Indoor Localization Method Based on WiFi Signals and Building Layout Model

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APPROVAL

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— Jure Tuta —

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[2] J. Tuta, M. B. Jurič. MFAM: Multiple Frequency Adaptive Model-Based Indoor Localization Method. *Sensors*, 18(4):963, 2018. MDPI, doi: 10.3390/s18040963.

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"Logic will get you from A to Z; imagination will get you everywhere."

— Albert Einstein.

Univerza *v Ljubljani*
Fakulteta *za računalništvo in informatiko*

Jure Tuta
Metoda za določanje položaja v prostoru na osnovi signalov WiFi in modela zgradbe

POVZETEK

Določanje lokacije znotraj prostorov na podlagi WiFi signalov je zaradi variabilnosti signala WiFi težka naloga. Posledično je bilo v preteklosti veliko poizkusov razvoja WiFi metod, ki uporabljajo dodatne informacije za natančno lokalizacijo. Ocena prehojene poti in inercijski senzorji, uporaba množice ljudi in ujemanje vzorcev, tehnologija Li-Fi in usmerjene antene itd. je le nekaj v preteklosti uporabljenih načinov za dopolnitev WiFi signalov pri razvoju natančnih in stabilnih metod. Glavna slabost takih metod se kaže v zahtevnem uvajanju zaradi uporabljenih tehnologij in zahtev: metode ocene prehojene poti niso primerne za stacionarne predmete, metode, ki uporabljajo množice ljudi, niso primerne za domače okolje, Li-Fi metode zahtevajo, da so mobilni terminali opremljeni z ustreznimi sprejemniki in tako izključijo mobilne telefone kot terminale.

V preteklosti so bile predlagane številne metode, ki bazirajo na prstnih odtisih signalov. Te metode zahtevajo kalibracijske meritve v prostoru v fazi implementacije metode. Večina teh metod ne naslovi vprašanj dolgoročne stabilnosti WiFi signalov, posledično se soočajo s težavami zaradi natančnosti nekaj dni po kalibraciji. Pogoste, drage in časovno potratne ponovne kalibracije so potrebne za reševanje teh težav. Metode, temelječe na matematičnih modelih, poskušajo eliminirati kalibracijske postopke s simulacijo širjenja signala. Večina teh metod vseeno privzame vsaj nekatere parametre propagacije kot fiksne in tako slabo naslovi variabilnost WiFi signalov in dolgoročno stabilnost. Izključno WiFi modelna metoda, ki uspešno naslovi te težave in zahteva, da mobilni terminal samo oddaja ali sprejema WiFi signale, je končni cilj WiFi metod za določanje položaja v zaprtih prostorih.

Ta doktorska dizertacija predstavlja novo metodo za določanje pozicije znotraj prostorov, z glavnim ciljem, da naslovi težave pri realni uporabi. Zato smo se osredotočili na razvoj metode z natančnostjo, ki je primerljiva z najsodobnejšimi metodami, hkrati

pa je cilj zmanjšati kompleksnost implementacije in vzdrževanje za dolgoročno uporabnost. Predstavljena metoda je modelnega tipa in implementira prilagodljivo delovanje, zato ne zahteva nobenega človeškega posredovanja. Dizertacija podrobno razpravlja o temah dolgoročne stabilnosti WiFi signalov, o metodah, temelječih na sprejemanju in oddajanju signalov, prihodnjih standardih WiFi, primerljivosti sorodnih metod in arhitekturnih vplivih z ozirom na realno uporabnost.

Naša metoda predstavljena v tej nalogi oceni prametre propagacije signala iz poznavanja pozicije dostopnih točk, arhitekturnega načrta z informacijami o predelnih stenah in s pomočjo opazovanja moči paketov, ki potujejo med dostopnimi točkami. Iz teh podatkov se propagacijski parametri definirani v modelu določijo v realnem času. Naprava, ki želi določiti pozicijo zajame informacijo o moči paketov, ki jih pošiljajo dostopne točke. Te meritve so uporabljene v algoritmu za določanje pozicije naprave, ki teče na strežniku.

Predstavljena metoda je bila primarno razvita in evalvirana v enosobni in večsobni postavitvi pisarniškega okolja. Sposobnost metode, da se enostavno prilagodi vsakemu okolju, je poudarjena z evalvacijo v dveh okoljih – pisarniškem in stanovanjskem. Med obema evalvacijama nismo spremenili nobenega parametra metode, kar indicira njeno univerzalnost. V nadaljevanju predstavimo tudi evalvacijo metode v dolgem hodniku, ker je v raziskovalnem področju lokalizacije znotraj prostorov tako okolje pogosto uporabljeno.

Evalvacija predlagane metode v pisarniškem okolju je rezultirala v povprečni napaki $2{,}63\,\mathrm{m}$ in $3{,}22\,\mathrm{m}$ za enosobno in večsobno postavitev. Druga evalvacija je bila opravljena v stanovanjskem okolju, za katerega nismo spreminjali metode ali njenih parametrov. Naša metoda je tekom evalvacije štirih neodvisnih setov meritev, od katerih je vsak sestavljen iz 17 lokalizacijskih točk, dosegla povprečno napako lokalizacije $2{,}65\,\mathrm{m}$ s standardno deviacijo $1{,}51\,\mathrm{m}$. Visoka natančnost lokalizacije ob upoštevanju zapletenega in realističnega večsobnega tlorisa, ki vsebuje več vrst sten, realistično pohištvo in motnje signalov iz sosednjih stanovanj, dokazuje uporabnost metode v praksi. Natančnost je primerljiva z najsodobnejšimi metodami, medtem ko naša metoda zahteva veliko manj zapletene postopke namestitve in/ali strojne zahteve.

V drugem delu teze posplošimo WiFi metodo, da lahko uporablja tudi druge frekvence poleg $2{,}4\,\mathrm{GHz}$ WiFi. Z definicijo fuzijskega algoritma, ki upošteva natančnost posameznih frekvenc, smo definirali MFAM metodo – večfrekvenčno prilagodljivo modelno metodo za določanje lokacije znotraj stavb (ang. multiple frequency adaptive model-based indoor localization method). MFAM metoda predstavlja eno prvih modelnih metod, ki lahko hkrati uporablja več frekvenc. MFAM metoda je bila evalvirana v stanovanjskem okolju na dveh frekvenčnih pasovih: 868 MHz in 2,4 GHz. Metoda je ohranila pozitivne lastnosti predlagane WiFi metode (tj. izključno modelni pristop, prilagodljivo delovanje, možnost široke uporabe na dosegljivi strojni opremi), hkrati pa rezultira v boljši natančnosti zaradi fuzije signalov več frekvenc. Uporaba več frekvenc je izboljšala povprečno napako iz 2,65 m pri uporabi WiFi na 2,16 m, s čimer se izboljša natančnost lokalizacije za 18 %; podobne izboljšave smo opazili tudi pri standardnemu odklonu.

Čeprav je natančnost predstavljenih WiFi in MFAM metod primerljiva, če ne boljša, kot trenutno najsodobnejše metode, je eden najpomembnejših dosežkov našega dela uporabnost metode v realnih situacijah in njena dolgoročna stabilnost. Definicija naše metode zagotavlja, da bo natančnost metode ob času postavitve enaka kot dneve kasneje brez človeške interakcije.

Ključne besede: lokalizacija, lokalizacija zontraj prostorov, modeliranje, porpagacija signala, načrt zgradbe, več frekvenčna lokalizacija

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Indoor Localization Method Based on WiFi Signals and Building Layout Model

ABSTRACT

WiFi indoor localization is a difficult task due to the variability of the WiFi signal. Consequently, there have been many attempts to develop WiFi-based methods which were aided by some other means to provide accurate indoor localization. Technologies like dead reckoning and IMU sensors, crowd utilization and pattern matching, specialized Li-Fi hardware and directional antennas, etc. were used to aid the WiFi in order to develop more accurate and stable methods. The main disadvantage of such methods lies in difficult deployments due to technologies and requirements: Dead-reckoning-aided methods are not suitable for stationary objects, methods leveraging groups of people and many individuals are not best suited for home environment, Li-Fi assisted methods require mobile terminals to provide Li-Fi connectivity and therefore rule out mobile phones as the most common terminal.

In the past, many fingerprinting methods were proposed; these require a survey in the area of localization during the setup phase. Unfortunately, the majority of fingerprinting-based methods do not address issues of long-term stability of the WiFi signals. Thus, they face accuracy issues a few days after the calibration; frequent, costly and time-consuming recalibration procedures are used to address these issues. Model-based methods try to eliminate calibration procedures by simulating signal propagation. Many of the methods assume at least some parameters of propagation as fixed and therefore poorly address the issues of WiFi's variability and long-term stability. A pure WiFi model-based method that successfully addresses these issues and requires a mobile terminal only for emitting or receiving the WiFi signals is the ultimate goal of the WiFi indoor localization.

This thesis presents a novel indoor localization method, with the main intent of addressing the issues of real-world applicability. Therefore, we focused on developing a method with accuracy comparable to the state-of-the-art methods, while reducing the complexity of deployment and minimizing the required maintenance for long-term deployments. The presented method is a model-based method, implementing self-adaptive operability, i.e. it does not require any human intervention. The thesis discusses in detail the topics of the long-term stability of the WiFi signal, receiving vs. transmitting methods, the future WiFi standards, comparability of the methods and architectural aspects with respect to real-world applicability of the localization methods.

Our presented method estimates the parameters of signal propagation, by knowing the positions of the access points, the architectural floor plan with the dividing walls and by monitoring power of the packets travelling between the access points. From this data propagation parameters defined in propagation model are inferred in an on-line manner. A device trying to define its position captures power information of the packets sent by the access points. Devices' information on the observed power is used to determine its position by an algorithm run on the localization server.

The presented WiFi method is primarily developed and evaluated in single- and multi-room office environments. The method's ability to be easily applicable in any environment is emphasized by its evaluation in two different environments – office and residential. Between the two, no parameters were modified, thus evaluations indicate universality of the method. Furthermore, we provide evaluation also in narrow hallway because in the field of indoor localization such evaluation environments are common practice.

During the evaluation of our proposed method in the office environment, we obtained an average error of 2.63 m and 3.22 m for the single- and multi-room environments respectively. Second evaluation was performed in the residential environment, for which the method or any of the parameters were not modified. Our method achieved an average evaluation error of 2.65 m with standard deviation of 1.51 m, during the four independent evaluations, each consisting of 17 localization points. High accuracy of localization, with acknowledgement to the intricate and realistic multi-room floor plan with different types of walls, realistic furniture and real-world signal interference from the neighboring apartments, proves the method's applicability to the real-world environment. Evaluation accuracy can be compared to the state-of-the-art methods, while our easily-applicable method requires far less complicated setup procedures and/or hardware requirements.

In the second part of the thesis, we generalize the WiFi method to be applicable

to the frequencies other than 2.4 GHz WiFi. By defining a fusion algorithm which considers accuracy of the individual frequencies, we have defined the MFAM method: Multiple Frequency Adaptive Model-Based Indoor Localization Method. The MFAM is one of the first purely model-based approaches capable of utilizing multiple frequencies simultaneously. The MFAM method was evaluated in residential environment on two frequency bands: 868 MHz and 2.4 GHz. The method retained positive properties of our WiFi approach (e.g. pure model-based, self-adaptive operability, wide applicability on affordable hardware), while improving the accuracy due to multi-frequency fusion. The usage of multiple frequencies improved the average error of localization from 2.65 m, while using only the WiFi, down to 2.16 m, in the case of multi-frequency fusion, thus improving localization accuracy for 18 %. Similar improvements were observed also for the standard deviation.

Although the accuracy of the presented WiFi and MFAM methods is comparable if not better than the state-of-the-art methods, one of the most important achievements of our work is the applicability of the method to the real-world situations and its long-term stability. The definition of our method ensures that the accuracy of the method will be the same at the time it is initialized, as well as days later, without any human interaction.

Key words: localization, indoor localization, modelling, signal propagation, building layout, multi frequency localization

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— Jure Tuta, Ljubljana, June 2018.

CONTENTS

Introduction

Anyone who has had the experience of walking or driving without knowing where they are knows the feeling of being lost. It is not a pleasant feeling and we humans feel incomplete not knowing where we are. Therefore, we have always strived to define our position relative to the known objects. Archeologists have discovered early maps defining distances to the neighboring settlements that date to the Babylonian Era; in Ancient Greece, early astronomers have started estimating the position of the planets and the Sun relative to the Earth. In modern age, Global Navigation Satellite Systems (GNSSs) provide the geolocation outdoors.

Never before in history was information about the precise location indoors so desirable. New technologies are developed every day that require the exact indoor location, yet such a widely deployable system does not exist. Can you imagine how an indoor localization and navigation system would ease the search of a specific product inside a shopping center? Or how could we optimize our time if a mobile phone would calculate the optimal route through a grocery store based on our shopping list? Can you imagine the possibilities in our smart homes of the future?

In this thesis, we describe our take on the indoor localization by developing a novel WiFi approach that has been proven in evaluation and that successfully addresses many deficiencies of the current approaches. Its main features are adaptiveness to the indoor changes, simple applicability by utilizing widely available hardware, and minimal impact on the network, since the devices which are trying to define position do not need to emit signals. In the second part of the thesis we generalize the WiFi approach to multi-frequency usage, as the underlying method is not build specifically for WiFi. We present evaluation on two signal sources: one is 2.4 GHz 802.11g WiFi and the other is proprietary home automation communication protocol operating on 868 MHz. We introduce the fusion method that considers the accuracy of each individual frequency and opens a possibility for adding more signal sources.

1.1 Motivation

We are living in the era when technology is starting to be implemented in every object of our lives. Devices that were purely mechanical in the past, such as door locks, radiator thermostats, switches, etc. are becoming smart and connected to the network. Concepts like Smart Homes, Industry 4.0, Smart Transport, etc. have a common denominator, which is the Internet of Things (IoT) paradigm. Ever since K. Ashton coined the expression “Internet of Things” [1], industry is pursuing the goal of creating ubiquitous systems in which every device is connected to the network.

Connection to the network enables the devices to exchange information, upon which algorithms can provide additional functionality to us - the end-users. The IoT visionaries predict a world in which seamlessly shared information between the devices in our homes, public spaces and factories ease people's lives. The IoT visionaries promise homes of the future will be aware of their inhabitants and adapt lighting, heating, entertainment, and security systems accordingly [2]. The smart homes of the future promise a fully adaptive living environment. Home heating systems which can detect that owners are on their way from work are on the verge of a wide deployment; future homes promise smart kitchens which will be able to detect and report the groceries we need. Even today the systems for controlling each light, air vent, heating element and window separately are available for high-end buyers; such systems will only evolve in the future decade and become more available.

Our homes are not the only environments which will benefit from the IoT; the IoT is an essential part of the Industry 4.0 paradigm [3]. Industry 4.0 is the current trend in manufacturing and production systems; it focuses on the communication and exchange of information between different machines and humans involved in a manufacturing process. Industry 4.0 is thought to be the fourth major step in the manufacturing industry, the first one being the invention of steam power during the First Industrial Revolution in the 18 th century, then the mass production and assembly lines in the Second Industrial Revolution in the 19th century and the third the automatization of the manufacturing process in the seventies. The Industry 4.0 promises decentralized management of the manufacturing process and communication between smart products, manufacturing machines and resources. As every integral part of the manufacturing process will be able to communicate, the manufacturing process will be able to adapt to the changes in the supply chain and product demand.

One of the properties of every device which is often beneficial to other IoT devices is its precise location indoors [4]. For example, we usually carry our mobile phones everywhere we go; it would be useful if the computer in our car detected that we have forgotten our mobile phone when leaving. Even further, if our homes were able to locate us by determining the position of our mobile phones, centralized home control system could adapt the heating and cooling of individual rooms accordingly. Localization is also a very important and not yet resolved problem of the industry [5, 6], e.g. implementation of a fully IoT-enabled transport system in the factories calls for accurate means of localization. Although there are several approaches to the indoor localization [7–9], researchers agree that the method which could be universal has not been developed yet [5].

The main goal of our research work was to develop an indoor localization method that would be suitable for the real-world usage; each design decision during the development was subjected to this goal. Our goal was to address the difficult calibration procedures, static usage of parameters in propagation models and hardware requirements of the existing methods. To accomplish this, we have set the following prerequisites.

- *WiFi approach*
  Our goal is not to confine the method to the WiFi signals, but if possible develop a universal method; because we have to begin the development and evaluations with some signals, we will primarily utilize the WiFi signals, as they are most commonly used in the field. WiFi is nowadays used everywhere to provide access to the Internet and consequently hardware has often been already deployed indoors; leveraging of the existing hardware simplifies new deployments, as it does not require any indoor construction work and at the same time lowers the investment costs. After the development of the new WiFi method, we would like to, if possible, extend our method to utilize other types of signals and develop a multi-frequency approach which would fuse information from signals of different frequency to provide an accurate indoor location.

- *Model-based approach*
  There have been many attempts to build WiFi-based approaches, but many of them are not usable in the real-world scenarios, due to the variations of the WiFi signal strength. We wanted to address this issue by building a method based on physical propagation of the WiFi signals, which will implement constantly-running self-calibration operability in the background, since not every method with static parameters is suited for highly variable WiFi spectrum [10]. WiFi signal exhibits heavy variability of the signal not only in the short term but also in the long term; this is often overlooked by other methods. If we observe the strength of the signal between two fixed points indoors for multiple weeks and heavily filter it in order to remove high-frequency variability, we will not observe constant values as some methods predict. Real-world model-based approach

that can be used for longer periods (e.g. weeks, months) without interruptions must address this issue. Any indoor localization method that requires initial calibration usually does not adequately address this issue.

- *Awareness of the architectural aspects*
  By providing information about indoor wall placement, we can improve the accuracy of the method especially indoors, where room sizes differ substantially. This is important in the modern residential environments, where placement of the walls indoors is not uniform. This fact is often overlooked by indoor localization researchers as the majority of the localization methods are developed in the office environment of the research institutions, where offices are of approximately uniform size. Moreover, in the related work review we will see that non-negligible portion of the methods are evaluated only in hallways of the buildings and therefore do not provide any information on the localization accuracy in the rooms.

- *Applicability on widely available hardware*
  The usage of special and costly equipment limits the universality and applicability of the method. For that reason, we have decided, with the real-world usability in mind, to develop a method on affordable and widely available hardware. In the related work review, we will mention localization systems that use ceiling lights which emit high frequency information by modulating the light output; but such systems require considerable changes to the infrastructure of the building and specialized mobile terminals capable of detecting such information. We have therefore set strict hardware goals for mobile terminals; the method should be possible to implement on the simplest device connected to the wireless network. The most basic information about a wireless signal for a device is the signal strength and therefore this is the only requirement for the device during the development of our method. For the building's infrastructure, we have decided to use common access points available on the market.

These goals and prerequisites, combined with passion for research, led us on a research journey described in the following dissertation.

1.2 Scientific Contributions

The main scope of this work is a novel indoor localization method that is based on the physical propagation of the signal through space and includes information about wall placement and its effects on signal propagation. The proposed method constantly monitors the signal propagation through the indoor spaces and adapts the model according to the changes. Contributions of our work to the scientific community can be summarized as follows.

- *Novel calibration method for indoor WiFi-modeled approaches.*
  The method presented in this work exhibits self-calibration operability, meaning that it always monitors the propagation of the WiFi signal through space and adapts the localization model accordingly. Therefore, the method detects the changes in the signal propagation in space and adapts to the changed space dynamics while not requiring any additional hardware. This approach to the online estimation of the propagation parameters can be adapted to a number of other model-based approaches.

- *Novel self-adaptive model-based WiFi indoor localization method that accounts for architectural aspects of the building layout.*
  Using the developed calibration method, we can build an indoor localization method which can be used in real world. To our knowledge, this is the first WiFi-only indoor localization method that utilizes information about the architectural aspects, infers the parameters needed for the propagation simulation from measurements, continuously adapts to the indoor situation without human intervention, does not need any additional hardware beside the APs, and does not require mobile terminals to be in access-point mode [11]. The method has been proven in evaluations in single- and multi-room office scenarios as well as in a hallway and residential building.

- *MFAM: Multiple Frequency Adaptive Model-Based Indoor Localization Method.*
  During the development of our WiFi method [11], we have developed the model without any assumptions about the underlying wireless protocols or its frequencies. Therefore, in our further research, we have extended our WiFi method and applied it to 868 MHz frequency of the home automation system. Fusion localization data from both the frequencies and the evaluation in

residential environment resulted in one of the first multi-frequency adaptive model-based indoor localization methods. The method was developed without any assumptions about the frequencies and opens the possibility of adding more signal sources in the fusion process of indoor localization; it provides a method which considers accuracy at each individual frequency when fusing information to determine the accurate indoor location.

1.3 Dissertation overview

The aim of the research work, upon which this dissertation is written, is to develop a *widely-applicable real-world indoor localization method*. The research area of the indoor localization has lately received a lot of attention, as the IoT devices, which are an integral part of the smart homes and Industry 4.0, could benefit from knowing the position of themselves and the surrounding devices with which they communicate. The presented dissertation describes the research journey we have made during the development of a novel method; we are convinced that the method addresses many deficiencies of the other approaches, while closely following our goal of the universal indoor localization method.

Chapter 2 provides information on related work in the field of the indoor localization and provides some background information on technologies used. Although we utilize technologies used by our method daily, there are some key details needed for the understanding of our method.

Chapter 3 elaborates on the limitations of current approaches and how those influenced our design decisions during the development of the method. We will discuss in detail the long-term stability of the WiFi signals and continue with a discussion about methods that require a mobile terminal to transmit in contrast to the methods that receive data needed for localization. The emerging and future WiFi standards and the difficulties of the method comparison are also discussed. Chapter 3 concludes with an elaboration on the positive side effects of the inclusion of architectural information into the localization method.

Chapter 4 provides a detailed description of the developed method. Each stage of the development is described in detail, while the mathematical and physical backgrounds are discussed. Chapter 4 continues with the base evaluation in single-room and multi-room office environments. A more challenging evaluation in the residential environment follows; this is less common in the research area of the indoor localization. Finally, we present evaluation in hallway environment, which is less challenging, but unfortunately used many times in the research area of indoor localization. Chapter 4 concludes with the discussion and conclusions about the proposed WiFi method.

During the development of the method in Chapter 4, we have limited our method to the WiFi signals; therefore, in Chapter 5, we generalize the presented method in regard to other wireless signals. We present MFAM, Multiple Frequency Adaptive Model-Based Indoor Localization Method, which is one of the first such methods available. We describe in detail how we had to adapt the method to a wireless network of home automation system, which is completely different in comparison to WiFi. The evaluation of the home environment with results that hold a promising future for the method are presented, followed by the discussion and conclusions.

Chapter 6 provides some discussion which is related to both previous chapters - 4 and 5. It provides summarization of the results, comparison to the baseline methods and some further analysis of the results (e.g. comparison of the standard deviation, etc.).

Chapter 7 concludes the main part of the presented thesis, while emphasizing on the scientific contribution of the presented work. In the end, we also provide some directions that we consider as interesting starting points for future research.

In the appendix, the reader will find Chapter A with the source code of our implementation of the presented method written in Wolfram Mathematica language and Chapter B with the Slovenian summary of the thesis.

2

Related work and Background

Our knowledge and understanding of the work conducted by other researchers is the foundation for the development of a new method. The knowledge of the others' work enables us to build upon their discoveries and findings and at the same time the understanding of their work enables us to identify their shortcomings. With a profound knowledge of both, we can identify the research challenges that lead us to the development of new and original approaches.

The first section of this chapter contains a review of the related work on the indoor localization; we will start with a wider description of the methods and later present the WiFi-specific approaches. The second section presents WiFi and some details needed for the correct understanding of our method and the design decisions. The last section contains the description of a typical home automation system. We will need the understanding of such systems in the Chapter 5, where we generalize the WiFi method for the multi-frequency usage and apply it to a home automation system.

2.1 Indoor localization

Localization is "the process of making something local in character or restricting it to a particular place" [12]. The indoor localization is therefore the process of restricting objects to a particular place inside buildings; or, in other words, finding out the unknown location for an object indoors. This has been an open research problem for many years and many different approaches have already been proposed.

To present a wide range of the localization approaches, developed in the past years, the first subsections present a recent classification of the localization methods. The selected classification divides the methods based on the type of the primary algorithm used for the localization. The classification further subdivides the methods based on the measurement techniques. In order to present the diversity of the localization methods, we present the relevant examples for each classification in the Section 2.1.1. After the reader is intrigued by the diverse possibilities, we focus on the review of the WiFi-based methods in the Section 2.1.2. We discuss two different approaches one can take while developing a WiFi-based indoor localization method. We provide the relevant related work and discuss the advantages, the disadvantages and the accuracy of the presented methods.

2.1.1 Classification of the indoor localization methods

One of the latest reviews of the advances on the indoor localization has been done by Yassin et al. [7], who classified the localization methods as shown in Fig. 2.1. They divided the methods into three groups, based on the positioning algorithms used:

- *Triangulation algorithms* are based on the process of determining the location of a mobile terminal (MT) by forming triangles to it from the known access points (APs). They further divided these algorithms based on the measurement techniques to the *Lateration-* and *Angulation-based triangulation algorithms*. In the former sub-group of this classification, there are algorithms in which the estimation of the distance between MT and APs is used; in the latter the angles of the formed triangles are used for determining location.

- *Scene analysis algorithms* are based on a survey of the indoor spaces. The measurement technique for these methods is usually fingerprinting; this is an offline step during which the recordings of values of a specific property in multiple locations indoors have to be made. The usual practice is to build a virtual mesh and record values in all of the vertices. During localization, the stage measurements

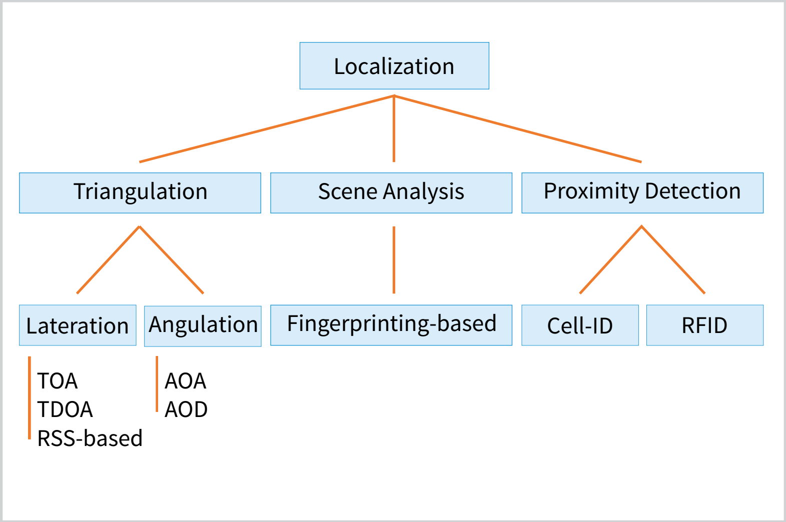


Figure 2.1
Classification of the localization methods [7].

from MT are compared to the recorded values and the location is estimated using the similarity.

- *Proximity detection algorithms* define the location by estimating the proximity to the known locations. Yassin et al. further divided this group based on the measurement techniques to *Cell-ID-* and *RFID-based proximity detection algorithms*.

Lateration-based triangulation algorithms usually work on the principles of Time of Arrival (ToA), Time Difference of Arrival (TDoA), Received Signal Strength (RSS) and Angle of Arrival/Departure (AoA/AoD). In outdoor scenarios, GNSSs usually leverage ToA and TDoA principles, e.g. Global Positioning System (GPS) [13]. One of the main challenges in such cases is time synchronization between the devices. In the GPS case, the atomic clocks inside the satellites keep all the satellite clocks synchronized, but the receivers still need to estimate this time with iterative estimations.

In the indoor localization research, attempts using ToA and TDoF have been made [14, 15]. Youssef et al. [15] evaluated their PinPoint system, running at 900 MHz FM radio waves, in the 130 m^2 indoor open area. They focus on ranging and not on position determination; therefore, their evaluation is aimed at determining the distance between one "log unit" (anchor point) and a test point. Their system achieved an average error of 1.2 m in the estimation of the distance with only 8 evaluation points in a single-room scenario. They comment that their worst result of approximately 5 m is "due to severe multipath environment" at that specific location. In cases where there was a more realistic distribution of walls in the setting, the effects of multipath would, by our opinion, become greater and therefore we could expect a worse result. Although a respectful average error in the distances between two specific points has been obtained, it is difficult to comment on the accuracy of the localization system implementing their distance estimation method. Priyantha et al. [14] have worked on the Cricket system, which provides the means for the infrastructure beacons to announce their location; they do not provide a full system evaluation in which the accuracy of the method could be inferred. The system utilizes ultrasound signals and therefore requires specialized hardware in mobile terminals.

