two test environments. The main reasons are the number of access points, the properties of the environments, and the overall quality of the positioning algorithms themselves.

Table 5.3: True position estimation accuracy for positioning algorithms and test environments.

Positioning Algorithm	Aarhus [m]	Mannheim [m]
Bahl et al. [BP00]	8.10	2.90
Haeberlen et al. [HFL$^+$04]	3.79	2.56

5.6.3 Experimental Results

In this section, we present our evaluation results focusing on the results for the more accurate Rice positioning algorithm. We omitted the results for Radar as they are overall very similar to those for the Rice algorithm and presenting them would only offer little additional information to the reader.

Estimation Accuracy

The proposed error estimation algorithms show noticeable differences in their performances as well as in their reactions to different environmental conditions and to the used positioning algorithms.

Overall, for the Aarhus dataset and with the Haeberlen et al. positioning algorithm, the Fingerprint Clustering approach delivers the best results (e.g., $1.13\ m$ at the median) even though the second best algorithm, the Best Candidates Set, is quite close regarding the $95th$ percentile (see Figure 5.26a).

Looking at the Mannheim dataset, the situation is different. Considering the $25th$, $50th$, and $75th$ percentiles, the Best Candidates Set algorithm now takes the lead with $1.10\ m$ at the median (see Figure 5.26b). This impression is also confirmed when taking a look at the average values for the error difference of the four algorithms and the two environments (see Table 5.4). Here as well, the Best Candidates Set algorithm performs best for the Mannheim dataset at $1.45\ m$, while the Fingerprint Clustering algorithm is ahead for the Aarhus dataset at $2.24\ m$.

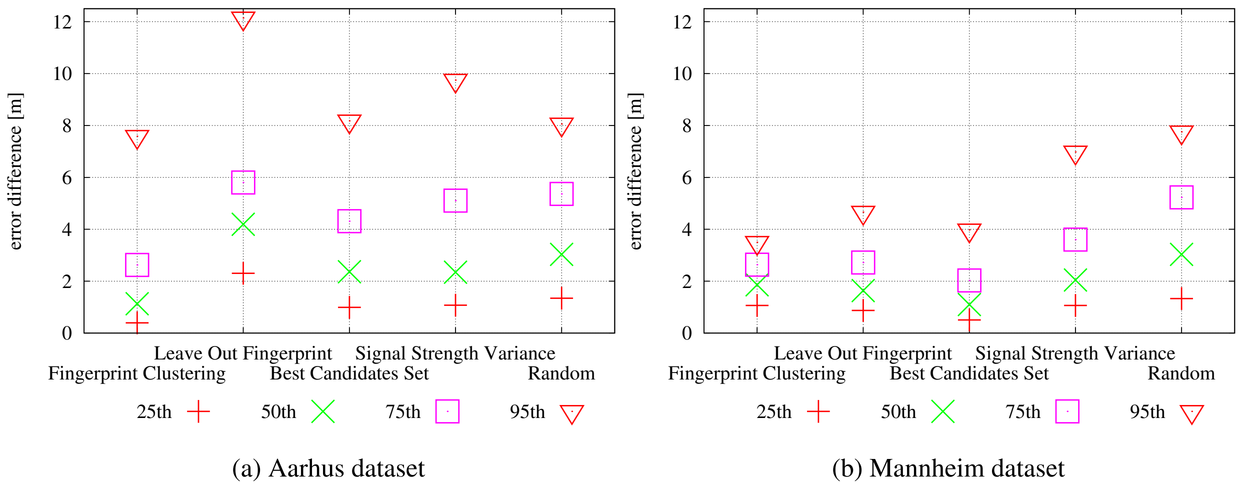


Figure 5.26: Overview of the performance of the different algorithms for the Aarhus as well as for the Mannheim dataset using the positioning algorithm by Haeberlen et al.

The reason for these differences are the different properties of the datasets. For example, as listed in Section 5.6.2, the average positioning error for the Mannheim dataset is noticeably lower mainly due to the higher number of access points available. As the Fingerprint Clustering algorithm tends to make very conservative error estimations, this leads – compared to the rather optimistic estimations of the Best Candidates Set algorithm – to the different results.

The opposite is true for the Aarhus dataset. Here, due to the generally larger errors of the positioning algorithms, the Fingerprint Clustering algorithm can deliver the best results while the other error estimation algorithms have difficulties, especially with estimating outlying errors.

For the results with the positioning algorithm by Bahl et al., the error estimation algorithms again perform better on the Mannheim data set. However, for this positioning algorithm, the Fingerprint Clustering algorithm has the best performance on both data sets with an average accuracy of $2.03\ m$ for the Mannheim data and $6.56\ m$ for the Aarhus data. The reason for the results of the Aarhus data set being several times worse is that the accuracy of the error estimation is impacted by the bad average position accuracy of $8.10\ m$ and also the high variation of the positioning accuracy. However, when comparing the decrease in position accuracy and error estimation accuracy, it can be noted that they are on the same scale.

Combining Algorithms

In addition to evaluating the accuracy of each error estimation algorithm alone, we have investigated if the accuracy can be improved by combining the algorithms using a machine-learning algorithm. We used the Weka machine-learning toolkit [WF05] for our experiments. In order to feed the output of our evaluations to Weka, we have implemented a small Java program that reads the evaluation results for the proposed error estimation algorithms and outputs an ARFF

Table 5.4: Average error difference for the Aarhus and the Mannheim dataset using the positioning algorithm by Haeberlen et al.

	Aarhus Dataset		Mannheim Dataset	
Algorithm	Avg. Error [m]	Std. Dev. [m]	Avg. Error [m]	Std. Dev. [m]
Fingerprint Clustering	2.24	2.91	1.90	1.09
Leave Out Fingerprint	4.68	3.53	1.95	1.47
Best Candidates Set	3.06	2.61	1.45	1.26
Signal Strength Variance	3.92	5.08	2.69	2.45
Random	3.58	2.84	3.43	2.39

file for the Weka tool. Before finally selecting a machine-learning method to use for combining the results, we experimented with different methods and concluded that the *Least Median Squared Linear Regression* method was most appropriate. This method uses regression to learn weights for a linear model. The weights are learned from a training set (e.g., either the Aarhus or Mannheim data set), and then the learned model is tested using a test set (e.g., the set that was not used for training).

The results of different combinations of the proposed algorithms as well as test and training data are listed in Table 5.5. When combining error estimates of all the algorithms and testing with the Mannheim data, an average result of $1.37\ m$ is achieved, which is a marginal improvement over the $1.45\ m$ for the Best Candidates Set algorithm alone. When testing with the Aarhus data, the result is $2.40\ m$, which is a bit worse than $2.24\ m$ for the Fingerprint Clustering algorithm alone. The table also lists results when only the output of the Best Candidates Set and Fingerprint Clustering algorithms are combined. These results are only a few centimeters better on average than when combining all algorithms. Given the small improvement, using a single algorithm seems like a better option than combining several algorithms, especially when considering the additional system complexity and increased computational requirements for running several algorithms in parallel and then combining their output.

Table 5.5: Results for different combinations of the proposed algorithms as well as test and training data for the positioning algorithm by Haeberlen et al.

Algorithms	Training Dataset	Test Dataset	Avg. Error [m]
All	Aarhus	Mannheim	1.37
Two Best	Aarhus	Mannheim	1.35
All	Mannheim	Aarhus	2.40
Two Best	Mannheim	Aarhus	2.36

Overestimation versus Underestimation

Some applications might have preferences with respect to an overestimation or underestimation of positioning errors. For instance, an application that has to alert a user in case that the estimated error is above a threshold might prefer overestimation in order to avoid to not alert the user in cases of large errors whereas the occurrence of unnecessary alerts might be more acceptable. On the other hand, an application that serves the user with information about points of interest (POI) in her proximity might prefer an underestimation of the error. This avoids that the area that has to be considered and thus the number of POIs gets to large which would potentially annoy or overwhelm the user. In Figure 5.27, the error difference distributions are depicted for the two most promising algorithms. The positioning system proposed by Haeberlen et al. is used and data for both test environments is displayed. In these distributions, underestimations result in negative values while overestimations lead to positive values. Our results show that the Best Candidates Set algorithm has a tendency to produce a higher amount of large overestimations. Also, when comparing the results for the Aarhus and Mannheim datasets, the distributions reveal that both algorithms produce a higher amount of large under- and overestimates for the less accurate Aarhus dataset.

Our proposed algorithms offer the possibility to adjust the error estimation performance to favor either under- or overestimation with algorithm-specific parameters. This comes at the expense of reliability, though. For example, for the Best Candidates Set algorithm, the size of the set can be varied. When considering more candidates in our evaluations, the number of errors that are underestimated decreases. But, at the same time, the amount of overestimation increases because more, perhaps physically far distant, positions are taken into account. The same is true for the Fingerprint Clustering algorithm: When adjusting the similarity threshold for the merging of clusters, the sizes of the resulting regions increase. This also increases the probability of the estimated and real position being located in the same region. But, at the same time, it also increases the average error difference in our evaluations. Therefore, here again, we have a trade-off between accuracy and reliability.

5.6.4 Discussion of Additional Factors

This section discusses the space and time complexity of the proposed algorithms, the influence of the number of position determination samples and the number of access points on the error estimation, and the GPS approach for the dilution of precision.

Space and Time Complexity

Considering the space and time complexity of our algorithms, we have to distinguish between those operating only on the training data and those also taking the measurements during the position determination phase into account.

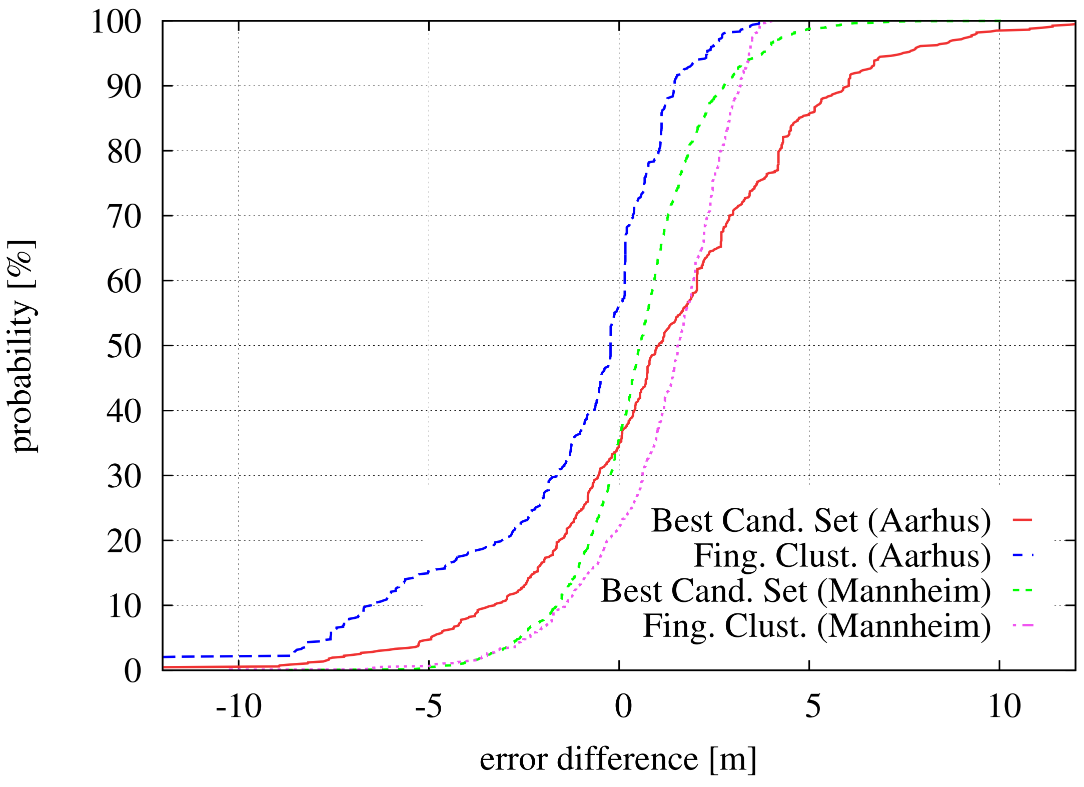


Figure 5.27: Distributions of the difference between estimated and real error.

For the former ones, computational complexity is not critical as the algorithms need to be run on the training data only once. This can be done on powerful systems before the deployment. The opposite is true for the space complexity. As the result of the algorithms has to be stored and processed on the mobile device, the amount of data is important.

For the latter ones, both space and time complexity are important. For each single position determination, a computation based on the current set of measurements as well as the training data takes place. Considering that this might as well happen on a mobile device, the algorithms have to be economical regarding CPU time and memory consumption. It turns out that both the Fingerprint Clustering and the Best Candidates Set algorithms are light-weight in terms of computations and space use. Please refer to Table 5.6 for details.

Table 5.6: Comparison of the space and time complexity for the proposed algorithms, where c is the number of initial cells, n is the number of fingerprints, p is the time complexity of the positioning algorithm, a is the number of access points in the online samples, b is the size of the Best Candidates Set, and h is the number of stored samples.

	Fingerprint Clustering	Leave Out Fingerprint	Best Candidates Set	Signal Strength Variance
Time complexity	$O(c)$	$O(n * p)$	$O(b)$	$O(a * h)$
Space complexity	$O(c)$	$O(n)$	$O(b)$	$O(a * h)$

Number of Position Determination Samples and Number of Access Points

From experimental results, King et al. [KHE07] conclude that the IEEE 802.11-LF positioning error is mainly determined by the number of access points and the number of signal strength samples used in the position determination phase. In this work, we do not present any algorithm that takes this fact explicitly into account. However, the previously presented algorithms indirectly adhere to this fact. For instance, the Fingerprint Clustering algorithm (see Section 5.6.1), when comparing similarity between clusters, iterates over the set of access points and, thus, handles the number of access points. The number of position determination samples is covered by the Signal Strength Variance algorithm (see Section 5.6.1) as the variance value stabilizes if the number of signal strength samples increases. However, it would be an interesting path of future work to analyze if the proposed algorithms could be extended to use such results more explicitly.

Dilution of Precision

In addition to the proposed algorithms, we also implemented an algorithm that computes a GPS-like DOP value based on the geometry of APs. The algorithm uses the equations for DOP values described in Borre et al. [BAB$^+$07]. However, a DOP value is not an error estimate in meters but a factor that has to be combined with an error estimate.

Therefore, we have evaluated if the accuracy of the proposed algorithms can be improved by combining their output with this GPS-like DOP value by multiplication. However, for all algorithms, the combination with the DOP value strongly reduces their accuracy. This suggests that GPS-like DOP values do not seem to be a promising error estimation approach for indoor IEEE 802.11-based positioning. The main reason is that the complex indoor propagation environment makes the geometry of the access points less important for the positioning accuracy than it is in the case of outdoor satellite-based positioning. This result is consistent with the analytical results for the impact of the geometry of access points on the position accuracy presented by Wallbaum et al. [Wal07].

5.6.5 Conclusions

In this section, we have introduced four novel algorithms to estimate the positioning error of IEEE 802.11-based positioning systems. Our algorithms exploit several different features to fulfill their task. We have proposed error estimation algorithms that only use training data as well as algorithms that only take the data available during the position determination phase into account.

All our algorithms deliver good results for estimating the positioning error for both environments and for the different positioning algorithms. The Fingerprint Clustering algorithm and the Best Candidates Set algorithm perform especially well. With either of these two algorithms, it is possible to estimate the positioning error of an IEEE 802.11-based positioning system up to a high degree of accuracy and with sufficient reliability. This is in contrast to the geometry-based algorithms used for GPS.

We have evaluated if using a machine-learning technique to combine several of the proposed algorithms can improve the precision of the error estimates. In our case, though, the gain is very small or the results even get worse. We therefore do not suggest to use a combination of the different algorithms but to rather use one algorithm alone. If the collected data has a good quality, we suggest to use the Best Candidates Set algorithm whereas in situations where the collected data is of lower quality, the Fingerprint Clustering algorithm should be used. Looking at the targeted use of the algorithms on mobile devices, this suggestion makes even more sense as the use of multiple algorithms – even though each single one is economical in terms of processing and storage demands – would waste precious resources.

CHAPTER 6

Context, Tracking, and IEEE 802.11-LF

Up to now, we have presented an overview of different problems that have to be dealt with when using IEEE 802.11-LF for position estimation, and we have contributed our own solutions to these problems. In the following section, we will present another approach to help solve some of these issues, namely the use of *tracking*. All algorithms presented until here only use static data. This means that they consider a fixed set of training measurements that is used to build the fingerprint database, and a single or only few consecutive measurements during the position determination phase to estimate a user's position.

Tracking extends this by furthermore considering the measurement and position history and possibly other available context information, and it is not limited to IEEE 802.11-LF. For instance, a navigation system in a car can further increase the accuracy of the position estimation by cross-validating the satellite-based estimates using available odometric data to extrapolate from former known positions. If the estimate of the satellite-based system and the extrapolated estimate differ, the system can omit using the latter or try to mitigate the error by using a combination of both systems.

If tracking is possible, it is generally preferable over the static approach as it yields the opportunity for higher accuracy and better update rates. The following Chapter describes our efforts to transfer the tracking approach into the domain of IEEE 802.11-LF. Furthermore, together with the use of fingerprinting techniques, we investigated the use of other possible context information sources that are available on modern mobile devices and can be used to improve the position estimation.

6.1 Context Information

Modern mobile devices offer a large number of sensors. Among these, we find accelerometers, temperature sensors, light sensors, magnetic compasses, microphones, and sometimes even more. As it has been shown by earlier research, for instance, the use of directional fingerprints and a compass can improve the positioning accuracy considerably [KKH+06]. However, this comes at the cost of an increase of the effort needed for setup and maintenance.

We therefore reconsidered the alternative use of a compass and furthermore how other sensors can be used to support the position estimation of a moving user. Regarding the information from most of the other sensors, we had to face the problem that – in distinction from using a compass – the information that can be gathered from these sensors built into mobile devices is highly varying. For instance, it does not really make sense to store information about the brightness at a certain position in a fingerprint as the brightness value is most probably subject to change throughout the day. Thus, we also restricted ourselves to the use of additional context information only during the position determination phase. In this phase, the most important information is the one about the user's motion. We therefore decided to use accelerometers and magnetic compasses.

6.1.1 Motion Mode

When considering a moving user, information about the user's mode of motion is an important help when trying to extrapolate the user's future path. If we are somehow able to identify whether a user is standing still or walking at a certain speed, we can – based on past position estimations – prioritize areas that can more likely be reached within the time between two consecutive position estimations and leave other areas that might be out of reach unconsidered.

In the past, much research has already been done in this area. Most often, dead reckoning with the help of low-cost but still specialized devices is used. These devices generally contain an accelerometer for every dimension, a gyroscope to detect rotation, and an interface to communicate the sensor readings. By mounting such a device on a person's foot, single strides, their length, and also their direction can be detected quite accurately. Using this information for dead reckoning, a positioning system can extrapolate a user's location from a known start position (e.g., see [RDML05, PEK+06, WKB08]).