RSS-based lateration algorithms usually estimate the location by modeling the propagation of the signal strength between APs and MT. The majority of the WiFi-modeled approaches can be classified in this category (a detailed description of these methods can be found in Section 2.1.2). We can find such approaches utilizing also other wireless technologies – e.g. the ultra-wideband (UWB) [16] and IEEE 802.15.4 [17] based technologies [18]. In the latter, the system consists of multiple wall-plugged sensor nodes, nodes which bridge IEEE 802.15.4, and Ethernet communications and active wireless tags, which must be attached to each tracked item. The system combines RSS based triangulation and round-trip time-of-flight measurements. Round-trip time-of-flight information can improve the accuracy of localization, but also introduces the need for the MT to emit data, which is not desirable, as is discussed later in the Section 3.2. Reported accuracy of 2.5 m has been obtained in rather simplistic evaluation environment, which is described as a "hallway". We discuss further on the effects of the evaluation environment in the Section 3.5. Yoon et al. [19] developed FM radio-based indoor localization method which models propagation of the signals through the indoor spaces. Leveraging FM infrastructure results in bigger distances between APs and MT, but as it has a more stable signal that WiFi [20], which in turn results in bigger error in localization than using WiFi. In [19], eight FM transistors were used at a distance between 2.1 km and 59.6 km, resulting in the accuracy of approximately 15 m. If the FM signals were aided by calibration and path matching algorithms, the reported error in localization was 6 m.

Angulation-based triangulation algorithms are less frequent in research publications on indoor localization, probably because more specialized hardware is usually required, which makes real-world deployments of such methods unrealistic. Such approaches usually require multiple directional-antennas, so that the angle of arrival or departure can be determined. Nevertheless, we can find some approaches, where multiple antenna requirement is substituted with other means. Niculescu et al. [21] mounted the antenna on a revolving platform and developed IEEE 802.11 based indoor localization system. It is easy to see that such approaches are not suitable for the modern smart devices, although they report an acceptable performance (2.1 m median error).

The measurement technique of the *scene analysis algorithms* is usually fingerprinting. Fingerprinting procedure is usually costly and undesirable in real-world deployments, as it takes a considerable amount of time and must be done repetitively. Many WiFi fingerprinting-based solutions have been proposed; they are discussed in Section 2.1.2. Chen et al. combined WiFi and FM radio fingerprinting in [20]. Although the absolute values of the average errors are not clearly shown, they report 83 % better accuracy when combining WiFi and FM in comparison to WiFi only. Their paper also touches upon an important fact of the WiFi fingerprinting methods; i.e. the temporal variations, which are discussed in 3.1. Non-WiFi solutions have also been proposed; they leverage television broadcast signals and cellular phone networks [22].

Although it is unclear how Yassin et al. [7] have meant to divide *Proximity detection algorithms* by using the measurement techniques, we will assume a wider perspective, meaning that Cell-ID stands for the techniques where MT defines its position by the unique identifications of the detected APs, and RFID stands for the techniques where APs scan and detect MTs in the vicinity. Another possibility is that Cell-ID stands for localization techniques that detect proximity of a GSM Cell ID [23–25]; a uniquely identifiable base transceiver station within GSM network, and RFID stands for the indoor localization methods utilizing radio-frequency identification technology [26–28]. Other solutions based on information transmitted by lights have been proposed and they can also be categorized in this group [29, 30].

There are also some approaches that can be classified as hybrids between different classifications. We have classified [29] in the last group, because its main contribution is light-based proximity detection, which calibrates attenuation-based RSS model. It uses Light-fidelity (Li-Fi) wireless network communication system which utilizes UV, infrared and near-ultraviolet light for communication. Researchers in [29] have mounted some Li-Fi lights in order to enable MT to detect proximity to a specific light source. When proximity is detected, the absolute position is known with relatively high accuracy, and propagation model can be recalibrated.

Lately there has been a lot of research into light- and vision-based indoor localization systems. For example, Pandey et al. [31] evaluated nine points in the space of $9\,\mathrm{m}^2$, utilizing six additional devices and obtained $0.3\,\mathrm{m}$ average error. RF based method cannot achieve such accuracy in real world setting. Even greater accuracy is presented by Ma et al. [32], who developed system with average error of $1.7\,\mathrm{mm}$ when localizing 56 points in $1\,\mathrm{m}^2$. Their system cannot be efficiently scaled, as it requires a projector projecting images above the evaluation space. These systems provide great accuracy, although they are not viable candidate for wide deployments.

This concludes a wide overview of the indoor localization principles which we will continue by examining the WiFi-specific approaches.

2.1.2 WiFi indoor localization methods

When developing a real-world solution with the intention of wide applicability, the price of deployment is always an important factor. In the deployment scenarios we are always trying to use affordable technologies. It is even better if the existing infrastructure can be leveraged to provide localization. While the building's infrastructure is usually in the domain of people deploying solution, we cannot say the same for the other end of the system – the mobile terminal. Especially in public locations, where we want to offer the visitors the means of the indoor localization (e.g. shopping centers, museums, parking garages, etc.), we usually do not have control of the capabilities of the MTs.

That is why it is not strange that many different approaches of indoor localization that have been researched utilize the WiFi signals. The WiFi infrastructure is widely available in the residential and business buildings and the majority of indoor locations nowadays have WiFi coverage. From the user's perspective, the majority of smart devices nowadays have the WiFi connectivity options, making the WiFi-based localization accessible to public without any significant investment in new technologies. There have been plenty of survey papers written on the indoor positioning systems, some focus on WiFi, others are more general but include WiFi approaches [7–9, 27, 33].

The WiFi localization approaches usually do not follow the naming in the classification by [7] discussed previously, which is meant for the general indoor localization techniques. We have mentioned the approaches that use WiFi during the discussion of *Fingerprinting Scene Analysis* and *RSS Lateration Triangulation-based approaches*. These two sub-classifications are in the context of WiFi approaches usually named *Fingerprinting-* and *Model-based methods*.

The following two subsections will discuss the methods and approaches to the indoor WiFi localization with the emphasis on presenting many diverse approaches and their recent successes.

Fingerprinting-based WiFi methods

The fingerprinting localization methods consist of an offline stage in which the survey of the RSS in the area of interest has to be performed. In the localization stage, the algorithms would search for the best match in the database or interpolate data from the database and estimate the location. The researchers analyzing different wireless signals for indoor localization agree that due to the temporal changes in the WiFi signal [34] emitted by the APs, no parameter calculated from the measurements can be assumed as fixed [10, 35].

One of the first attempts at RF indoor localization was by Microsoft Research team as described in [36, 37]. They explored a simple fingerprinting method while at the same time also tried to build a modeled approach. Their fingerprinting method has achieved "room level accuracy" [37], with median errors of approximately 3 m. Their attempt at a model-based method had worse results and was heavily influenced by the fingerprinting method, as propagation model is built upon it.

There have been many attempts at simplifying or easing the requirement of the fingerprinting procedure. The research done by Chan, Chiang et al. [38] shows a simple fingerprinting algorithm which was improved by utilizing clusters of mobile terminals. Nodes inside the cluster are located with the fingerprinting algorithm; the knowledge about the clusters of mobile terminals, by coincidence discovered by ZigBee, is then used to collaboratively correct the error of the algorithm in the location estimation. Authors report the best-case accuracy of 2.6 m, when peers collaborate, and 3.5 m, when there is no collaboration. Results show a great benefit of using additional signals, although ad-hoc collaboration, as described in the research, requires MT to be able to communicate via ZigBee, which is nowadays not regularly available in mobile phones and other connected devices.

A similar approach is the one done by Kim et al. [39]. They used anonymous mobile users to automatically collect fingerprinting data, while tracking their location via inertial sensors, and to progressively build a radio map on the server. The questions about time frame of the collected fingerprints arise in such approaches. The WiFi signal exaggerates variability in the time domain, as is further discussed in Section 3.1. Therefore, only fingerprints collected in the short time period, before the localization occurs, can be considered for providing long-term accurate results. We must consider these approaches as not best-fitted for real-world application, because they utilize many subjects (i.e. the crowd) to build a RSS map. This is also not simple to achieve in many situations, where there are not many subjects in the area of interest – e.g. home/residential environment and industry applications. The reported accuracy of approximately 6 m is worse in comparison to the previously discussed methods. Our method uses online calibration approach to eliminate the need for the user's intervention when re-calibrating.

Such collaborative approaches assume that mobile terminals are willing to collaborate in the localization process. In real-world battery-powered devices at least the energy-related concern arises, as such collaborative work will have an impact on the battery. In the recent years when privacy is a great concern, collaboration-based localization methods also raise questions about the privacy of specific nodes. Lately, there has been also a lot of research effort put into optimizing the fingerprinting process as can be seen in [40, 41].

Recently, the solutions that fuse data from inertial measurement units (IMU) and the WiFi localization systems became a popular topic in the research of indoor localization. IMUs have become affordable and therefore the manufacturers of mobile devices (e.g. phones, tablets, etc.) have started to implement them, which in term increased the interest of the research community into exploring their potential. A typical IMU consists of a multi-axis accelerometer, a gyroscope and a magnetometer. For example, the work, done by Alvarez, Alonso and Trivino [42], proposes the activity recognition system that uses WiFi-based location system, combined with accelerometers for the body posture recognition. Their WiFi localization system is using a fuzzy-rule-based classifier that was generated on a training set obtained by fingerprinting the environment. Deng [43] exploits the fusion of IMU data and the WiFi location service that is based on fingerprinting, by using the extended Kalman filter in the data fusion process. As we would like to define the localization approach that would suite the future of IoT, this is not the best solution. The majority of proposed IoT devices are not handheld and therefore we cannot acquire useful information from the IMU sensors.

The works done by Wu, et al. [44, 45] show that the channel state information (CSI) can be more accurate and stable than RSS. Their work emphasizes the problem of defining the path loss (fading) exponent and other environmental parameters. Their research defines the path loss exponent in a per-AP manner. It can be seen that the definition of variables in the propagation model is one of the greatest difficulties of the modeled approaches. We are convinced that the model used in the real environment should adapt these variables to the changes in the setting, as people and other present WiFi devices all have an influence on the wireless signal propagation, due to interferences, scattering, reflections, etc. Thus, our research is devoted to defining these values in an online manner and without human intervention. Regarding the utilization of information about WiFi, other than RSS (e.g. CSI, SNR), we are devoted to developing the methods which can be used on every simple WiFi-connected device; in some devices, information other than indication of RSS is difficult to obtain – e.g. Android, which is one of the biggest mobile platforms, gives only information about RSS through the provided API [46].

There are some approaches that exhibit the properties of fingerprinting and model-based approaches; the authors of [47, 48] present an approach where advanced modeling is used to simplify the requirement of fingerprinting in comparison to the classical methods. Fingerprinting in corridors of a building is used to obtain the training data, which is later used in complex Support Vector Regression based algorithm that predicts RSS in non-surveyed positions indoors. The impressive accuracy of 1.66 m is reported in [47]. The method does not address the problems of the variable WiFi signal in the real-world environment (as will be discussed in Section 3.1). Because the method does not implement the procedures to adapt to such changes, we can assume that for a long-term period the accurate positioning fingerprinting has to be redone; this is also the reason for classifying this method in this category. Similar approach by SVM usage can be found in [49], although only used for classification of locations and not exact indoor localization.

Model-based WiFi methods

The model-based approaches try to mathematically define the propagation of the wireless signal; therefore, these methods are usually mathematically more complex. On the other hand, the model-based methods try to eliminate the biggest deficiency of the fingerprinting methods – i.e. the required and frequent fingerprinting procedure in order to maintain the long-term accuracy. Sometimes it is difficult to draw the line between the fingerprinting methods and model-based methods, as some methods utilize both approaches (e.g. [44]). Usually such methods utilize the fingerprinting in the offline phase and then utilize a more advanced model approach in the localization phase instead of a simple interpolation for the localization.

We could say that the model-based approaches that use only WiFi RSS to determine the location had to be developed for the cases where we do not have access to any other sensors and the training sets cannot be obtained. Thus, it is not surprising that there was a significant research effort put into the localization of specific APs in a non-surveyed environment. These methods can be used for discovering the attacks on the wireless networks and for discovering the WiFi jammers. The works done by Cai et al. [50] and Chen et al. [51] try to provide the methods for efficient localization and detection of the malicious APs. The authors in [50] have performed an evaluation only in the virtual environment and do not report on the median or average accuracies, while the authors of [51] report on a 3 m median error in determining the position of the malicious AP. A similar approach is taken by Koo and Cha [52] in effort to develop the WiFi localization scheme. The results from these publications show that it is possible to build a model-based localization technique even when the access point we want to localize does not cooperate with the localization procedure. The case that is addressed during our research work is different, as both the mobile terminal and the infrastructure share a common goal in determining the location of the mobile terminal. We are convinced that the results obtained from our joint effort can surpass these approaches.

Bisio et al. [53] proposed a method in which the propagation map is not defined by the means of a space sampling, but instead on the pure physical models of the finite-difference time-domain simulations. In this approach, the effects of the other devices and movable objects were not properly addressed, meaning that this method can be problematic in real-world situations. Olivera et al. [54] used a probabilistic-based method to determine the position of the robot on a WiFi map. Former authors chose the modeled approach, based on the radio propagation model. They emphasize the selection of correct values for the parameters of the model; we cannot stress enough the importance of determining the correct path loss exponent and other constants inside the models. Many different approaches are taken to obtain the correct values. As is the case with the fingerprinting methods, also in the modeled approaches there was research done to utilize the anonymous crowd for getting the samples. In the work done by Zhuang et al. [55], these values are used to calculate the parameters of the WiFi propagation model. Our proposed method has one similarity with [53] - our method also builds a map of the model-predicted RSS on the server, but in contrast to [54] and [55], we have proposed an online calibration procedure that is able to cover the real-world dynamics of the indoor space, as the parameters can be determined on the fly.

As we have seen in the previous section, some research is devoted to identifying the improved metric over RSS. Francisco and Martin [56] propose their own metric for the characterizing radio signal space for the wireless device localization. As said before, information about RSS is available on all devices, which cannot be said for other properties of the wireless signals. The choice of other-than-RSS information therefore limits the applicability of the method on the available hardware.

In the research area of the modeled approaches, we can find the use of other sensors to augment the WiFi localization data in an effort to provide even better results. The work done by Zampella et al. [57] provides the fusion-based approach, where the model-based WiFi location extracted from RSS and time-of-flight (ToF) data is fused with the data from the IMU sensors. Their algorithms were modeled separately for different walking styles as it was calibrated on per-user basis. The authors are aware that the use of their system in real-world deployments is problematic, since a time-consuming calibration was done for each user, mobile terminal and AP separately. On the other hand, Chiou et al. [58] used the Kalman filter to fuse data from the WiFi propagation model and the measurements of SNR data to obtain location information. This approach also uses additional hardware – reference points (WiFi tags) to build infrastructure for the localization system. The indoor localization approach taken by Stubing [59] requires additional hardware – WiFi transponders. This is ideal for his use case; he was developing a trauma-center WiFi real-time patient and personal tracking. These solutions are not ideal for the generic solution we want to propose. Fusion systems also enable us to fuse multiple types of signal indicators as was done in [60]. Their fusion model is based on the adaptive Kalman filtering, which uses RSS, power ratio, SNR and velocity data from mobile terminal as input. They are aware that the constant velocity model is not the best choice, as it could be improved with the usage of the accelerometer. Fusion systems demand some other source of data rather than the WiFi signal. We are trying to avoid additional hardware, demanded by other data sources, to build a reliable WiFi-only system for the IoT. This system can be later improved and built-upon with the help of other sensors and data fusion for the specific localization case.

The approaches that usually leverage the knowledge about architectural aspects of the indoor spaces are the ray-tracing methods. The ray-tracing methods can be considered a sub-group of the model-based approaches, because they focus on the directions, reflections and power propagation of the signals emitted from the WiFi-enabled devices. These approaches are usually computationally complex, because they calculate the signal strengths at specific points due to the direct and reflected paths. Examples of such approaches can be found in [61, 62]. Some other research works also present the approaches aware of the indoor setting. An example of such a work can be found in [63], where the possible transitions between the rooms are included into the location determination, although this work addresses only the determination of the room and not the exact location.

The first of the four works that are closely related to our work was submitted by Tarrio et al. [64]. Their view on the localization is heavily influenced by the consideration of real-world deployment limitations; their goal is to minimize the calibration procedures while improving the accuracy of localization. They propose the positioning algorithm to calculate the position of a mobile node in an ad hoc network from a set of the distance estimations to the anchor nodes. They model the propagation of the signal via free-space path loss antenna attenuation; the localization method is based on finding the location with the least square error of the calculated (modeled) and measured RSSI. Their work does not provide clear answer about how the described calibration procedure can be used in multiple environments, without a time-consuming setup phase. They only provide a recommendation for the parameters to be experimentally determined. Our approach has an online real-time calibration procedure defined, as we are calculating the model parameters from the readings of the signal properties between APs and the architectural map of the building, translated into the network data structure.

A paper by Xiao et al. [65] presents the deployment of the machine learning techniques to a non-line-of-sight WiFi modeling. They propose multiple algorithms to the problems of a non-line-of-sight identification and localization which use the WiFi RSS measurements only. They claim that their solution is robust and can be trained in one environment and then utilized in another, which makes the solution generic. Xiao et al. used the machine-learning techniques, including the classifiers and support vector machines, to determine the model based on a collection of measured RSS signals. One could argue that this is a fingerprint-based approach, but the training samples are used to build sophisticated mathematical models for localization. They agree that the proposed method has limitations, due to the costly training phase in which data must be acquired for the machine learning process to consume.

The third core paper that corresponds to our research is written by Durmont and Corff [66]. They emphasize the environmental dynamic and the problems of models which often overlook these. The algorithm is run online and does not require any offline calibration procedure. The propagation maps are estimated online, using the data sent by the mobile device. We are also trying to capture the environmental dynamic, by having an online algorithm that would not require an offline calibration procedure. Our work does not estimate the parameters only by analyzing the data sent by the mobile device, but also by analyzing the signals emitted by APs and captured by other APs. This is the only approach so far that enables the technique to easily adapt to the changes indoors and can be therefore easily transferred into real-world situations.

Last but not least is a paper written by Du, Yang and Xiu [67]. Their approach is to modify the AP firmware to provide a scanning feature to the APs. Therefore, a specific AP does not only provide wireless connectivity to other mobile devices, but also scans the neighborhood for the beacons sent by other APs. Our method is based on similar firmware changes, although the details of the changed firmware differ. They use the WiFi anchors with a known position to build the propagation models which are then used to build fingerprint maps. The parameters of the model are based on the analysis of the uplink traffic from the WiFi anchors to APs. If our approach is translated into context of Xiu et al., in our setting, every access point becomes an anchor and a receiver of the signal at the same time. If the infrastructure has 4 APs and one anchor, their approach has ideally 4 measurements to infer the parameters of propagation; our approach would have in the same setting (5 devices) up to 20 measurements from which the parameters could be determined.

The last four papers (i.e. [64], [65], [66] and [67]) are closely related to our work, as they use only the WiFi signals for building models which are then used for the location estimation. The majority of these papers and many other papers in this section do not have calibration- and maintenance-free methods for keeping up with the dynamic of the space in which the localization method is deployed. Our approach modifies the firmware of the APs to expose the advanced features (already provided and used by APs); levering these features, we can detect signals from other APs on a selected AP. Therefore, we can acquire multiple measurements of the signal propagation and by knowing the position of each AP, we can calculate the propagation parameters for a specific environment. These data can then be averaged over some period of time if our future experiments will show the usefulness of such approach.

In order to provide a valid comparison between the methods, they must be evaluated in similar conditions. Therefore, we present Table 2.1 in which we review the selected WiFi methods, with the emphasis on the evaluation environment and reported accuracy. In the table in column “Evaluation environment description”, the keyword “hallway” means that the majority or even all evaluation points were positioned in the hallways. If the evaluation environment is denoted as “hallway”, we do not provide the size of the indoor area, but rather combine the length of the hallways. The majority of the methods marked “hallway” were not evaluated in one straight hallway, but rather in a mesh of hallways in the building. From the table, we can see that many authors evaluate their methods in a rather simplistic environment, sometimes consist-

Table 2.1

The review of the selected WiFi-based related methods. A line in the table denotes a split between modeled and fingerprinting approaches by our criteria.

Method	Evaluation environment description	Number of infrastructural devices [a]	Approximate average accuracy [m]
Padmanabhan [37]	125 m, hallway	3	2.94
Chan [38]	300 m^2	11	2-3 [b]
Kim [39]	3600 m^2	70[c]	6.9
Deng [43]	40 m, hallway	8	2.8 [d]
Wu [44]	30 m, hallway	3	1
Bisio [53]	72 m^2, single-room	5	2.3
Olivera [54] [e]	100 m, hallway	3	2
Zhuang [55]	250 m, hallway	7	4 [f]
Zampella [57]	90 m, hallway	4	5.5 [g]
Chiou [58] [h]	80 m, hallway	4	1
Eleryan [61]	65 m^2, single room [i]	4	3
Ji [62]	140 m, hallway	5	3 [j]
Lim [34]	600 m^2	8	2.9
Tarrio [64]	100 m^2	4	3.1 [k]
Xiao [65]	60 m, hallway	3	2.41 [l]
Dumont [66]	400 m^2	10	4
Du [67]	120 m, hallway	7	2.4 [m]

[a] These devices include all the devices needed for the system to operate: APs, anchors, sniffers, etc.
[b] Heavily depends of the number of clusters, discovered by coincidence via ZigBee.
[c] Estimated by 40 needed paths and 5-25 detected APs indoors, could be much more.
[d] Reported value is for the WiFi method, below 1 m, in case we use IMU sensors.
[e] Fusion approach; method utilizes also odometry data from the robot they are trying to localize.
[f] Accuracy heavily depends on the crowd-based survey; 90 min is needed for the accuracy of 4 m.
[g] Reported value is for the WiFi method if assisted with IMU; values below 1 m are reported.
[h] Time-consuming setup stage, based on which, one could argue this is a fingerprinting method.
[i] Evaluated in a residential environment.
[j] Reported for a stationary case which is similar as ours.
[k] Reported value is for the WiFi method, 2.7 m in the case of Bluetooth, 2 m in the case of WSN.
[l] When evaluating in independent environment (section "Validation"); based only on 8 evaluation points.
[m] Accuracy depends on a number of anchors; the value in the table is the best reported value using 4 anchors.

ing of only hallways in the buildings. Sometimes, it is also difficult to understand the evaluation procedure and the map of the indoor spaces, as authors tend to give little information on the evaluation environment.

2.2 WiFi

WiFi (also written as Wi-Fi) is a wireless local area technology for the devices based on IEEE 802.11 [68] standard. The trademark Wi-Fi is owned by the Wi-Fi alliance, meaning that they test and approve the devices to be labeled as "Wi-Fi Certified". In terms of OSI model IEEE 802.11, the standard defines Layer 1 (Physical layer – PHY) and media access control (MAC), which is part of Layer 2.

The most known and used protocols of IEEE 802.11 are 802.11b, 802.11g, 802.11n and 802.11ac. The first two utilize 2.4 GHz frequency, the last one utilizes 5 GHz, while 802.11n primarily utilizes 2.4 GHz, but can optionally be used also in the 5 GHz mode.

Although WiFi is a widely used technology, there are some details that are not widely known. This chapter provides information which improves the understanding of the work presented in this dissertation.

2.2.1 RSS vs. RSSI

Received Signal Strength (RSS) is the measurement of the physical property of power in the received radio signal, while RSSI stands for *RSS Indicator* and is defined by IEEE 802.11 standard [68]. Mobile devices and radio frequency (RF) front ends in them usually do not implement the precise measuring of RSS information in milliwatts. 802.11 standard defines RSSI as a value between 0 and 255 (Table 15-2, page 2226 in [68]). The exact definition can be found in section 15.2.3.3, p. 2227: "This parameter is a measure by the PHY of the energy observed at the antenna used to receive the current PPDU. RSSI shall be measured during the reception of the PHY preamble. RSSI is intended to be used in a relative manner, and it shall be a monotonically increasing function of the received power." [68]. PHY stands for a physical layer and PPDU stands for "physical layer protocol data unit". In simpler terms, PPDU is the currently received Layer 1 frame and RSSI, defined by standard, is an unsigned 8-bit value, indicating its RSS. PPDU datagram is divided into:

- *PHY Preamble* which is used for the synchronization of the receivers and is usually 144 bits long (shorter preambles exist in different extensions of the physical layer, described in sections 15. to 22. of the [68]);

- *PHY Header* which contains different fields needed for a successful Layer 1 transition (e.g. modulation specification, time needed to transmit MPDU, CRC fields) and is usually 48 bits;
- *MPDU* (MAC protocol data unit) which is Layer 2 802.11 frame that contains MAC addresses, higher level datagrams, etc. and can be up to 2304 bytes long (without encryption). More often it is around 1500 bytes, as most of the traffic in the WiFi network is downstream, and usually Ethernet 2 connects the upstream networks with the selected WiFi network.

As we can see, the RSSI value is estimated from less than approximately 1 % of the received data which is at the start of every fragment. Another problem in practice is also that manufactures can define their own "maximum RSSI value", as can be seen in [69]. For example, Cisco System WiFi chips define 100 as maximum value, Atheros-based cards use 127, while some higher values may even mark error states [69]. As can be seen, the chip-manufacturers define their own range of values and the relationship between RSS and RSSI.

Usually we cannot access information of per-packet-RSSI on the scale 0 to 255. Everyone who has observed RSSI information on a device in practice knows that the usual data reported to the end user is presented as the integer values, usually between -100 and -40, which would suggest the dB scale. 802.11 standard defines the abstraction of link to the higher layer entities through the management entities. The abstraction of MAC Layer is called MLME and provides two separate values, called DataFrameRSSI and BeaconFrameRSSI, which, by standard "hold RSS value in dBm" of the Beacon and Data frames respectively. The standard also warns (Table 6-7 p. 605): "This may be time averaged over recent history by a vendor-specific smoothing function" [68]. In the standard there is no definition about how 0 to 255 values are averaged and scaled into these values.

Everyone who has observed RSSI information on a device in practice knows that RSSI information usually changes rather slowly. Knowing that information from the previous paragraph, we could assume that something like a sliding window average is used. We also must not forget the next layer in the stack – the operating system (OS) of a modern device which provides interface between the programs running on a device and the WiFi module. In close-sourced OSs it is unlikely we will get to know its impact, but in open-sourced OSs we can check the source. For example, checking the Android's source code reveals in `wifi/java/android/net/wifi/WifiStateMachine.java` that the polling interval for RSSI is 3000 ms [70]; therefore, it is not possible to get finer-grained information about RSSI on a standard Android device.

To sum up - RSSI information from two different devices are hardly comparable, because the absolute values depend on the hardware of the RF front end, firmware and OS. It is reasonable to expect that the values from two devices that have the same hardware, firmware and operating system can be compared. Methods that use RSSI information at MT and do not address this issue cannot be considered for real-world deployments, because two different devices can sample completely different values in the same position just due to their hardware and firmware.

The problems we pointed at in this section are rarely properly addressed in the field of the indoor WiFi localization. We have developed our system with these facts in mind; in Section 4.2 we present the development of the method and how we have addressed these issues.

2.2.2 *Beacon frame*

The beacon frame is one of the management frames, emitted by APs or devices in the ad-hoc WiFi network that announces the presence of a device, provides information on capabilities of a device and instructs any receiving device on how to connect to it if desired. The beacon frames are by default emitted approximately every 100 ms. The packets are sent to the broadcast Layer 2 address. We will be utilizing RSSI information of the beacon packets to build our self-calibration procedure.

2.3 *Home Automation Systems*

More and more people, while yearning for the smart homes of the IoT, install different automation systems in their homes. These systems usually rely on a wireless communication protocol other that the WiFi, due to its high-power demands. The frequency spectrum is regulated by the International Telecommunication Union (ITU) and local governments, therefore frequencies used in the home automation systems differ by the region. Many lighting solutions utilize the ZigBee Light Link standard [71] (e.g. Philips Hue, Osram Lightify, etc.), which uses a 2.4 to 2.5 GHz band. This band, by

ITU specification [72], should be available worldwide without any additional restrictions imposed by the local governments. Many heating and security solutions usually utilize protocols on lower frequencies to avoid interference with the frequency-crowded 2.4 to 2.5 GHz spectrum. The Danfoss Living system utilizes z-wave protocol which in North and South America operates on the 902 to 928 MHz "Industrial, Scientific and Medical" (ISM) radio bands, while in Europe it utilizes the short range device band - SRD860 (863 to 870 MHz) specified by ECC Recommendation 70-03 [73]. Honeywell's Evohome and eQ-3's HomeMatic are two separate automations systems sold only in Europe, which communicate via their custom protocols on SRD860 bands.

S. Laufer and C. Mallas [74] reverse engineered parts of the HomeMatic wireless protocol, while trying to execute an attack on it. Their work is significant for our research because they showed detailed information of the protocol used by HomeMatic devices and later developed the open source solution Homegear [75] which enables the interaction with HomeMatic devices via the appropriate receiver, connected to the computer.

WiFi networks and networks of home automation systems differ – WiFi networks are usually part of a bigger network that consists of multiple devices – computers, servers, mobile devices, APs, etc. All devices are usually connected by the IPv4/IPv6 protocol; therefore, each device is available from the server on which the localization algorithms are running. Home automation systems usually consist of multiple devices, which communicate over some proprietary protocol; only one device is usually connected to the IP network and acts as a gateway or a base station. Usually, only this device is addressable from the localization server over the IP protocol. The described properties of the home automation system influenced the implementation of our proposed localization method to a home automation network described in Chapter 5.

3

Limitations of current approaches

In order to successfully develop a novel indoor localization approach that would challenge the existing approaches, one must firstly carefully study the field and know the technology used thoroughly. Then one can contribute to the scientific field, by addressing the weaknesses of the existing approaches. This chapter will present our research and findings on the variability of the WiFi signal and discuss the decisions that have later influenced our work.

3.1 Long term stability of the WiFi signal

RSSI of the WiFi signal is known to have high variability [42, 66, 69], which in terms means that we have difficulties achieving higher accuracy localization. In order to further inspect the stability of the WiFi signal in real-world environment, we have designed a long-term experiment. In our offices, which are described in Section 4.3.2, we have set up multiple access points. For 8 weeks we have periodically (i.e. every minute) connected to each AP and recorded the reported RSSI of the neighboring APs. The APs were running DD-WRT operating system with default configuration settings. The only changed settings were settings of the network configuration (ip, mask, gateway) and the wireless SSID and password. The DD-WRT does not support dynamic transmitting (TX) power adaption; the power was left at default value of 71 mW. APs were operating in a mixed 802.11b/g mode and have had default value

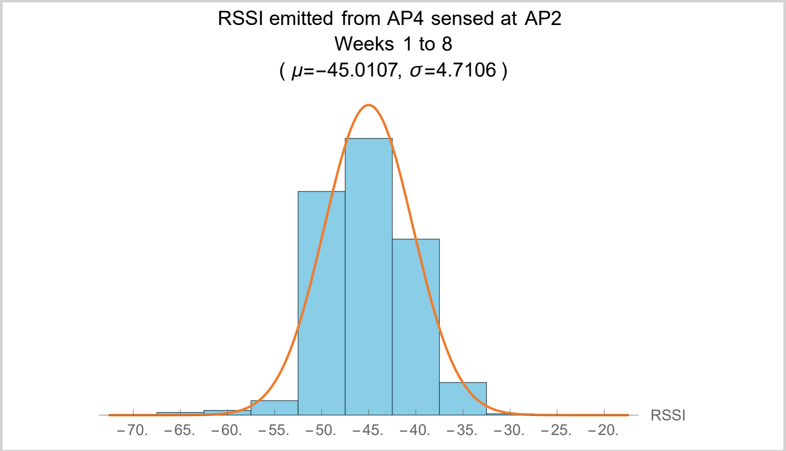


Figure 3.1

Histogram of the sensed RSSI values with the corresponding normal distribution function.

for the interval of beacon packets - 100 ms.

Selecting a pair of APs and analyzing the distribution of the measured RSSIs between the two could lead to wrong results of the propagation model if the propagation parameters were inferred from these measurements, because one had to assume that propagation parameters are static, which is not true, as can be seen in [10]. Figure 3.1 shows a histogram of our captured RSSI between AP4 and AP2 as defined in Section 4.3.2. We have fitted the data to a normal distribution function and obtained an average value $\mu = -45$ dB and a standard deviation $\sigma = 4.71$. The access points were 9.06 m apart. This in terms means that we can expect 68 % of the measured values between −49.7 dB and −40.3 dB.

Many model-based approaches define the propagation parameters as static inputs to the methods. These values are usually defined based on other's research or by the measurements in the environment. The usual starting point, when developing a path-loss based indoor localization method, is the free-space path loss propagation model, expressed by the equation (3.1) – e.g. [36, 58, 62, 76, 77].

$$PL = PL_0 + 10\gamma \log_{10} \frac{d}{d_0} + \Delta \tag{3.1}$$

In the equation above PL stands for the total path loss at the distance d, PL_0 is the total path loss at the distance d_0, γ is the path loss exponent and Δ is the Gaussian random variable with zero mean accounting for variations of the mean and is often referred to as shadow fading [67]. The path loss exponent γ equals 2 for the free-space (line-of-sight, no nearby obstacles) propagation. The path loss exponent could be smaller than 2 in environments where there is a line-of-sight between the emitter and the receiver and the shape of the room acts as a waveguide (e.g. tunnels, long narrow hallways, etc.). In the environments, where signal is heavily obstructed, the indoors values are typically in range of 4 to 6 ([78], Tbl. 4.7.2).

Using (3.1) we can see a great variability of the RSSI results in the big differences in estimated distances. If we select the value of $\gamma = 2$, we can see that RSSI values between −49.7 dB and −40.3 dB could result in distances 9 ± 4.5 m. If we use higher real-world indoor values, the range of the interval becomes smaller – down to ±1 m. We must not forget that also in the real-world indoor situations the rooms where $\gamma < 2$ could occur, the interval becomes even greater [78].

As we can see, RSSI information exhibits high variation which becomes even more

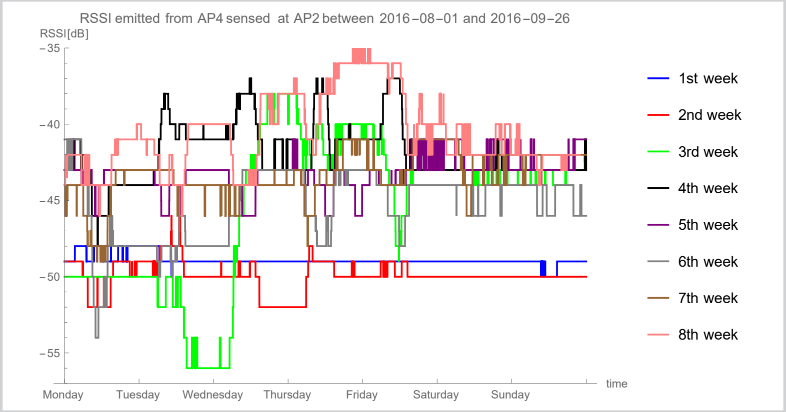


Figure 3.2

RSSI values in the course of 8 weeks, plotted by every week.

important if we set the values in the context of the distances and average room sizes (mind that these values are only for $\pm 1\sigma$ range).

Returning back to our 8-week experiment, plotting the RSSI values with the median filter of 2 hours in relationship to time, results in Fig. 3.2. We can see that even with the heavy filtering of the signal, it stills shows great variance in the course of eight weeks.

There are two plots with seemingly much more stable values (weeks 1 and 2). The explanation for these two "abnormalities" can be found in the fact that these two weeks, the majority of the employees in our laboratory had time off and was not present. More interestingly, we can observe the lower values for these 2 weeks, which in the end means a worse received signal strength.

Two plots with the most variable data during these weeks were identified as data plots of week 3 and week 8. A plot similar to Fig. 3.2, but with isolated data for these two weeks, can be found in Fig. 3.3. A wide range of the values from week 3 can be quickly identified (mind that the y-range of the Figs. 3.2 and 3.3 is the same). The filtered values range from −56 dB to −38 dB, while the unfiltered values are in the range of −90 dB to −29 dB. From Fig. 3.2 we can also identify that although the variability of the whole week's data is high, we can identify 3 to 6 regions when the signal was approximately stable; similarly can be said for the data in week 8.

To analyze the measurements on the week-by-week basis, we have made a similar

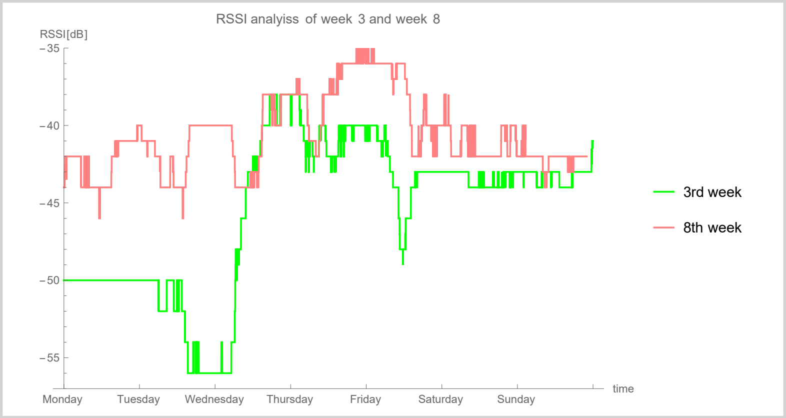


Figure 3.3

Analysis of week 3 and week 8.

histogram as in Fig. 3.1, but on weekly basis, which can be seen in Fig. 3.4. We can see that although we are using the unfiltered data and we are still on the weekly time scale, RSSI is more stable if compared to Fig. 3.1 (i.e. standard deviation of the distribution of variable is smaller).

These findings affect the fingerprinting methods, because we can see that the changes in the average RSSI between the two fixed points change on hourly basis. These changes are difficult to measure manually and the fingerprinting database often cannot be updated in such short time periods. This means that the fingerprinting approaches can be deployed and evaluated immediately after with respective accuracy, but in the long term the evaluation results will often worsen.

This section clearly shows that the parameters of propagation change over time. The awareness that RSSI between two fixed values changes due to a natural distribution of the RSSI with $\sigma \neq 0$ can be found in most of modeled approaches. On the contrary, there are only a few authors who properly address the issue of changing μ in time, as is emphasized in [10] and proven by our observations.

While developing a modeled approach, we will implement a *self-adaptive* procedure that will constantly monitor RSSIs between AP and adapt the model to changes, therefore addressing the issue of this section. Furthermore, only the measurements of RSSI between APs in a fixed amount of time, before the localization occurs, will affect the model. All older measurements will be disregarded and will not affect the

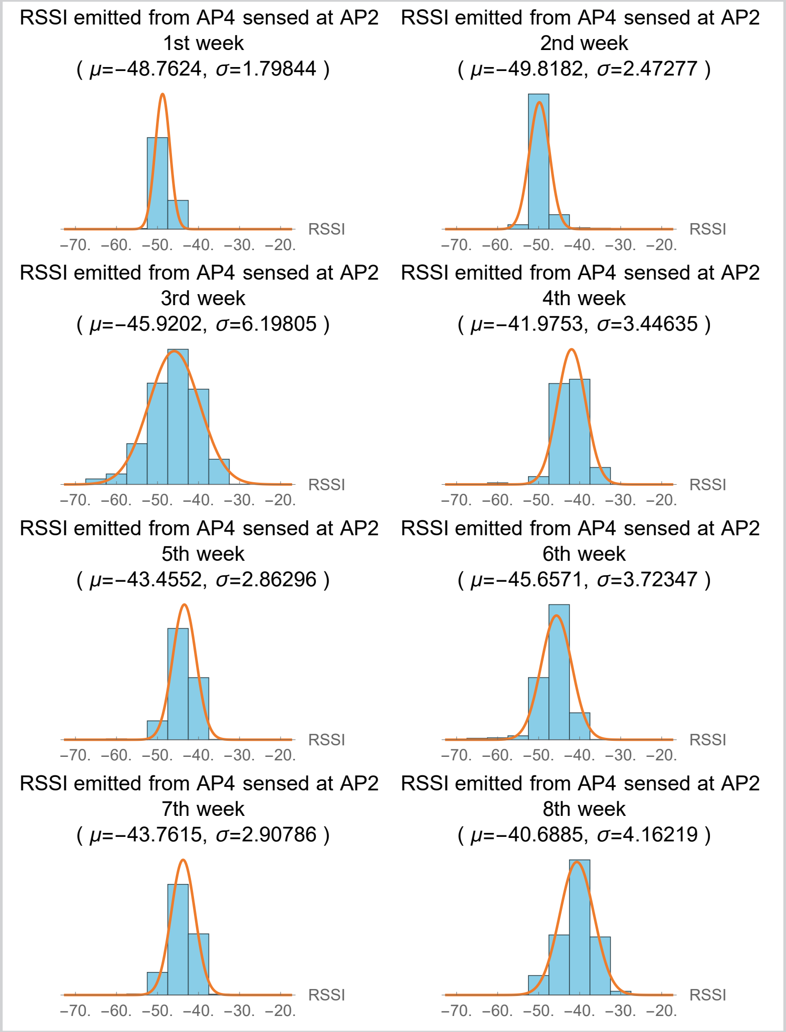


Figure 3.4

Histograms and the corresponding normal distributions for each of the 8 weeks.

model; therefore, the localization approach will not include any predetermined/fixed propagation parameters.

3.2 Rx vs. Tx methods

In telecommunications abbreviations Rx and Tx stand for reception and transmission respectively. When designing an indoor localization approach based on RSSI, regardless of it being fingerprinting- or model-based, we must decide if MT will be localized via its received or transmitted signals. Both approaches have their strengths and weaknesses which are briefly described in this section.

Rx-based systems usually consist of:

- APs which are at known positions and emit signals,
- MT at an unknown location and analyze incoming information from the APs (determining RSSI).

We have already mentioned one huge disadvantage of the Rx-based methods – the receivers and the software API implementations in different MT differ (section 2.2). The fingerprinting methods are usually Rx-based and this disadvantage is often left unaddressed by the authors. If the device used to calibrate the fingerprinting method and the device we want to localize differ, the values are not comparable in absolute terms. Therefore, the implementation of the search in the database of fingerprints cannot be trivial. The advantage of the Rx-based methods is that bigger deployments can be achieved, as the devices are not transmitting data and therefore not using the bandwidth. Similarly, GPS and other GNSS do not transmit any data, but only receive information from the satellites. We can imagine the technical challenge we would face today if the designers of the GPS would develop a Tx-based solution – billions of devices would try to use the narrow bandwidth in the device-to–satellite communication protocol in order to obtain the localization, not to mention the power requirements for the transmission of the signal.

Tx-based systems usually consist of:

- MT at an unknown location, emitting signals,
- APs at known positions, analyzing the traffic from the MT.

Tx-based methods have several real-world-deployment disadvantages; firstly, they take up the bandwidth as described. Secondly, nowadays, when the battery capacity is still limited for portable devices, the transmission process takes considerably more power than the reception. Their advantage is that simpler algorithms can be made - when we transmit a signal to localize a device, we have one common source of the signal which has fixed, yet unknown power. This is interesting for solving a system of propagation equations, where the originating point has constant power across propagation formulas to different APs where signal has been sensed. To address the issues of non-comparability of RSSI data raised in Section 2.2, in the case of Tx-based methods, one should be aware that APs are part of the infrastructure and therefore under the control of the building's owner, who is usually the one implementing the localization. Therefore, the owner can deploy the same type of APs to get comparable values even in absolute terms.

If one would like to overcome the requirement for the same hardware for all the APs, we see two options. Option one is that manufacturers unify and standardize the RSSI values and how they correlate to the physical measure of signal power. This is probably not likely to happen, as it would require considerable work and collaboration between manufacturers; it is not likely that any researcher has the influence needed to achieve this. Even if manufacturers would agree on RSSI measurements today we probably would not see the results quickly as usually design of a new RF frontend, testing, certification and mass production and availability can take years. Second option is to include the effect of different hardware into the model of a model-based approach. Research-wise, this is much more plausible solution. Further discussion on this topic is provided in Chapter 6.

Our proposed localization method is an Rx-based solution which is more suitable for real-world deployments. By carefully utilizing the difference of signals to each of the APs, we will make our system independent of MT. If one analyses closely the proposed method in Section 4.2, one would see that our method requires the difference of two reported RSSI values, proportional to the difference in RSS. Therefore, a linear function mapping RSS to RSSI satisfies our condition. From our evaluation, we have concluded that this condition is satisfied on our evaluation equipment.

3.3 IEEE 802.11ah

The WiFi technology and its underlying protocols are constantly evolving. In the May of 2017 an Amendment 2 [79] was published to the IEEE 802.11 standard [68], which introduced a new protocol *802.11ah*. The new protocol is also called HaLow and introduces a new 900 MHz frequency band to the conventional 2.4 and 5 GHz.

The transfer speeds of the new band will be considerably lower, but the range of the signal will be greatly extended. This new band is specially designed for a variety of power-efficient use cases in IoT, smart homes, connected cars, agriculture, healthcare and industry. The range of the new band is nearly twice as much as today's WiFi and is less susceptible to the penetration loss when waves travel through the walls or other similar barriers. Therefore, it is even more important for the future to develop a model-based indoor WiFi localization system that will not need fingerprinting processes, as they are time consuming and therefore costly to deploy in the real world.

The hardware supporting 802.11ah is not yet commercially available; nevertheless, it is in our best interest that the developed methods support also the future WiFi standards. Therefore, it is wise to develop methods without any assumptions about the underlying wireless protocol. Because of the unavailability of hardware, we have focused the evaluation on 2.4 GHz WiFi. Another possibility would be the usage of 5 GHz (802.11n/ac), but it is significantly worse at penetrating obstacles and consequently has a smaller reach indoors.

Another future WiFi standard is currently coming to the market – the *802.11ad*. It introduces another frequency of 60 GHz and promises theoretical maximal speeds of 7 Gbps. Higher frequency enables faster speed, but at the same time limits the signal propagation. The signal of 802.11ad typically cannot penetrate walls, therefore it is not usable for a wide area of multi-room localization; but at the same time, it can give accurate information about the room if the signal from such AP is detected.

With future usage in mind, we defined the method without the assumptions about the frequencies of the signals or the underlying protocol, as can be seen in Section 4.2. Furthermore, in Chapter 5, we present the implementation of the method on signals and protocols not associated with the 802.11 standard, showing that the presented method is not limited to the IEEE 802.11 signals only.

3.4 Comparability of the methods

The RF localization methods are heavily influenced by the environment; the propagation of the signal through walls is difficult to define, as effects like reflections, refraction, diffraction, absorption, scattering of the signal, interference, etc. influence the propagation of the signal. These effects result in the signal strength, which is not only dependent on the obstacles and the distance in the direct path between AP and a specific point but is also influenced by the rooms and the spaces surrounding both.

Because the evaluation environment has such a big influence on the signal propagation, the indoor localization methods are difficult to compare. The standard practice in the research area of the indoor localization is that the authors evaluate the proposed method in the available environment and then compare the localization errors with the competing methods. The localization errors are usually defined as distances between the method's location prediction and the ground truth which is the known position of the mobile terminal during the localization procedure. We can find review papers utilizing such approach in [7–9, 22, 27, 80]. A survey with the focus on the comparability of the indoor localization methods and their evaluation can be found in [80]. The author emphasizes the lack of detailed information on the evaluation and the lack of real-world evaluations.

The researchers from other fields would argue that such benchmarking cannot be considered as a valid comparison. In the research fields of the digital signal processing, benchmarking can be done with common datasets upon which the algorithms are run and the results are then compared. Standard benchmarks can be found in the fields of image recognition, video object tracking, analysis of bio-medical signals, etc. These are usually research areas where the input signal is digital and well-defined, while the ground truth can be defined manually by the experts – e.g. digital images and corresponding labels which represent an object in frame, ECG signal and the corresponding QRS complex definitions, etc. This is not the case with the indoor localization where there is a variety of the input signals for the researchers to utilize. In Section 2.1 we have presented a variety of related works where the input signal and the values include, but are not limited to: offline fingerprinting map, RSSI values at specific anchors, Li-Fi, IMU sensors, architectural maps, etc.

An expert from another field could also propose a simulator which would be used for benchmarking. If we neglect the problems of simulating a wide range of the input signals and focus only on the RSS simulation, the answer is clear: the majority of the model-based approaches are trying to simulate the RSS propagation. If a simulator of the real-world RSS propagation existed, then it would also be trivial to convert it to a model approach with the 100 % accuracy.

We have already discussed some problems about the common benchmarking in Section 3.1. In terms of long-term temporal stability of the RF signal, a potential architect of a common indoor localization benchmark should know how to address the issue of temporal instability, influences of other devices in the rooms, issues of different hardware and RSSI values (as discussed in Section 2.2.1), etc.

There have been proposals of a common testbed solution in [81]. Although such proposals are still young, they are welcome, as they provide opportunities for the growth of the research field. The method described in this dissertation already shows the deficiency of the common testbed proposed in [81], as our method could not be tested because of its specific requirements which are described in Section 4.2. Some researchers in the field of the indoor localization agree that competitions would provide a means of common benchmarking. Organizers, which would have a difficult job of setting the evaluation environment and the possible input parameters, could invite the researchers to deploy their solutions and then we could get results comparable in real world.

As we can see, the benchmarking of the indoor localization approaches is difficult. For the time being, it is the authors' job to describe the evaluations in enough detail for a valid comparison; in the majority of papers there are not many more details than a map and a simple description of the hardware. We are convinced that for a valid comparison the authors should provide a lot more details. For example, due to different common architectural practices, the walls in different parts of the world differ; it is also known that the vertical position of the APs can influence the results, which should be described in detail; the papers also rarely provide the details on other devices in the area of interest (e.g. were the devices which were part of the evaluation the only devices using RF spectrum), etc. We will address the presented matter with a detailed description of both evaluation environments in Sections 4.3.2 and 4.4.1.

3.5 *Architectural aspect*

The comparison of the outdoor and indoor environments results in one main difference – the presence of walls and other architectural elements. These aspects have a significant influence on the signal propagation. Firstly, the power loss during the propagation through them is significantly bigger than when propagating through air or vacuum [78]. The influence is mainly dependent on the material, thickness and the frequency of RF signal. For instance, 5 GHz WiFi offers higher transfer speeds than 2.4 GHz, but on the other hand it is much more susceptible for the distance- and obstacle-based power losses. Therefore, a reliable signal with the promised transfer speeds is hard to obtain one or two concrete walls away and we cannot expect a reliable propagation through the floors.

We can say that the fingerprinting approaches include the effects of the architectural aspects, because the offline fingerprinting procedure and the localization procedure both take place in a real-world environment, where RSS is affected by the propagation through them. On the other hand, the model-based approaches rarely take the architecture of the building into consideration, but more often include some simplified factor which accounts for this effect; e.g. neglecting this effect in [64], a constant factor for power loss, regardless of the distance in [65]. Some methods are not focused on the multi-room scenario; therefore, the dividing wall modeling is not in their interest, e.g. in [53]. Some authors (e.g. [62]) are aware of the deficiencies of the constant or proportional modeling of the walls in cases of a non-uniform wall coverage and the different types of dividing walls.

Non-constant models of the effect can be found in [37], where the authors include the wall effect by an empirically derived factor which is used proportionally with a number of penetrated walls up to a certain number, after which the wall effect is considered to be constant. The ray-tracing method usually focuses on the reflection of the signals on walls and not on the propagation, e.g. in [61], but we can also find the opposite, e.g. in [62]. The authors in [67] model the effect of the walls in proportion to the distance. Therefore, their method does not need specific information about the placement of the walls, but approximates that the number of the walls between two points is proportional to the distance. We can argue that, considering the real-world propagation (scattering of the signal and multipath), this can be said for their primary evaluation, as it was done in the hallway, where they placed the majority of the APs and evaluation points.

As discussed in Section 3.1, hallways are theoretically easier for the modeling of propagation, as propagation has fewer losses than in other indoor environments. Out of the reviewed works, many (e.g. [54, 55, 57, 58, 60–67]) evaluate the methods only in the hallways, as can be seen in the Table 2.1. It can be argued that using favorable evaluation environments improves the results of the methods and hides bigger errors that would appear in real-world scenarios.

Considering the above, we have decided that since the modern buildings all have digital floor maps, including them into the method is not too difficult and does not represent too big of a burden. This inclusion is beneficial, especially for real-world environments, where there is no uniform wall placement. Furthermore, we have decided to address the issues of different wall types found in modern buildings.

The last thing worth-mentioning is the fact that the indoor localization methods are usually evaluated in one environment only. Rarely do the research papers present the methods that are challenged in multiple environments. The usual choice for the evaluation environment is the faculty or the research laboratory building which usually consist of long hallways and small to mid-size offices. Out of the reviewed approaches, we could find only [61] evaluated in a residential apartment. The floor plan and the objects inside the offices (e.g. desks, cabinets) usually differ significantly from the residential buildings. Because we have a goal of developing a universal method for the localization in the IoT, we have performed both the evaluation of the WiFi method in the office and the residential environment.

4

Novel model-based WiFi method

The previous chapter presented the limitations and challenges we have identified prior to the development of the method presented in this chapter. Therefore, the development of the WiFi method presented in this section and its evaluation are heavily influenced by the discussed topics. The first section of the following chapter presents the intuition upon which we have developed the method which is then described in detail. Sections 4.3 and 4.4 present the evaluation results in two very different evaluation environments; an office environment at the university and a residential environment in a modern apartment. Last but not least evaluation in long hallway is presented in section 4.5. The discussion follows the evaluations and at the end of the chapter we also provide brief conclusions.

4.1 Intuition behind the method and high-level overview

Our goal was to develop a model that would be suitable for the real-world usage; each design decision was subjected to this goal. The motivation for the development of a new method was to address the difficult calibration procedures, the static usage of the parameters in propagation models and the hardware requirements of the existing methods. To accomplish this, we have set the following prerequisites:

- *Pure model-based WiFi-only approach*
  As shown in Section 2.1, only the pure model-based methods are suitable for big scale deployments. The methods that do not require fingerprinting or any other static parameters of RF signal propagation are suitable for real-world deployments, as it is also emphasized in [10].

- *Self-calibrating operability*
  A frequent recalibration method must be autonomous and should not require human intervention. Frequent recalibration ensures the method to be self-adapting to the indoor changes. The results from the experiments presented in Section 3.1 show a long-term temporal instability of the WiFi signal, which confirms the claims in [34]. Only a method which constantly adapts to the changes in the environment can be used in real-world deployments.

- *Awareness of architectural aspects*
  The input data of our algorithm consists of information about the access points and the wall placements, in order for the method to provide localization with

respect to the architectural structure of the building. As discussed in Section 3.5, we anticipate this data to be beneficial, especially in the real-world evaluation environments.

- *Applicability on widely available hardware*
  We could maximize our chances of success by using advanced and costly equipment, which would provide more stable signals and reliable data readings, but we rather decided to develop the methods on affordable and widely available hardware. More advanced mobile terminal equipment could also provide other information than RSSI (e.g. CSI), but this would limit the method usage to only such devices.

As we have seen in Section 3.1, it is difficult to deterministically model signal propagation, due to temporal variations. Therefore, we have decided that we need to implement real-time feedback loop between the current state of the indoor propagation and the propagation model. This feedback should be implemented by some devices that would measure the current state of the RSS at known positions and provide information to our method. Some approaches exist that place additional devices indoors (e.g. [67]). Because there are already multiple APs in the area of interest, it is in our opinion unnecessary to introduce additional devices, as we can use the available APs. Because the majority of the commercially available APs do not implement a feature that would report RSSIs of the received beacons from other APs, we will have to address this challenge.

We can minimize the influence of different hardware by ensuring the same type of APs across the area of interest, which is the usual procedure in the field of the WiFi localization. The same APs are used to address part of the issues discussed in Section 2.2.1. This design decision does not diminish our real-world applicability as the deployment of the WiFi localization system to a selected area is usually done by the owner of a building, who can control the installed hardware and ensure unified APs. Even further, usually, when a specific indoor location is equipped with multiple WiFi APs, the same type of APs are used throughout the building.