This approach has several major flaws, though. Firstly, the used sensors normally have a certain drift. This leads to increasingly bad results for longer times without a reinitialization at a known position. Whereas – to a certain degree – this problem can be mitigated by the use of maps, the second problem is not as easily solved. As such a systems needs information from a foot- or leg-mounted high quality sensor system, a user needs to carry the sensor unit at her leg or shoe. While this might be feasible for certain specialized application scenarios, it is not an acceptable approach for everyday usage.

Despite these problems, to us, motion information still seems like a valuable addition from which a positioning system can benefit. Thus, we relaxed the requirements to fit our targeted application scenario of positioning usable in everyday life. Instead of using specialized sensor units to detect single steps or even steps at all, we confined ourselves to using the accelerometers that are built into modern devices to only detect the motion *mode* a user is in.

Even without detecting single steps, we claim that we can still use the readings from an accelerometer to detect the mode of a user's motion. Figure 6.1 depicts this approach. As shown here, the accelerometer readings strongly vary depending on whether the user is standing still (depicted in red), walking at about 1 $\frac{m}{s}$ (depicted in green), or walking fast at a speed of 2 $\frac{m}{s}$ (depicted in blue). The measurements for this experiment were made using the built-in accelerometer of an HTC Desire cellular phone.

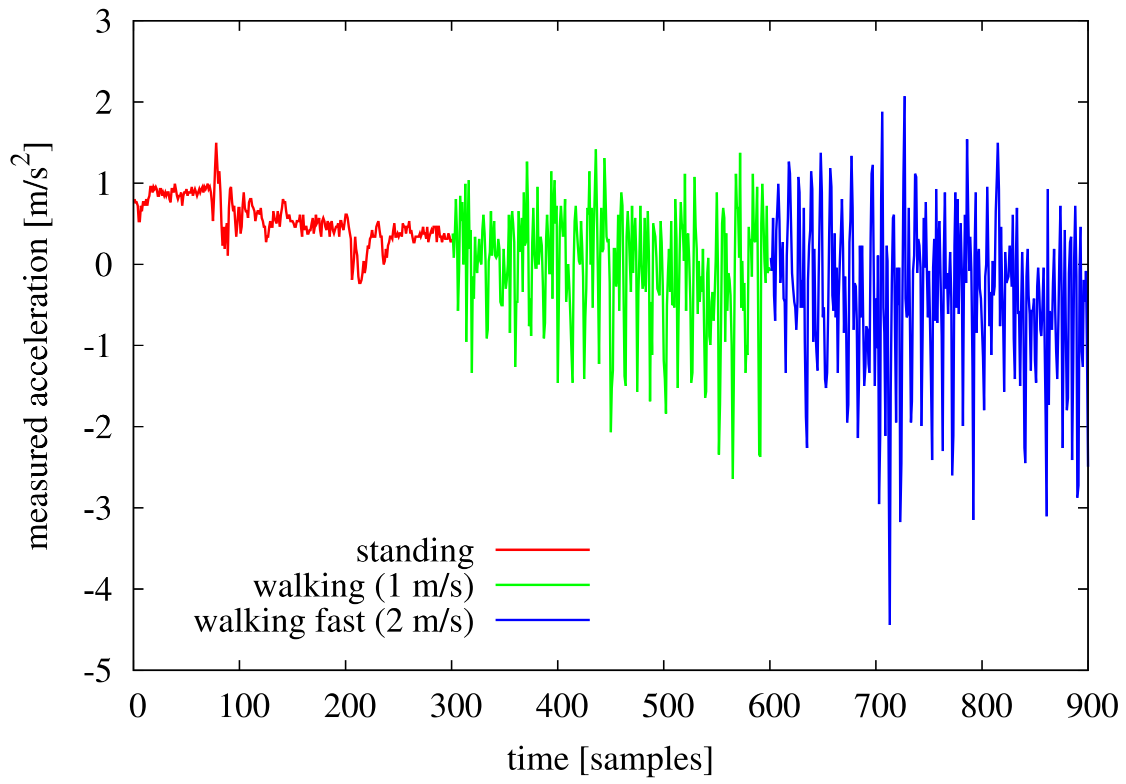


Figure 6.1: Accelerometer readings for different motion modes.

However, Figure 6.1 also demonstrates that the use of the accelerometer's raw values hardly leads to the desired results. We have a major area of acceleration values that is shared among all three motion modes. Thus, one single measured value or even an average of several values would probably lead to similar results for all three modes. To compensate for this, we decided to use what we call the *acceleration spread*. Instead of using single values, we determine the range of the measured acceleration values within a certain time frame. In our case, we used a time frame of one second – this corresponds to about ten measurements and offers a good compromise between accuracy and responsiveness. The difference between the highest and the lowest measured acceleration within that time is used as an indicator for the motion mode. As we can see in Figure 6.2, this offers a far better indicator for the motion mode. In the Figure, the red dotted line depicts the threshold between standing still and walking, whereas the green dashed line represents the threshold between walking and walking fast.

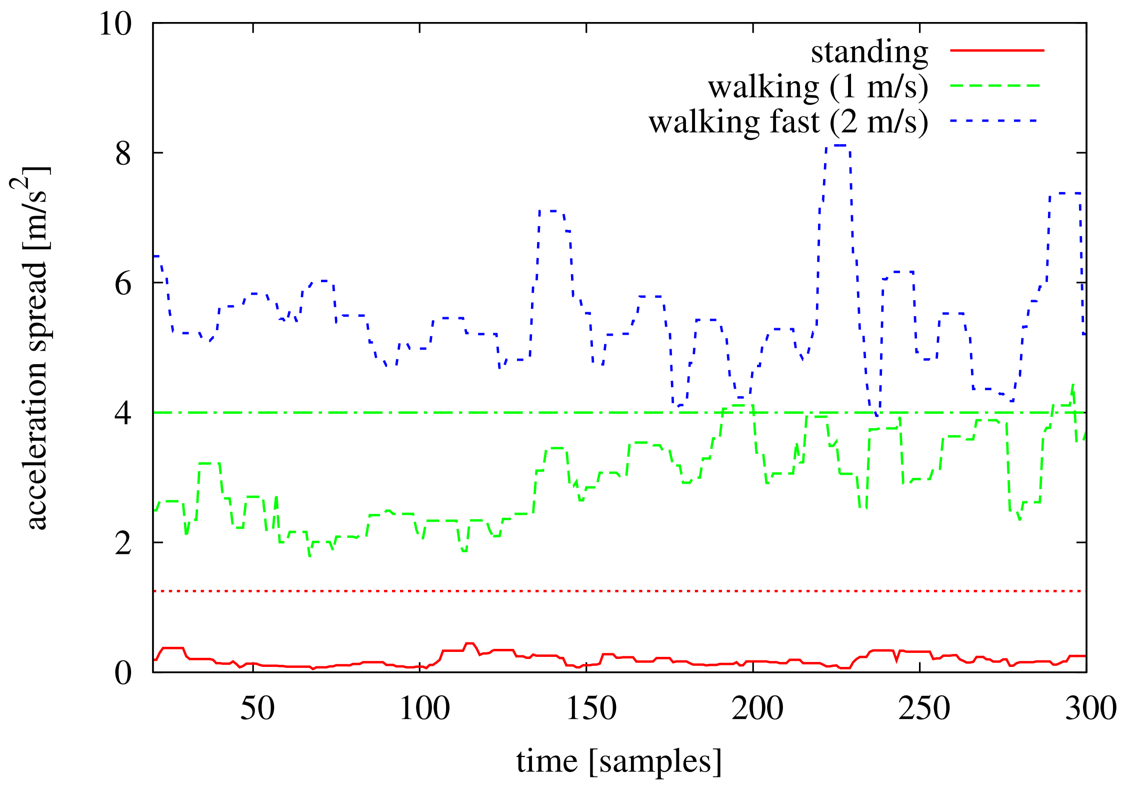


Figure 6.2: Acceleration spread for different motion modes.

Another important aspect of our approach is the independence of a fixed device location and orientation. Compared to other systems that rely e.g., on foot mounted accelerometers, we wanted to use the accelerometers that are integrated into modern communication devices. In such a scenario, we cannot assume the device and thus the accelerometer to be in a fixed location or orientation. For instance, a user using a mobile phone to navigate in an office building might either hold the device in landscape or portrait mode in front of her. We therefore decided to combine the values from all available dimensions of acceleration into one integrated value. This is achieved by computing the orientation-independent average of the single acceleration values and by then using this value to compute the acceleration spread.

Figure 6.3 depicts this and shows that using the average acceleration spread to detect a user's motion mode works independently of the devices orientation. In the Figure, the three lower diagrams show the readings of the three built-in accelerometers of an HTC Desire cellular phone that was carried while walking along one of our office corridors. The topmost diagram shows the combined acceleration spread and the boundaries used to distinguish between a standing and a walking user (red dashed line), respectively between a walking and a fast walking or running user (green dashed line). During the course of the data collection, the device was turned several times from upright into landscape orientation. Also, the display of the device was rotated to either face the user or point upward to the ceiling. The results of these rotations can be identified from the readings of the single accelerometers but are effectively mitigated by our approach. As a result, we can reliably detect the mode a user is moving in without having to know the device's location or orientation.

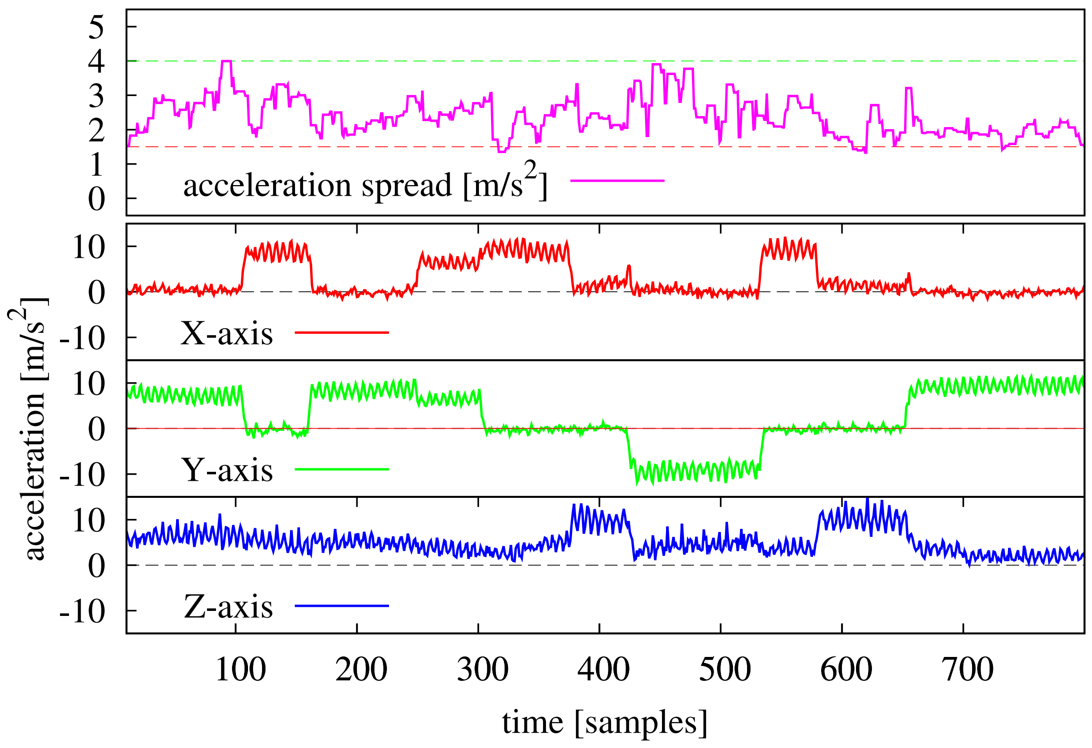


Figure 6.3: Difference between the accelerometer readings for different device orientations.

6.1.2 Motion Direction

Besides a user's mode of motion, a second important context information is the orientation a user is heading. As we have seen in Chapter 5, the orientation has a major influence on the positioning accuracy of IEEE 802.11-LF systems. As the user's body attenuates the signals from IEEE 802.11 APs, the orientation has an influence on the measured RSSI values. While creating different subsets of fingerprints for each direction a user might be facing noticeably increases the accuracy, it also results in a large increase of the necessary effort [KKH$^+$06]. For our approach, we therefore decided to only use information about the user's heading for a motion prediction.

Knowing the direction a user is facing gives us the possibility to predict where she will be moving during the course of her motion. Thus, we can use this information together with information about the motion mode to support an IEEE 802.11-LF algorithm by additionally applying dead reckoning as a support technology. Figure 6.4 depicts this. In the Figure, areas colored in green have a higher probability of the user moving there whereas areas colored in red have a lower probability. Depending on the accuracy and the reliability of the sensors, the size of these regions can be adapted. The underlying positioning system can now incorporate the predictions made by dead reckoning into its own position update process.

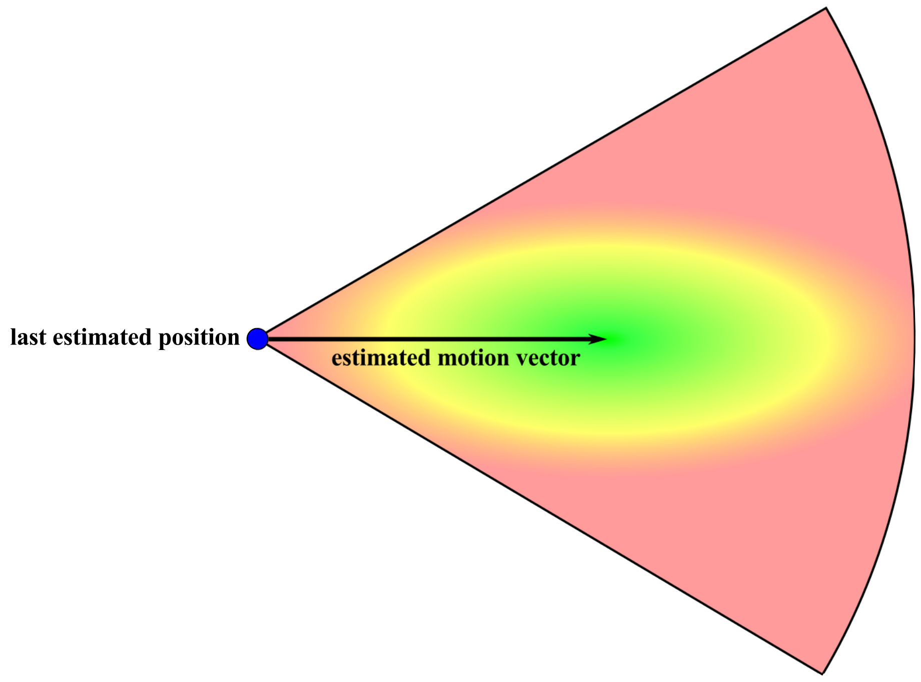


Figure 6.4: Motion speed and direction influence the probability of future locations.

6.1.3 Topology Information

Another type of context information that we consider to improve the positioning accuracy of our IEEE 802.11-LF system is the building geometry. Similar to the addition of map information to other dead reckoning systems, we use this additional information to derive possible and rather improbable alternatives for the user motion. Consider a set of several probable positions in a past step: If the measured user motion and direction do, for instance, lead through a wall for the last estimated position, we can assume that either this position estimation or the other sensor readings must have been erroneous. Furthermore, if the distance between two subsequently estimated positions is improbably large, we can similarly assume that there must have been an error.

With regard to the distance between two subsequently estimated positions, other simpler approaches often use the Euclidean distance. Especially inside buildings, this is problematic. That is why we consider the real *topological distance* between two positions. The topological distance between two positions is the true distance that a person would have to cover to get from one position to the other while respecting obstacles like walls or furniture. For our experiments, we have created an implementation of this metric that computes the topological distance based on the available data for the building structure. Our approach is exemplarily depicted in Figure 6.5. Whereas the Euclidean distances between the position marked with a red square and the positions marked in green and blue are the same, the topological distance is highly different. To walk from the red marked position to the green marked one, it is necessary to leave an office, pass through the hallway, and enter another office (see the dotted line in the Figure). Thus, a passage from the red marked position to the blue marked one might be feasible within a time frame of a few seconds, but walking to the green marked one is not probable. As a basis for our sanity checks during the position estimation, we therefore use the topological distance.

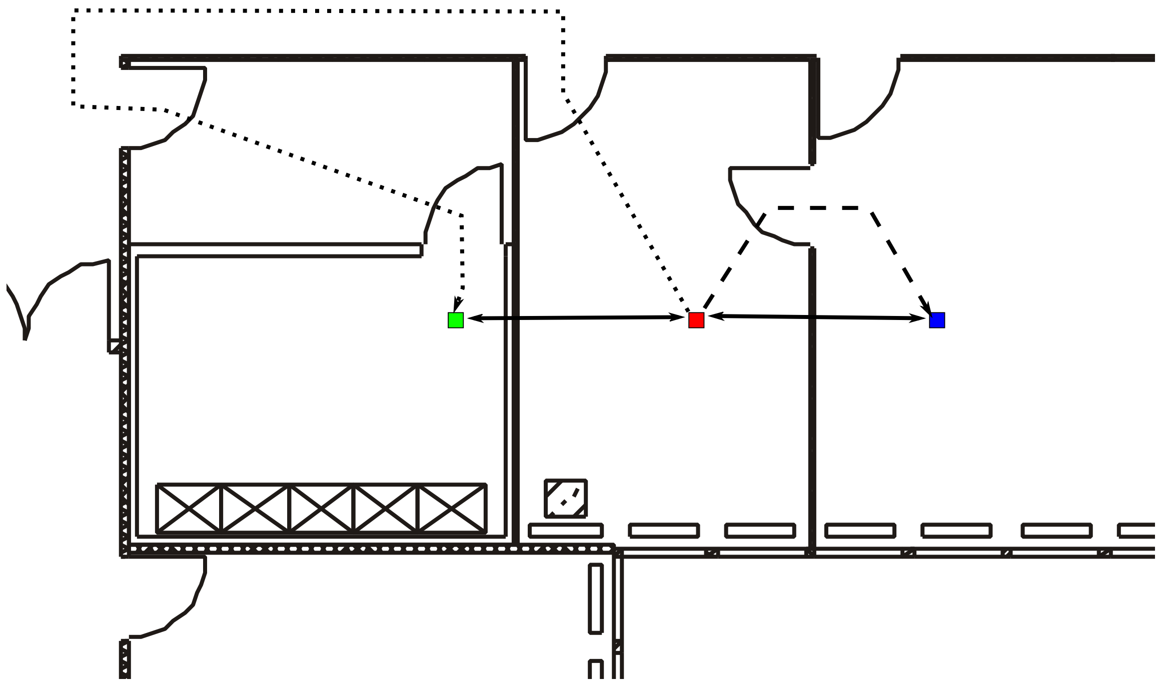


Figure 6.5: Difference between Euclidean and topological distance.