Having the same hardware for the APs assures us that the readings of the RSSI from two different APs are comparable also in the absolute terms. From the readings of the RSSI of the beacon packets, emitted by a specific AP at other APs, we can estimate the propagation model. By knowing the propagation model for each AP, we can model the propagation of the RSSI for all APs in the localization process. During the estimation of propagation and the propagation modeling, we will have to address the challenges of wall inclusion and the real-world propagation (e.g. the effects of multipath, scattering, etc.).

During the localization stage, we will use a mobile terminal, for which we do not know how its RF frontend is related to the ones found in the used APs. Therefore, we will derive the characteristics of the RSSI, which can be compared (in the absolute terms) to our propagation model, while considering the challenges described in Section 2.2.1.

High-level overview and the main steps in the proposed localization method are presented in Fig. 4.1. Our localization method can be divided into the *data acquisition stage*, the *path loss modeling stage*, the *propagation simulation stage* and the *localization stage*, which are presented in Fig. 4.1. During the data acquisition stage, the server periodically queries (Position 1 in Fig. 4.1) each router for the survey (Position 2 in Fig. 4.1) of the RSSI of the signals emitted from other access points (Position 3 in Fig. 4.1). This information is used to infer the parameters of the space in the path loss

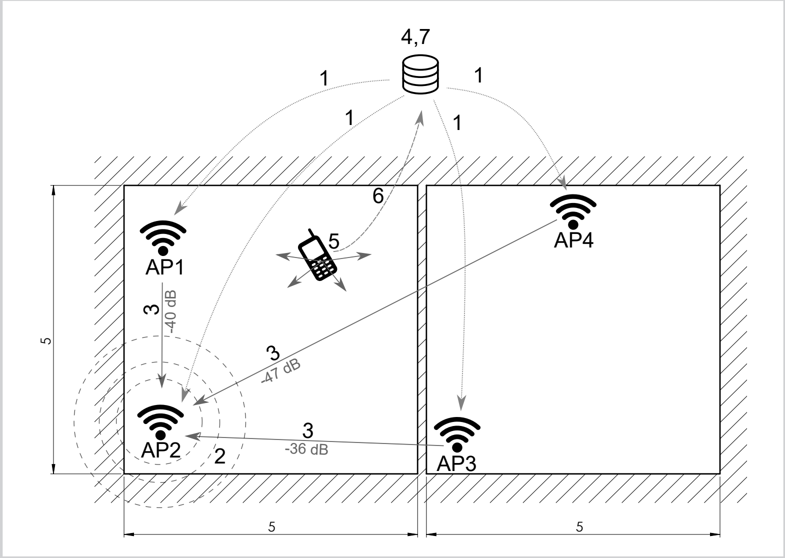


Figure 4.1

High-level overview and the main steps in the proposed localization method.

modeling stage. After the attenuation parameters are determined, the propagation for each AP can be simulated via the selected propagation model (Position 4 in Fig. 4.1). In the localization stage, the mobile terminal surveys the WiFi spectrum for the APs in reach and determines RSSI for each of them (Position 5 in Fig. 4.1). This information is then sent (Position 6 in Fig. 4.1) to the localization server, which determines a point in the simulated propagation map that fits the measured RSSIs (Position 7 in Fig. 4.1).

4.2 Method description

The following subsections provide a detailed description of the four stages of the proposed localization method. The section presents our proposed Self-Adaptive Model-Based Wi-Fi Indoor Localization Method published in [11].

4.2.1 Data acquisition stage

The first stage of our method is the data acquisition stage, during which the data needed for building our propagation model is captured. In the data acquisition stage, the localization server queries each AP for the results of the site survey. The site survey is a process in which AP scans the WiFi channels and captures the RSSI information of the beacon packets sent by the APs in reach. The results that list APs and their respective RSSI are then stored in the database on the localization server. Every time the RSSI data from AP is acquired, the updated propagation parameters are calculated for the current setting.

When calculating the attenuation parameters for a specific AP, we query the database for the measurements of the signal originating at this specific AP and detected by other APs. The obtained data is then filtered by the median filter in order to eliminate the signal outliers that can occur in the signal, due to the instability of RSSI. Figure 4.2 shows an example of the filtered RSSI data, from which the parameters are inferred. The figure presents a nearly ideal case, where RSSI captures do not overlap due to the effects of the indoor spaces. In the real-world setting, it can happen that RSSI from the most powerful AP (e.g. AP3 in Fig. 4.2) drops below the values of other APs or vice-versa.

There is no standard definition of how the RSSI value is measured, thus the values, the scale and any correlation with the measured values of APs depend of the manufacturer's implementation, as discussed in Section 2.2.1. Therefore, the usage of different

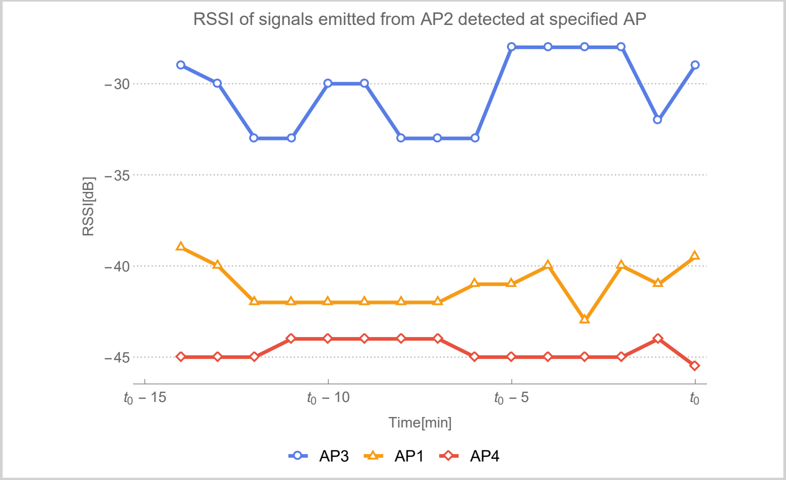


Figure 4.2

Example of the signals emitted from AP2, detected at AP1, AP3 and AP4. t_0 is the time at which we initialized the sampling method.

APs at this stage would make the RSSI values incomparable. That is why all the researches, building model-based approaches with the help of parameters sensed at different APs, use the same hardware for the APs, as can be seen in [34, 64, 67]. This fact is also acknowledged during the development of our method. For this or any other similar method to be adopted by the public, hardware manufacturers or IEEE should standardize the RSSI values. When deploying WiFi infrastructure in a building (e.g. airport), APs are often of the same type, which solves the problem of non-standardized RSSI values.

In the Table 4.1, we can see an example of the data stored on the localization server. For example, the first row of the table shows the detected RSSI of -52 from AP with specified MAC address, while performing a survey at the AP with IP 10.1.23.250.

The database of measurements at the localization server is the result of the data acquisition stage of the proposed localization method. From this data our method infers the parameters of the signal propagation through indoor spaces, as discussed in the following sections.

Table 4.1

Example of the data in the database on the localization server.

id	source[a]	destination[b]	power	timestamp
1	C0:56:27:34:92:89	10.1.23.250	-52	1488459486
2	C0:56:27:29:0E:65	10.1.23.250	-59	1488459546
3	C0:56:27:29:0C:DC	10.1.23.251	-63	1488459594
...	...	...	...	...

[a] MAC address of the AP emitting the signal.
[b] IP address of the AP where signal was detected and RSSI recorded.

4.2.2 Path loss modeling stage

The second step in our localization method is the path loss modeling stage in which we utilize the known physical properties of the RF signal propagation and the measurements obtained in the previous step, to infer the parameters of the signal propagation. This section presents all the steps in the development of the method to give a comprehensive understanding of the method to the reader.

We have started the development of the path loss modeling stage with the log-distance path loss model for the propagation-parameter estimation, as it is often used as a baseline for the model-based method development, e.g. [60, 67]. The path loss model can be expressed as previously showed in Section 3.1 by Eq. (3.1).

Let us begin with the formal definitions of the entries in the database, presented in Section 4.2.1 (Table 4.1). We will mark the RSSI values, captured by the data acquisition stage of our method, with $RSSI_{j,i}$, where j labels AP_j at which the signal was measured and i stands for AP_i from which the measured signal was emitted. Therefore the value $RSSI_{j,i}$ represents the "power" column in Table 4.1, while j represent AP with the IP specified in the "source" column and i denotes AP with the MAC address in the "destination" column of the database.

When identifying the parameter γ_i at the time t for the propagation of the signal originating from the AP_i, we query the database for the last h $RSSI_{m,i}$ and $RSSI_{n,i}$ collected in the interval δ, where m, n represent a pair of APs, which are not AP_i. Knowing the spatial positions of the access points, we can obtain the distances $d_{i,m}$ and $d_{i,n}$, which are the distances between AP_i and AP_m or AP_n. Rewriting Eq. (3.1) with the introduced indexes provides us with an equation that we can use to determine γ_i.

$$RSSI_{m,i} - RSSI_{n,i} = 10\gamma_i \log_{10} \frac{d_{i,m}}{d_{i,n}} \tag{4.1}$$

The path loss exponent γ_i for the access point AP_i can then be calculated by utilizing a least squares regression of Eq. (4.1). Our preliminary evaluation showed that this propagation method oversimplifies the propagation and does not give us satisfying results.

The experimental evaluation, as presented in Section 4.3, showed that omitting measurements from AP, which is positioned on the same wall as AP_i, would result in better accuracy of the method. For example, the parameters for AP2 in Fig. 4.1, calculated based on the measurements gathered at AP3 and AP4, would give a better performance than if the measurements from AP1 and AP4 were used. In our preliminary research, we have tested multiple arrangements of the APs and observed this phenomenon.

The difference in the parameter estimation was appointed to the primary reflection of the signal which occurs on the wall near which the transmitting AP is mounted. The wall acts as a reflector of the signal and our hypothesis is that the receivers which are positioned perpendicularly to the wall have an overall better signal strength than the similarly positioned AP that are parallel to the wall. The position of the external antennas which we positioned parallel to the wall could also be a factor. We have positioned them parallel, as this is the usual practice of placing the APs - either mounted directly on the wall, or placed on a shelf near the wall, with the back of the device, where the antennas are connected, facing the wall.

To account for this phenomenon, we have extended the log-distance path loss model with the parameter β_i, which accounts for the effects in the angle difference between the direction of the direct-signal-path and the normal vector to the wall on which AP is mounted. Our extended log-distance path model can be written as:

$$RSSI_{m,i} - RSSI_{n,i} = 10\gamma_i \log_{10} \frac{d_{i,m}}{d_{i,n}} + 10\beta_i \log_{10} \frac{d_{i,m}}{d_{i,n}} \times \left(\alpha_{i,m} - \alpha_{i,n}\right) \tag{4.2}$$

where the additional symbol introduced $\alpha_{i,j}$ is defined as:

$$\alpha_{i,j} = \frac{\sphericalangle\left(n_i, s_{i,j}\right)}{\pi/2} \tag{4.3}$$

In Eq. (4.3), n_i represents a normal vector to a plane, defined by the wall on which AP_i is positioned; $s_{i,j}$ represents a vector with the direction of the direct signal path between AP_i and AP_j; and $\sphericalangle\left(n_i, s_{i,j}\right)$ denotes the sharp angle between vectors n_i and $s_{i,j}$ in radians. The normal vector can be calculated from the data inputted to the method—information about APs and wall placement.

With Eq. (4.2), we can use the data from all measuring APs as input into least squares, fitting to determine the values γ_i and β_i. This means we have $N \times (N-1)/2 \times h$ measured data points to infer the parameters of the signal propagation, where N is the number of AP in the reach of AP_i. This results in an overdetermined system of equations in which the usage of the least squares regression finds the parameters with the best overall fit.

The final form of the formula for inferring the parameters of propagation includes the effect of the walls. The method's input includes the information about the placement of the APs and the walls; therefore, it is trivial to calculate the number of walls between APs. The list of the walls is the initial input into the method. The list of walls contains a parameter which describes the wall type. Table 4.2 gives an example on how the wall information for the indoor spaces, displayed in Fig. 4.1, is inputted to the method. Wall-type 1 represents thick concrete walls and wall-type 2 represents thin plaster walls. As we can see, the map of the indoor spaces is inputted into the

Table 4.2

Example data representing the indoor walls in Figure 4.1. Information about the architectural aspects of the indoor spaces is passed as an array of weighted line segments, representing the map of the indoor spaces. The weights of the line segments represent the wall type.

x_1	y_1	x_2	y_2	type
0	0	10.2	0	1
0	0	0	5	1
0	5	10.2	5	1
10.2	0	10.2	5	1
5.1	0	5.1	5	2

algorithm as an array of the line sections, with one extra parameter representing the wall type. With this method, we ensure that although the algorithm requires information about the indoor spaces, this information is not difficult to obtain during the deployment of the method.

The actual values of the impact of the walls on the signal propagation are difficult to obtain and generalize. We use the values recommended by the European COST action 231 [78] for the effects of specific wall types on the propagation. These are only the starting values and due to the adaptive nature of our method, the errors in these values are partially corrected through the calculation of the propagation exponent. Equation (4.4) represents the final formula for inferring the parameters of the propagation:

$$\begin{aligned}\left(RSSI_{m,i} - W_{m,i}\right) - \left(RSSI_{n,i} - W_{n,i}\right) &= \\ &= 10\gamma_i \log_{10} \frac{d_{i,m}}{d_{i,n}} + 10\beta_i \log_{10} \frac{d_{i,m}}{d_{i,n}} \times \left(\alpha_{i,m} - \alpha_{i,n}\right) \end{aligned} \tag{4.4}$$

where $W_{k,i}$ represents the effects of the walls between AP_i and AP_k. To compute the value $W_{k,i}$, the method searches through the list of walls, which we have defined as the input parameter into the method. The method counts the number of walls between AP_i and AP_k, grouped by their type. In the final stage, we apply the effect of each wall-type and then calculate the cumulative effect. An effect of a single wall-type is an integer value representing the decrease of the RSSI value while the RF signal transverses the wall of specific type. If information about the wall types cannot be obtained, the default values for a plaster or concrete wall can be used. In this case, we can expect a bigger average localization error in the buildings with mixed wall types.

When calculating the parameter γ_i from Eqs. (4.1), (4.2) or (4.4), it is important that the distance ratio $\frac{d_{i,m}}{d_{i,n}}$ is not close to 1. If $d_{i,m} \approx d_{i,n}$, then due to the variations in the WiFi signal, we can get the values $\gamma_i < 0$, which would mean that the signal gets stronger, while traveling away from the antenna. Such situations occurred often in our office multi-room evaluation, where AP3 was positioned approximately equidistant from all other APs. To provide a failback for such cases, we checked if the inferred γ_i is lower than half of the power-loss factor in a theoretical free space propagation ($\gamma_i < 1$). In such case, we will set γ_i to the value proposed by the ITU standard for the commercial buildings ($\gamma_i = 20$). We have chosen the failback parameter for the commercial building instead of the one for the office, as the office building power-loss exponent is bigger, because there are usually more walls in the office buildings that the signal has to penetrate. Our method explicitly calculates the number of walls and their effect; therefore, we have chosen commercial buildings, which are similar but tend to have fewer dividing walls.

4.2.3 Propagation simulation stage

After having collected the data in the data acquisition stage and having identified the parameters in the path loss modeling stage, we can use the obtained parameters to simulate the propagation of the signal through the building. The main purpose of the third step in the method is to calculate a simulated propagation map on the server.

As we have the calculated parameters of the signal propagation, we can choose a model to simulate the propagation of the signal through the building. We chose a model which was specifically built to estimate the path loss inside a closed area for the propagation simulation. Therefore, we have decided to use the ITU indoor propagation model [82]. The model is developed and regularly updated by the International Telecommunication Union which is an agency of the United Nations. The ITU model tries to account for the reflections and diffractions caused by the objects, the channeling of energy, motions inside the room, multipath effects, etc. The ITU model provides guidance on the indoor propagation over a frequency range from 300 MHz to 100 GHz. The basic model can be expressed as [82]:

$$PL_{i,j} = 20\log_{10}\left(f\right) + \gamma\log_{10}\left(d_{i,j}\right) + L_f\left(n\right) - 28 \tag{4.5}$$

where $PL_{i,j}$ is the total path loss of a signal originating in the access point AP_i at point j in dB, f is frequency in MHz, γ is the distance power loss exponent, $d_{i,j}$ denotes the distance in meters between AP_i and the point j. $L_f(n)$ factor accounts for the loss between the floors, which is currently not in the focus of our research, so we will omit its effect. The ITU whitepaper gives predictions for the power loss coefficients and other parameters for specific frequencies and building types. As we have measured the power loss exponent in the data acquisition stage of our method, we have adapted the ITU model by using our own measured values.

The inclusion of the proposed parameter β and the effect of the walls into the ITU model results in Eq. (4.6) which calculates the power loss at a specific point j, in which $\alpha_{i,j}$ is defined by Eq. (4.3). This time $s_{i,j}$ represents the direction of a signal from AP_i towards point j:

$$PL_{i,j} = 20\log_{10}\left(f\right) + \gamma_i \log_{10}\left(d_{i,j}\right) + \beta_i \times \alpha_{i,j} \times \log_{10}\left(d_{i,j}\right) + W_{i,j} - 28 \quad (4.6)$$

The values of frequency f are easily determined by the readings of the APs or by parsing the status report of the AP. The values that describe the location properties between point i and point j (e.g. distance $d_{i,j}$, the effect of the walls on propagation $W_{i,j}$ and angle $\alpha_{i,j}$) can be easily determined by using the map of the indoor spaces, which is the input parameter to our method. By knowing the values of γ_i and β_i for each of the APs from the previous stage, we can simulate the path loss between AP_i and any other point on the map.

In the final stage of the propagation simulation stage, the localization server computes the expected power losses in the indoor spaces in the mesh pattern and constructs the radio propagation map - PL_i - for each AP_i. The parameters (division) of the mesh must be set in conjugation with the size of the area of interest, the computing resources and the acceptable error, as the size of the mesh determines the minimal average error.

4.2.4 *Localization stage*

The previously described three stages (Sections 4.2.1, 4.2.2, 4.2.3) of the method run constantly and independently of the localization stage. The first stage periodically queries the APs, while the second and third stages compute the propagation maps when data is updated. The localization stage presented in this subsection is initialized by the user, when trying to obtain the location.

Initially a mobile terminal surveys the available APs. On the mobile terminal, we do not have a similar problem as in the data acquisition stage, where this information was unavailable to the end-user. Mobile terminals usually present RSSI information to the end-user to give the user the information about the signal strength. Even if this information is not available in a numeric form, any applications that will leverage the presented method usually have access to this information through the operating-system libraries. The list of available APs is then sent to the localization server for further processing.

To account for variations in RSSI, our method samples the RSSI 3 times. Consequently, we get a vector of 3 measurements of RSSI, labeled as $RSSI_{MT,i}$, for each access point AP_i. The mean value for each AP is then used for localization. The localization point is thus defined as:

$$RSST_{MT} = \left\{Mean\left[RSSI_{MT,1}\right], Mean\left[RSSI_{MT,2}\right], ...\right\} \tag{4.7}$$

When determining the position of a mobile terminal, we cannot directly compare the absolute values of the estimated path loss values and the readings from the mobile terminal, because they were collected on a different hardware. Additional losses in the mobile terminal can also be due to the obstructions by people holding mobile devices, different materials from which the mobile terminal (e.g. mobile phone) is made, different additional cases that are added to mobile terminals, etc. The assumption for the method development is that these effects are equal on all sampled signals during a specific measurement. If we assume that the difference in the RSSI readings between APs is a consequence of the path loss model (Eq. (4.4), (4.5) or (4.6)), we can assume that the difference between the received powers in dB scale is the same in the output of our proposed propagation simulation stage and in the measurements.

The model assumes that the most powerful measured reading is the most stable one, therefore we subtract $max\left(RSST_{MT}\right)$ reading from each $RSSI_{MT,i}$. Because we know from which AP_k $max\left(RSST_{MT}\right)$ originated, we subtract the value of the simulated propagation map from the propagation simulation stage PL_k from all PL_i. Then we can get the position of the mobile terminal by finding the point on the map which has the smallest error, when comparing the measured differences $RSSI_{MT,i}-RSSI_{MT,k}$ and the simulated values $PL_i - PL_k$. The point with the minimum difference is outputted at an estimated location for the mobile terminal by our method.

4.3 Experimental evaluation in the office environment

The following section presents the experimental evaluation in the office environment. We have first chosen the office environment, because the evaluation in the laboratories of research institutions is a usual practice and most commonly found in the related work.

The first subsection will define the base ground and some prerequisites for the evaluation, followed by a detailed description of the single- and multi-room evaluation environments. We have decided to first evaluate the method and its underlying model in a single-room environment, because it is without any additional variables (e.g. wall effects). In single-room environments, we also observed higher influences of the parameter β, as described in Section 4.2.2, because in multi-room environments the effects of the multipath and scattering usually become stronger and diminish the effect of β. This does not mean that single-room environments are not important, as many industrial applications display such properties – many production halls in factories are without the dividing walls and commercial buildings are usually open-spaced.

After having obtained the model's base performance in a single room, we continued the evaluation in a multi-room environment. In the last two subsections, the results obtained during our evaluation are presented. In the following Sections 4.4 and 4.5, we will present the evaluation in the residential environment as well as in a hallway.

4.3.1 Experimental Prerequisites

To eliminate the need for fingerprinting, our method requires the capability of the APs to survey the WiFi channels and report RSSI of the neighboring APs. The majority of the APs in the market nowadays have this functionality built in as it is an integral part of the automatic determination of the most suitable channel for the WiFi communication. Usually, information about the readings is not available to the end user. This is one of the reasons why, besides its popularity, we chose one of the most widely used wireless routers — Linksys WRT54GL. It has multiple open-source third-party firmwares available (e.g. DD-WRT [83], OpenWRT [84]) that expose surveying information to the end-user. This is the biggest deviation from our development goal of the real-world usability, but because this functionality is already built into the routers, it could be easily exposed by the manufacturers. For the research purposes, DD-WRT- and OpenWRT-based firmware is available on the market for many APs.

Surveying is a periodically re-occurring event. If its frequency is too high, this results in an additional load on the WiFi network which is unwanted, as it impacts the data-transfer performance on the wireless network. A too low frequency means that the changes in the WiFi network we want to adopt will took too much time to become meaningful and effective. A closely related parameter is the number of historical surveys h our method will use. Choosing too many will have similar consequences as a too long period. Too little would result in a higher influence of the RSSI variance than desired. After an elaborate testing, we have chosen $1\,\mathrm{min}$ as a scanning period and $h = 15$ history points. This ensures that the changes that are due to long-term temporal instability of WiFi and the changes in the indoor space will have a significant effect in less than $10\,\mathrm{min}$, as they will be present in more than $50\,\%$ of the data-points used for the calculation. The third important parameter for the data acquisition is

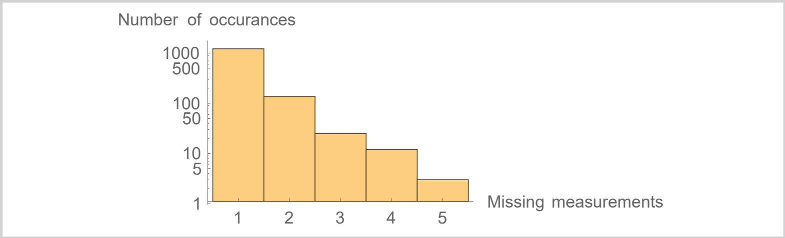


Figure 4.3

Missing detections of AP4 at AP2.

the median filter window size. We chose the windows of size 3 to eliminate the high frequency noise from the data.

During the propagation simulation, another important parameter is the density of the mesh for the propagation simulation. We have chosen a value of 0.2 m, as it provides a mesh five times denser than the density of the evaluation. We have, as presented in Chapter 4.3.3, chosen to evaluate our method in a mesh pattern, where the evaluation points are spaced 1 m apart.

In real-world situations, one must predict a situation in which a specific AP performs a survey and does not detect one of the APs. We have analyzed eight weeks of surveying the data between two APs. In Fig. 4.3, we can see a number of occurrences, when the difference between the two consecutive $RSSI_{j,i}$, between AP_i and AP_j in the database, was more than 1 min, thus indicating that while AP_j was reforming a survey, it did not detect AP_i. The experiment lasted for 80.640 min; note the logarithmic scale on the y-axis.

The results of this analysis show that the probability that AP_i did not properly detect AP_j while performing the survey was 1.7 %. To account for such situations, we advise to select 15 data points in the last 16 min. The experimental data show that the probability of such an event occurring, if choosing 15 history data points in the interval of 16 min, is 0.34 % per AP pair. During the evaluation presented in Sections 4.3.3 and 4.3.4, the situation where two measurements would be missing in the window of 16 min did not occur. The implementation of the method predicted to continue without the missing points, which would result in the calculation with only 14 history points in the case of the two missing measurements. Because our system is heavily overdetermined, the method would still result in the location determination.

4.3.2 Description of evaluation environment and protocol

The main goal of our method development was to develop a method that is usable for real deployments and applicable to the real-world scenarios; therefore, we had to set our evaluation procedure carefully. The first evaluation environment are our offices at the university, as it is common for the indoor localization methods to be evaluated in the offices of research institutions.

The office evaluation area is displayed in Fig. 4.4. From the architectural point of view, the left wall is a thick concrete wall, the right wall is made of plaster, the wall at the top is filled with office storage closets from floor to ceiling, and at the bottom, there is a huge window spanning the wall. This means that we have four different types of materials from which the WiFi signal can be reflected. The access points are positioned as represented in Fig. 4.4 at approximately $2.1\,\mathrm{m}$. The thin dashed gray lines represent the virtual mesh. At the crossings of the vertical and horizontal lines, except at the points in which the APs are positioned, we have evaluated our proposed method. All figures with the results presented in this section have a coordinate system matching the one in Fig. 4.4, with the axis origin in the point marked with the "$(0,0)$" annotation. In the case of AP4, we could not position the AP at the crossing of the virtual mesh (position at $(7.25,6)$), due to spatial constraints, so we had to position it at $(7.25,5.75)$. The cross hatched blocks beside the desks represent a $1.6\,\mathrm{m}$-high divisors between the workspaces.

Our office is usually full during workdays from 7.00 a.m. to 6.00 p.m.; during this time, more than 50 different WiFi-enabled devices enter or exit the WiFi range. The devices include laptops, tablets, mobile phones and smart watches. During the night or during the weekend, at least 10 devices use the WiFi spectrum. To put a heavier load on the system, we have decided not to connect APs to the Internet via the Ethernet cable. APs were set in the repeater mode and connected to the Internet via 5th AP. We have checked that 10 different APs are in the range of our room (including the 4 we used for the evaluation). The evaluation environment also contained other than $2.4\,\mathrm{GHz}$ wireless signals, including $5\,\mathrm{GHz}$ WiFi (802.11ac) and Bluetooth. A Bluetooth speaker, which uses a similar $2.4\,\mathrm{GHz}$ band, was present in the evaluation environment. To saturate the channels even further, we configured all APs to use the same channel and maximized interference between them. For the mobile terminal, we chose Raspberry Pi 2 with a simple USB dongle (commercial name WIPI)

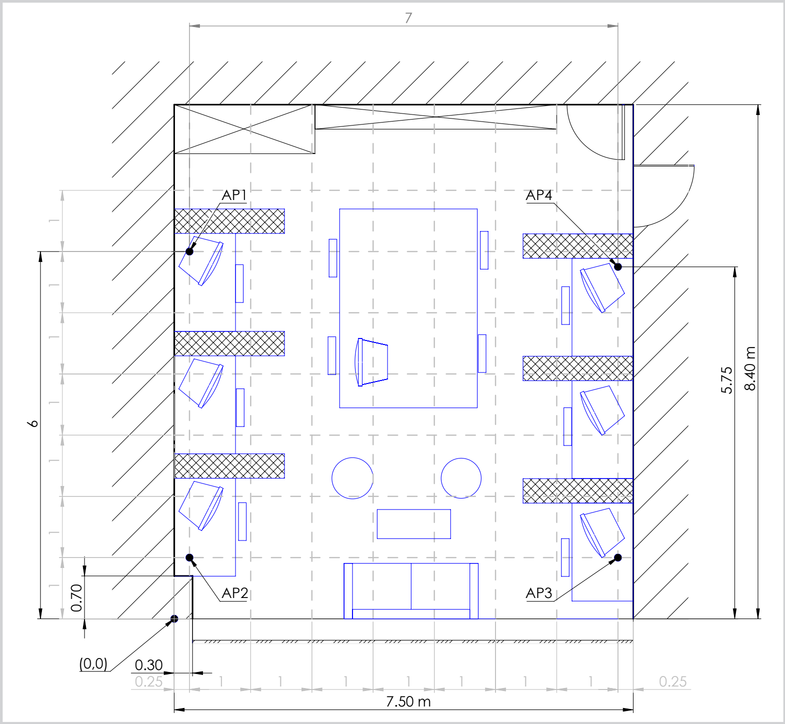


Figure 4.4

The evaluation environment in a single-room scenario.

that provided the WiFi connectivity. We chose this wireless connectivity option, because it is one of the simplest available: it has a single WiFi PCB antenna and low power (FCC testing reports a maximal power below 11 dBm [85]). We have captured RSSI values of the WiFi APs, with a "iwlist [interface] scan" command build into the Linux distribution. During the evaluation, the mobile terminal was held at approximately head-height position. More advanced equipment used for the evaluation of our method could produce even better results. At the mid-bottom of the room in Fig. 4.4, we can see a commodity area which exhibits some properties of a non-office environment. This is also the area where the Bluetooth speaker is positioned.

For our multi-room office evaluation, we have extended our evaluation into the office next to ours. This time, we purposely positioned APs in a non-symmetric man-

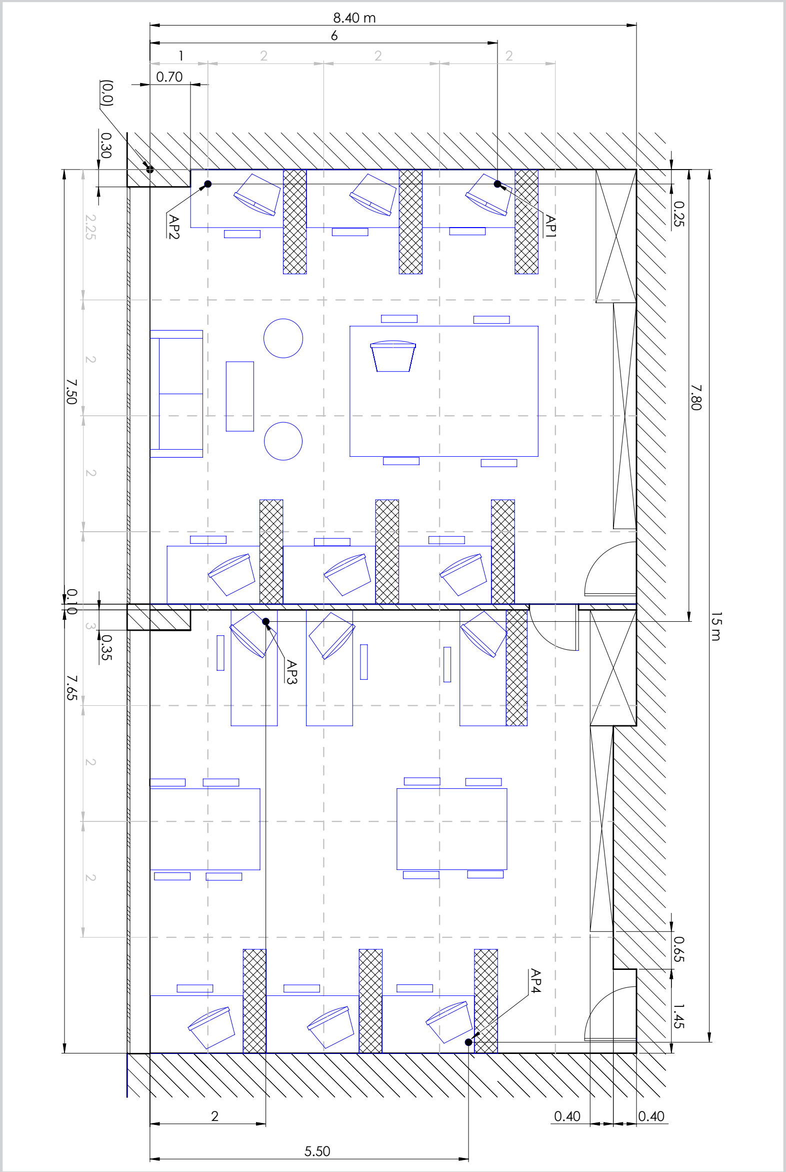


Figure 4.5

The evaluation environment in a multi-room scenario.

ner. As the accuracy of the methods that infer the parameters from the space depends greatly on the number of devices used (e.g. APs, anchors, WiFi transponders, etc.), we have decided that we will double the area, but keep the same number of devices. The evaluation environment for a multi-room setup is presented in Fig. 4.5. The room exhibits fewer divisors between the worktables, smaller desks from which signal bounces and no community area. Because the dividing wall between the two offices is made of plaster, we used $-4\,\mathrm{dB}$ as the value of the wall's effect, as proposed by COST 231 [78].

The evaluation in this environment consisted of 24 evaluation points, marked in the Fig. 4.5 as the crossings of the dashed light-gray lines. The coordinates of the evaluation points can be expressed as $\{(x, y); x \in \{2.25, 4.25, 6.25, 9.25, 11.25, 15.25\}, y \in \{1, 3, 5, 7\}\}$.

This concludes the description of the single-room and multi-room office evaluation environment. We have put an emphasis on the detailed description, as such information gives the true context when comparing two methods. Such detailed information about the indoor spaces is often exempted from the published research papers, therefore it is difficult to compare the results in the context of the evaluation environment. Since the evaluation environment can have a great impact on the final results and the accuracy of the method, future authors should provide similar descriptions.

4.3.3 Single room evaluation

In this section, the results of the office evaluation of our proposed method are presented. We present the results of the progressive steps, during the development of our method, to provide the reader the full insight into the development of the method. We have evaluated our method by localizing 52 reference locations, as described in Section 4.3.2.

As the reader can recall from Chapters 4.2.2 and 4.3.1, the method utilizes the last 15 measurements, captured by the system, in the last 16 minutes before the localization process. As the determination of the parameters of the propagation for a specific AP utilizes the measurements from other 3 APs, we generally have 45 measurements from which the propagation parameters are inferred. In the case of using all 45 measured points with the γ-only localization method, which implements the propagation model given in Eq. (4.1), more than 2/3 of the data points are heavily influenced by the effects of reflections under big angles. Figure 4.6a shows an overview of the directions of the

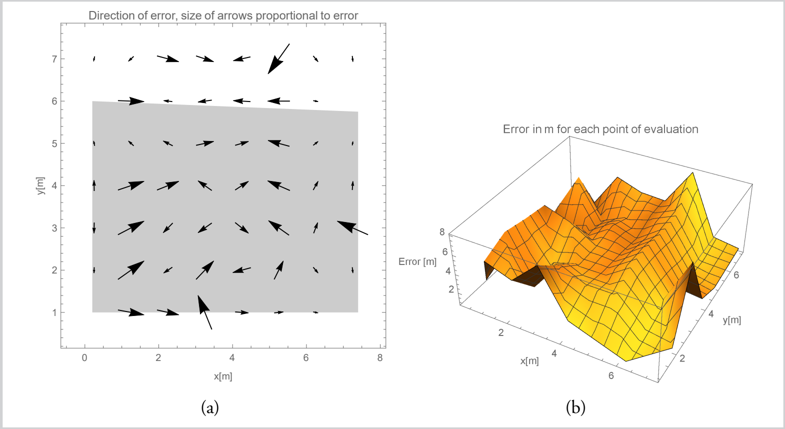


Figure 4.6

4.6a The direction of the errors in the case of using all available data for the calculation of γ, the vertices of the gray polygon mark the position of the APs; and 4.6b the value of the localization error for each reference point if all RSSIs are used for calculation.

errors made by such a method. In every point of the evaluation, we can see a point representing a direction of the error. The size of the arrows is proportional to the error they are representing. We can see that only the reference points close to APs were located accurately. Figure 4.6b shows the value of the localization error for each reference point.

As described in section 4.2.2, γ inferred from APs that are positioned on the opposite walls gives better results. The mean and median errors are compared in Tab. 4.3. We can observe more than a 25 % improvement of average error if specific APs are omitted. In Tab. 4.3 and following tables with the results, label "omitted APs" refer to the results for which γ was calculated by omitting the RSSI readings from the APs positioned at the same wall. Therefore, γ for specific AP_i was calculated by the RSSIs

Table 4.3

Comparison of the mean and median errors made by γ-only method.

Used RSSIs for γ calculation	Mean Error [m]	Median Error [m]	Standard Deviation [m]
all APs	3.64	3.45	2.06
omitted APs	2.64	2.51	1.43

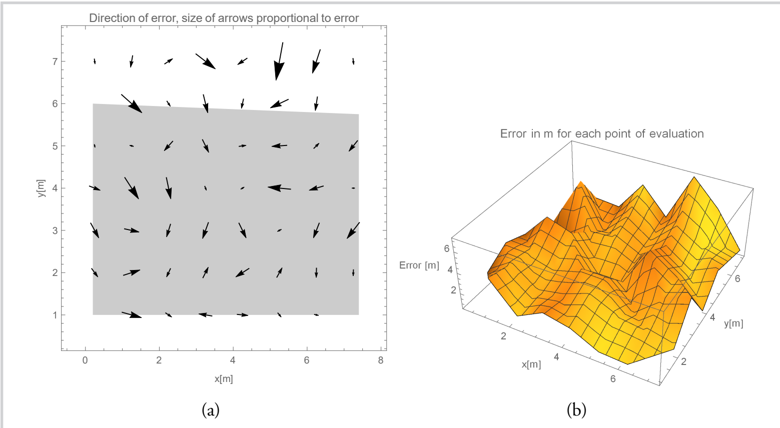


Figure 4.7

4.7a The direction of errors in the case of omitting APs on the same wall for the calculation of γ, the vertices of gray polygon mark the position of the APs; and 4.7b the value of the localization error for each reference point, when omitting the selected RSSIs.

captured at the APs positioned on the opposite wall.

Figure 4.7 presents the measured error value and displays the direction of the errors, when determining the location in the evaluated environment, in the case we only use RSSI reported by APs on the opposite wall.

The sampling sequence started at the point $(1.25, 1)$ and continued along the x-axis of the room towards $(6.25, 1)$. Next, we collected data from $(7.25, 2)$ towards $(1.25, 2)$ and so on in left-to-right and right-to-left pattern. The arrow lengths in Figs 4.6a and 4.7a cannot be directly compared. Table 4.3 presents the absolute difference in values

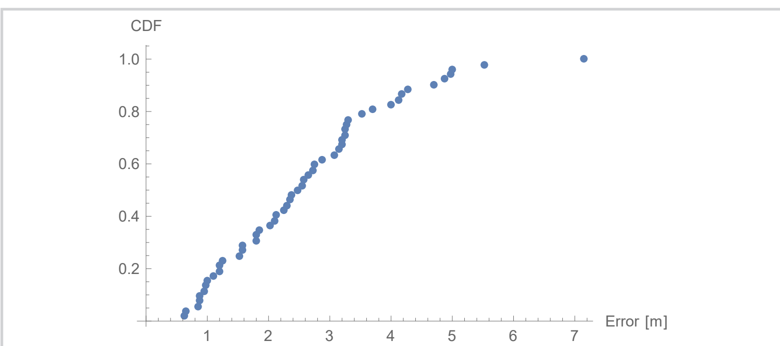


Figure 4.8

CDF of the error of the 52 reference points.

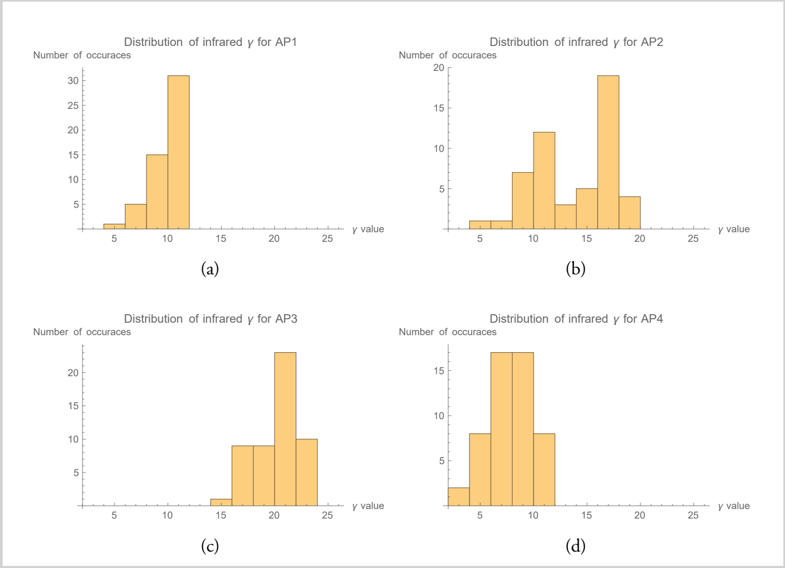


Figure 4.9

Histogram representing all 52 calculated γ for each AP during the evaluation: 4.9a AP1; 4.9b AP2; 4.9c AP3; and 4.9d AP4.

between these two approaches. In Fig. 4.7, we can see a more even distribution of the errors through space. We can see one significant error made at the evaluation position $(5.25, 7)$. The error in this case is nearly 2 m bigger than in 95 % of other measurements. This is also clearly shown in Cumulative Distribution Function (CDF) in Fig. 4.8.

The path loss exponent is sometimes thought of as a constant for all APs. This could be under the influence of misinterpreting different models, which propose specific values (e.g. COST231 line-of-sight model, ITU models, etc.). Figure 4.9 shows the distribution of the calculated γ parameters for each AP. In Fig. 4.9a, we can see that AP1 was most stable when 88 % of the calculated γ span the values between 8 and 12. γ for AP3 and AP4 have the expected symmetrical distributions. Interestingly, AP2 has a clearly visible non-symmetrical distribution, as its values reside in two groups. The first major group spans values from 8 to 12, the second from 14 to 20.

We wanted to investigate the cause of non-symmetrical distribution of γ for the AP2, therefore we performed the temporal and spatial analysis. Figure 4.10 shows that the first few measurements had extremely low γ value (below 10), which then

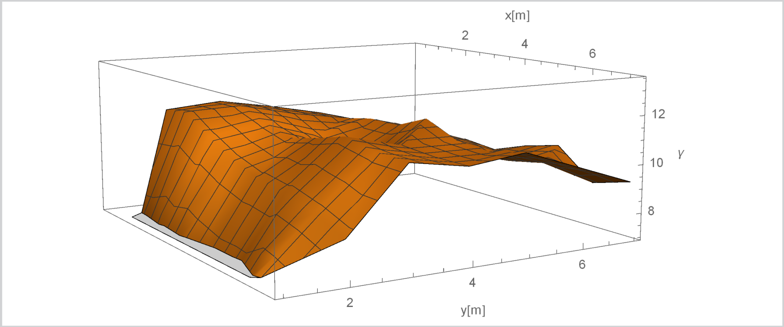


Figure 4.10

γ value calculated for every evaluation point.

suddenly rose to higher values and, during the length of the experiment, slowly started to fall. A sudden change in the WiFi spectrum during the evaluation resulted in the non-symmetrical distribution of γ values in Fig. 4.9b.

Introduction of the parameter β (as defined by Eqs. (4.2) and (4.4) of our method) improved the simulation of the signal propagation, which resulted in better accuracy of

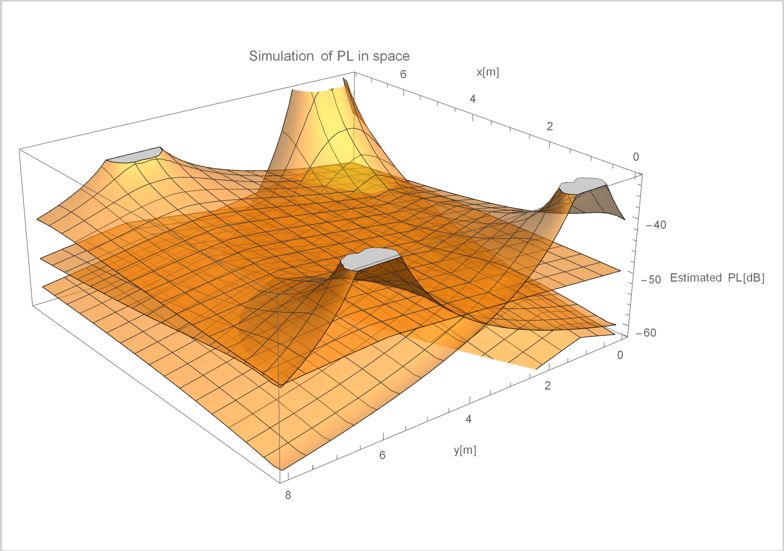


Figure 4.11

The output from the propagation simulation stage of the method — simulation of the path loss in the evaluating space, emitted by four APs.

the overall results, although we can find one measurement whose location prediction significantly worsen. We can see the improvements of prediction in Fig. 4.11 in which the output from the propagation simulation stage is shown. Figure 4.11 presents the results from the propagation simulation stage of our proposed method. It shows the estimated path losses (z-axis) in space (x- and y-axes) for each of the four APs (four meshes). Therefore, by selecting a specific (x, y) in space, we can obtain information about the estimated path losses from all 4 APs in the selected point. If we concentrate on the propagation emitting from AP2 (right in the figure), we can see that its propagation prediction at the AP1 (front middle in the figure) is lower than the nearer AP4 (left in the figure), although AP4 is 50 % further away from AP2 than AP1.

In Tab. 4.4, we can see how the introduction of the parameter β improved the accuracy in comparison to the γ-only model in which all APs were used. For easier comparison, the accuracy of the γ-only model, with the AP on the same wall being omitted, is kept. Table 4.4 shows we have achieved an even better improvement in comparison with the γ-only model which uses all APs. We can see a 9 % improvement in the median error of the proposed method if we compare it to the γ-only method. The worsening of one of the localizations can be seen in Fig. 4.12 at the position $(1.25, 6)$, which is also one of the reasons for a smaller improvement in the average error. The vertices of the gray polygon in Fig. 4.12a mark the position of the APs during the evaluation. We can observe a big difference in errors between the evaluation points inside and outside of the polygon.

For easier comparison of the discussed models, Figure 4.13 presents CDFs of all three models. From the figure, we can see the influence of omitting the APs which are positioned at big angles in relation to the normal vector of the wall. A second impor-

Table 4.4

Comparison of the mean and median errors made by all three discussed methods.

Used RSSIs for γ calculation	Mean Error [m]	Median Error [m]	Standard Deviation [m]
all APs	3.64	3.45	2.06
omitted APs	2.64	2.51	1.43
Proposed method	2.63	2.29	1.45

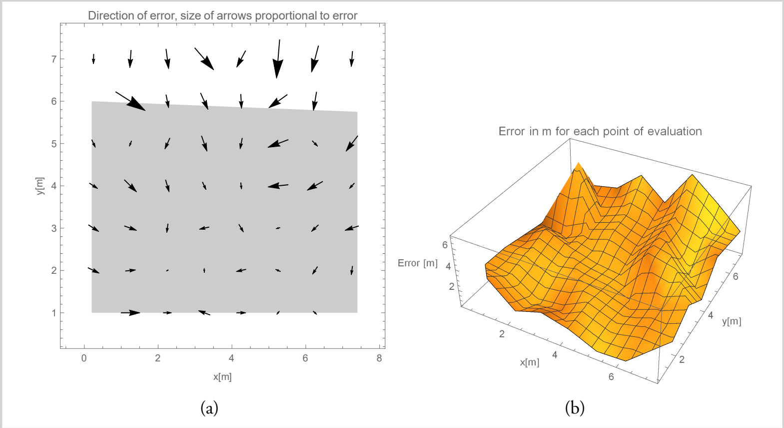


Figure 4.12

The errors of the proposed method 4.12a The direction and the relative size of the localization errors, the vertices of the gray polygon mark the position of the APs; and 4.12b the value of localization error for each reference point.

tant observation is that we were successful at including all the APs into the localization process, while retaining the accuracy of the "ideally placed APs" in the case of "γ-only – omitted APs".

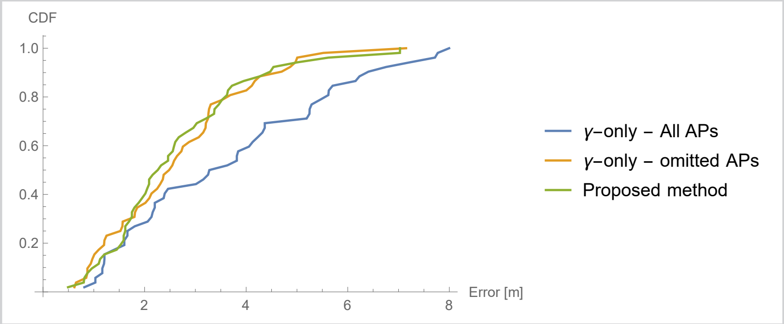


Figure 4.13

CDFs of the errors of all three discussed methods.

4.3.4 *Multi room evaluation*

After a successful evaluation in a single room office environment, we have extended our evaluation space to the neighboring office. The details of the evaluation space are presented in Fig. 4.5. Table 4.5 presents the results of the evaluation in a multi-room environment; for easier comparison with the single-room environment, the results

Table 4.5

Comparison of the single- and multi-room evaluations in the office environment.

Evaluation of Proposed method	Mean Error [m]	Median Error [m]	Standard Deviation [m]
Office single room	2.63	2.29	1.45
Office multi room	3.22	3.48	1.58

from the proposed method in Tab. 4.4 are shown.

In this evaluation, the sampling sequence started in the left room at the point $(2.25, 1)$ — i.e. lower left corner – and continued through the left room in a left-to-right, right-to-left pattern. After the last measurement in the left room at the position $(2.25, 7)$, there was a significant pause when we had to transfer our equipment into the second room, where the sampling started at $(13.25, 7)$, continuing in a top-to-bottom, bottom-to-top pattern, finishing at the point $(9.25, 1)$. Figure 4.14 presents the direction and the value of the errors during the multi-room evaluation.

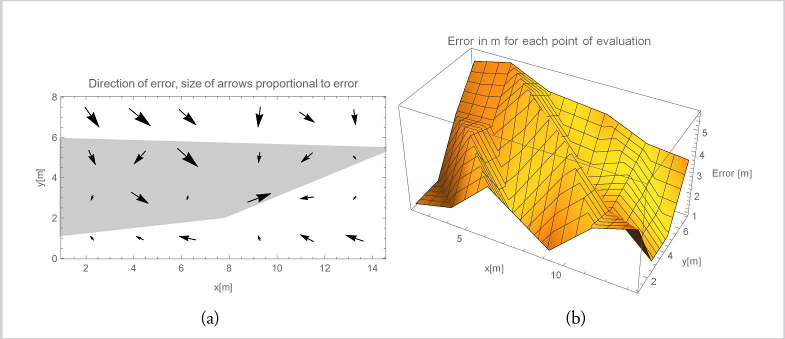


Figure 4.14

4.14a The direction of errors in the multi-room evaluation, the vertices of the gray polygon mark the position of the APs; and 4.14b the value of the localization error for each point.

4.4 Experimental evaluation in residential environment

As discussed in Section 3.5, the usual practice in the research field of the indoor localization is the evaluation in a single environment, which is usually the office space of the research institution. Even further, many methods are evaluated only in the hallways and therefore the representativeness of their reported accuracy could be argued.

For the residential evaluation, we have chosen an environment that would differ as much as possible from our office environment. The evaluation of the indoor area with similarly sized rooms, similar types of walls and the only difference being in the furniture would not be adequate for the goal of the real-world applicability for our method. Therefore, we have chosen a small modern apartment with multiple rooms, divided by different types of walls, which are described in detail in Subsection 4.4.1. The results from the evaluations are presented in Subsection 4.4.2.

4.4.1 Description of evaluation environment and protocol

We have selected a real-world evaluation environment – a modern two-bedroom apartment, constructed in 2009. It has six rooms and a mixture of brick and plaster walls. Room sizes range from 5 to 30 m^2. The apartment has been equipped with real-world furniture and fixtures used by a young family. We have set up a 2.4 GHz WiFi network consisting of four APs. Research done by Shimosaka et al. [86] shows that in RF based localization optimization of the positioning of the APs can result in accuracy improvements. For our evaluations we have not tried to optimize the position of the APs in any way, as it is our intent to evaluate the method in realistic environments. We have set one WiFi AP in the middle of the apartment and the others in the corners of the area of interest, as shown in Fig. 4.15. All APs were connected to the router via wired Ethernet network. Because the evaluation is in a real-world setting, the WiFi network was not isolated. At any given moment, we could detect between 10 and 20 different WiFi networks in range. The positions of the APs differ due to the constrains posed by the real-world furniture setting. They ranged from the position on the table 0.5 m above ground to the position above the closet at 2.3 m.

The mobile terminal used in the evaluation was the same as in the office environment, as described in Section 4.3.2. During the evaluation, the mobile terminal was held at approximately head-height position. During the evaluation design, we have determined 17 evaluation points in the apartment. The points were arranged in a mesh as depicted in Fig. 4.15 – the crossings of dashed gray lines represent the evaluation points. The mesh size and position were delegated by the real-world setting; we could not position the evaluation points in some areas where, due to furniture, we could not perform valid measurements. The spacing between the evaluation points is 2 m and 2.5 m for the width and length of the apartment respectively. The sampling sequence in all four evaluations was the same; we started at the lower left position $(0.5, 0.5)$ and

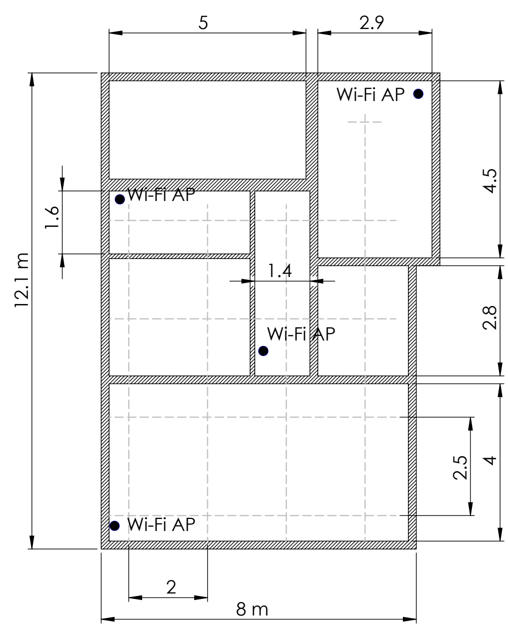


Figure 4.15

The map of the evaluation in residential environment.

measured the positions in the left-to-right and right-to-left pattern, finishing in the top evaluation point.

The properties of the evaluation mesh also dictate the mesh in the propagation simulation stage of our method. Having the evaluation points in the positions where the propagation simulation stage does not simulate the propagation would, by definition, result in the best possible accuracy bigger than $0\,\mathrm{m}$. Therefore, we had to choose a mesh with a uniform size that would fit the evaluation points. The biggest (coarsest) possible mesh has the size of $0.5\,\mathrm{m}$. Another possible reasonable value is $0.25\,\mathrm{m}$, while a value of $0.1\,\mathrm{m}$ is too fine, considering the expected accuracy and the standard deviation of the method. We have chosen a mesh with a uniform size of $0.5\,\mathrm{m}$, as such an error is more than acceptable in the real-world localizations of people and objects indoors.

Because we have developed our method in the office environment, we were even more interested in the accuracy and stability of the method in a completely different evaluation environment. Therefore, we have performed four independent measurements in every evaluation point on different days and times and obtained 4 datasets (DS). For the WiFi devices, we made sure that between the evaluations the devices were powered off for at least one hour (in order to cool the chipset to room temperature) and that they were powered and operational for at least one hour before the evaluation, to eliminate possible thermal variations due to the initial heating that can influence the results [87].

4.4.2 Experimental evaluation

During the four evaluations in the residential environment, we have obtained the presented results. Table 4.6 presents the mean and median errors with a standard deviation of all datasets and their average. We can observe the average error of 2.65 m, which is significantly better than in the office multi-room environment; the average median error has also decreased from 3.48 m to 2.59 m, while the standard deviation has stayed approximately equally small. The average values of the experiment show us that, assuming the normal distribution of the errors, approximately 84.1 % of the values have an error smaller than 4.16 m. This result, considering that the evaluation in the residential environment is completely different than the environment in which method was developed, further points toward universality of our method and its real-world applicability to any indoor space.