6.2 Tracking with Particle Filters

Especially in mobile robotics, the accurate and reliable estimation of a device's location has already been well studied in the past. Different types of sensors have been examined that can be used to estimate a robot's location. Among these are laser range finders, ultra sonic range finders, camera vision, and other techniques. One major problem that researchers have to face when working in the field of mobile robotics and with these sensors is that the readings of most sensors are subject to environmental noise. For instance, the readings of a laser range finder might be disturbed by sunlight or because of materials that reflect the laser beam in an unfortunate fashion.

To handle such noisy signals, a common approach both from a theoretical as well as from a technical perspective is the use of filters. Filters take the incoming sensor measurements and try to mitigate the effects of the environmental noise on the signals. Especially important among these filters is the *Kalman filter* introduced by R. E. Kalman in the year 1960 [Kal60]. With a Kalman filter, it is possible to predict the state a system is in if not the state itself but only emissions depending on the state and disturbed by noise can be measured. The filter has some restrictions, though. The most important one is that it can only be used if the underlying problem can be modeled in a linear fashion.

To compensate for this limitation another class of filters has been introduced in the past (e.g., refer to [RAG04]). This class is made up of the so-called *Particle filters* (PF). Particle filters – or *Sequential Monte-Carlo Methods* (SMCs) – are also used to e.g., predict the hidden state of a system from which only noisy signal emissions can be measured. But, in contrast to the Kalman filters, particle filters can also handle problems which cannot be modeled linearly.

This is achieved by not using a formal representation of the posterior probability density (the probability for the different possible states at a certain point in time) . Instead, the density is represented by a large set of so-called particles. Each particle has a weight that is computed based on properties of the underlying system. The sum of all particles – with their weight and their position in the state space – is used as the representation of the posterior.

Often called a *Sequential Importance Sampling* (SIS) filter, a PF is a sequential filter and thus evolves over time as more and more measured samples become available. As such, the progress of a particle filter is generally modeled in a cycle of several consecutive steps that are preceded by a bootstrapping process. In the beginning, an initial distribution of the particles is assumed. This, in many cases, is a uniform random distribution in the state space. Upon the reception of a new measurement, the particles are moved within the state space. For this, different types of *motion models* can be used. By using a *sensor model* subsequently, the weight of each particle is updated depending on its new position and the measurement. Then, the particle weights are normalized, and the particles in their entirety represent the posterior after that measurement. As this type of PF does also have some limitations, e.g., the continuous degeneration of the particle cloud, variations of the basic PF approach use a resampling step. This type of filter is generally referred to as *Sampling Importance Re-sampling* (SIR) filter and can help to avoid the degeneration. In case of such an SIR PF, particles with a very low weight are eliminated and new particles are re-sampled from the posterior distribution.

Especially for position estimation with the use of noisy sensor data, particle filters have shown to be very effective, and they are widely used for this purpose nowadays. We therefore decided to base our own tracking algorithm on an SIR filter, too.

6.2.1 Particle Motion Model

The motion model as part of the ongoing progress of a PF is used to move particles within the state space. This can generally be done in several different ways. Our basic mode is a simple Gaussian random motion. In the beginning, all particles are randomly distributed over the covered area using an uniform distribution and are given a weight of one divided by the number of particles. The, for each round of the PF and each particle, at first, a direction is randomly chosen. This direction is used together with a randomly chosen distance to advance the particle to a new position. Whereas the direction is drawn from a uniform distribution of values between $0°$ and $360°$, for the distance, we use a normal distribution with parameters chosen to represent a walking person.

Of course, with this basic approach, particles are able to leave the area that is covered by our training data. For this case, we have implemented two different behaviors: One choice is to restrain oneself from moving the particle if it otherwise moves outside the covered area. In this case, the particle simply stays at its current position. The second possibility is to let the particle move. This results in the particle being removed during the next weight update as no new weight can be assigned to it due to the lack of fingerprint information.

We also extended our motion model to make use of additional context information. One addition is the consideration of information about the true motion of a user. Knowing the user's speed and her direction of motion, we can use this information to adapt the particle motion accordingly. If the user is moving fast or if a longer time has passed between two consecutive updates, particles are allowed to advance farther from their current position. Furthermore, if the direction in which a user is moving is known, the particle motion is adapted to let the particles move only in this direction. To gather information about the user motion, we have considered several different approaches. One is the use of external sensors and a compass, as it was already described in the earlier part of this chapter. Another possibility is the use of historic information about the user's positions. From these, we try to extrapolate both a motion direction and the speed.

A second major addition to the motion model is the incorporation of information about the topology of a building. The particle cloud can be seen as a probability distribution of the user's whereabouts. Furthermore, the movement of each single particle can be seen as a possible user motion that could have happened in the covered area. This is especially true when we use the additional context information to decide on the particle motion. As a user is not able to pass through obstacles like walls, we apply these constraints to the particles, too. If a particle movement leads to crossing a wall, that movement is canceled. Similar to when a particle leaves the covered area, we, in this case, either let the particle stay at its current position, or we remove it from the particle set.

6.2.2 Sensor Model

As stated in the former sections, another important step in the progress of a PF is the computation of the particle weights. Generally, an importance density is used for this purpose. In our case, we had to face a special design difficulty when implementing the weight update for the particles. We wanted to improve the performance of IEEE 802.11-LF by the use of a particle filter. Thus, we also wanted to stick to the general LF approach, and use the information from an underlying fingerprint database for the weight update of the particles. The difficulty in this case is that, in general, each fingerprint only represents one single point within the two- or three-dimensional state space. But we obviously do not want to limit the particles to this limited set of available positions.

We therefore continued our earlier work and used our grid cell representation of the information in the fingerprint database to create what we call an *importance density grid*. With this approach, we can use the information from the fingerprints to cover the whole *area* for which fingerprint information is available. During the weight update phase of the PF, we, for each particle, identify the cell in which the particle is located. Then, the information of the fingerprint that owns that cell is used to compute the new particle weight.

Compared to the motion model, the possibilities to influence the performance of the particle filter are rather limited with this type of sensor model. As it mimics the Gaussian process used by the Rice LF system to compute the weight for the single particles, the parameters to adjust the sensor model are very limited. For the cases where settings had to be made, we used the values that have been recommended in the literature or the ones that are properties of the used hardware.

6.3 Evaluation

We now give an overview of the methodology we used to evaluate our tracking algorithm. At first, we will introduce the details about the evaluation of the sources for context information, especially the motion detection algorithm, before we continue with presenting information about the overall tracking system.

6.3.1 Motion Mode

To evaluate the motion detection algorithm, we collected short data sequences of about $30\ s$ length and also longer sequences of about $100\ s$ for each motion mode. Whereas the former sequences were used to identify the thresholds to distinguish between the different modes, we used the latter ones to evaluate the algorithm. The devices used for collecting the data were an HTC Desire smartphone running Android 2.2 and an HTC Hero smartphone running Android 1.5. The phones were held in a natural fashion in front of the user during the collection. Furthermore, during the collection of the longer data sets, the device was rotated several times in different directions. For each motion mode, we randomly selected sequences of ten measurements from the evaluation data sets, computed the acceleration spread, and – from that value – determined the motion mode. This experiment was repeated 1000 times for each motion mode.

6.3.2 Particle Filter

For the evaluation of the particle filter-based IEEE 802.11-LF system, we collected a new set of measurements within the hallways, two lecture halls, and several offices located on the second floor of the building A5-B of the University of Mannheim. The newly collected data set covers an area of $57\ m$ times $32\ m$. Collecting another set of measurements became necessary for two reasons: First, we wanted to consider the scenario of a moving user. This would not have been possible by using the data that was already available to us as it only incorporated single live positions. To emulate a moving user, we, however, needed subsequent tracks of live positions. Second, since our other sets of measurements had been collected, considerable changes with regard to the installed access points had taken place. Thus, using the existing training data together with newly collected live measurements would not have been feasible.

Training data

The training data used to train the algorithm and to create the fingerprints was collected within our test environment by applying a grid spacing of $1\ m$. In total, 459 reference spots depicted by the blue squares in Figure 6.6 were laid out within our test environment and we collected 100 consecutive measurements at each spot. As the Figure further depicts, our training data covers the three longer hallways, two large lecture halls, and several offices adjacent to one of the hallways. The other offices did not belong to our department and were therefore left out during the data collection. Furthermore, in the areas in the offices and the lecture halls where spots are missing, furniture or other obstacles prevented the collection of data. The recollection of the data became necessary as our existing live datasets did not reflect a moving user very well. Additionally, the existing training data could neither be reused as several access points in the area had been moved or replaced in the meantime since it had been collected.

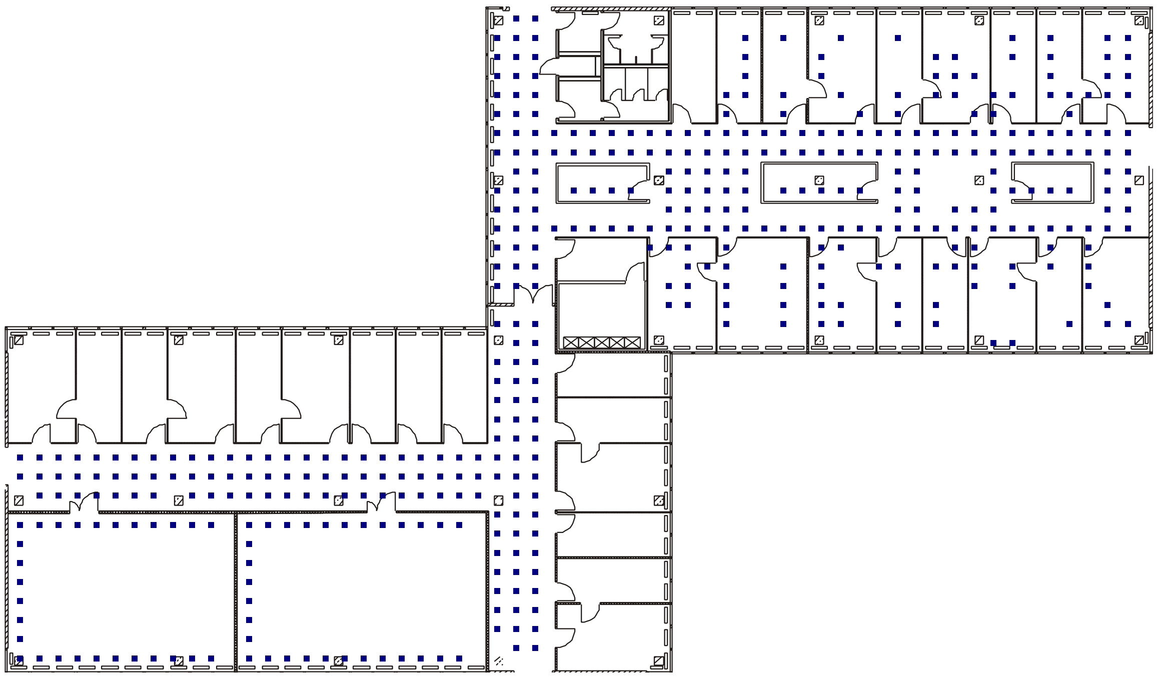
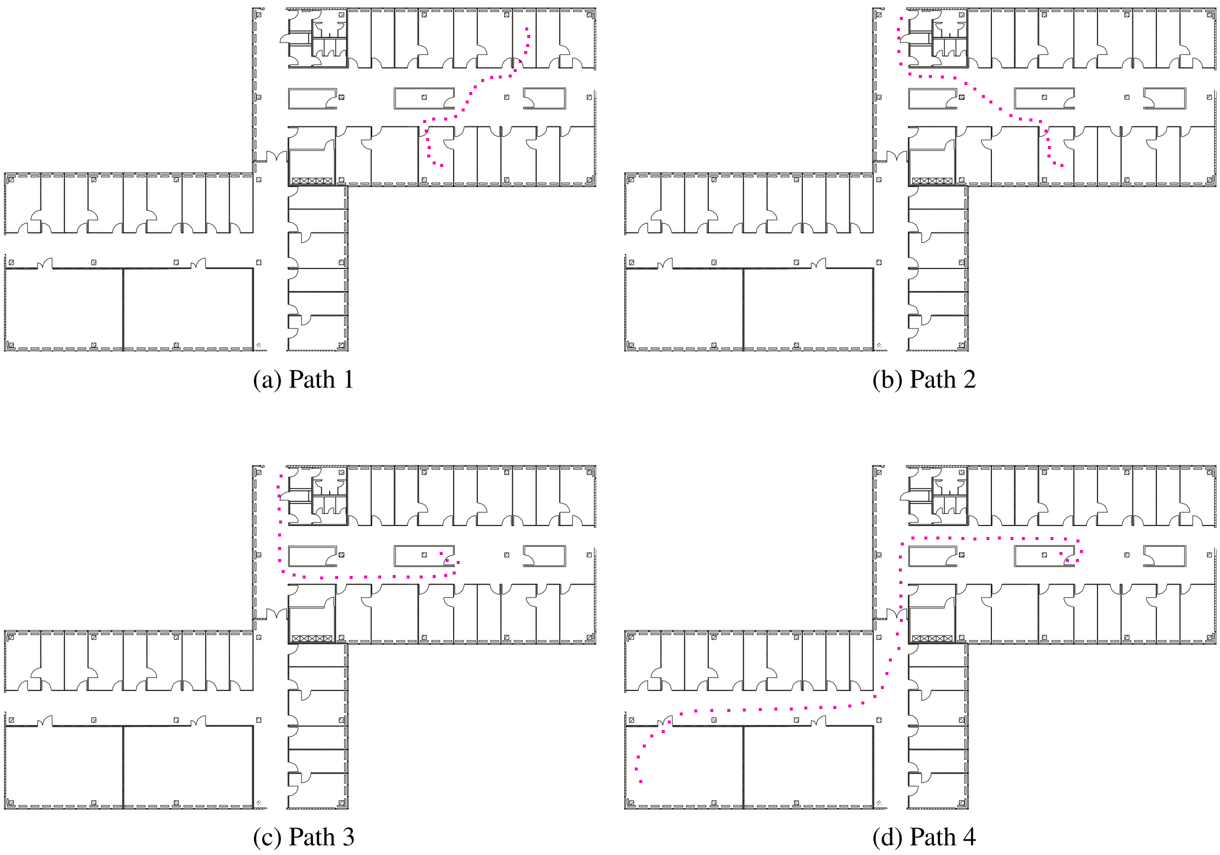


Figure 6.6: Overview of the collected training data for the PF-based WLAN-LF system.

Live data

We additionally defined a set of four paths within our test environment (see Figure 6.7). The first path starts at one of the offices, crosses the hallways, and ends in another larger office (Figure 6.7a). The second path leaves that office, turns left, and heads for the restrooms (Figure 6.7b). From there, the third path goes back through the hallway and into the kitchen (Figure 6.7c), from where the fourth path finally starts and heads for one of the two lecture halls (Figure 6.7d). In total, the four paths consist of 112 spots depicted by the pink squares in the Figures. Again, at each spot, we collected 100 measurements to be able to emulate a user moving through the hallways and offices.


(a) Path 1 (b) Path 2

(c) Path 3 (d) Path 4

Figure 6.7: Overview of the four paths that we used to collect the live data for our PF-based IEEE 802.11-FP algorithm.

Emulation

During the emulation, our algorithm was given a random selection of 20 measurements per reference spot to build the fingerprint database and to create the importance density grid. This was followed by the initialization of the PF. For the PF, we used 500 particles that, initially, were given an equal weight, and were randomly distributed over the covered area. Following the just introduced paths, we then randomly drew one measurement from the data for each live spot and used that measurement and the signal model to update the PF. Finally, after each update, we computed the weighted average of all particle positions as the estimated position of the user and stored it together with the real position for later reference. The basic experiment was repeated 250 times for statistically stable results.

6.4 Results

This section presents the evaluation results for our algorithms. At first, we deal with the evaluation of the algorithm to detect a user's motion mode. There, we furthermore elaborate on the use of different devices and explain in what regard our approach is dependent on the user. This is followed by the results of the evaluation of the overall tracking system. We present the results for the use of the PF alone and then show how the additional use of further context influences the positioning performance.

6.4.1 Motion Mode

Table 6.1 gives an overview of the results for the motion mode detection algorithm. In the case of a standing user holding the device in front of her, the algorithm detects the correct motion mode in $\approx 95\%$ of all cases. If the mode is estimated incorrectly, the user is estimated walking in 4.4% of all cases and walking fast in less than 1% of all cases. For a walking user, the performance is even better with a correct estimation rate of $\approx 97\%$. In only 0.5%, the user is estimated to stand and, in 2.2%, the user is estimated to walk fast. Finally, a fast walking user is estimated to walk fast in $\approx 80\%$ of all cases. In the remaining cases, she is estimated to walk at normal speed.

Table 6.1: Performance of our motion mode detection algorithm.

	est. standing	est. walking	est. walking fast
standing	94.9	4.4	0.7
walking	0.5	97.3	2.2
walking fast	0.0	19.9	80.1

As we can see from the results, our algorithm performs really well. Especially the detection of a standing and of a walking user is very accurate. The estimation errors that happened in the former mode are mainly induced by rotating the device. Looking at the moving user, we see that also the detection of the normal walking mode is quite reliable. Most errors occur during the detection of a user walking fast. Here, we have an error rate of almost 20%. But, if we think of the targeted application scenario of our system, this drawback actually seems acceptable as the user is never estimated to be standing still. Thus, both when using the data to increase the positioning performance of a location fingerprinting system, and also when adapting a user interface to different motion modes, we always correctly assume the user to be in motion and can react accordingly. To mitigate the detection errors for a standing user, probably a running weighted average that also incorporates several past mode estimations would be a good possibility.

6.4.2 Particle Filter

In this section, we present the results of our PF-based IEEE 802.11-LF system. For the first results, the PF was used without any additional information. We neither incorporated information about the history of estimated positions nor performed any post-processing of the estimated positions. The only parameter that was adjusted during this evaluation was the particle weight below which particles are removed from the particle cloud and replaced by new particles. The values selected for the evaluation were chosen due to the distribution of particle weights during several test runs. This distribution is depicted in Figure 6.8. As the Figure shows, most of the particles have a weight close to zero; only few particles have a noticeably higher weight. The particle motion is based on an assumed user speed of 1 $\frac{m}{s}$ with a high degree of randomization as well as randomly chosen motion directions for each particle.