Table 4.6

Comparison of the mean and median errors made by the WiFi method in the residential environment

Dataset	Mean Error [m]	Median Error [m]	Standard Deviation [m]
DS1	2.50	2.55	1.31
DS2	2.43	2.55	1.21
DS3	2.89	2.55	1.62
DS4	2.77	2.69	1.91
Average	2.65	2.59	1.51

To analyze the consistency of errors through the four datasets, we can focus on Fig. 4.16. It shows the directions and proportional sizes of the error in all 4 datasets for each of the evaluation points. In Fig. 4.16, the vertices of the gray polygon depict the positions of WiFi APs. The error arrows in the vicinity of the evaluation point are always shown, so that in the top-left corner is the error from DS1, in top-right corner from DS2, in bottom-left corner from DS3 and in bottom-right corner from DS4. We can see that the sizes of the arrows in a specific point are similar, regardless of the evaluation, meaning that our method is stable and gives repeatable results. From the figure, we can also see that the errors in localization in the bottom-right corner of the

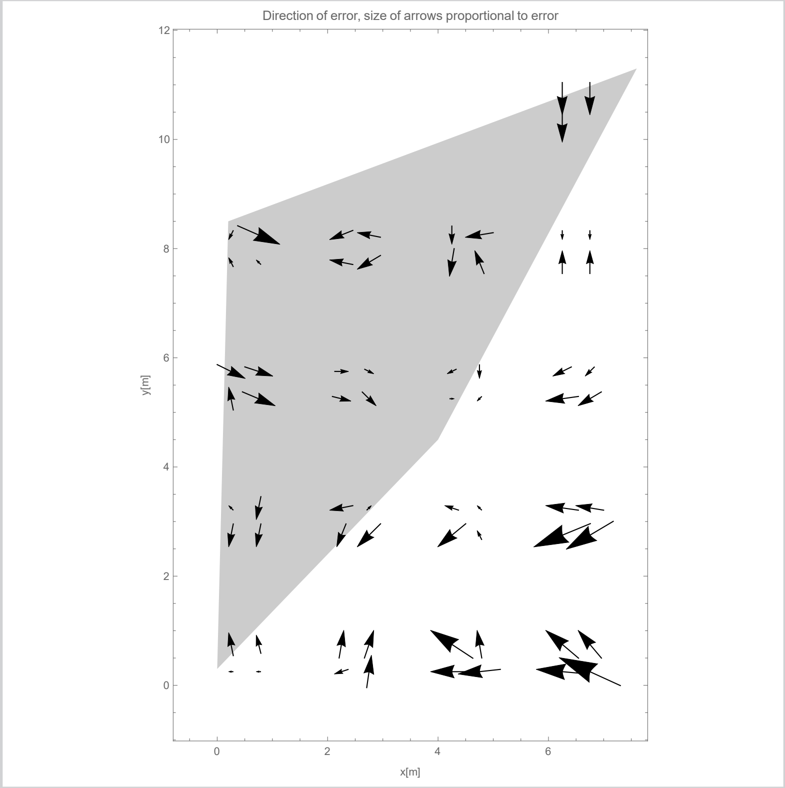


Figure 4.16

The directions and the proportional size of errors for the localization of all four datasets. Vertices of the gray polygon show the positions of the WiFi APs.

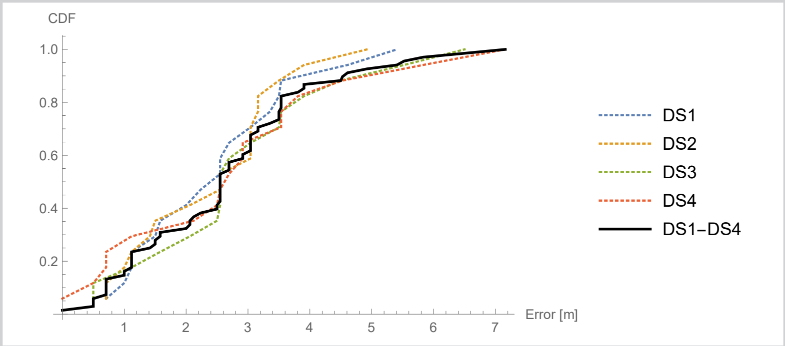


Figure 4.17

CDF of errors in individual DSs and CDF of all evaluation points.

map are considerably bigger than elsewhere. The correlation with the position of the APs can be observed - the points with high average localization errors are positioned far away from the polygon, marking the positions of the APs.

If, due to the position of the WiFi APs, we would exempt the three lower right evaluation points (i.e. positioned at $(4.5, 0.5)$, $(6.5, 0.5)$ and $(6.5, 3.0)$), the average error would be $2.19\,\mathrm{m}$ with the standard deviation of $1.11\,\mathrm{m}$, meaning that $84.1\,\%$ of the values have an error smaller than $3.30\,\mathrm{m}$.

Figure 4.17 shows CDF of each of the four datasets individually with dashed lines, and overall CDF across all datasets with a thick solid line. From Figs. 4.16 and 4.17, we can see that, although the four evaluations were performed at different times and days, the error distributions are similar and therefore our method produces stable results.

Similarly, as in the previous sections, a 3D map of errors is presented in Fig. 4.18. We can see the value of errors in each point of the evaluation for all datasets; for each dataset, we can see a mesh showing the size of errors during the evaluation. In the right corner of the Fig. 4.18, we can clearly see bigger errors from the bottom-right part of the Fig. 4.16. In the left part of the figure, we can see, similarly as in Fig. 4.16, the evaluation point $(0.5, 8.0)$, where the evaluations DS1, DS3 and DS4 gave an accurate result, while the evaluation DS2 had a non-negligible error. This is something we can expect in a highly-variable WiFi spectrum, and at the same time, we can see that other measurements done at approximately the same time do not exhibit extreme errors (the previous measurement was DS2 at $(1.5, 8.0)$ and immediately after we have done the measurement DS2 at $(6.5, 10.5)$). We can therefore hypothesize that this probably was

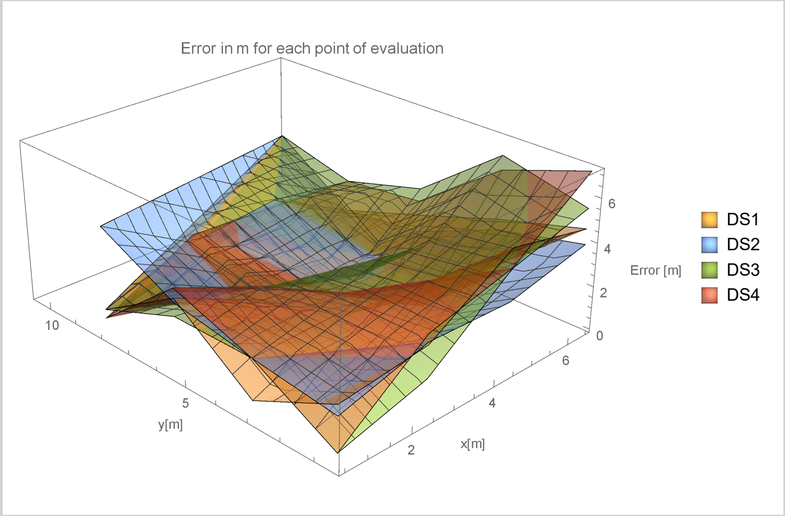


Figure 4.18

The error values of localizations in each evaluation point of all four DSs.

not an error during the estimation of the signal propagation, but rather a deviation, when sampling the three RSSI surveys at the mobile terminal.

4.5 Experimental evaluation in a hallway

As emphasized in Tbl. 2.1 and Section 3.5 a lot of authors tend to use hallways as the evaluation environments. This section provides evaluation of the proposed method in such environment in order to further show the usability and applicability of our method. At the same time this evaluation eases the comparison with such related methods. Subsection 4.5.1 describes the evaluation environment and Subsection 4.5.2 presents the results.

4.5.1 Description of evaluation environment and protocol

To perform evaluation in a long hallway we had to borrow the hallways of neighboring building - Faculty of Chemistry and Chemical Technology. Their floorplan consists of three wings, in which we can find long hallways connecting the offices and the laboratories. The map of one of the hallways can be seen in Fig. 4.19. Hallway is approximately 36 m long, on one side (the left in Fig. 4.19) the hallway expands

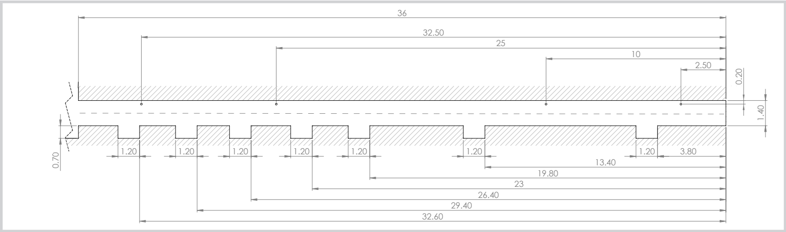


Figure 4.19

The map of the hallway evaluation environment.

into mid-sized room, on the far right side of the hallway there are doors, which were partially closed during the experiment. Four APs were positioned alongside one of the walls; they were all connected to a router via wired Ethernet network. The original APs that provide WiFi connectivity to the students at the faculty were operational during the experiments.

The mobile terminal used in the evaluation was the same as in the previous evaluations. During the evaluation we have moved the MT alongside the centerline of the hallway, which is approximately 0.5 m away from the APs. We have evaluated the method at every meter, therefore in 35 evaluation points. We have begun at the far-right in the Fig. 4.19 and finished where hallway expands into the room. We have chosen a mesh with a uniform size of 0.5 m, as such an error is more than acceptable in the real-world localizations of people and objects indoors and such mesh fits the grid of our evaluation points.

4.5.2 Experimental evaluation

During the evaluation, we have obtained results presented in Tbl. 4.7. We can observe average error of 3.72 m, median error of 2.55 m and standard deviation of 3.85 m. Small value for median error and bigger values of mean and standard deviation hints

Table 4.7

Comparison of the mean and median errors made by the WiFi method in the hallway environment

Evaluation	Mean Error [m]	Median Error [m]	Standard Deviation [m]
hallway	3.72	2.55	3.85

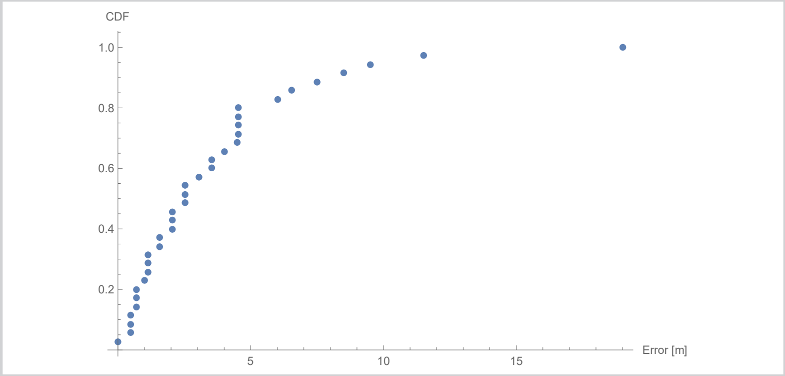


Figure 4.20

The CDF of the errors in the hallway evaluation environment.

at few outliers having significantly bigger errors than majority of the evaluation points. This can be confirmed by CDF in Fig. 4.20.

From the Fig. 4.20 we can see that there are some outliers in term of error of the localization. The two points with the biggest errors (i.e. 19.0 and 11.5 m) are two consecutive evaluation points 21 and 22. If we exempt these two points from the calculation, the median error falls to 3.0 m and standard deviation decreases to 2.4 m. We get similar values also if we exempt RSSI detections of wrongly detected most powerful AP from these two evaluations and therefore MT is positioned only by RSSI measurements to the other 3 APs.

A more detailed analysis of the captured data shows that for approximately two minutes two APs have started to emit stronger-than-expected signals. For the model calculation this is not a problem, because the rest of 15-minute timeframe ensures that such outliers do not have great effect on the model. We see bigger errors at positions 21 and 22 m from the right wall in the Fig. 4.19. If model calculated correct values, why do we see the two big errors? The problem is with detection of the signals at MP. We have checked the captured data and we have seen strong deviation from the expected values of the RSSI at the MP. The raw data captured at the MP when evaluating in evaluation point 21 can be seen in Fig. 4.21. The mean values of RSSIs (used for location determination as discussed in 4.2.4) are written in bold. We can see that AP furthest away (at the far right in Fig. 4.19) has the biggest RSSI and therefore is much bigger than expected and therefore MT is localized with big errors. As we can see the

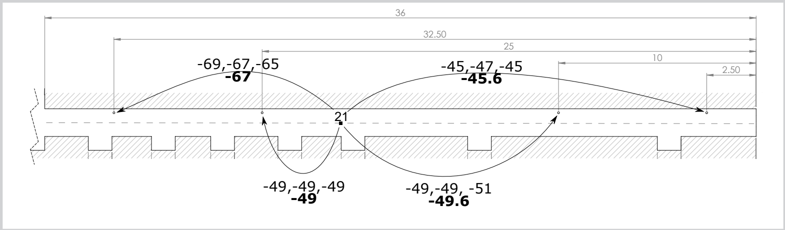


Figure 4.21

RSSIs at the MP at the evaluation point 21.

biggest problem is not with the proposed method itself but due to the RSSI detection at the MT.

Nevertheless, it is also true that we can expect bigger average error in hallway scenario as average error in case of random positioning is bigger. In case we randomly set the position of the AP we can expect average error of $11.92\,\mathrm{m}$ in case of hallway and $4.86\,\mathrm{m}$ in our residential environment. This means that for the localizations in which MT detected unexpected RSSI values, average error can be up to 3 times bigger and similarly also maximal error (12.35 vs. $36.0\,\mathrm{m}$). In such cases when we measure small positive values (error cannot be negative, their average value is up to a few meters), a few outliers having big values (big errors) greatly influence the outcome of the mean. Therefore, in such cases it is more sensible to compare values by the median value. Comparison of the median value shows that our hallway evaluation has better median error than multi room office evaluation and (multi-room) residential evaluation, while has slightly worse performance than single-room office evaluation.

The proposed method was designed for real-world indoor localization, meaning that such scenario is completely opposite to the method's intent. Our proposed method is one of the few model-based that addresses the number and type of the walls between AP and MT, which are not present in such evaluation environment. Moreover, method includes parameters which include the specific position of the APs in relation to the closest reflective surface (the wall beside which AP is positioned), which in such evaluation case is constant and the same for all APs. We can see that even if the method was not designed for such scenarios it still gives similar results than in other (more difficult) evaluation procedures.

If it would be in one's intent to show the best results, one could filter out the scenario in which MT detected RSSI values in unexpected manner or repeat the evaluation in those two evaluation points to get better RSSI detections. As we want to be fully disclosed about the evaluations we have included those two evaluation points in the original form.

4.6 Discussion

In the previous sections, we have presented the proposed method and the four evaluations we have designed to also test the usability and versatility, apart from the accuracy of the method. This chapter provides some further discussion about the presented results.

All the analysis and manipulation of the data presented in evaluations has been described in the published papers and presented thesis, no additional steps were taken during the evaluation or analysis to achieve better results (e.g. pruning the data for outliers). Every data manipulation (e.g. filtering with median filter) has been explicitly stated in the thesis: During the data acquisition stage raw data obtained from the APs is stored (no filtering or any other data manipulation is applied). When calculating the attenuation parameters in the path loss modeling stage the data is filter by median filter as discussed in Section 4.2.1, paragraph 2. Filter's window size 3 is specified in Section 4.3.1 - "Experimental prerequisites", paragraph 2. During the localization stage we use mean of three samplings of the RSSI at the MT, as specified 4.2.4 in order to partially address the problem of outliers and variability of the RSSI data.

We have published results on all the evaluations in office and residential environment. We have not performed other evaluations, of which data would not be presented in this thesis in order to, for example, hide worse-performing evaluations. We have not repeated evaluations in any point even if we were confident that an evaluation point is an outlier and therefore has significant impact on average performance of the evaluation – e.g. section 4.5.2, evaluation point 21. As can be seen from evaluation maps (i.e. Figs. 4.4, 4.5, 4.15, 4.19) all our evaluation points were determined via geometry-based patterns, and all the evaluation points were included in the analysis – we have not exempt any evaluation point in order to improve the accuracy of the evaluations.

Presented deduction of the model is mostly based on physical (theoretical) properties of signal propagation. We have included one parameter to include the effect we have observed empirically – the parameter β. In our preliminary testing and evaluations, we have tried to use linear and trigonometric relationships between the angle and the parameter β and consequently the effect on the RSSI. From the experience

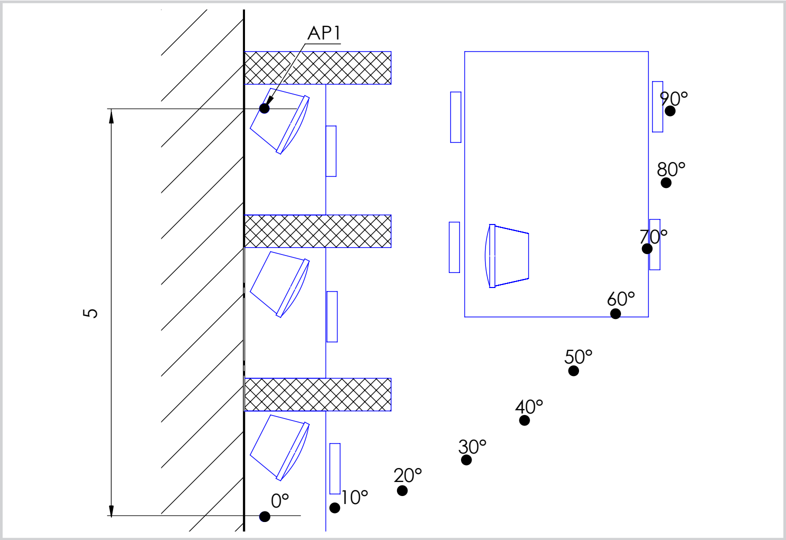


Figure 4.22

Setup of the experiment intended for confirmation of inclusion of the β parameter.

of dealing with formulas in which angles have the effect on the result one would assume that trigonometric function should be the correct approach. In the end we have chosen linear dependence, as it simplifies the model and in some preliminary testing resulted in better localization accuracy.

In order to further confirm the linear approach to the included angle we have designed an experiment, which is presented in Fig. 4.22. We have set one emitting AP (in Fig. 4.22 marked as AP1). Second AP was moved in semicircle around the AP1 at a distance of 5 m. At each selected angle we have recorded 15 RSSIs (one per minute) of the signals emitted by the AP1. A third AP was placed statically to monitor the RSSI of the signals coming from AP1 in order to confirm that no major change in the emitting powers occurred and that measurements at each angle can be compared.

Figure 4.23 present the result of statistical analysis. Light orange dots in the chart present measured RSSI values at a specific angle. These values at individual angle were used to calculate the statistics of normally distributed value at each angle – the mean and standard deviation. Dashed blue lines denote the mean, and $\pm\sigma$, $\pm2\sigma$ and $\pm3\sigma$ intervals. Solid red and green line present the linear- and sine-dependent model trained on the data obtained in the experiment.

As the distance between AP1 and receiving AP is constant (5 m) we should see a constant value of the mean (darkest blue dashed line) – i.e. horizontal line in the figure. The trend of higher RSSI values at bigger angles can be seen from the figure, meaning that effect observed during preliminary evaluation is confirmed. At the same time, we can see that distribution of the RSSI around mean is order of magnitude bigger than difference between linear and sine model. The average difference between the two models is approximately 13 % of the averaged standard deviation therefore it is very difficult to determine which model better reflects the measurements with any statistical significance.

Let's examine the worst-case scenario – when RSSI was most stable and the difference between the models are the biggest. We have measured most stable RSSI at angle 40°, where standard deviation was 0.9 and mean was -37.67. The biggest difference in the output of the two model is 0.9, which is equal to 1σ. If we want stable method, where we can expect real-world distribution of the RSSI and achieve confidence interval of e.g. $\pm 2\sigma$, then an average difference of 0.13σ in the model should not influence the results dramatically.

Moreover, if we acknowledge the fact that obtained RSSI is integer value, then only in the 3 out of 10 angles we can observe difference of the (rounded) outputs of the two models – angles 0°, 60° and 90°. From the results we can see that other effects have far

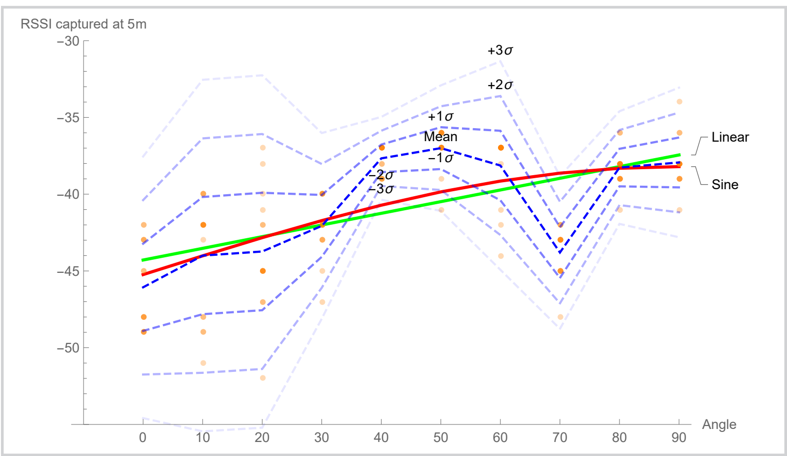


Figure 4.23

Statistical analysis of the experiment intended for confirmation of inclusion of the β parameter.

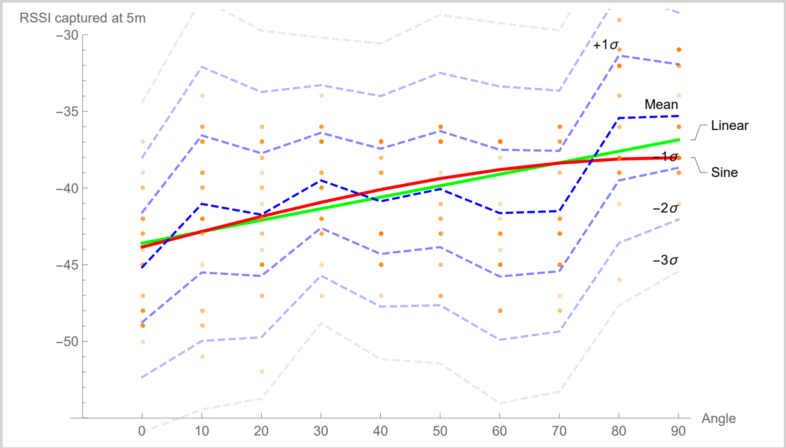


Figure 4.24

Statistical analysis of the experiment intended for confirmation of inclusion of the β parameter – exclusion of the interreference.

bigger influence on the measured RSSI values than change from linear- to sine-based model. Such effects include: multipath, interference, shadowing, etc.

To further show that deviations of the values from linear and sine values in Fig. 4.23 are due to the multipath, interference, etc. we have performed another set of measurements in range $0°$ to $90°$ in the same room (i.e. to have the same effect of the indoor setting on the signal) but with different positions of the APs. The receiving AP was at the same distance from the transmitting AP as in the first set of the measurements. Due to the different spatial position of the APs in the room (although at the same relative position to the wall), locations in the indoors of the receiving AP were changed and therefore the influence of interference etc. was changed for each of the evaluation points. Fig. 4.24 presents similar results as Fig. 4.23, only that we have included measurements from both experiments.

The inclusion of multiple measurements in one figure, although captured at differently positioned APs, is not problematic as in our methods the values for β_i are calculated based on detections of the RSSI at different positions (angles and distances) in space. We can see that value of the mean in this figure more closely follows the linear and sine approximation, but we can still see that difference in the two approximation is negligible in comparison to the deviation of the data.

One of the concerns, when designing the evaluation procedure, was how to define the sampling procedure. The first option would be to assure that the evaluation of each of the evaluation points is most independent from all the other points. This would bear consequence in experiments taking a lot of time – for 52 evaluation points we would need approximately 17 hours to take the measurements if we approximate 20 minutes per each evaluation point. Out of these 20 minutes, 16 minutes are used for gathering the required independent measurements of the data acquisition stage and the rest to sample RSSI at the mobile terminal and move the equipment. To achieve an even greater independence of the measurements one could turn the APs off in between the measurements, while also cooling them to the room temperature and ensuring that they are at a stable thermal state before proceeding to the next point. This evaluation procedure is even more difficult to realize, as we could get only a few measurements per day. The second option is to try to get the measurements in the evaluation points in the shortest time possible. Such procedure enables us to get a lot of the datasets in a relatively short amount of time. The second big advantage is that by minimizing the timeframe of the dataset, we also minimize the changes in the environment and therefore obtain comparable results. For example, if a timeframe for a single dataset in the office environment would span 17 hours, we would include the measurements when the office was full and the measurements in the night, when the office was empty.

We have chosen the second option, therefore we tried to keep the sampling procedure quick. This consequently means that some evaluation points share some of the data from the data acquisition stage. The evaluation of the 52 evaluation points in the single-room evaluation took approximately one hour, as we needed between 1 and 2 minutes for each evaluation point. This means that if there would be an unexpected occurrence in the WiFi signal (e.g. one of the APs would start to emit the signals at much higher power) and if it would last for about 5 minutes, we could observe its effect in three to five evaluation points. Considering the specified sampling sequence in the description of each evaluation environment, while observing the results in 4.12a and 4.14a, we cannot detect any sequences with relatively high or low errors. We can therefore conclude that no such events occurred during the presented evaluations. Due to the reasons discussed in the Chapter 5, the timing of the evaluation in the residential environment differs. The evaluation of the WiFi RSSI in each of the evaluation points in the residential environment is approximately 6 to 10 minutes apart.

The evaluation of the single-room and multi-room office environments took place more than a week apart, with no changes to the system, except for the changing of the position of the two APs. Because our method, by its definition, utilizes only the measurements gathered in the last 16 minutes for the location estimation, it can be used for long-time deployments. The results in the accuracy of the two evaluations more than a week apart confirm these claims empirically. An even stronger evidence of the universality of the method are the results obtained in the evaluation environment of a modern home. The method was developed and initially tested in the office environment, but after it has been moved to the residential environment it showed even better results. Between the evaluation of the system in the multi-room office scenario and the evaluation in the residential environment, we did not change any part of the WiFi localization algorithm. We have only connected the APs and the server to the network and inputted a new map of the indoors (positions of the APs and the apartment's walls), yet the proposed method resulted in an even more accurate evaluation that the one in the office environment.

The robustness and adaptiveness of our method is also confirmed by the comparison of Figs. 4.10 and 4.7a. Although we can see a significant change in the parameter γ in the second row of evaluation, we cannot detect a big change in the accuracy of the results in the bottom two rows of Fig. 4.7a. This means that some non-identified factor changed the transmission or the propagation properties of the AP2. From the Fig. 4.10 and the resulting accuracy, we can see that the system successfully adapted to the 4 to 5 dB change in the environmental parameter γ. If the method used static parameters for the signal propagation, we can speculate that the accuracy of the results could not be the same before and after the change. Regarding the possible factors that influenced the change, we cannot scientifically prove any. As discussed, we tried to keep the environmental data as stable as possible during the evaluation, but of course there are parameters we could not control – e.g. a number of WiFi devices and people outside the two rooms, etc. The AP in question, i.e. AP2, is positioned near the window and one of the possibilities we cannot exempt is also the effect of the heating of the unit due to the direct sunlight. Regardless the cause, the method successfully adapted to the change and gave good results, as can be seen from Fig. 4.7a.

The examination of Fig. 4.13 reveals a big difference in the accuracy of the model, when we omitted the APs located on the same wall. In real-world situations it is nearly impossible to provide two ideally placed APs for each of the APs to obtain the same results we have in the "γ-only – omitted APs" case. Therefore, we have searched for ways to include all APs, while still taking into account the observed phenomena. This is why we have extended the model with the parameter β in Eq. (4.4). The similarity between the CDF of the method with the omitted APs and the CDF of the proposed method shows how we successfully included the phenomena of the wall, acting as an antenna reflector, into the method.

A careful examination of Fig. 4.13 reveals that the evaluation points with the lowest localization error are better localized with the omitted γ-only method, defined by Eq. (4.1). The most accurate 30 % of the points can be up to 40 cm more accurately localized than with the proposed method, but on the other hand, we see that in the range of the bottom 30-70 % usage of the proposed is beneficiary, as the proposed method provides better results. To answer the question about why the error in the lower part of the CDF is less important for the method evaluation, we must put the accuracy numbers in context. When localizing a subject who is holding a mobile terminal in his hands it is less important if the method in the 30 % of the best measurements gives an error of 1 m instead of 0.6 m, as these locations are in the reach of the subject; it is more important that the measurements which have an error of 2.5 m do not result in bigger errors. The small difference in errors can also be due to the setting of the experiment. From the data observed between the γ-only experiments (the one with all APs and the one with the omitted APs), we know that in single-room scenarios the position of the APs has a non-negligible influence. In real-world deployments we cannot assume that each AP will have two other APs at a desired position for the acceptable parameter estimation. The accuracy in the real-world evaluation in the residential environment, where we could not influence the positions of the APs, as we were constrained by the locations of the sockets for wired Ethernet network, confirms that our method can adapt to the real-world environment.

The accuracy of the evaluations in different evaluation scenarios can also be compared with respect to the area and number of the dividing walls. In the single-room experiment, the evaluation environment measured approximately 60 m^2. While retaining the same number of the devices, we have effectively doubled the area in the multi-room office environment, while introducing a thin dividing wall made of plaster. In the residential evaluation environment, we have kept approximately the same area and the same number of APs, but introduced multiple dividing walls. Five walls were made of brick and concrete and two were thin-plaster walls, similar as in the multi-room office environment. We have not optimized the placements of the APs, as we wanted real-world limitations of placement and infrastructure to influence our results. The effect of the evaluation point versus the position of the APs can be seen in all four evaluations. In the single-room office environment we can see the biggest errors at the top of Fig. 4.12a – these points are also the points outside of the polygon, marking the positions of WiFi APs. Similarly, we can see the biggest errors at the top row of the evaluation in 4.14a. Interestingly, the points of evaluation in the bottom and bottom-right parts of the map do not exaggerate big errors, although they are outside the gray polygon. This could be due to the bottom wall which is made of glass, but further evaluation would be needed to confirm the effect of the windows on the signal reflection.

Every RSSI model- and fingerprint-based WiFi localization method is prone to errors when unexpected situation occurs and one or more devices start to emit more powerful signals than usual. It can also be the case that one of the devices starts to report much higher values than expected, therefore the error can also occur at the receiver. The researchers of the modeled and fingerprint approaches try to avoid such situations during the evaluation. One such occurrence can be seen in Fig. 3.2, on Thursday night of the 8th week. We can see a period of a few hours, when the signals received by AP2 and emitted from AP4 have reached its maximum. Such events are usually handled by our method, but in this case a similar thing occurred also on the connection between AP3 at AP1, as displayed in Figure 4.25a. Because we were present in the office at the time, we decided to investigate the situation and perform a sampling at each point of the evaluation.

Figure 4.25a presents how the signal emitted from AP3 was detected at the other

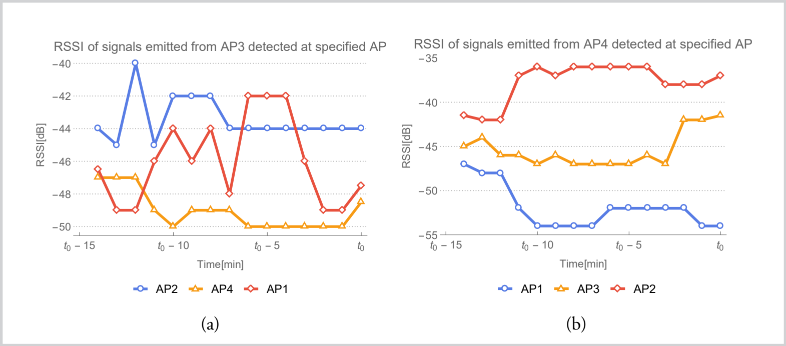
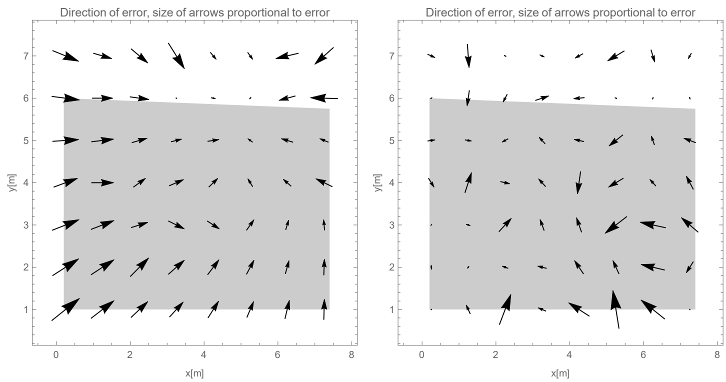


Figure 4.25

4.25a 15min time frame of signals emitted from AP3 during the unusual period; and 4.25b 15min time frame of signals emitted from AP4 during the unusual period. t_0 is the time at which we initialized the sampling method.



(a) (b)

Figure 4.26

4.26a Error directions without the implemented failback at the unusual event on Thursday of week 8; and 4.26b Error directions with the implemented failback at the unusual event on Thursday of week 8.

three APs. The expected value for the AP1 is to be the least powerful, because it is positioned at the furthest position. Similarly, in Fig. 4.25b, we would expect AP1 to have the highest RSSI, as it is the AP closest to the ideal place on the opposite wall. Such measurements of the signals resulted in negative values for the exponent path loss parameter. Figure 4.26a shows the directions of the errors for the full evaluation, which we were able to perform during this event without the implementation of the failback procedure discussed in Sec. 4.2.2. Our method can detect similar events as it calculates the unexpected (i.e. negative) values for γ. This is another advantage of our method in comparison to the fingerprinting methods which cannot detect such situations.

Implementing the failback procedure on this dataset gave us great results. We obtained an average error of 2.43 m, and a mean error of 2.00 m, which is number-wise better than our evaluation experiment. Because nearly 50 % of the γ-values were replaced, no other significance should be given to these values, other than our method giving usable results even in such circumstances. Figure 4.26b presents the evaluation errors in the case of the used failback. The comparison of the two sub-figures in Fig. 4.26 shows the big difference that the implementation of the failback makes.

It is always difficult to compare the accuracy of the indoor localization methods. As methods are diverse, it is impossible to design a test set on which all the methods would be evaluated. Implementing multiple methods and evaluating them in common environment is the only possibility, but usually impossible to do due to hardware and software constrains. This usually originates from the authors of the papers, who often describe the evaluation environment vaguely. Information about the evaluation environment, other than the basic geometry, is often exempt from the published papers. We have tried to give as much detail as possible about the evaluation space to give the possibility of repeating the evaluation and create awareness that such information is necessary for even the simplest comparison.

While we were gathering information for the comparison table, presented in Section 2.1.2, we had a lot of problems defining the evaluation environment properties. At the end, the only property upon which were able to do the comparison is the approximate size of the evaluation environment and the number of devices. Even while comparing the size of the evaluation area, we have found many methods which present the indoor localization approaches and have done the evaluation only in hallways and did not properly evaluate the method in complex indoor areas. We are convinced that the indoor localization methods should be evaluated in the real-world indoor environments; these usually include multiple rooms, whose effect should be included in the evaluation. Another interesting observation that arose while comparing the methods is that all methods, except one, were evaluated in the office environment, usually in the indoor spaces of faculties and other research institutions. It is safe to assume that these evaluation environments are the same as the environments in which the methods were developed and therefore do not represent an independent evaluation environment. In our case, we have developed the method at the evaluation environment presented as "the single-room office evaluation environment", but we have also provided the evaluation in an independent evaluation environment – "the residential environment", presented in Section 4.4. We have not done any changes to the WiFi localization method, when moving the experiment from the office to the residential environment. An outsider from the field could argue that the evaluation of the method in the same environment as its development is, as one would utilize, the same dataset for learning and evaluation of some algorithm.

Another problem of the evaluation of the indoor localization method is that the accuracy of similar methods often depends greatly on the number of deployed APs, anchor points, beacons, etc. RSSI values, as the name suggests, indicate the received signal strength (RSS) values. The RSS value of the wireless communication signals of any type in a real-world indoor setting exaggerates heavy variability due to wall reflections, a multi-path effect, etc. Therefore, having four stations – which in turn means four fixed origins in the triangulation problem - results in localization variability. The number of the WiFi points in relation to the size of the indoor area has a key influence on the accuracy. The only thing stopping us from changing the odds of this ratio is the real-world implementation and practicality. The development of a WiFi localization method with one AP in every room and the evaluation in a floor plan consisting of many small rooms would result in small mean and median errors if we would only set the location of a mobile terminal to the center of a room, from which we sense the AP with the highest RSSI. Utilizing 5 GHz WiFi which is worse at penetrating the walls than the 2.4 GHz would further improve our results; the usage of a future 802.11ad which has a carrier frequency of 60 GHz would even further isolate the room during the localization. Real-world usability of the localization method is the most important limiting factor to the number of WiFi APs. Therefore, we have limited ourselves to four APs for this evaluation, which is only one more than the minimum number required for any triangulation-based localization method. Having that one extra AP enables us to correct the errors due to the variability of the RSSI.

We evaluated our method in a realistic scenario and got an average error between 2 and 3 m in the static measuring conditions in the single-room evaluation, and 3 to 4 m in the multi-room evaluation in the office environment. In the residential environment in which the method was neither previously developed nor evaluated, we achieved the average error of 2.65 m, with a standard deviation 1.51 m, while having the average median error of just 2.59 m. The comparison of our results to the papers surveyed in Section 2.1.2 is, as can be seen, heavily influenced by the information provided by the authors. Du et al. [67] report a similar 2 to 3 m accuracy, but the results are difficult to compare, regarding different method requirements. Their main evaluation (and therefore the majority of the evaluation points) is in a long narrow hallway, which is one of the places where the path loss factor is the lowest [78]. From their RSSI error it can be seen that the RSSI error at points which are not in the corridor (points numbered 15 to 25) have the most variance and contain the evaluation points with 10 % of the biggest errors. Dumont et al. [66] report a mean error of 3 to 4 m in an area approximately 4 to 5 times bigger than ours, and with 2.5 times more APs. Lim et al. [34] give great emphasis on the number of APs involved into the localization procedure. From their final results it can be seen that, when using 4 APs, the median error of their approach is about 3.5 m in an experiment, where the mobile terminal was in AP mode and emitted signals towards APS for 2 min. Tarrio et al. [64] report similar errors in experiments with the similar surface of interest.

During the survey it was sometimes even difficult to understand if the localization method requires for the mobile terminal to be in AP mode, or if the authors have managed to develop the method in which the mobile terminal is a passive device in the network, while localizing. Presented results confirm that our method achieves similar accuracy as other existing methods, therefore confirming that the indoor WiFi-only localization method that does not require the mobile terminal in an access-point mode or any additional hardware, can be implemented. Main scientific contribution of this thesis is a pure model-based WiFi-only approach that implements the self-calibrating and self-adapting operability for the real-world deployment. Our method considers the effects of the architectural aspects (e.g. propagation loss through walls) and is applicable on widely available hardware. Presented method requires multiple APs and a single localization server to run, thus making it ideal for the applications in a variety of indoor situations.

Synthesizing the information obtained in all three evaluation procedures results in two important facts. Firstly, our method is highly applicable to the multi-room indoor localization scenarios, as it is maintenance-free and results in a low localization error. Secondly, we can see that higher localization errors often occur in the areas which are outside the polygon connecting the APs. This can be observed in the top rows of Figs. 4.12a and 4.14a, and also in the bottom-right part of Fig. 4.16. Similarly, we can observe some of the biggest errors in the bottom row of Fig. 4.26b, although not much emphasis can be put on this particular result due to a number of γ-values replaced, as discussed previously. The results therefore show us that the positions of the APs have a great effect on the accuracy of the method. In the residential evaluation, we were also constrained by the infrastructure – the positions of the furniture, Ethernet- and electrical-sockets. As placement of the APs influence the accuracy, this opens a possibility for further research in defining the optimal spacing of the APs and consequently resulting in the improved accuracy of the proposed method.

A careful reader of this thesis has learned that the comparison of different methods for the indoor localization is extremely difficult. The main reason for this is that in the research field of the indoor localization, the methods are not commonly evaluated in the same evaluation environment and at the same time the evaluation environment greatly influences the outcome of the evaluations. There are many reasons why the methods are not compared in the same environment; just to name a few that we have faced, when we have thought about the implementation of such a common evaluation environment:

- The hardware constrains – Due to the variety of the methods, it is difficult to build an evaluation environment in which multiple methods can be evaluated – e.g. some methods utilize Bluetooth, some Li-Fi, other WiFi signals, some require specially build anchors, etc.

- The working principle of the method – The methods have a different core working principle; some utilize a fingerprinting procedure, some crowds of people, others calibration procedures and some do not have such requirements.

Therefore, the usual comparison of the indoor localization methods in research papers usually consists of the data, such as we have presented in Table 2.1. Usually, the average error of the method is compared to some additional properties of the method. Examples of such reviews can be found in [7–9, 33]. We have focused our comparison on the size of the evaluation area and the number of devices needed by the evaluated method. The reader of this thesis should not be focused only on the accuracy column, as the size of the evaluation space and the number of the devices used should also be considered. With the intent to help the reader who is not involved in the research field of the indoor localization to better understand the accuracy of the localization, we have defined a simple value, by which we can compare the methods. For the comparison we have selected the methods that are presented in Table 2.1 and have not been evaluated in simplistic hallway. We have compared those methods to our proposed method. As we are interested into the real-world applicability of the method, we were focused on the accuracy of the method, the number of devices needed for the method and the area in which the accuracy was obtained.

The area and the number of devices are not independent values. Having a much bigger evaluation environment usually calls for a greater number of access points and other hardware; therefore, we have first defined the values defined as the ratio between the area of the evaluation and the number of devices. This way we have obtained a measure of the evaluation environment and we can quickly identify that the evaluation of the method proposed by Bisio et al. [53] needs one device for each $14\,\mathrm{m}^2$, while

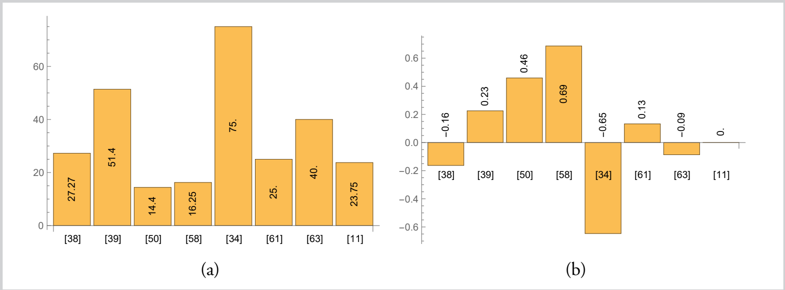


Figure 4.27

4.27a Comparison of the ratios between the area of the evaluation and the number of the devices; 4.27b Comparison of ratios between the average error size and the index in 4.27a.

the evaluation by Lim needed only one device per $75\,\mathrm{m}^2$. This is the statistical value which can be misleading, as any triangulation-based approach usually needs at least 3-4 devices. The results obtained are presented in the Fig. 4.27a.

Nevertheless, if we compare the ratios between the average error during localization and the previous value, representing the size of the evaluation space, we can get some value to compare the methods. In Fig. 4.27b, we have normalized this value to our method in order to make a better comparison of the related work methods.

In Fig. 4.27b, we can see 3 methods performing better than ours. Firstly, Chan's [38] method heavily depends on the number of clusters discovered opportunistically via ZigBee. The usage of the crowd makes it rather unsuitable for the home environment, industry or less crowed spaces. On the other hand, it can be implemented in a museum or other heavily populated spaces. The method proposed by Lim has two real-world drawbacks: firstly, during the localization, the mobile terminal emits signal from the location for 2 minutes, therefore it is rather slow, as the object has to be positioned in one place for 2 minutes. Secondly, the mobile terminal must send information out constantly during these two minutes in order to be localized, which limits the method's applicability in heavy crowded areas. Dumont's method [66] is marginally better in comparison to ours, but also requires the terminal to send information, in contrast to our method which works only on the received signals.

Directly comparing results of our hallway evaluation to the methods presented in Tbl. 2.1, which are model based and were evaluated in a hallway environment results in:

- Olivera et al. [54] present fusion approach, they fuse WiFi localization with odometry data provided by the robot they are trying to localize. It is expected that method that gets direct feedback from the wheels of the robot (data provided by the encoder) can achieve better results than WiFi-only method.

- Zhuang et al. [55] present method which utilizes crowdsensing in order to address variability of the RSSI. Background services track movements of the users through IMU sensors constantly and monitor the RSSI. Combination of the data together with data about users' daily routines presents base data upon which localization models are built. The evaluation results in worse accuracy than our method, not to mention drawbacks for real-world implementations, e.g. constantly running services in the background that drain mobile phones' battery and the need to constantly track users in order to update the database are not best fitted for present needs.

- Zampella et al. [57] present another fusion approach that fuse WiFi information (RSSI and ToF) with dead reckoning data. Their RSS WiFi method has worse results than results obtained in our case, as it results in median value of approximately 5.5 m, in comparison to our 2.55 m. Their fused approach is theoretically oriented as it requires IMU sensors in the foot of the person walking indoor. Due to accurate IMU readings they claim their fusion approach results in average errors in the order 1 to 2 m.

- Chiou et al. [58] present an indoor localization system which has one significant drawback, i.e. it has two calibration procedures, one can be performed in advance, second "must be performed at the beginning of the on-line stage", therefore this method is not suitable for real-world evaluations. Method's evaluation includes sampling the SNR of the WiFi immediately before the evaluation at approximately every 5 m. Also, the sampling procedure for the calibration is difficult as wireless receiver has to be set on a turntable and values have to be captured towards multiple directions. Such difficult and non-realistic deployment procedure results in accuracy much better than ours.

- Ji et al. [62] propose a method which has similar error as our evaluations. One of the biggest drawbacks for the real-world deployment is that mobile terminal emits the signal for approximately 1 min and the sniffers placed in the indoors determine position based on their measurements during this time. As discussed in 3.2 such approach is not best suited for crowded spaces. Also, as can be understood from the paper, they calibrated the method using calibration measurements at the same 30 points as they have later used for evaluation, such condition is unrealistic for real-world deployments.

- Xiao et al. [65] proposed indoor localization method presents method which requires "an extensive indoor measurement campaign in order to collect training data for the model", although the results from this training are applied into different scenario for validation. Validation consist of only 8 evaluation points. Results of the method by Xiao are a slightly better than our method, although no information is provided about how often and in which cases new training data should be obtained. Our method does not require any training data and achieves slightly worse results.

- Du et al. [67] present method which has slightly better performance in hallway scenario but requires device to emit the signals in order for the APs to record the RSSI, as discussed in 3.2 such approach is not best suited for crowded spaces.

The proposed method has been developed with the main aim of providing the localization for the IoT devices. Many of them will be deployed in our homes, where there are no crowds of people that would provide the fingerprinting samples. Many devices are also stationary, with no usable data from IMU sensors. Although our method has been built with the localization of the IoT devices of the future in mind, it is also applicable to different scenarios. Our method, which does not saturate the WiFi channels by requiring the terminals to be in the AP mode, has great potential in heavily crowded places. Providing means of the localization is in the best interest of the airports, commercial buildings, museums, etc. These buildings usually already have a WiFi infrastructure and offer mobile applications for visitors, which provide information, means of payments, ticketing, etc. The applications would benefit if the indoor location could be determined and better information could be given to the users. The localization of tools and equipment in production halls is a common problem in the industry. Our method's ability to adapt makes it a candidate for such deployments, because of the frequent movements of large metal objects, with non-negligible impact on the WiFi propagation. When developing our method, we have tried to keep the hardware and software requirements simple for the method to be easily applicable and extendable. Although outside the scope of our research of the pure WiFi model-based approaches, the simplicity of the application of our proposed method gives researchers the opportunity to utilize our method and our propagation models in their own work.

4.7 Conclusions

We have presented a novel localization method that was developed with the main aim of the real-world applicability. Our proposed method is purely model-based, with no static input parameters. As it implements a continuous self-calibrating and self-adapting procedure, it adapts to the changes in the WiFi spectrum. The only location-depended input parameter to the method is the map of the indoor spaces with the specified positions of the walls and the APs. All other parameters that influence the signal propagation (e.g. the exponential path loss parameter) are measured and calculated by the method from the signals captured by the APs.

Our method utilizes well-known FSPL and ITU propagation models which we have extended with additional parameters. The first parameter describes the effect of the direction of the direct-signal path in reference to the wall on which the emitting AP is mounted. We have confirmed that, especially in the single-room situations, these factors are important for the accurate RSS predictions; in multi-room situations, the effects of the walls that cause multipath and scattering diminish the effect. The second parameter describes the effect of the walls on the signal propagation. Contrary to the office buildings, in the modern residential buildings, where the distribution of the walls and the sizes of the rooms are not uniform, information about the position of the walls presents an important factor for the improved accuracy.

During the development of the method, we made sure to properly address the deficiencies and limitations of the related methods, as presented in the Chapters 2 and 3. Primarily we have designed a real-world evaluation procedure, in which we have evaluated the method in an environment which is completely independent of the development environment. Thus, the method has not been altered between the development, the initial evaluation in the office environment and the evaluation in the residential environment. The development and the evaluation environment also exhibit different properties of the floor plan, structural elements and interiors. We have also provided the evaluation with uniformly distributed evaluation points between the hallways and rooms to address the deficiencies, which we have emphasized in Tbl. 2.1. Secondly, we have addressed the problems of the long-term temporal variations of the method which assume static input parameters of the signal propagation, as discussed in 3.1.

The method fully addresses the problems of long-term stability of the WiFi signals, by utilizing the measurements of the RSSIs between APs in a timeframe of 16 minutes, before the localization occurs. Therefore, the presented WiFi localization method is one of the few methods that have the same accuracy the moment they are deployed and days, months or years later, without any human intervention. Thirdly, our method does not require mobile terminals to be in the AP mode and thus do not saturate the WiFi channels, which is especially important for the real-world deployments in the crowded public spaces. Although the method has been evaluated on the WiFi signals, it was designed with the future networks in mind and is theoretically independent in regard to the protocol and frequency. An important property we wanted to achieve is the applicability on widely available and affordable hardware. The APs we used are popular open-sourced Linux-based WiFi access points; although we have changed the firmware, this is not deal breaker in terms of applicability. As discussed, we have changed the firmware to collect RSSI information, we could have got otherwise, but exposing this information should not be difficult for the manufacturers if desired. At the same time, the only requirement for the MT is the possibility of recording RSSI of the APs in reach, thus any WiFi connected device should be able to act as the MT. Finally, we have provided a detailed descriptions and maps of the evaluations in order to enable other researchers to make valid comparisons.

To our knowledge, this is the first WiFi-only indoor localization method that utilizes information about the architectural aspects, infers the parameters needed for the propagation simulation from the measurements, continuously adapts to the indoor situation without human intervention, does not need any additional hardware beside the APs, and does not require the mobile terminals to be in the access-point mode.

We have evaluated our method with a great emphasis on the real-world conditions and have chosen a realistic environment for the evaluation (e.g. non-ideal position of the APs, intricate floor plan of the residential evaluation, evaluation in an environment independent of the development, etc.). The evaluation has proven that our method achieves useful accuracy for the indoor localization with the average and median accuracies 2 to 3.5 m. This makes the results of our method comparable with the best other methods, of which the majority requires either more complex initial configuration, the devices that are more sophisticated, or both. For a justified interpretation of the evaluation results, it should also be noted that, in contrast to many other methods, we have chosen a realistic environment and not an optimized environment in which our method would have performed even better.

An important goal, we have set at the beginning of the research and focused the development of the presented localization method on, is to develop a universal method for the indoor localization. Therefore, we wanted to develop the method that would work in different types of networks and would be frequency independent. The mathematical derivation and the physical background are in theory frequency-independent, so in the following chapter, we will present our take on the localization method that utilizes multiple frequencies simultaneously to give the end-user more accurate results.

5

Generalization of the method to multiple frequencies

The prediction of the IoT future foresees ubiquitous systems, where every device will be connected to the network to communicate with the surrounding devices. Predictions similar as the one stated do not define the communication technologies or the protocols. While developing the indoor localization technologies, it would be wise not to limit ourselves to WiFi. We acknowledged this fact early in the development of the proposed WiFi localization method in the Chapter 4 and, as stated in Motivation (Section 1.1), we wanted, if possible, to develop a method that would not be limited to the WiFi technologies and could be extended to other communication protocols and frequencies. Multiple frequency localization method presented in this chapter has been published in [88].

This chapter presents the generalization of the WiFi-only indoor localization methods to the multiple frequency usage and is structured as follows: Section 5.1 presents the motivation and intuition behind the multiple frequency usage, Section 5.2 presents the difficulties and changes we had to make to generalize the presented WiFi method, while Section 5.3 presents the evaluation environment. Section 5.4 provides analysis of the stability of the signal at selected non-WiFi frequency and Section 5.5 presents the results of the evaluation, while Section 5.6 provides the discussion and comments to the evaluation. The final remarks and conclusions are presented in Section 5.7.

5.1 Introduction to the multiple frequency method

If we were to summarize the workings of the WiFi method presented in Section 4 in as few lines as possible, these would be: "The method estimates the parameters of signal propagation, by knowing the positions of the APs, the architectural floor plan with the dividing walls and by monitoring RSSI of the packets travelling between the APs. A device trying to define its position (the MT) captures RSSIs of the packets sent by the APs. MT's information on the observed RSSIs is used to determine its position by a complex algorithm run on the localization server." As we can see, the vital information needed for the method can be obtained in different wireless networks and is not limited to WiFi.

In every RF-based wireless network we have devices communicating by emitting and receiving signals. Structural devices with well-known positions (e.g. devices mounted to unmovable objects) can be used as APs. If a device can send and/or receive the signal and we can obtain information about some characteristics of the received signal which is influenced by the traveled path in a predictable manner, we can utilize this characteristic for the localization method, similar to the one presented in Section 4. A careful reader of Chapter 4 has noticed that, during the design of the method, we have not limited ourselves to the WiFi technologies. The physical formulation of the signal propagation and consequently the presented model can theoretically apply to any frequency.

To utilize the increasing number of frequency bands typically used indoors to simplify and improve the accuracy of the indoor localization, we have extended our indoor WiFi localization method and designed the MFAM indoor localization: a localization method based on *Multiple Frequency Adaptive Model*, an indoor localization method, which uses multiple frequency bands simultaneously. It is based on the physical model of the signal propagation and can detect and adapt to the changes in the environment that influence the signal propagation. This way we have achieved for our method to be much less sensitive to the changes that can happen indoors.

Furthermore, with our method we have successfully reduced the number of required access points (AP). Typically, indoor localization requires many devices emitting or receiving wireless signals. For example, for wireless Internet we need one WiFi AP to cover a room. For indoor localization, we must typically provide the coverage of at least three APs in the same area, just due to the triangulation principle. Localization methods typically require even more APs for better accuracy. On the other hand, if an indoor location (e.g. apartment) heavily relies on the wireless home automation system, as is the case in our evaluation environment, we can utilize the already present signals to improve the accuracy of localization. The devices used in our real-world evaluation were part of a heating system, so for the purpose of localization no extra home automation device had to be installed in the evaluation environment. Our indoor localization method utilizes multiple signal frequencies and therefore requires considerably fewer APs of a specific type for the same localization accuracy.

5.2 Generalization of the method

We have designed the MFAM with the specific objective to use the multiple frequency signals to improve the accuracy and simplify the requirements regarding the equipment. There are some fundamental differences between the WiFi networks and home automation networks, that dictated some changes in the data acquisition stage, as presented in this section.

During the development of the data acquisition stage, we were mainly focused on

OSI Layers 1 and 2 of the communication protocols. These layers ensure a physical transmission of the signals and provide means of control. We leverage them to get the RSS/RSSI information. There are specifics in each individual network, but the steps to the RSS-based indoor localization system are similar.

First obstacle for any researcher trying to implement RSS based localization to a home automation system would be gathering the RSS information. More specifically, it is much more difficult to obtain the RSS data in the home automation system than in the WiFi network. The WiFi networks and equipment are widely used and consequently there is a lot of third-party development of the software and firmware for the APs. As the reader can recall, we therefore used the third-party firmware on the APs to obtain the needed RSS information in the WiFi network. On the other hand, the home automation system user communities are smaller and consequently there is no third-party support for the firmware of the devices. Not surprisingly, we could not find a similar third-party firmware for the devices used in the home automation system that would expose the needed information.