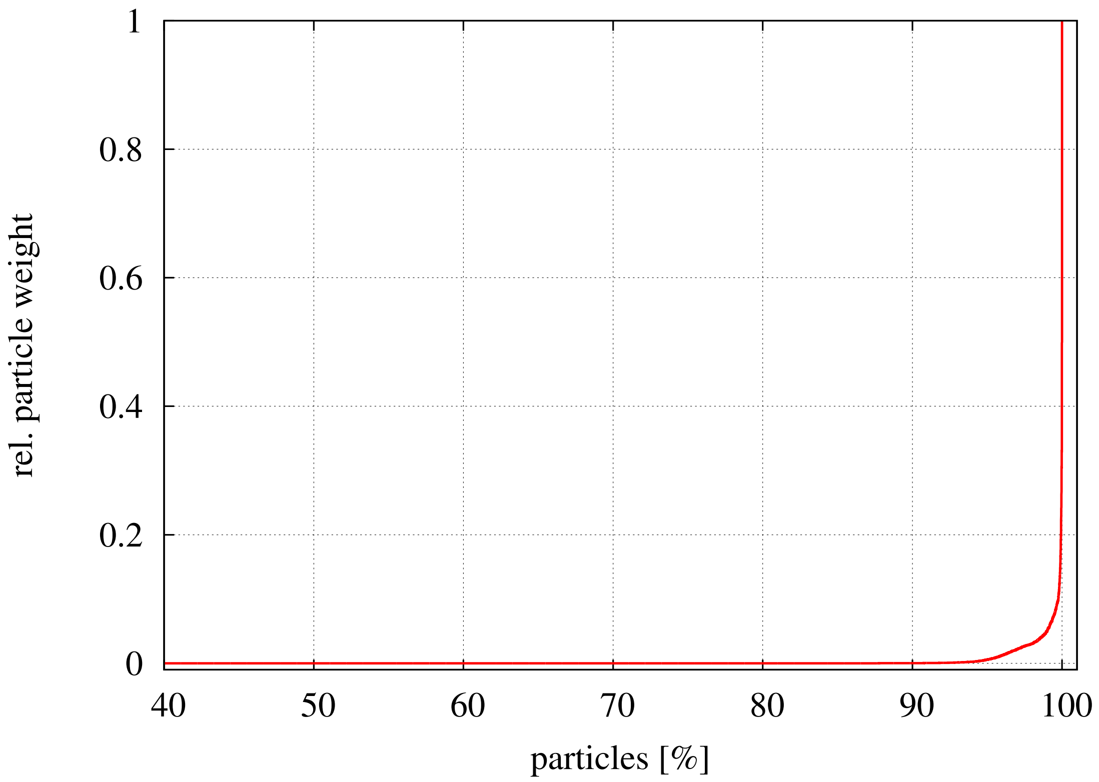


Figure 6.8: Distribution of particle weights.

From Table 6.2, we can see that, during the run of the particle filter, more than 90% of the particles have a relative weight of less than $1 \cdot 10^{-3}$. This shows that the PF generally succeeds in identifying few particles which are given a high weight whereas all other particles are only given a small weight. With regard to location estimation, this is a promising result.

Table 6.2: Distribution of particle weights for selected thresholds.

Rel. particle weight	Particles [%]
0	44.24
$1 \cdot 10^{-15}$	54.10
$1 \cdot 10^{-12}$	59.55
$1 \cdot 10^{-9}$	68.01
$1 \cdot 10^{-6}$	80.19
$1 \cdot 10^{-3}$	92.77

Using this information about the particle distribution, we defined several drop thresholds for the relative weight below which particles are dropped. Considering the actual performance of our basic PF implementation when estimating a position, we then evaluated the PF to see how a variation of the particle drop threshold influences the positioning accuracy. As a benchmark for our own algorithm, we used the Gaussian variant of the Rice algorithm provided with the same data sets for training and evaluation. The results of our experiment are depicted in Figure 6.9. We can clearly see that, for the basic approach, a variation of the drop threshold only has an at most minor influence on the positioning results. The use of a particle filter has a remarkable effect, though. As shown in the Figure, the average positioning accuracy increases by about $40\ cm$. This is mainly due to the particles implicitly storing state information, which makes them much better suitable for tracking applications compared to the Rice algorithm that makes an independent estimation for every position. Of course, if the live spots were given to the algorithms in a random order, the results would change in favor of the Rice algorithm. For our following experiments, we fixed the drop threshold to a value of 10^{-6}.

One negative property of IEEE 802.11-LF systems is the rare occurrence of large errors. Motivated by the already promising results of the basic implementation, we extended our basic PF-based IEEE 802.11-LF algorithm by what we call a *sanity check*. If two subsequently estimated positions lie too far apart from each other, we suspect this to be caused by erroneous measurements and thus do not use the estimated position. To estimate the usefulness of such an approach, we evaluated several different possible configurations for the maximum allowed distance between to consecutive positions.

For the particle filter itself, this procedure has several implications. With regard to the particle cloud, one possibility is to simply ignore the expectedly false estimated position and to reset the whole system to an initial state. Another one is to ignore the estimated position but to keep the particle filter and all of its particles in their current state. And, finally, a third possibility is to reset the filter to the state of the last (valid) position estimation. The performance results

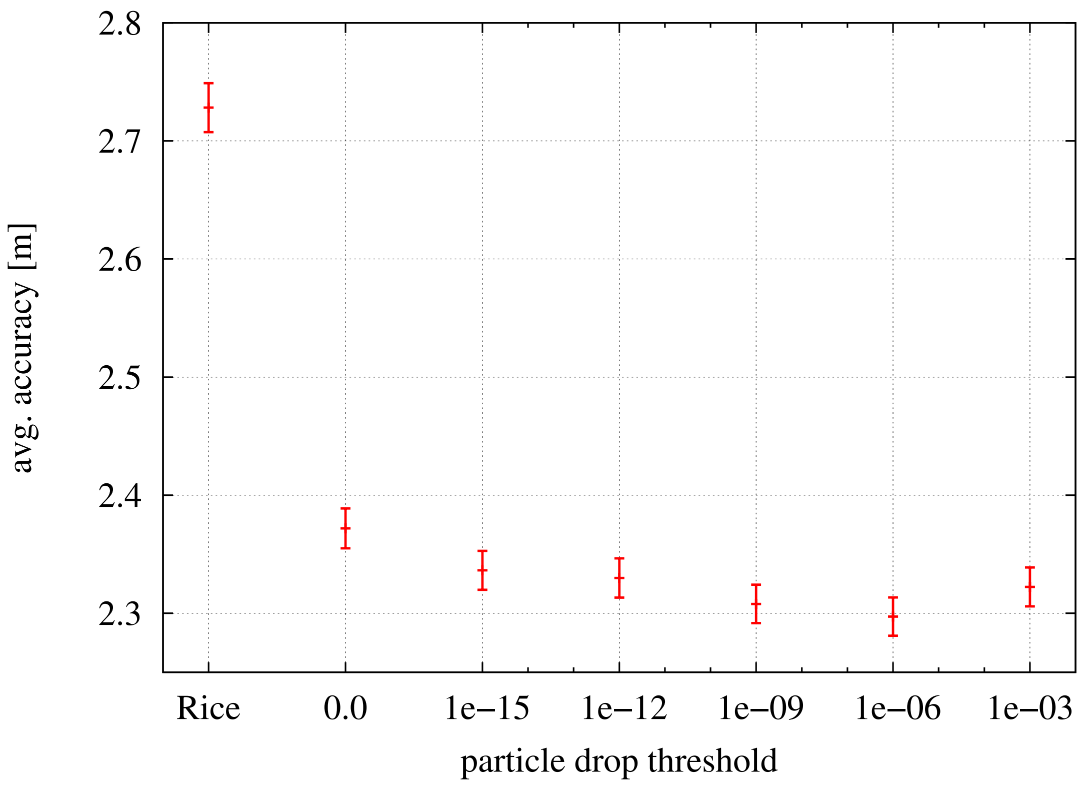


Figure 6.9: Positioning accuracy with different particle drop thresholds.

of the different variants to handle such improbable positions are presented in Figure 6.10. As shown there, the use of the plain distance-based sanity check can slightly improve the average accuracy if the particle filter is kept in its current state. If the filter is completely re-initiated or if a rollback to the previous state is performed, the results are worse.

In the latter step, we have used the Euclidean distance between two subsequently estimated positions to decide whether a user motion is feasible or not. However, as we have seen earlier, this distance is often deceiving. Especially in the environments mainly targeted by our systems – namely indoor environments –, it gives a wrong impression from a human perspective. Therefore, we furthermore extended the sanity check to make use of an often readily available type of context information: building maps. With these maps, we can account for obstacles in the path between two positions and thus more accurately estimate whether a certain position advancement is possible. The following Figure 6.11 shows the results of this extension. While the improvements only seem minor at first sight, the reader should note several aspects of this addition. Firstly, the use of topological information only makes sense for larger displacements between consecutive position estimates. For small values, both distances differ seldom significantly in our test bed. Thus, the approach only leads to significantly better results for larger allowed values. Secondly, the main reason for using the sanity check is to avoid the rare occurrence of large errors. Succeeding here only means a minor increase in average accuracy because

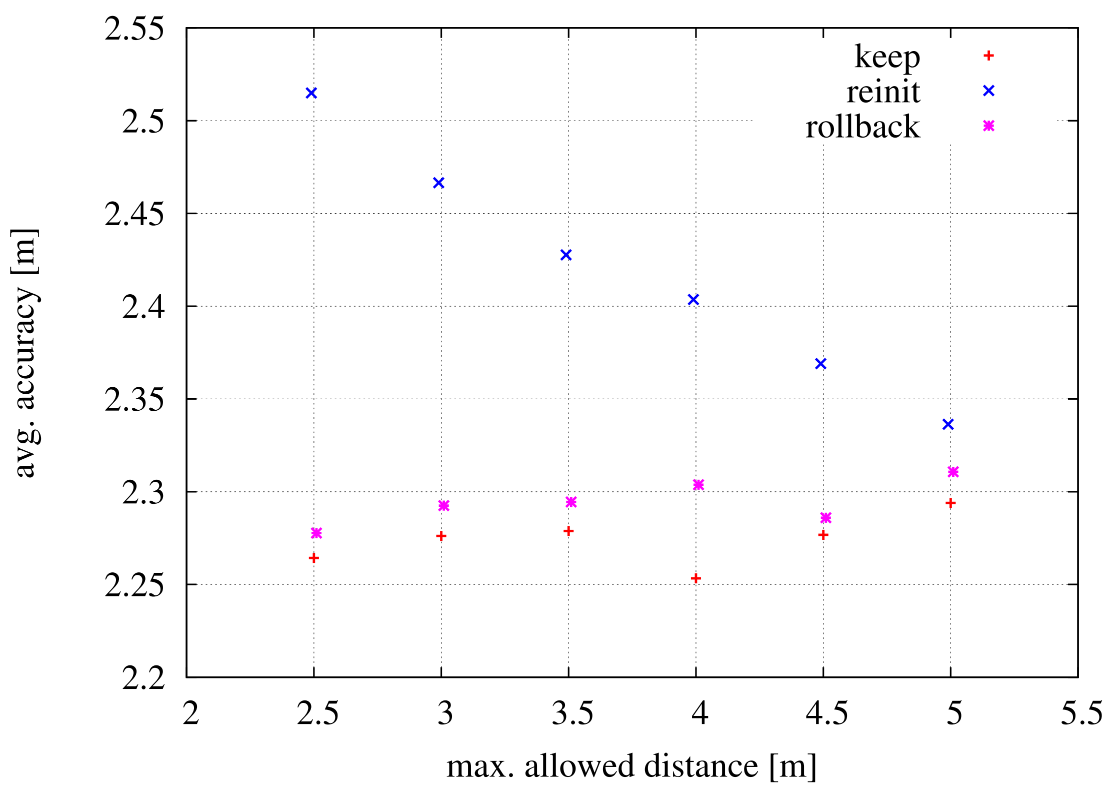


Figure 6.10: Positioning accuracy when performing a sanity check.

of the rare occurrence of large errors but a large increase in usefulness for the user of such a system.

Of course, if our system has access to topological information about the building structure, it is sensible to also use this information for other purposes beyond the sanity checking. In the context of a particle filter, such an additional purpose is, for example, to restrict the particle motion based on the building topology. Therefore, we extended the motion model responsible for the particle motion to respect the building topology, too. If, during a particle position update, the particle's new position cannot be reached directly due to obstacles like walls, then the particle is either not moved, or is removed from the particle cloud.

The performance results of this extended motion are rather disappointing, though. In both cases, when the particle is not moved or when it is removed from the cloud, the achieved positioning accuracy is far worse than without considering the floor plan during the particle movement phase. Both variants achieve an average accuracy of roughly $2.60\ m$. To our understanding, the reason for this result is the random motion of the particles. Particles that, for instance, are located in an office room are only able to leave that room with a quite low probability as they would have to move through the door. As a result, they either stay locked in the room and diverge over time because of losing weight, or they are removed instantly on their attempt to cross a wall. This loss of many particles is the reason for the reduced performance.

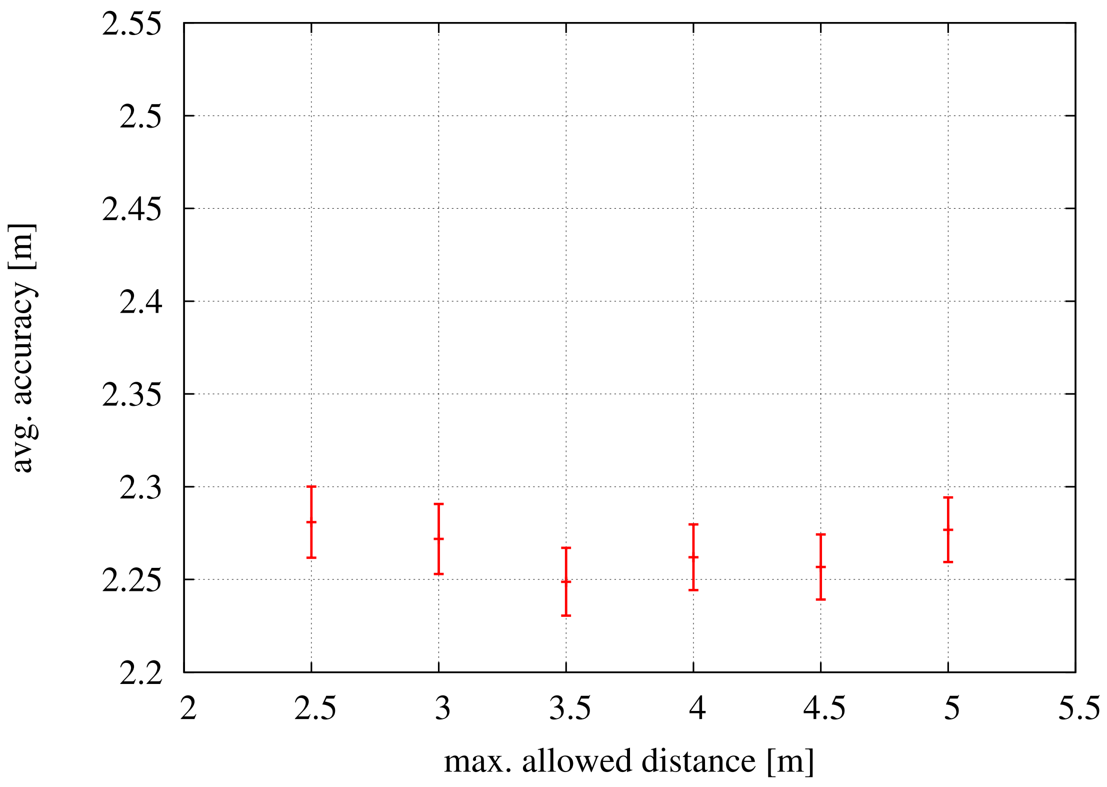


Figure 6.11: Positioning accuracy when performing a sanity check and using floor plan information.

Considering these drawbacks, we decided to once again extend the system to make use of further available context. As stated in Section 6.1, modern mobile devices – especially smartphones and laptops – are equipped with accelerometers and often also with electronic compasses. As shown, we can use the information from these sensors to detect the motion mode and direction of a user. Extending the idea of influencing the motion behavior of the particles, we use information about the user's speed and direction of motion during the position update phase of the particle filter. If we know that a user is moving westwards at normal walking speed, we apply these settings combined with a certain amount of randomness to each of the particles during the position update. Particles that, for instance, would leave the covered area due to this type of motion again either stay at their current position or are removed from the particle cloud. The same is true for particles that would have to cross a wall due to the desired movement.

However, to our surprise, instead of a high increase in accuracy, using this further improvement of the algorithm only marginally improves the positioning results. After a thorough investigation, we could find the reasons for this behavior in our collected training and test data. When collecting the training and live data and defining the paths for the live data, one of our main intentions was to create a scenario that was supposed to be both realistic and as challenging as possible. Therefore, all data were collected during normal office hours. Additionally, we selected challenging movement paths, still reflecting real movements that occur in our daily routine. Based on our experience with IEEE 802.11-LF-based position estimation, we can say that the paths chosen to emulate a moving user reflect situations that are quite hard to handle for a positioning system. For instance, the small passages in the hallway depicted in the upper half of Figure 6.6 all have a similar signal characteristic. Thus, we often had the case that the particle cloud falsely entered the upper passage. Due to the restrictions on the particle motion, this resulted in a situation where the particle cloud remains trapped above the kitchen room and, thus, resulted most ultimately in large errors for the affected run. This situation is also quite well reflected in Figure 6.12, which depicts the spatial distribution of large positioning errors. From the Figure, we can clearly identify different regions that are prone to large errors due to signal similarities. These regions are depicted by increasingly green colored grid cells.

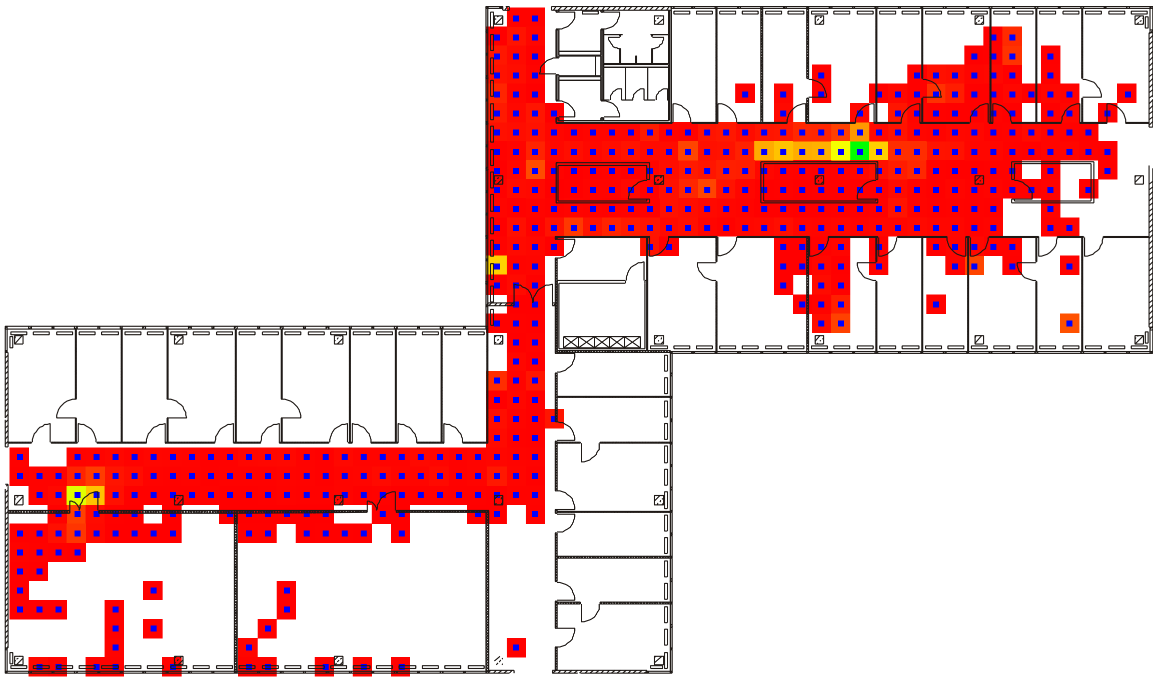


Figure 6.12: Overview of areas within our test bed that are especially susceptible to large errors.

Nonetheless, an evaluation of, for instance, the second path shows that, in a less unfriendly setting, our approach performs exceptionally well. There, it achieves an average error of less than $1.6\ m$ and produces errors of less than $3.95\ m$ in 95% of all cases. This indicates that our results presented here give a rather conservative estimate of the performance of our tracking system.

Finally, we repeated the last experiment with an additional level of complexity by not only checking whether a particle would have to cross a wall on the direct path between two subsequent particle positions but by also checking whether or not there exists a path between the two positions shorter than a given maximum distance when considering the floor plan information. While the emulation for this type of settings took several times longer than for the simple approach, the increased effort does not result in a much higher accuracy. The results are even worse than when using the simple approach to restrict the particle motion. Considering the source of information that is used to decide where particles should be moving, this is not surprising. The direct check represents the user much better, as she herself is moving in a certain direction and at a certain speed. The alternate path a particle could have taken, for example, around corners, would have caused different sensor measurements if the user had taken that path. Thus, this type of indirect movements reflects the user behavior worse and consequently yields to worse results.

6.5 Discussion

The following section briefly discusses several aspects of our work that, despite the already promising results of our algorithms, influence the results, and, thus, deserve further attention.

6.5.1 Motion Mode

At first, we will cover the user and device dependability of our motion mode detection algorithm and discuss the influence of the measurement window size.

Influence of the User

Of course, different users can have a different motion profile. During the course of our experiments, we have seen that the thresholds used for one user do not necessarily fit for another user. Therefore, it would be infeasible to use the same thresholds for everybody.

The system we have developed offers the possibility for a short user-based calibration step. The user is asked to stand still, walk, or walk fast for a timespan of $30\ s$ each. Based on the data collected in this time, the system then computes user-specific threshold values for the different motion modes and stores them for later reference. At first, the measurements for each motion mode pass a high- and lowpass filter that eliminates the topmost and bottommost one percent of the measurements. We do so to filter out outliers. Then, for the threshold between standing and walking, we calculate the difference between the measured acceleration spreads and use the value of a standing user plus one third of the difference as the threshold. For the threshold between a walking and a fast walking user, we use the average of the values measured for the two modes. The reason for the different handling of the thresholds is our insight that a standing user is easier to detect and thus allows for a more rigid selection of the threshold.

This calibration step helps us to maintain the high accuracy of our system for different users. While it at first might seem cumbersome to have to calibrate a device for every user, we have made the observation that mobile devices like smartphones are rarely shared between people and, thus, this step generally has to be performed only once for each device.

Influence of the Device

For our measurements, we used two different devices: An HTC Desire smartphone and an HTC Hero smartphone. Whereas we only presented the results for the HTC Desire smartphone in Section 6.3.1, the estimation results for the HTC Hero smartphone are almost identical. Even the values that were learned as thresholds for a single user were almost identical on both devices. This suggests that, at least for a given device class, for instance the smartphones from one manufacturer, it might be sufficient to only have the user calibrate one device and then transfer the calibration information to other devices belonging to the same class.

Measurement Window

We used a time frame of about one second or ten measurements for the sliding window from which the acceleration spread was computed by our system. During our experiments, we also tried other values. However, the chosen ones performed best. For lower numbers, we faced the problem of not covering a complete motion cycle of at least one step. When reducing the window further, we even ended with values close to zero for all types of motion as only single points with constant acceleration were detected in the motion cycle. For larger values, single spikes in the measurements had a long-lasting effect on the detected spread and thus decreased the achieved accuracy, especially when changes in the motion mode occurred.

6.5.2 Compass

During our work, we used the integrated compass of the smartphones as well as a digital compass attached to a laptop computer via a universal serial bus (USB) connection. However, as our test environment has metal walls, one major problem we had to face was a high deviation off the measured angles. When, for instance, walking in one direction along one of the hallways, the compasses measured arbitrary values. When performing the same kind of test in a second building with walls made up of less inducing materials, we observed a much friendlier behavior of the compasses. To still allow for a proper evaluation, we measured the behavior of the compass devices under normal operation, created a simulation model, and used that model instead of measured data during the emulation of our algorithms.

6.6 Conclusions

Using a particle filter as an underlying algorithm for the tracking of a user with the help of IEEE 802.11 and LF has clearly proven to be a suitable approach. Even without the use of additional context, the PF offers an already increased positioning accuracy. This is achieved by explicitly considering the history of both the particle positions and the measurements. If additional context information is incorporated as well, the results can be further improved. The use of map information and a sanity check of subsequent positions mainly helps to reduce the occurrence of rare large errors. From a usability perspective, this is an important improvement even though it only results in a minor increase in the average positioning accuracy. Regarding the metric used for the sanity check, we have seen that the use of the topological distance yields to better results. This is not surprising as it represents the possible user motion far better than the use of a simple Euclidean distance.

The additional use of motion information, on the other hand, offers the potential for much bigger improvements. To gain the data necessary for a motion mode estimation, accelerometers and digital compasses, as they are already built into many modern mobile devices, can be used. Our results show that data from these sensors offers the possibility for a robust and reliable estimation of the user's motion mode. As we have seen during our experiments, using this information can reduce the average error to values of far less than two meters. However, we have also made the observation that adverse conditions result in much smaller increases of the accuracy. An analysis of our training data showed problematic similarities between certain areas in our test bed that resulted in a reduced performance. In a practical deployment, we would resolve this by relocating the APs to create more distinctive characteristics for these areas.

There are also some other aspects that would allow for a further tweaking of the system's performance in case of a productive use. For instance, while using the idea of an importance density grid helped us to combine the concepts of LF and PFs, it also introduces a new source of errors. During the resampling phase of the PF, particles are randomly placed in the grid cells according to the importance density grid. However, as the layout of the grid does not take the building topology into account, this can result in a new particle being placed on one side of a wall while a particle responsible for the grid cell's total weight is located on the other side. As this obviously leads to a degradation of the accuracy, such a behavior should be mitigated for future use.

A second aspect that offers some room for future work could be the occurrence of split particle clouds. Here, for example, a k-means clustering would offer a good solution to detect such a situation, and to handle it. While we did not follow this idea in favor of other interesting features, this would be a worthwhile path for future activity.

CHAPTER 7 Roaming between Positioning Technologies

The previous chapter has discussed tracking – and thus the use of additional information like a position history and motion information – to improve the overall quality and accuracy of the position estimation. As we have seen, the use of this additional information available due to the consideration of the user's motion yields to noticeable improvements. However, it also causes new problems. This chapter deals with one of the most urging ones: the problem of choice. A user who is roaming around will most probably find herself in situations where more than one positioning system is available. While GPS generally can only be used outdoors, the precise location estimation with IEEE 802.11-LF is most often only used indoors and in areas close to buildings. Furthermore, also the signals from GSM cell towers can be used for location estimation in many situations. Thus, when entering or leaving a building or in the surrounding areas, more than one system might often be available. The following chapter deals with the question when to automatically choose which system. Considering the definition of *suitable*, in our case, we consider the most accurate system to be the most suitable one.

This definition, of course, is not necessarily valid under all circumstances. Depending on the application scenario, other factors like, for example, the energy consumption of different positioning systems, privacy considerations, or the required use of the communication infrastructure can be additional decisive factors. If, for instance, a user wants to keep information about her whereabouts private, she would rather use GPS for a position estimation instead of an IEEE 802.11-LF system or GSM positioning, which probably both rely on a central server for the matching of the live measurements and fingerprints or aggregation of the data from different base stations.

7.1 Error Estimation

We base our decision on which system to use on the accuracy that can be expected from the different available systems. As such, we need information about how much trust we can spend on a given position estimate. On the one hand, if the position estimate is uncertain, we better avoid using it. On the other hand, if the positioning system is very sure about a position estimate, this is an indicator that we can use the estimate without a high probability for errors. To gather information about the accuracy of estimated positions, the positioning systems offer different quality metrics.

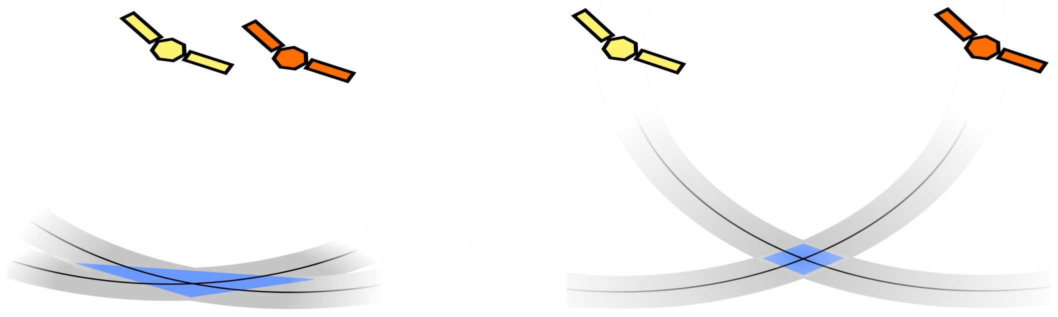
7.1.1 Error Estimation for IEEE 802.11-LF

In Chapter 5, we have introduced several different possible approaches for the error estimation of IEEE 802.11-LF-based positioning systems. As not all of the algorithms presented there perform equally well, we decided to only use the *Fingerprint Clustering* and the *Best Candidates Set* algorithms to estimate the error during the evaluation of our selection algorithms. To remind the reader, the *Fingerprint Clustering* algorithm identifies regions of similar signal properties in the area that the positioning system covers. It then uses the size of the region that the estimated position is contained within in order to conclude on the error. The larger the region is, the higher is this expected error. The *Best Candidates Set* algorithm relies on the internal order of possible candidate locations during the process of the position estimation. If the candidate locations are far apart from the final position estimate, the probability for a large error is high.

7.1.2 Error Estimation for GPS

With the DOP, GPS also offers a value that can be used to estimate the error to be expected during the estimation of a position. The DOP is calculated from several different system parameters. Looking at the technical realization, we have already seen that GPS is based on lateration with TOF measurements. The satellites, circling the earth on a medium height orbital path, continuously broadcast signals, including the precise time and information about their current orbital position to the GPS receivers on the earth's surface. While the satellites are equipped with multiple highly precise atomic clocks that furthermore are constantly synchronized among each other and a base station on earth, the GPS receivers are generally only equipped with quite imprecise quartz clocks to save costs. To still be able to precisely compute the TOF of the signals received from three satellites and to use this information to estimate the receiver's position, the signals of a fourth satellite are used to compensate for the temporal shift of the local clock. This process of time synchronization is an additional source of error. It induces a range in which the distance measurements from the device to the different satellites lie. GPS accounts for this error by computing a so-called *Time Dilution Of Precision* (TDOP) value as part of the overall DOP.

Besides the TDOP, the geometric constellation of the satellites has a major influence on the positioning accuracy. If the satellite constellation is bad, the effect of a high TDOP is much larger than for a good geometric setting. Figure 7.1 depicts this problem in a simplified fashion. While the thin black circles depict the real distance between the satellites and the GPS receiver, the gray shaded area depicts the uncertainty induced by the TDOP. The blue plane gives an overview of the area in which the real position may be located. As we can see, this area is much larger in case of a bad geometric satellite constellation. Thus, from information about the orbital positions of the satellites, the receivers first compute the geometric constellation of the used satellites and, from this constellation, then compute a measure called *Geometric Dilution Of Precision* (GDOP). The GDOP integrates information about the TDOP as well as about different DOP subtypes, namely the *Horizontal Dilution Of Precision* (HDOP) and the *Vertical Dilution Of Precision* (VDOP). Based on the GDOP, the receiver then calculates an overall error estimate.



(a) Example for an adverse satellite constellation.

(b) Example for a good satellite constellation.

Figure 7.1: Influence of the satellite constellation on the DOP.

As further details of the error estimation with GPS are beyond the scope of this thesis, we, for the following experiments, relied on the values that were supplied to us by the used GPS receiver.

7.1.3 Error Estimation for GSM

The use of GSM to estimate a user's location has been extensively studied in the past, as well (e.g., [VLHdL07]). Being a radio-based wireless system, many of the different techniques that have been introduced in the beginning of this thesis can be also used for GSM. In practice though, most of the commercially deployed systems either use a simple *Cell of Origin* (COO) approach, compute a centroid from all or the strongest received cell towers, or use the RSSI of the GSM signals, a radio propagation model and lateration to estimate a user's position.

Depending on the technique used, several different possibilities are feasible to estimate the error that has to be expected. For lateration, a geometric approach similar to that of GPS can be used. If a simple centroid is computed, then the overlapping area of the transmission ranges of the cell towers gives a good estimate for the possible error. As we have no deeper insight into the internal algorithms used by our devices, we, similar to the case of GPS, rely on the estimated error values supplied by the GSM-based positioning service on the device for our evaluation. Even if we were not able to verify it completely, we assume the device to use a server-based lateration approach.

7.2 Data Collection

To evaluate the performance of different selection algorithms, we collected several data sets in and around the office building A5 on the premises of the University of Mannheim and in a large free area in front of the University's main cafeteria. Figure 7.2 depicts the areas covered by the different data sets around the building A5.

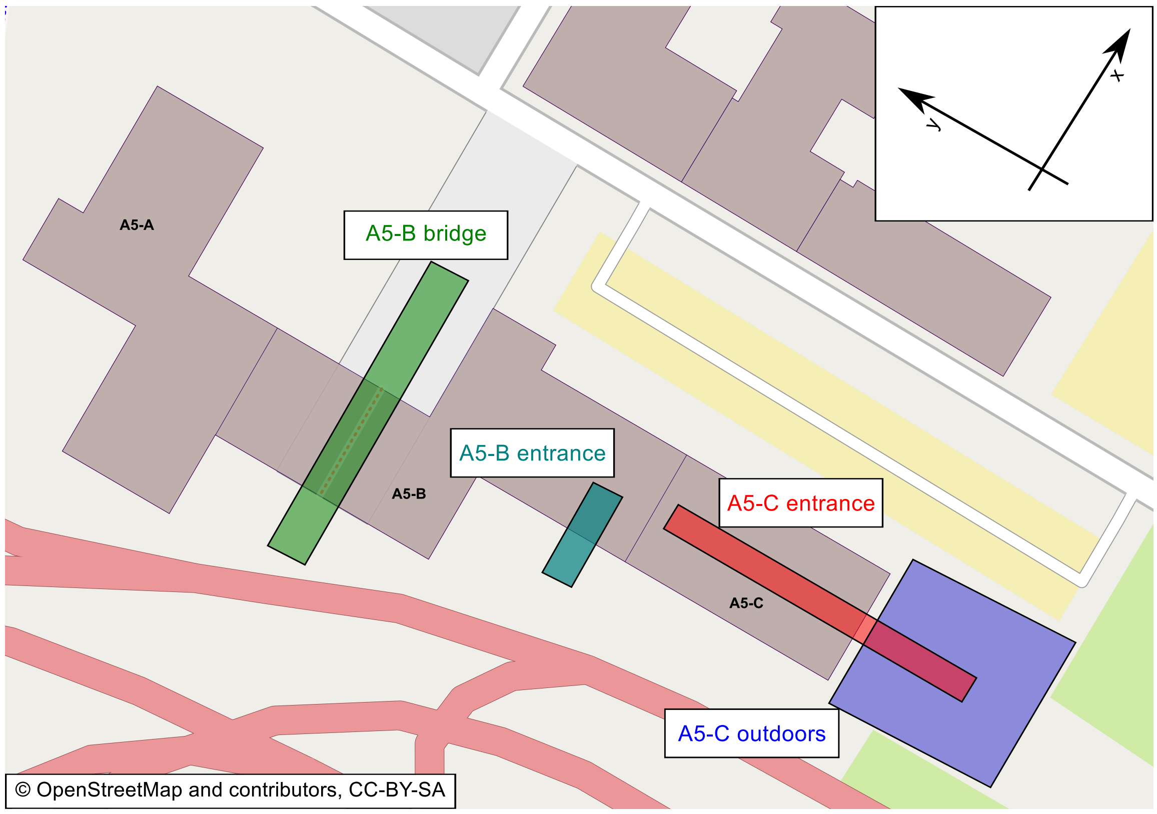


Figure 7.2: Overview of the roaming scenarios.

The data set denoted *A5-C outdoors* was used to get a general idea of the behavior of the different systems. It further serves as a demonstrator for the influence of environmental objects such as trees. The *A5-C entrance* data set implements a scenario of a user entering a building. It is accomplished by the data set *A5-B entrance*. The latter one was collected as, for the *A5-C entrance* data set, GPS was – opposed to our expectations – still functional even at the far end of the hallway inside the building. Thus, this data set was not usable to emulate the fading of the GPS signals in buildings. The last data set we collected around our office building is the *A5-B bridge* data set. This data set represents a special scenario where the user stays outdoors all the time but passes from one side of the building to the other side using a large underpass at ground level. Figure 7.3 gives an impression of this environment.

For each set, we applied a grid of reference spots to the covered area. The distance between the grid lines was, depending on the surroundings, either one or two meters. An overview of the properties of each data set is given in Table 7.1. Regarding the coordinates, we used a local

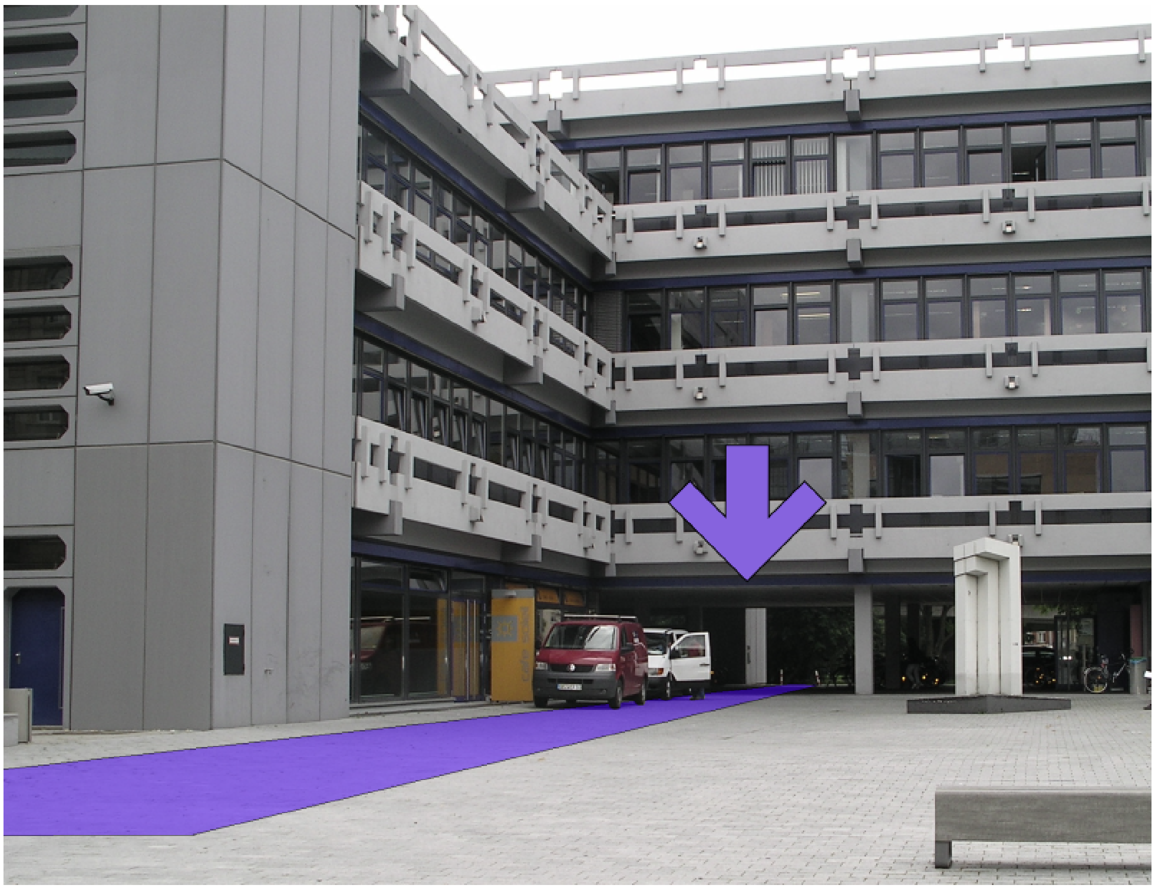


Figure 7.3: Picture of the A5-B underpass scenario.

coordinate system and defined a mapping to the WGS-84 coordinates supplied by both the GPS- and the GSM-based position estimates. This was necessary to be able to directly compare the IEEE 802.11-LF-based positioning system and the other systems.

Table 7.1: Properties of the different measurement scenarios.

	Dimensions $[m^2]$	Number of spots	Grid spacing $[m]$
A5-C outdoors	20 x 24	120	2
A5-C entrance	1 x 46	46	1
A5-B entrance	1 x 22	22	1
A5-B bridge	2 x 62	62	2

The data was collected with an HTC Hero smartphone. It was equipped with built-in GPS and GSM chipsets and an IEEE 802.11 interface according to the IEEE 802.11g standard. On the software side, the smartphone was running Google Android as operating system, and we used an own application written in Java to access the data from the different positioning systems and the IEEE 802.11 hardware. To mitigate the need for the device to reinitialize the different positioning systems at the beginning of each single measurement, our application – once started – continuously collected information from all three positioning systems. The collected information was written to a log file on the local storage space of the device, together with information about the ground truth for later use. We followed this approach as, for instance, an initial *fix* – the first position estimation of a GPS receiver once it is started – can take up to 45 minutes under adverse conditions.

Regarding the type of stored information, we, for both GPS and GSM, stored the estimated position together with the estimated error as returned by the positioning services on the device. Opposed to this, for the IEEE 802.11-LF-based position estimation, we stored the necessary raw data to be able to create the fingerprints. After the raw data collection was done, we, in a second step, aligned the readings for the different systems. For all the GPS and GSM position estimations, the WGS-84 coordinates were transfered to our local coordinate system. For the IEEE 802.11 measurements, we firstly created a fingerprint database containing fingerprints for all reference spots by using all the available measurements. We then used each single measurement and the fingerprint data base to estimate a position using the Rice algorithm. Furthermore, for each estimated position, we computed an error estimate with the *Fingerprint Clustering* algorithm and with the *Best Candidates Set* algorithm introduced in Chapter 5. The aligned samples for all three systems were finally stored in a second file.

7.3 Evaluation

Of course, an essential part of the roaming process between different positioning systems is the determination of the best time to switch and the selection of the systems to use next for position estimation. However, the ability of the different systems to accurately estimate the error that has to be expected is not equal. Thus, before we introduce our different approaches to decide which system to use, we at first give a quick overview of the quality of the error estimation in our scenarios.

Figure 7.4 shows the error estimation ability of both GPS, and the GSM-based system. Both tend to significantly underestimate the positioning error. The error that the systems expect to be inherent in the estimated position is much smaller than the real error. The Figure also shows that, while for GPS the error difference is almost 100% located between $-50\ m$ and $+50\ m$, the GSM-based system has a noticeably large amount of about 6% of even larger underestimations. Comparing these results to the ones we have achieved with our own algorithms for estimating the error of IEEE 802.11-LF-based position estimation, we can see that our algorithms perform noticeably better.

7.3.1 Basic Selection Algorithm

As a first approach to select the most suitable positioning system, we implemented an algorithm that always selects the system that *pretends* to offer the lowest error. Under the premise of

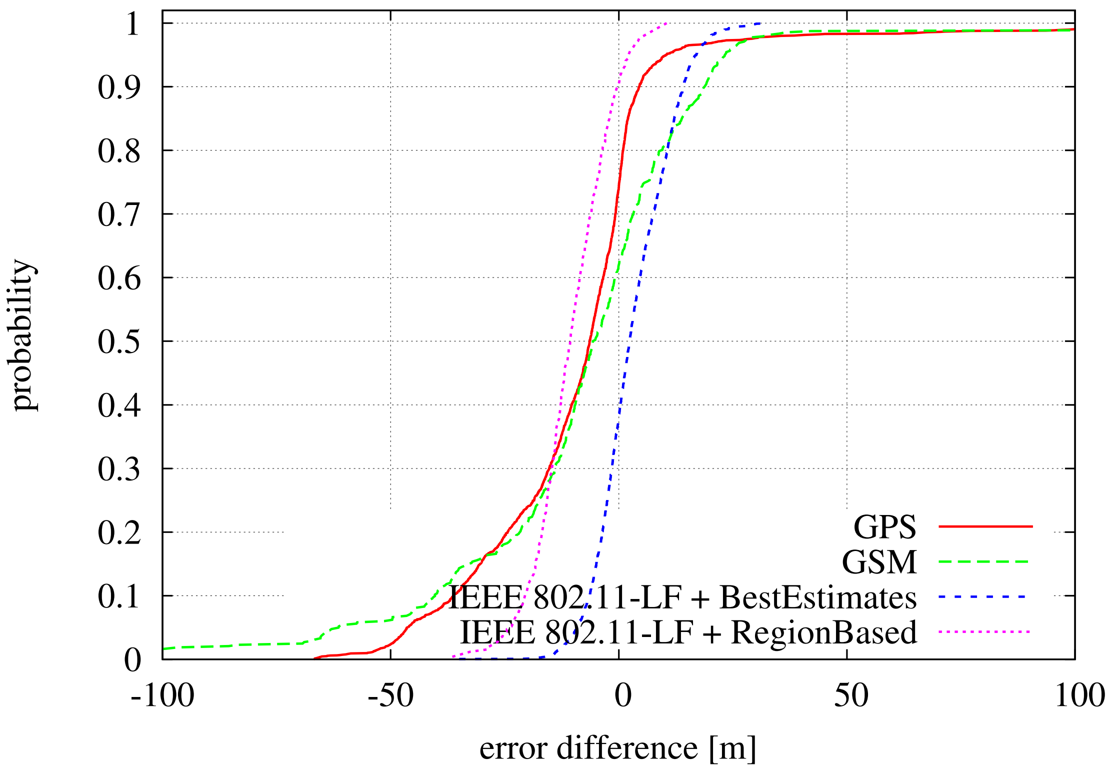


Figure 7.4: Error difference for GPS, GSM, and IEEE 802.11 during our measurements.

completely accurate error estimations, this would obviously lead to perfect results with regard to the selected system. Unfortunately, the latter is not the case. Figure 7.5 gives an overview of the results of our basic algorithm.

The Figure further depicts the influence of the time used to collect samples at a certain position and shows up to which percentage the optimal system was chosen. We evaluated these aspects to see how an increase in the number of measurements influences the selection performance. As shown in the Figure, the performance increases when the amount of collected samples increases. While for our emulation the effect of an increased collection time is only of secondary importance, this aspect would be of high impact in a real application. For instance, when GSM-based positioning is used to estimate a position, the system only returns few position estimations per minute. With GPS, the situation is slightly better with roughly one position estimate every second. However, the highest rate of position estimations can be delivered by the IEEE 802.11-LF system with up to 100 measured samples per minute.

7.3.2 Functional Selection Algorithm

With regard to our experience with both the basic algorithm as also the properties of the position estimation with GSM and GPS, we extended our basic approach by adding a reliability measure. As shown at the beginning of this section, the different systems offer different characteristics.

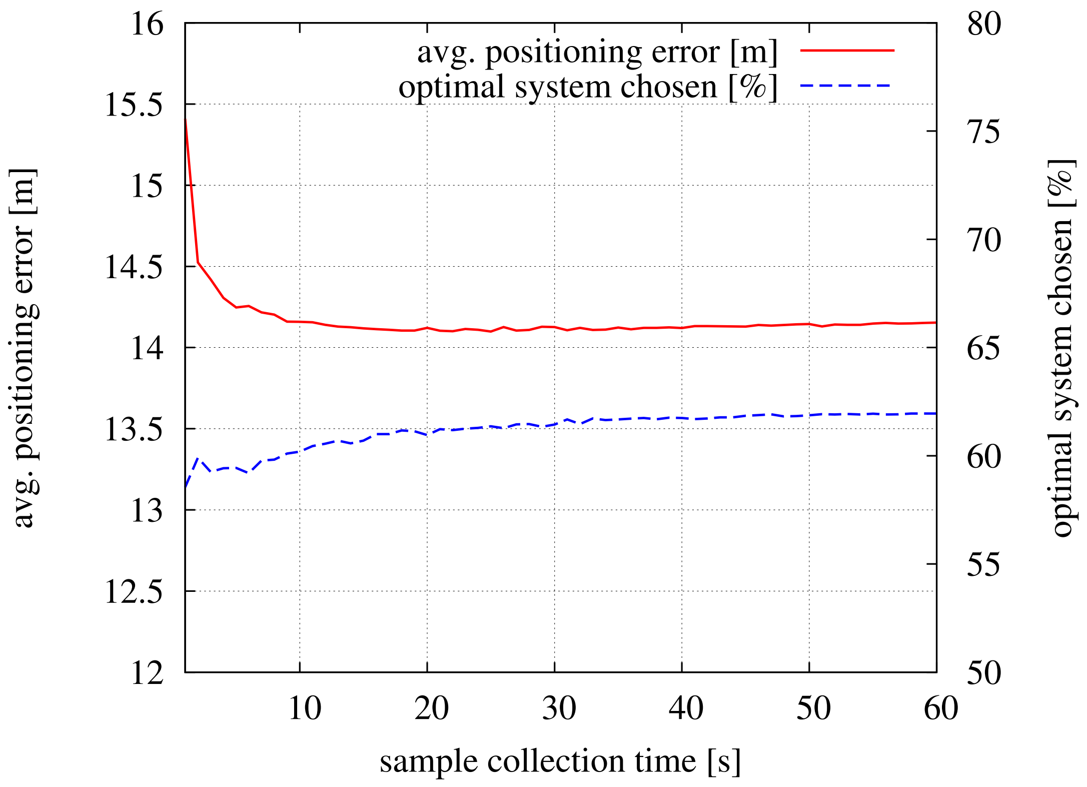


Figure 7.5: Results of our basic selection algorithm.

Based on our training data, we calculated a weight parameter for each system. The parameter is used to value the estimated error and as such influences the selection of the system either in a positive or a negative way. This improves the results slightly, but it still has a major drawback: As the factor is constant over the entire spectrum of possible estimated errors, it does not account for system-specific properties. During our evaluation, we realized that the quality of the error estimation offered by the different systems varied depending on the sizes of the real and the estimated error. The error estimation for GPS, for instance, was more accurate for real positioning errors between $30\ m$ and $40\ m$ than it was for real positioning errors between $10\ m$ and $20\ m$. In a second step, we therefore used our training data and a machine-learning approach to compute reliability functions for each single positioning system. The functions were used to replace the static factor. Figure 7.6 exemplarily depicts this approach for GPS.

By replacing the static factors by the weight functions, we were able to further increase the selection accuracy. Compared to the basic selection algorithm where only about 50% of all estimated positions have a real error of less than two meters, this number, for example, increases to more than 80% if our functionally weighted selection algorithm is used. The reason for this improvement is the increased number of selections in which the optimal positioning system is chosen.

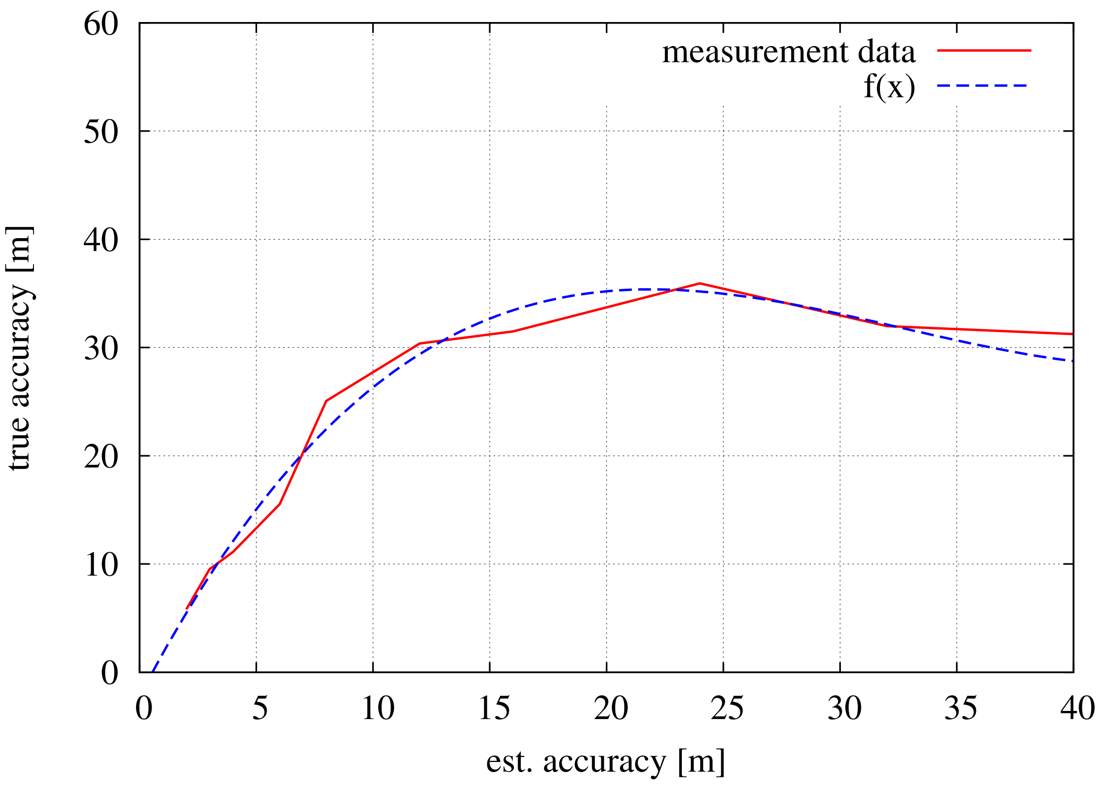


Figure 7.6: Functional approximation of the real positioning error based on the estimated error of GPS.

7.4 Discussion

During our work, we had to overcome numerous problems. The most prominent ones are discussed in the following.

7.4.1 Systematic Differences

The position estimates returned by GPS and GSM positioning services on the Android platform are, as already mentioned earlier, longitude, latitude, and elevation values in the WGS-84 coordinate system. WGS-84 is one of several possible coordinate systems that are used in science and by industry to pinpoint locations on the earth's surface. A specially defined coordinate system is necessary, as, opposed to common meaning, our earth is not a perfect ball. As depicted in Figure 7.7, the earth's true shape is instead more or less similar to an ellipsoid.

Whereas WGS-84 is well suited when large areas are considered, Cartesian coordinate systems are a better choice in case of mapping tasks within a limited scope. To map WGS-84 longitude and latitude values to a Cartesian plain, several different approaches have been proposed in the past (e.g., refer to [HBD89]). However, due to the limited extent of our test bed, we decided to take an even simpler approach. At first, we, for each position, calculate the distances

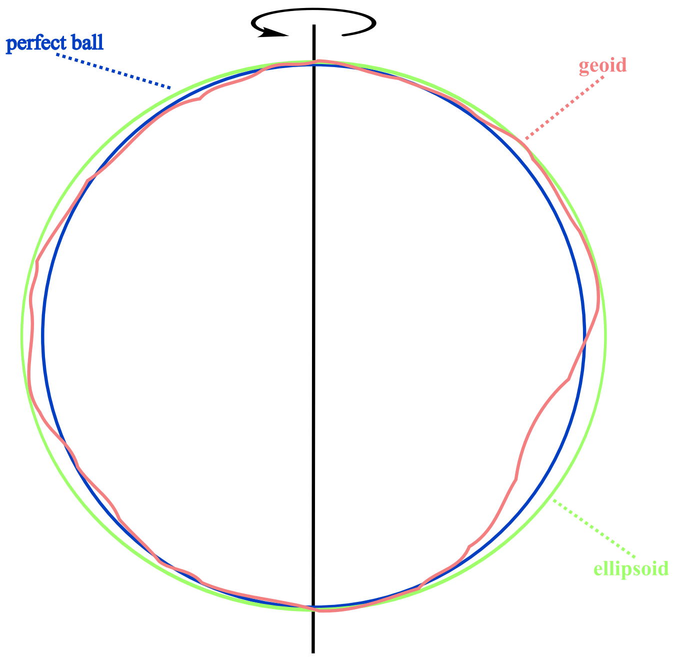


Figure 7.7: Examples for different representations of the shape of the earth.

between the estimated position and the coordinate axes of our local coordinate system using the WGS-84 coordinates. Then, as our local coordinate system's axes are rotated with regard to the WGS-84 axes, we furthermore perform a rotation around the origin (also refer to Equations 7.1 - 7.4). This results in the representation of the WGS-84 coordinates in our local coordinate system. While our mapping is not completely accurate, the errors induced by it are very small and can be neglected.

$$x_1 = (x_{ew} - x_{0l}) * 111320 * cos(y_{0l}) \tag{7.1}$$
$$y_1 = (y_{ew} - y_{0l}) * 111320 \tag{7.2}$$
$$x_2 = (x_1 * cos(\alpha)) + (y_1 * sin(\alpha)) \tag{7.3}$$
$$y_2 = (-1 * x_1 * sin(\alpha)) + (y_1 * cos(\alpha)) \tag{7.4}$$

Another systematic difference between the used systems is the type of error estimation. For the IEEE 802.11-LF system, the returned error value represents a radius around the estimated position in which we expect the true position to be located. Even though we thoroughly researched the publicly available information on the devices used by us and also attempted to contact Google as the manufacturer of the devices' operating system directly, we, for the GPS- and the GSM-based positioning systems, could not certainly verify what type of measure is returned. Therefore, as it seems to be the most reasonable interpretation, we also interpreted the values returned by the other systems in the same fashion as those returned by the IEEE 802.11-LF system.

7.4.2 Application Requirements

During our work with the positioning systems on the HTC smartphone, we have also learned valuable lessons with regard to the application requirements. For GPS, the most important fact is the initial delay that one has to wait until the GPS receiver will deliver the first position estimation – the so-called *initial fix*. The reason for this delay is that the receiver at first has to identify the signals of the available GPS satellites from the received signal spectrum. In case that no further information is available, this can take a long time.

If the receiver already has a local version of the so-called satellite almanac, it can look up which satellites should be receivable at the current time and place. This, of course, requires both a rather good estimate for the current time and at least a rough estimate of the receiver's geographic region. But it also significantly speeds up the process of obtaining an initial fix. On a smartphone that generally also has a wireless data connection, the almanac and the other information could be obtained quite easily, for instance, from an Internet data base. This in turn offers the major advantage that the application and especially the GPS positioning service do not have to be running in the background at all times. Instead, both can be started on demand and still offer a first fix in an acceptable time. This helps to save precious battery time, CPU cycles, and memory at the cost of a required Internet connection.

7.4.3 Postponed IEEE 802.11-LF

In a real setting, the IEEE 802.11-LF system should – at least with regard to the positioning service – also reside on the mobile device. For our evaluation, though, we decided to only *collect* the necessary information with the mobile device and to *use* that information afterwards for an evaluation with the help of emulation. This has several advantages. One is the heavily reduced software development effort. Using this approach, we could keep the size of the software running on the mobile device rather small and use existing tools for the evaluation of algorithms on our desktop computers. But the more important advantage is the increased flexibility. Whereas for the GPS- and GSM-based systems the position estimation on the device acts as a black box, the position estimation with IEEE 802.11-LF is an open book to us. By collecting the raw data, we could easily experiment with different amounts of data used for creating the fingerprints, for estimating the position, or for supplying to the error estimation algorithm. This gave us a better insight into these areas compared to the other systems where such insights were not possible.

7.4.4 Satellite Motion

We have identified another both interesting and important aspect during our studies: The influence of the satellite motion when using GPS. The GPS satellites are not geostationary but circle the earth once every twelve hours. Our measurements for the different scenarios took between one and two hours each. Thus, during the run of the single measurements, the constellation of the receivable satellites changed.

This was especially noticeable for the *A5-B bridge* scenario. Figure 7.8 depicts the positioning error for GPS in this scenario during our measurement. For the line of reference spots at the Y-coordinate 2, the error follows the expected path: In those areas where we would expect a good reception of the satellites' signals, we have a rather good accuracy. In the areas under the bridge and close to the buildings (X-coordinates from about -5 to 40), the error increases. For the second line of reference spots at the Y-coordinate 4, though, the same assumptions do not hold. There, for several spots under the bridge, the accuracy is significantly better. We explain this difference with the constellation of the satellites during our measurements. At the relevant positions under the bridge, there is a quite small opening to the South-East where the horizon is visible. We assume that, during the collection time of the second row of reference spots, a satellite emerged from beyond the horizon and could be received at these positions. This resulted in a better satellite constellation and thus in better positioning results.

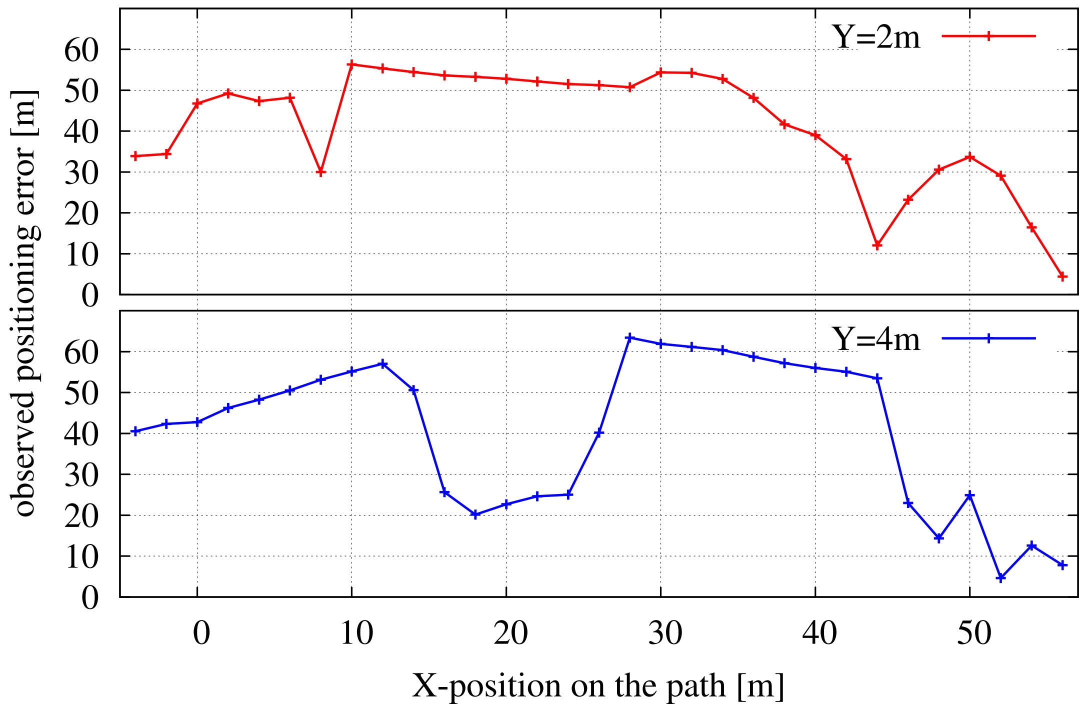


Figure 7.8: Influence of the temporal satellite constellation on the accuracy.

Our results therefore imply that the accuracy of position estimations with GPS is considerably dependent on the satellite constellation. For the same position, depending on how many satellites are receivable and how their positions are, it is possible to obtain strongly varying results. This insight was confirmed later on by the Civil Engineering Office in Mannheim. There we were told that for an optimal accuracy, special GPS receivers that remain at a fixed location for at least twelve hours have to be used. These devices consider all position estimations during that time-frame to allow for a very precise final estimate.

7.5 Conclusions

In this chapter, we have presented a solution how to select the best suitable positioning system in case that several systems are available. We have shown that the simple use of the estimated error values returned by the different systems already yields to usable results. However, when additionally using a static weight factor or, even better, a function to further evaluate the returned error estimates, the performance of the selection process can be further increased. For the latter approach, we achieved a selection accuracy of more than 80% even under the adverse conditions that our scenarios offer. We have further shown that environmental factors have a large influence on the accuracy of the used positioning systems and, thus, also on our selection process. For instance, when GPS is considered, the constellation of the satellites has a major influence on the achievable positioning accuracy. Even in situations where one would expect GPS to deliver bad results, the system can still perform well due to a fortunate satellite constellation. Finally, we have identified several different aspects that are related to the used application that can have an influence on the choice of the used positioning system. Especially restrictions with regard to the user's privacy can require an adapted selection mechanism. This also points out a probable path for future work. Especially the use of additional context information as the one we used for our IEEE 802.11-based tracking system could offer an even better and foresightful selection of the best positioning systems for every situation.

CHAPTER 8 Selected Application Scenarios

In this chapter, we give the reader a brief impression of what the introduced techniques can be used for in practice. For each application domain, we first describe the application and then point out how our novel techniques offer valuable contributions to it.

8.1 Educational Media

These days, the recording of lectures is common and a widely accepted procedure among teachers at universities and other educational institutions worldwide [OL02]. To allow for an easy recording of the lecture, only audio, the slides, and, in rare cases, the image of the lecturer are recorded. This type of recordings tends to get rather boring to watch over time, no matter how interesting the original presentation was. For professional video productions, the solution to this problem is to hire a camera team that concurrently records different perspectives of the lecture (e.g., the lecturer, the audience, persons asking questions, and a total view). In a post-processing step, the different streams are cut together according to video production rules. This creates a diversified video that is more interesting to watch. For everyday usage at a university, though, this approach is far too expensive.

Therefore, a solution that was developed in our department is an automatic lecture recording system [LLKE09]. The system consists of several remotely adjustable cameras, a screen capture component for the lecturer's slides, at least one audio capture component, and a central instance that aggregates the collected data and directs all other components (the *director*). The central director follows a set of implemented video production rules to automatically cut together the video streams from the different sources to create a final recording of the lecture, without the need for further manual processing. It uses a random function to switch between the different sources, and supports different sensory inputs that can be used to influence the decisions.

One situation that often occurs in recorded lectures is a question coming from the audience. If a student asks a question during a recorded lecture, it is desirable to take her in the focus of at least one camera. There are several reasons for this: Firstly, if the camera is equipped with a directional microphone, taking the student into focus helps to record the audio of the question properly. Secondly, for the viewer of a recording, this helps to keep the video more interesting. Of course, for this to work, the camera has to know the position of the student asking the question. To achieve this, we extended the director component of our system with an additional sensory interface to an IEEE 802.11-LF based positioning system. Students taking part in the lecture were equipped with Asus MyPal Personal Digital Assistants (PDAs) to allow them to give feedback and to take part in quizzes during the lecture. On these PDAs, we installed two additional software components. One is used to allow for a localization of the PDA in the lecture hall. The second component has the purpose to allow students to announce their intent to ask a question, similar to raising their hand. Upon such a question event, the localization component – the IEEE 802.11-LF client – estimates the position of the PDA and communicates this position to the automatic director. The director can then point and zoom one of the cameras in on the student. Once the lecturer gives the floor to the student, the images from that camera can be used in the lecture video to show the questioner, and, depending on the overall camera setup, to even allow for advanced video recording techniques like a shot and countershot scenario where both face each other.

As such, the use of our positioning techniques allows for the creation of more versatile and interesting recordings and ultimately helps to increase the learning impact of such recordings.

8.2 Paper Chase

In the area of leisure activities, LBSs have gained increasing importance during the last few years. For instance, these days, the continuous collection of information about ones own position is common when being out for skiing or snowboarding, hiking, on bike trips, or even when simply being out for a walk. Afterwards, this information can be used to gain further data like the traveled distance, the mastered height difference, or the achieved top speed. Furthermore, due to the availability of inexpensive devices, new activities have been invented that not only collect position information for later reference and replay but where the position plays a central role in the activity itself. *Geo Caching* is a good example for such an activity. In this activity, someone hides an object (e.g., a box containing a message or a goody) and publishes the exact coordinates where to find it on the Internet. Other people can then try to find the hidden object and are asked to replace it with something else. Inspired by this, during our research, we developed a virtual *Paper Chase* game. Similar to the classic children's game, one player deploys hints and the other players have to follow these hints to a final goal. Traditionally, chalk markings or colored tapes act as hints; in our version, we completely rely on virtual marks. One player places the marks at selected positions using a software on her mobile device. The positions are then communicated to a game server via a mobile data connection and can afterwards be accessed by the client software running on the other players' mobile devices. The software on the hunters' devices now constantly checks whether hints are in the proximity of the player. If this is the case, the mark is either displayed on a map or, if the player is aiming the device's camera in the right direction, it is displayed in an augmented reality view on the device's screen. The latter mode is depicted in Figure 8.1.

As we can see here, location information can be well used to adapt classic leisure activities towards a more modern approach. Continuing in this direction, the subsequent step is to further enhance the game by adding additional features that would not be possible with the classic approach.

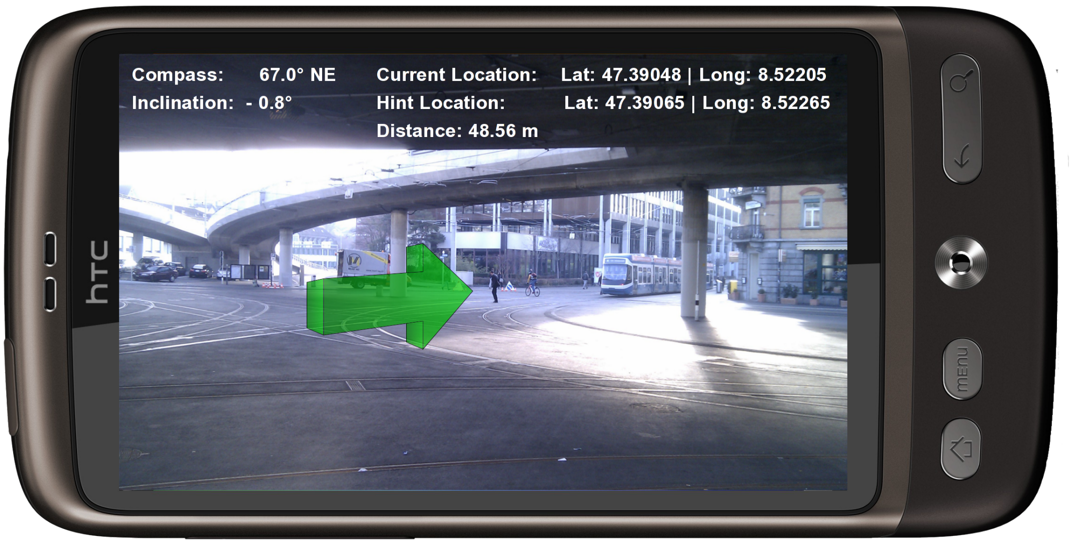

Compass: 67.0° NE
Inclination: - 0.8°
Current Location: Lat: 47.39048 | Long: 8.52205
Hint Location: Lat: 47.39065 | Long: 8.52265
Distance: 48.56 m

Figure 8.1: Example for the augmented reality view of our paper chase application.

Such an application serves as a good demonstration of the technologies that have been introduced in this thesis, too. Whereas, when relying on only one positioning technology, the system would be limited to either indoor or outdoor usage, our introduced techniques can help to make such a game application usable without environmental limits and with a higher satisfaction for the players, especially also due to the increased quality of the position estimation.

8.3 Automatic Handover

The last example for a scenario where the systems presented by us are of great help is the roaming between different APs or even between different communication technologies. Due to the proliferation of fast and reliable data connections for mobile devices, more and more applications rely on an always available connectivity. However, if we, for example, consider a train that enters a tunnel, the connection is lost almost instantly. Applications that are in the process of exchanging data while such an outage occurs will probably stall or even fail. To avoid such a failure, it is of great help to inform applications about *foreseeable* connection losses in advance in order to give them the possibility for a proper preparation. In case of a train and its limited degrees of freedom regarding the motion direction, such a concept can be implemented quite easily. However, it is by far more complex for a freely roaming user.

Our technologies target to provide help in this case. Especially the tracking system introduced in Chapter 6 can help to provide the information that is necessary to notify affected applications in advance of a possible connectivity loss. Based on the estimation of the motion mode and direction, applications can be given a grace time to finish network related tasks until, as known from topological information, the network connectivity is lost or a roaming between different systems takes place. This highly increases the usability of applications and, thus, results in a better user satisfaction. Without the knowledge about the user's position and motion, such an proactive behavior would not be possible.

CHAPTER 9 Conclusions and Outlook

The following concluding chapter sums up the findings of this thesis, gives an overview of lessons learned, and points out topics that are still open for further consideration.

9.1 Conclusions

As we have seen, the position estimation with IEEE 802.11 and LF is still a field of active research and has the potential to highly influence the direction in which future mobile and location-based services will develop. As a viable alternative in situations where GPS is unavailable, the position estimation with IEEE 802.11-LF would already today be a suitable solution for many different LBSs if the effort necessary for the setup and maintenance of the fingerprint database was not too large. For this problem, we have presented two solutions in this thesis, that can effectively help to reduce the effort and thus allow for an easier and faster deployment of IEEE 802.11-LF-based position estimation.

The first approach presented is *Quick Fingerprinting*. It relies on the observation that the training data that is collected at adjacent reference spots can be used to increase the quality of the fingerprints for other neighboring positions. We have presented two different schemes to merge the training data, the more promising one depending on a weight factor. The merging of data from adjacent reference positions results in a noticeable improvement of the positioning accuracy. However, the even more important aspect is that, even when reducing the amount of training data by up to 80%, our approach still retains almost the same average accuracy as without a reduction. This is a major improvement considering the cumbersome task of collecting the training data.

Furthermore, we have presented an alternative that reduces the effort even more effectively. This method is called *Region-based Location Estimation*. As shown in this thesis, the signals of single IEEE 802.11 APs tend to have a similar characteristic as long as one stays within a structurally limited area like an office room. As a result, fingerprints created for reference spots lying in such an area also tend to be rather similar. Our algorithm exploits this by automatically identifying regions of similar signal properties. Then, it creates only one single fingerprint for each region. This has two major advantages. Firstly, the overall number of fingerprints is reduced. This helps to reduce the computational and storage requirements of an LF-based system. Secondly, the training data can be collected for a region and no longer needs to be collected on the basis of numerous single spots. Thus, it is no longer necessary to stay at fixed positions during the collection. Instead, we can move along predefined trajectories through our area of operation while collecting the training data. Compared to the approach of using a grid of reference spots, this is another major improvement that helps to reduce the overall time needed for data collection to a fraction, at the cost of only minor reductions in the achieved average accuracy.

Additionally, we used the regional property of the IEEE 802.11 signals to solve a second urging problem that IEEE 802.11-LF-based positioning systems generally have. While they offer a competitive positioning accuracy, they also suffer from the rare occurrence of very large errors. To avoid users getting frustrated when using an IEEE 802.11-LF-based positioning system, we therefore have developed and evaluated several different methods to estimate the positioning error that has to be expected for a given position estimate. Of the four proposed algorithms, two performed especially well. One of them is *Fingerprint Clustering* which also relies on the regional signal properties and the idea that, if a user collects measurements within such an area, it is quite probable that small scale variations of the signal lead to a selection of any of the fingerprints that also lie in the appropriate region. We therefore developed a measure to estimate the error that has to be expected based on the size of the region the estimated position lies in. The second algorithm that also performed very well is called *Best Candidates Set*. It uses internal information from the IEEE 802.11-LF system to estimate the error. During the estimation of a position, such a system normally creates a ranking of all fingerprints in the database. Based on the geographical distribution of the n best candidate fingerprints, the *Best Candidates Set* algorithm calculates an error estimate. While both algorithms perform really well in estimating the error, it depends on the quality of the collected input data which algorithm is superior. The *Fingerprint Clustering* algorithm with its more conservative error estimation is better suited for input data with a lower quality. The *Best Candidates Set* algorithm performs better if the collected data has a higher quality.

While the position estimation of users inside buildings can already be improved a lot with these techniques, it is still not sufficient for all types of applications. Instead, the widespread availability of a precise tracking of users within buildings offers an even larger amount of possible new applications, equally in the private, the commercial, and the scientific sector. Therefore, in the second part of this thesis, we have presented an algorithm that uses a Sampling-Importance-Resampling particle filter to track users with the help of IEEE 802.11-LF. Even the simple use of a particle filter without any additional information already improves the achievable positioning accuracy. However, we furthermore extended the system to make use of additional context information that can be gathered on a mobile device like a smartphone. We have implemented an algorithm that can monitor the accelerometer built into mobile devices and is thus able to accurately determine a user's motion mode. Furthermore, our system makes use of information about the user's motion direction. This information can be gathered by, for instance, reading a digital compass built into many modern devices. Finally, we have extended the system to also allow for the use of topological information: Our system uses the information from a map to allow for a sanity check of subsequent position estimates. Whereas generally the Euclidean distance is used for this purpose, we instead use the topological distance. This offers a much better representation of possible user motions. While our system is also able to apply map-based motion restrictions on the particle motion, it has turned out that this does not improve the accuracy significantly.

Of course, moving users are not limited to the coverage area of a single system and also a single position may be covered by different positioning systems. Thus, we further investigated possibilities to allow for a proper selection of the best suited positioning system for a particular situation - and compared the behavior of the error estimation of three different positioning systems, namely GPS, GSM-based positioning, and IEEE 802.11-LF-based positioning using an extensive set of collected data. From the results of this comparison, we derived different algorithms that can be used to select the best suitable system based on the estimated errors from all three systems. From our algorithms, the one that performs best uses a set of different functions to weight the reliability of the error estimation of each system before selecting the best suitable one. This approach increases the rate of selecting the optimal system noticeably.

Finally, we presented several applications that act as showcases of how position estimation techniques in general and the techniques introduced in this thesis in particular can be used to create interesting applications that are fun, helpful, attractive, and informative to the user and offer a high added value over non-location-based applications from the same realm.

9.2 Outlook

While we have thoroughly investigated the algorithmic side of tracking users and devices with the help of IEEE 802.11-LF during our work, there are still open questions that should further be considered in the future. For example, one major open topic for IEEE 802.11-LF-based position estimation still is the device dependability of the collected measurements. Even though there have already been promising efforts in the past to create mappings between different devices or device classes [Kjæ06], there is still much room left for improvement. In addition, also the consideration of environmental and situation specific effects like humidity, the number of people present, or open doors are a field that still offers the possibility to further improve the positioning with IEEE 802.11-LF.

Similar to our own approach of considering the motion context of a user, another interesting idea is to incorporate even further context to increase the accuracy of LF with IEEE 802.11. For example, a mobile device that is equipped with a camera can easily determine the brightness around itself. This information can be matched with information from a building management system. Based on the time of day, whether a device measures a high brightness, and if the light in a given room or area is known to be on or off, it is rather easy to check that the user cannot be located within a certain room. With regard to LF, fingerprints for that room thus would not have to be considered during the position estimation. Consequently following this approach, the amount of context can almost infinitely be increased as long as mobile devices are equipped with the necessary sensors and information about that context can be mapped to the stored fingerprints. As a result, this gives interesting possibilities for further interdisciplinary research.

Of course, this is only a selection of topics that allow for a further engagement in the area of position estimation with IEEE 802.11 and LF. Also, other technologies arising these days are definitely worth to be considered for their suitability with regard to position estimation. Among these, especially LTE should be mentioned that, in combination with so-called pico- or femto-cells, seems to be a promising candidate for an upcoming ubiquitous networking infrastructure that could also be leveraged for a precise position estimation.

Bibliography

[BAB$^+$07] K. Borre, D.M. Akos, N. Bertelsen, P. Rinder, and S.H. Jensen. *A software-defined GPS and Galileo receiver: A Single-Frequency Approach*. Birkhäuser, 2007.

[BD05] Christian Becker and Frank Dürr. On location models for ubiquitous computing. *Personal and Ubiquitous Computing*, 9(1):20–31, January 2005.

[BHM$^+$06] Vladimir Bychkovsky, Bret Hull, Allen Miu, Hari Balakrishnan, and Samuel Madden. A measurement study of vehicular internet access using in situ wi-fi networks. In *Proceedings of the 12th international conference on Mobile Computing and networking*, MobiCom '06, pages 50–61, Los Angeles, CA, USA, September 2006. ACM Press.

[BMK$^+$00] Barry Brumitt, Brian Meyers, John Krumm, Amanda Kern, and Steven A. Shafer. Easyliving: Technologies for intelligent environments. In *Proceedings of the 2nd international symposium on Handheld and Ubiquitous Computing*, HUC '00, pages 12–29, Bristol, UK, September 2000. Springer-Verlag.

[Bol08] Philipp Bolliger. Redpin - adaptive, zero-configuration indoor localization through user collaboration. In *Proceedings of the 1st ACM international workshop on Mobile Entity Localization and Tracking in GPS-less environments*, MELT '08, pages 55–60, San Francisco, CA, USA, September 2008. ACM Press.

[BP00] Paramvir Bahl and Venkata N. Padmanabhan. Radar: An in-building rf-based user location and tracking system. In *Proceedings of the 19th IEEE international Conference on Computer Communications*, InfoCom '00, pages 775–784, Tel Aviv, Israel, March 2000. IEEE Computer Society.

[CDMF00] Keith Cheverst, Nigel Davies, Keith Mitchell, and Adrian Friday. Experiences of developing and deploying a context-aware tourist guide: the guide project. In *Proceedings of the 6th international conference on Mobile Computing and networking*, MobiCom '00, pages 20–31, Boston, MA, USA, August 2000. ACM Press.

[CSG05] F. Cavallo, A.M. Sabatini, and V. Genovese. A step toward gps/ins personal navigation systems: real-time assessment of gait by foot inertial sensing. In *Proceedings of the international conference on Intelligent Robots and Systems*, IROS '05, pages 1187–1191, Edmonton, AB, Canada, August 2005. IEEE Computer Society.

[CY05] Xiaoyong Chai and Qiang Yang. Reducing the calibration effort for location estimation using unlabeled samples. In *Proceedings of the 3rd IEEE international conference on Pervasive Computing and Communications*, PERCOM '05, pages 95–104, Hawaii, USA, March 2005. IEEE Computer Society.

[DLR77] A. P. Dempster, N. M. Laird, and D. B. Rubin. Maximum likelihood from incomplete data via the em algorithm. *Journal of the Royal Statistical Society. Series B (Methodological)*, 39(1):1–38, 1977.

[DPSB08] Erik Dahlman, Stefan Parkvall, Johan Skold, and Per Beming. *3G Evolution: HSPA and LTE for Mobile Broadband*. Academic Press, 2 edition, 2008.

[DVDLT07] David Dearman, Alex Varshavsky, Eyal De Lara, and Khai N. Truong. An exploration of location error estimation. In *Proceedings of the 9th international conference on Ubiquitous Computing*, UbiComp '07, pages 181–198, Innsbruck, Austria, September 2007. Springer-Verlag.

[Fox05] Eric Foxlin. Pedestrian tracking with shoe-mounted inertial sensors. *IEEE Computer Graphics and Applications*, 25(6):38–46, November 2005.

[Gas05] Matthew S Gast. *802.11 Wireless Networks: The Definitive Guide, Second Edition*. O'Reilly Media, Inc., 2005.

[HB01] Jeffrey Hightower and Gaetano Borriello. Location sensing techniques. UW CSE 01-07-01, University of Washington, Department of Computer Science and Engineering, Seattle, WA, USA, July 2001.

[HBD89] John W. Hager, James F. Behensky, and Brad W. Drew. The universal grids: Universal transverse mercator (utm) and universal polar stereographic (ups). Technical report, Defense Technical Information Center, Ft. Belvoir, Fairfax, VA, USA, 1989.

[HFL$^+$04] Andreas Haeberlen, Eliot Flannery, Andrew M. Ladd, Algis Rudys, Dan S. Wallach, and Lydia E. Kavraki. Practical robust localization over large-scale 802.11 wireless networks. In *Proceedings of the 10th international conference on Mobile Computing and networking*, MobiCom '04, pages 70–84, Philadelphia, PA, USA, September 2004. ACM Press.

[HHS+99] Andy Harter, Andy Hopper, Pete Steggles, Andy Ward, and Paul Webster. The anatomy of a context-aware application. In *Proceedings of the 5th annual ACM/IEEE international conference on Mobile computing and networking*, MobiCom '99, pages 59–68, Seattle, WA, USA, August 1999. ACM Press.

[HT00] Harri Holma and Antti Toskala. *WCDMA for UMTS: Radio Access for Third Generation Mobile Communications*. John Wiley & Sons, Inc., New York, NY, USA, 1st edition, 2000.

[JBPA06] Yiming Ji, Saâd Biaz, Santosh Pandey, and Prathima Agrawal. Ariadne: a dynamic indoor signal map construction and localization system. In *Proceedings of the 4th international conference on Mobile Systems, applications and services*, MobiSys '06, pages 151–164, Uppsala, Sweden, June 2006. ACM Press.

[Kal60] Rudolph Emil Kalman. A new approach to linear filtering and prediction problems. *Transactions of the ASME – Journal of Basic Engineering*, 82(Series D):35–45, 1960.

[KBH07] Thomas King, Thomas Butter, and Thomas Haenselmann. Loclib,trace,eva,ana: research tools for 802.11-based positioning systems. In *Proceedings of the 2nd ACM international workshop on Wireless Network Testbeds, Experimental evaluation and Characterization*, WinTECH '07, pages 67–74, Montreal, QC, Canada, September 2007. ACM Press.

[KHE07] Thomas King, Thomas Haenselmann, and Wolfgang Effelsberg. Deployment, calibration, and measurement factors for position errors in 802.11-based indoor positioning systems. In *Proceedings of the 3rd international conference on Location-and Context-Awareness*, LoCA '07, pages 17–34, Oberpfaffenhofen, Germany, September 2007. Springer-Verlag.

[Kjæ06] Mikkel Baun Kjærgaard. Automatic mitigation of sensor variations for signal strength based location systems. In *Proceedings of the 2nd international conference on Location- and Context-Awareness*, LoCA '06, pages 30–47, Dublin, Ireland, May 2006. Springer-Verlag.

[Kjæ07] Mikkel Baun Kjærgaard. A taxonomy for radio location fingerprinting. In *Proceedings of the 3rd international conference on Location-and Context-Awareness*, LoCA '07, pages 139–156, Oberpfaffenhofen, Germany, September 2007. Springer-Verlag.

[KK08] Thomas King and Mikkel Baun Kjærgaard. Composcan: Adaptive scanning for efficient concurrent communications and positioning with 802.11. In *Proceedings of the 6th ACM international conference on Mobile Systems, Applications, and*

Services, MobiSys '08, pages 67–80, Breckenridge, CO, USA, June 2008. ACM Press.

[KKH$^+$06] Thomas King, Stephan Kopf, Thomas Haenselmann, Christian Lubberger, and Wolfgang Effelsberg. Compass: A probabilistic indoor positioning system based on 802.11 and digital compasses. In *Proceedings of the 1st international workshop on Wireless network testbeds, experimental evaluation & characterization*, WiNTECH '06, pages 34–40, Los Angeles, CA, USA, September 2006. ACM Press.

[KM08] Mikkel Baun Kjærgaard and Carsten Valdemar Munk. Hyperbolic location fingerprinting: A calibration-free solution for handling differences in signal strength (concise contribution). In *Proceedings of the 6th IEEE international conference on Pervasive Computing and Communications*, PERCOM '08, pages 110–116, Hong Kong, March 2008. IEEE Computer Society.

[Kü05] Axel Küpper. *Location-based Services: Fundamentals and Operation*. John Wiley & Sons, 2005.

[LCC$^+$05] Anthony LaMarca, Yatin Chawathe, Sunny Consolvo, Jeffrey Hightower, Ian Smith, James Scott, Timothy Sohn, James Howard, Jeff Hughes, Fred Potter, Jason Tabert, Pauline Powledge, Gaetano Borriello, and Bill Schilit. Place lab: device positioning using radio beacons in the wild. In *Proceedings of the 3rd international conference on Pervasive Computing*, PERVASIVE '05, pages 116–133, Munich, Germany, May 2005. Springer-Verlag.

[LKE08] Hendrik Lemelson, Thomas King, and Wolfgang Effelsberg. A study on user acceptance of error visualization techniques. In *Proceedings of the 5th international conference on Mobile and Ubiquitous Systems: Computing, Networking, and Services*, Mobiquitous '08, pages 53:1–53:6, Dublin, Ireland, July 2008. ICST.

[LLKE09] Fleming Lampi, Hendrik Lemelson, Stephan Kopf, and Wolfgang Effelsberg. A question managing suite for automatic lecture recording. *Interactive Technology and Smart Education*, 6(2):108–118, 2009.

[NLLP04] Lionel M. Ni, Yunhao Liu, Yiu Cho Lau, and Abhishek P. Patil. Landmarc: indoor location sensing using active rfid. *Wireless Networks*, 10(6):701–710, November 2004.

[OL02] Thomas Ottmann and Tobias Lauer. Means and methods in automatic courseware production: Experienceand technical challenges. In *Proceedings of World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education*, pages 553–560, Montreal, QC, Canada, October 2002. AACE.

[PBM$^+$09a] J. Prieto, A. Bahillo, S. Mazuelas, R. M. Lorenzo, J. Blas, and P. Fernández. Adding indoor location capabilities to an ieee 802.11 wlan using real-time rtt measurements. In *Proceedings of the Wireless Telecommunications Symposium*, WTS '09, pages 113–119, Prague, Czech Republic, April 2009. IEEE Computer Society.

[PBM$^+$09b] J. Prieto, A. Bahillo, S. Mazuelas, R.M. Lorenzo, J. Blas, and P. Fernandez. Nlos mitigation based on range estimation error characterization in an rtt-based ieee 802.11 indoor location system. In *IEEE International Symposium on Intelligent Signal Processing*, WISP '09, pages 61 –66, Budapest, Hungary, August 2009. IEEE Computer Society.

[PEK$^+$06] J. Parkka, M. Ermes, P. Korpipaa, J. Mantyjarvi, J. Peltola, and I. Korhonen. Activity classification using realistic data from wearable sensors. *IEEE Transactions on Information Technology in Biomedicine*, 10(1):119 –128, January 2006.

[RAG04] Branko Ristic, Sanjeev Arulampalm, and Neil Gordon. *Beyond the Kalman filter: particle filters for tracking applications*. Artech House, 2004.

[Rap01] Theodore S. Rappaport. *Wireless Communications: Principles and Practice*. Prentice Hall PTR, second edition, December 2001.

[RDML05] Nishkam Ravi, Nikhil Dandekar, Preetham Mysore, and Michael L. Littman. Activity recognition from accelerometer data. In *Proceedings of the 17th conference on Innovative Applications of Artificial Intelligence*, IAAI '05, pages 1541–1546, Pittsburgh, Pennsylvania, July 2005. AAAI Press.

[SFL05] Ross Stirling, Ken Fyfe, and G&eacute;rard Lachapelle. Evaluation of a new method of heading estimation for pedestrian dead reckoning using shoe mounted sensors. *The Journal of Navigation*, 58(01):31–45, 2005.

[SRF$^+$92] S.Y. Seidel, T.S. Rappaport, M.J. Feuerstein, K.L. Blackard, and L. Grindstaff. The impact of surrounding buildings on propagation for wireless in-building personal communications system design. In *Proceedings of the 42nd IEEE Vehicular Technology Conference*, pages 814–818, Denver, CO , USA, May 1992. IEEE Computer Society.

[SS98] P. Samarati and L. Sweeney. Protecting privacy when disclosing information: k-anonymity and its enforcement through generalization and suppression. In *Proceedings of the IEEE Symposium on Research in Security and Privacy*, Oakland, CA, USA, May 1998. IEEE Computer Society.

[STB09] Stefania Sesia, Issam Toufik, and Matthew Baker. *LTE, The UMTS Long Term Evolution: From Theory to Practice*. Wiley Publishing, 2009.

[SV04] Jochen H. Schiller and Agnès Voisard. *Location-Based Services*. Morgan Kaufmann, 2004.

[Swe02] Latanya Sweeney. K-anonymity: a model for protecting privacy. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, 10(5):557–570, October 2002.

[VLHdL07] Alex Varshavsky, Anthony LaMarca, Jeffrey Hightower, and Eyal de Lara. The skyloc floor localization system. In *Proceedings of the 5th IEEE international conference on Pervasive Computing and Communications*, PERCOM '07, pages 125–134, White Plains, NY, USA, March 2007. IEEE Computer Society.

[Wal07] Michael Wallbaum. A priori error estimates for wireless local area network positioning systems. *Pervasive and Mobile Computing*, 3(5):560–580, October 2007.

[WF05] Ian H. Witten and Eibe Frank. *Data Mining: Practical Machine Learning Tools and Techniques, Second Edition (Morgan Kaufmann Series in Data Management Systems)*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 2005.

[WGS04] Department of defense world geodetic system 1984 – its definition and relationships with local geodetic systems. Nima technical report, 2004.

[WHFaG92] Roy Want, Andy Hopper, Veronica Falcão, and Jonathan Gibbons. The active badge location system. *ACM Transactions on Information Systems*, 10(1):91–102, January 1992.

[WKB08] Widyawan, Martin Klepal, and Stéphane Beauregard. A novel backtracking particle filter for pattern matching indoor localization. In *Proceedings of the 1st ACM international workshop on Mobile Entity Localization and Tracking in GPS-less environments*, MELT '08, pages 79–84, San Francisco, CA, USA, September 2008. ACM Press.

[YA04] Moustafa Youssef and Ashok Agrawala. On the optimality of wlan location determination systems. In *Proceedings of the Communication Networks and Distributed Systems Modeling and Simulation Conference*, CNDS '04, Seattle, Washington, January 2004. ACM Press.

[YA05] Moustafa Youssef and Ashok Agrawala. The horus wlan location determination system. In *Proceedings of the 3rd international conference on Mobile Systems, applications, and services*, MobiSys '05, pages 205–218, Seattle, Washington, June 2005. ACM Press.