The second biggest difference in the two networks utilized for the localization is the difference in the topologies of the networks. The WiFi networks could be labeled as peer-to-peer networks in the context of our method discussed in Chapter 4. Every AP in the network can directly communicate with any other reachable AP. We, therefore, were able to gather information about RSS between any two pairs of the APs in the case of the WiFi network. On the contrary, the topology of a typical home automation system is usually star-shaped. These networks usually have one device, often named "gateway" or "base station", which is the center point of the star-shaped network topology. This means that every communication between two devices is routed through the gateway device. Therefore, even after overcoming a challenge of gathering the RSS values, we will have to adapt to the specifics of the star-shaped network topology.

The topology of the network is an important factor also when it comes to the communication with the server on which the localization algorithms are running. Nowadays, when algorithms are run on servers (cloud-based infrastructure), it is trivial to communicate with the devices connected to the IPv4/IPv6 in the WiFi network. The WiFi devices are usually always connected to the IP network and therefore, we can connect to each device from the server on which the localization algorithms are running. On the other hand, using the networks with the devices not directly connected to the IP network, results in a much more challenging design of the data acquisition layer. In such networks, only one device is usually connected to the IP network and acts as a bridge between the two networks. This device is usually the gateway device of the star-typed network, but not necessarily (e.g. KNX-based networks, Honeywell Evohome system). Only this device is addressable from the localization server over the IP protocol and a direct communication with other devices is usually not possible.

To infer the parameters of the propagation model of the WiFi network, we can connect to each AP and gather information about RSSI of the signals, emitted from the devices in range. While using the gateway-based networks, we have no means to connect to a specific device. Consequently, we cannot get information about the received packets in a similar manner.

It is a usual practice in the home automation system for the devices to periodically send status packets to the base station. Such packets are important for the base station, as it must know which devices are in its range, their state (e.g. open/closed switch, high/low digital sensor value, etc.) and their properties, such as the battery status. The base station usually receives these packets and stores their information in order to provide information about a particular device to the end-user. One of the properties often communicated between the devices is also information about the signal strength, in order for the base station to warn the user about poor reception during the communication with a specific device. Therefore, in a typical home automation network, we can usually get some information about RSS between a device in the network and the base station. Some home automation networks have separate information about RSS for two different communication directions – one RSS information for the downlink (i.e. from the base station to the device, measured and reported by the device) and one RSS value for the uplink (i.e. from the device to the base station, measured by the base station).

Figure 5.1 helps us to understand the differences more clearly. If we use the WiFi signals (as discussed in Chapter 4), we can calculate the propagation parameters for each AP_i (Fig. 5.1 $i \in \{1, 2, 3\}$), by monitoring the RSS/RSSI values at the APs receiving signal from the AP_i. The packets emitted by AP_i and detected by other APs have a common origin, therefore the value PL_0 in Eq. (3.1) is constant across detections. In the home automation network, we have only one common source of the signal for which we can get the RSS readings at multiple places. As indicated in the right part of Fig. 5.1, the signals emitted by the base station (in the image labeled

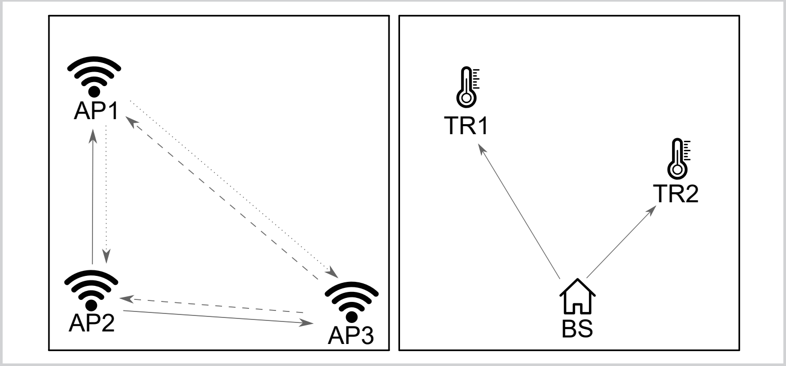


Figure 5.1

The differences in the WiFi network (left) and the home automation network (right) that influence the data acquisition layer.

as "BS") are measured by the receiving devices in the network (e.g. room thermostats labeled as "TR1" and "TR2"). As we have inputted the positions of these devices in the indoor spaces to the method, we can still calculate the number of the dividing walls and account for their effect. The figure also clearly presents the consequence of the differences presented above, i.e. we can only have one set of the propagation parameters in the indoor spaces and not a set for each AP as in the WiFi network. The inferred parameter, set in the WiFi network for a single AP, therefore exaggerates the effects of a specific AP placement, the room shape and the obstacles near the AP, which all have an influence on the signal propagation [78]. In the case of the home automation system and a single set of parameters, these exaggerate much less specific properties of a single AP, but represent the averaged propagation model for the signals of a specific frequency.

The rate of the possible RSS measurements also differs in the two different network types. In the WiFi network, the only thing bounding the rate of this information is the time needed for a single scan and the setting of the beacon-packet interval for the network. This results in a possibility of having RSSI information recorded at a specific AP multiple times per minute. Many devices of a typical home automation system are battery-powered, because these systems are designed to be implemented in the existing houses with a limited possibility of the changes of the electrical wiring, thus the home automation devices usually save on energy. One of the most common ways of reducing the power consumption is to have longer periods between two status packets, which can be up to a few minutes apart.

We have described the differences of a typical home automation network that influence the data acquisition stage. Of course, they are also reflected in later stages, as already indicated - due to longer time periods between the packets, the timeframe of the measurements included in the path loss modeling stage has to be longer. Similarly, when a mobile terminal tries to define its position, it must measure the RSS to the APs that are in reach. In the WiFi network, a mobile terminal scans for the beacon packets which are periodically emitted in the network. In the home automation system network, there are usually no beacon packets that would announce the presence of a network. Therefore, the only measurements a mobile terminal can obtain are the measurements of the RSS of the status packets, emitted by the devices towards the base station.

The discussed reasons result in the fact that in most of the home automation systems, the mobile terminal must be kept in the evaluation point for a longer period, compared to the WiFi network. This is induced by the networks, the rate of the status packets sent by them and the number of the status packets needed by our method. Manufacturers usually define the communication protocol and the rate of the status packets, with the aim of preserving the battery power in devices, as discussed in [74]. In the devices constantly connected to the mains power (lighting solutions, relay devices, etc.), this deficiency could be easily overcome by the manufacturers, which would further improve the accuracy of our localization method and simplify the usage.

Finally, due to the lack of research on the propagation of the signals through the walls at the frequencies used by different networks, we could not define the impact of the walls on the signal propagation, based on the past research. Rather, we had to define them experimentally ourselves, as described in the following sections. The resulting values are the initial values for our system. Due to the adaptive nature of our method, the method adapts automatically and overcomes the potential errors induced by these parameters.

5.2.1 *Multiple frequency fusion*

One can imagine that fusing the output from multiple single-frequency localization is not an easy task; a simple averaging function at this stage could even worsen the results. Let us imagine a frequency f_i at which our method produces perfect results ($0\,\mathrm{m}$ mean average error of the localization and a very low standard deviation). If we were then to use this frequency f_i and another f_j in our proposed MFAM method, and average the outputs, the MFAM method would worsen the results of the proposed single-frequency method presented in Chapter 4.

A better way of fusion would therefore be to use the weighted average, where the weights would represent the overall estimated accuracy at this specific frequency. When combining multiple frequencies for the localization, we must therefore consider the accuracy at each individual frequency. We can deduce our proposed fusion method in terms of the statistical measures of accuracy and precision. The precise method will always output approximately the same value for the same input parameters, which is not necessarily close to the real-location (in this case it is inaccurate). The accurate method will output the location close to the real-location, although locations can be scattered (in this case we call it imprecise). In our case, due to different signal frequencies and the difference in the signal propagation at these frequencies, the precision of the localization at single frequency varies. In the distribution of values, the precision is measured by a standard deviation; the higher the precision, the smaller the standard deviation, and vice-versa. Therefore, we have weighted the outputs from the single-frequency localizations by reciprocal value of the standard derivation, as indicated by the following formula, where symbol $\left(x,y\right)_{MFAM}$ represents the localization of the MFAM method, SD_f is the standard deviation at a specific frequency f, and $\left(x,y\right)_f$ is the location as predicted by the utilizing frequency f.

$$\left(x,y\right)_{MFAM} = \frac{1}{\sum_f \frac{1}{SD_f}} \left(\sum_f \frac{1}{SD_f} \left(x,y\right)_f \right) \tag{5.1}$$

Because it is impossible to estimate in advance the value of the standard deviation for a specific frequency at a specific location, it should be determined empirically.

This section described the steps needed to generalize our proposed WiFi method to the networks defined by typical home automation systems. In the next sections, we will discuss the evaluation environment, the stability of the signal at selected home automation frequency and the details of the implementation of the MFAM method.

5.3 Evaluation environment and protocol

The evaluation environment was the same apartment as described in the residential evaluation of the WiFi method (Subsection 4.4.1). We evaluated our MFAM method on a mixture of the WiFi signals and the home automation system. The position and

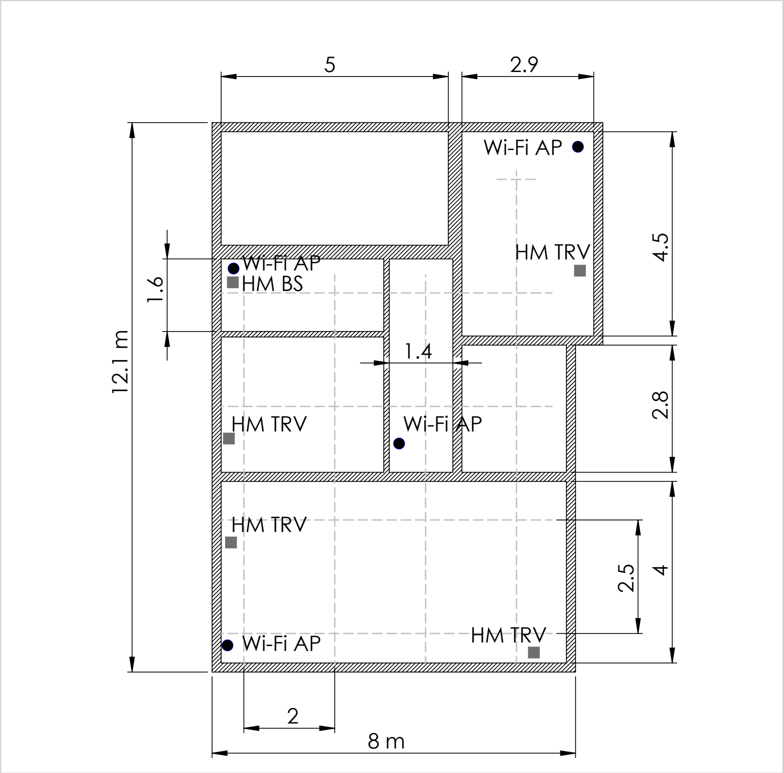


Figure 5.2

Evaluation environment of the MFAM.

the setting of the WiFi system is the same as already discussed. Regarding the second network, we could have chosen a wireless network which works on a similar 2.4 GHz band (e.g. Bluetooth network, 2.4 GHz ZigBee-based system like Philips Hue, etc.), but we wanted to evaluate our MFAM method in a much more challenging evaluation. We have therefore chosen HomeMatic home automation system, which operates at 868 MHz.

HomeMatic system is popular in Europe, as it includes devices for thermal control (heating and cooling), lighting (dimmers, relays, switches, etc.), security (alarms, sensors, door locks), and other devices, such as smoke detectors, etc. The home automation system in our evaluation consists of a base station (in Fig. 5.2 marked by

"HM BS"), connected to the wired Ethernet network, a wireless relay and 4 digital thermostatic valves. We could not influence the position of these devices in our evaluation environment (e.g. thermostatic valves were attached to the radiators, etc.). Our system is not the only one using the SRD860 frequency spectrum in the evaluation environment, as we could sense the HomeMatic packets originating from the neighboring apartments. To ensure an approximately constant transmitting power of the HomeMatic devices, we have used only the readings from the thermostatic valves, which are in Fig. 5.2 marked as "HM TRV". We have eliminated the signals from the wireless relay, because it is powered from the mains power (as opposed to the battery-powered digital thermostats) and therefore has a different operational mode, especially regarding the frequency of the sent status messages and the transmitting power [74].

Laufer et al. [74] reverse engineered parts of the HomeMatic protocol to explore the possibility of an attack on the system. They showed that the systems emit status packets approximately every 3 minutes. They also discuss the details of the battery saving strategy of the devices and consequently the modes of the operation and communication between the device and the base station.

The four used thermostatic valves were all positioned between 0.3 and 0.6 m above ground; two of them were positioned without direct obstacles, and two of them were behind furniture and therefore heavily obstructed.

To enable our Raspberry Pi 2 based mobile terminal to communicate with the HomeMatic devices, we have equipped it with the HomeMatic communication module (HM-MOD-RPI-PCB), which is an 868 MHz wirelesses communication module, connected to the Raspberry Pi via the UART interface. RSSI of the HomeMatic devices were captured using the Homegear software (version 0.6.7), which we have installed and configured on the Raspberry Pi. The Homegear software utilizes HM-MOD-RPI-PCB to capture all wireless HomeMatic packets and their respectful RSSIs. The evaluation protocol was similar as discussed in 4.4.1 with differences in timing as discussed in Section 5.2.

5.4 Analysis of long term stability of the 868 MHz signals

Similarly as in Section 3.1 analysis of the stability of the 868 MHz signals would provide insight into data entering the proposed method and result in better understating of the evaluation results. Due to time constrains and some problems with initial setup of the experiment we were not able to perform 8-week experiment as in WiFi case, but

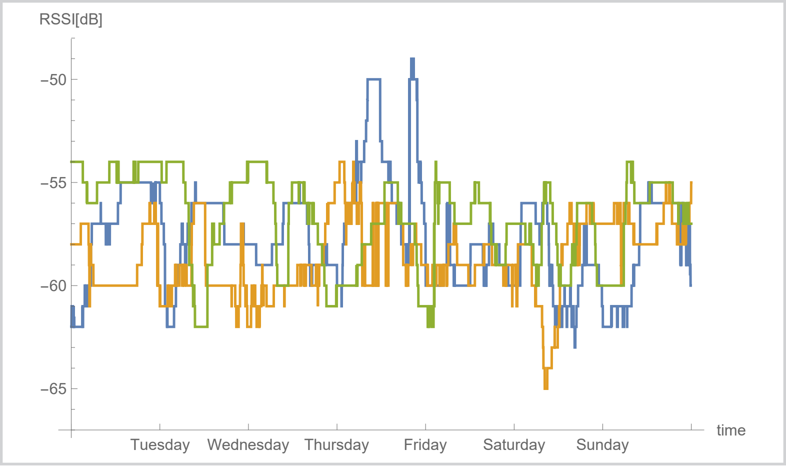


Figure 5.3

RSSI values of 868 MHz signal reported by a HM TRV in the course of 3 weeks, plotted by every week.

rather a 3-week experiment, during which we have captured data of the HomeMatic system. We were interested into RSSI data at two different points. One was the data from which we infer the parameters of signal propagation in path loss modeling stage of the MFAM, and secondly was stability of the reading at the MT which we use in the single-frequency localization stage to obtain the location in the indoors.

Figure 5.3 present data captured in the 3 weeks at the gateway or base-station device. The data was captured and filtered similarly as the data in Fig. 3.2 – we have queried the gateway for the information every minute and then applied median filter with window of two hours. The original (unfiltered) data has mean of −57.62 dB and standard deviation of 5.93 dB. This data represents the RSSI detected at the lower-left HM TRV in Fig. 5.2 of the signals emitted by the HM BS. As we can see data from which the propagation parameters of the models are inferred is noisier than WiFi data, which had standard deviation 4.71 dB through the 8 weeks, as discussed in 3.1.

At the same time, we captured data at the MT through the 3 weeks. The MT was stationary positioned at the same spot as the central (hallway-positioned) Wi-Fi AP in the Fig. 5.2. The captured data is presented in the Fig. 5.4. Data in the figure is similarly filtered with median filter with window size of two hours, but as discussed in 5.2 we were only able to obtain the RSSI data approximately once every three minutes. The captured (unfiltered) data exaggerates much less variability as the

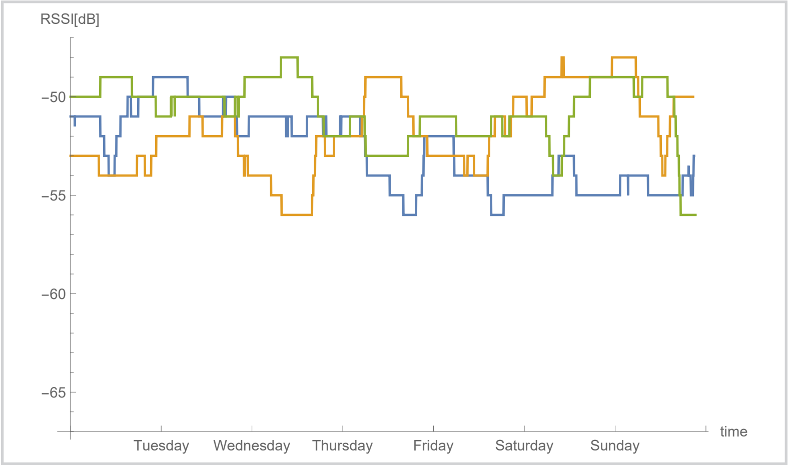


Figure 5.4

RSSI values of 868 MHz signal reported by a MT in the course of 3 weeks, plotted by every week.

standard deviation is only 2.50 dB, with the mean of −51.96 dB. These readings are much more stable and have smaller distribution as Wi-Fi readings.

Our results indicate that there is major influence of the transmitter and receiver when analyzing 868 MHz signals and their stability. As we cannot get information on the specifics of the HM TRV devices or the communication module on the Raspberry PI, we can only speculate. Because HM TRV are mass produced devices with great emphasis on low final-cost of the product, without any intent of the usage of the RSSI information, the RF frontend and the RSSI measuring circuits did not get much attention during the development. On the other hand, the communication module from which we get RSSIs at MT is device build with the sole purpose of providing 868 MHz connectivity to Raspberry PI, therefore we speculate that much more emphasis was put into design of the communication module.

The presented observations of smaller distribution when observing signals at Raspberry Pi hold true even for the cases when there is not such big difference between the traveled distances of the signal. We have observed similar values of the variation regardless of the chosen HM TRV. The only analysis that stood out is the analysis of the signals emitted by the middle left HomeMatic device in Fig. 5.2 and captured by the MT. We would assume that this would be most stable signal, as this HM TRV is the closest to the MT, positioned approximately 4 m away and there is only one thin

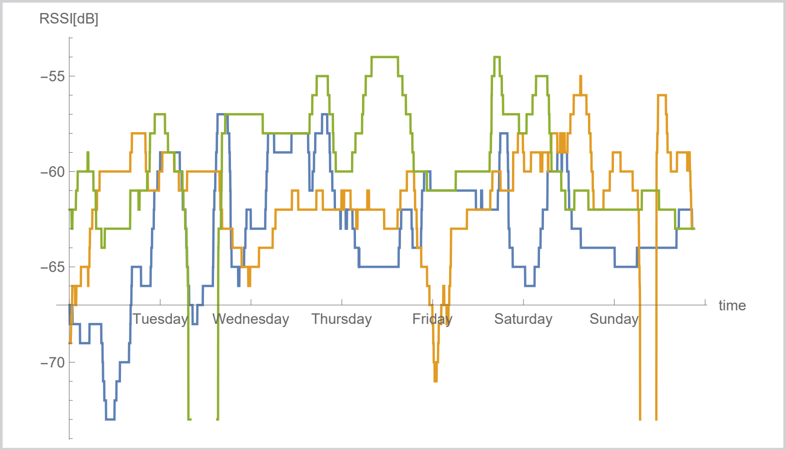


Figure 5.5

RSSI values of 868 MHz signal reported by a MT in the course of 3 weeks, plotted by every week.

plaster wall between the two devices. Figure 5.5 presents the readings, filtered the same as data in Fig. 5.4. Standard deviation of the readings is substantially bigger and has value of 4.77 dB, therefore the distribution of the RSSIs in this case is much bigger.

5.5 Results

This section presents the results of the evaluation of the MFAM method on the networks based on 2.4 GHz and 868 MHz signals. To prove that our method achieves better results when utilizing two or more frequency bands, we will first present the localization results using a home automation system, and then present the fused results of the home automation system and the WiFi localization, presented in 4.4.2. In the last subsection, we will show the results for the combined signals and present the accuracy improvement.

5.5.1 HomeMatic home automation system based localization

In the HomeMatic scenario, we had to define the values of the parameters, which describe the influence of the walls on the signal propagation. We have numerically calculated the impact of the walls on the SRD860 signals, for both wall types, on each of the datasets, and cross validated the results on other datasets.

An example of the results of the coarse wall parameter definition is shown in Fig.

Table 5.1

The comparison of the mean and median errors made at 868 MHz.

Dataset	Mean Error [m]	Median Error [m]	Standard Deviation [m]
DS1	2.89	2.50	2.00
DS2	3.39	3.04	1.91
DS3	3.39	3.16	1.47
DS4	3.16	3.35	2.14
Average	3.21	3.01	1.88

5.6. The darker the color at a specific point in the graph, the higher the average accuracy while using those parameters. In a finer analysis, we have further narrowed the parameter values: in the case of thick walls in the range of 16 to 30 dB, and in the case of thin walls to the values in range between 0 to 21 dB; in both cases with 3 dB steps. With another set of numerical modeling of the wall effects and cross-checking with the other datasets, we have set the wall parameters to be 6 dB in the case of thin walls and 27 dB in the case of thick walls. We will further discuss these findings in Section 5.6.

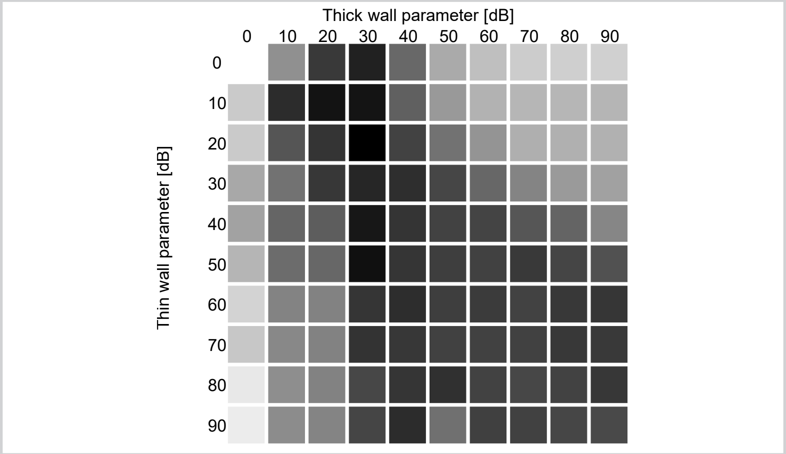


Figure 5.6

Wall parameters definition for the HomeMatic signals.

Table 5.1 presents the mean error, the median error and the standard deviation of all four datasets. We can see larger average and mean errors than in the WiFi case (Tbl. 4.6). These values alone are borderline acceptable, but we are more interested in the possibility of improving the results of the WiFi method, by utilizing both frequencies in the MFAM method. The average mean error is 3.21 m, which is 21 % larger than in the WiFi evaluation. The averaged median error is 16 % larger, while the standard deviation is 25 % worse.

5.5.2 *Multi-frequency localization*

We have utilized the fusion method, as discussed in Section 5.2.1, to combine the single-frequency localizations of the WiFi signals (Tbl. 4.6) and the home automation system signals (Tbl. 5.1). For the standard deviations required by the fusing function, we have used the averaged standard deviations, provided in both tables, as they are based on better and worse performing datasets DS1 to DS4.

Table 5.2 presents the mean error, the median error, and the standard deviation, when we combined both frequency bands. We can observe better mean and median errors than in any of the previous cases. We can observe 18 % and 33 % better accuracies in comparison to the WiFi and HomeMatic average errors respectively. We can also observe similar 17 % and 31 % improvements of the standard deviation.

Figure 5.7 shows the proportional error sizes and the directions of the errors in all four datasets. The light-gray polygon (the one that is the same as in Fig. 4.16) has the vertices in the positions of the WiFi APs, while the dark-gray polygon has the

Table 5.2

The comparison of the mean and median errors, made by MFAM method, combining the signal at 868 MHz and 2.4 GHz.

Dataset	Mean Error [m]	Median Error [m]	Standard Deviation [m]
DS1	2.04	2.11	1.25
DS2	2.27	2.18	1.21
DS3	2.02	2.16	1.20
DS4	2.32	2.09	1.55
Average	2.16	2.14	1.30

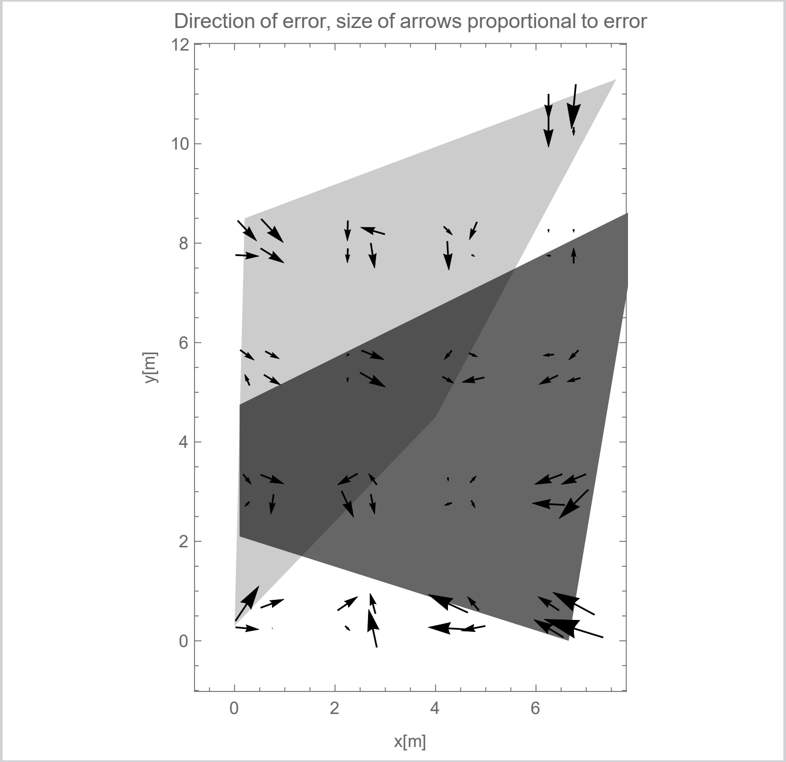


Figure 5.7

The directions and the proportional size of errors for the localization of all four datasets. The lighter gray polygon's vertices show the positions of the WiFi APs, the darker polygon marks the HomeMatic devices.

vertices in the positions of the HomeMatic radiator thermostatic valves (as marked in Fig. 5.2).

5.6 Discussion

Figure 5.6 presents the results of the coarse optimization of the wall effects in the HomeMatic evaluation. The darker the square at a specific combination of the thick and thin wall parameters, the higher the average accuracy of the method while using those parameters. Firstly, we can see that the results are much more sensitive to the changes of the thick wall parameters than to the thin wall parameters. This can be appointed to the evaluation environment. As can be seen from the map in Fig. 5.2, there are only two thin plaster dividing walls in the apartment (i.e. one dividing the two small rooms in the left part of the apartment and one dividing these two rooms from the hallway). All the other walls are thick, made of brick and concrete. Only one of the HomeMatic APs (marked as "HM TRV" in Fig. 5.2) is positioned in one of these two rooms, and at the same time most of the evaluation points are outside of them. This results in a small overall effect of the parameter of the thin walls on the signal propagation.

In the bottom-left corner of the figure, we can see that we get less accurate results (i.e. lighter color) when plaster walls are defined as having a bigger impact than brick-and-concrete walls. We get similarly bad accuracy if we appoint a high effect to the thick walls while neglecting the thin walls, which can be seen by a light color in the top-right corner of the figure. This shows that although there are only two plaster walls in the apartment, we cannot neglect their effect. We get much better results if we treat both wall types as having approximately the same effect (i.e. diagonal from top-left to bottom-right). The resulting values in the bottom-right corner show good overall results, while exaggerating the impact of both wall types. In such cases, the method is confined to the room, but such values result in lower accuracy in the bigger rooms. An interesting observation is also that we get the worst average accuracy if we neglect both types of walls, as can be seen by the white square in the top-left corner of the figure. This further proves that information about wall placement is important for the indoor localization methods, especially in the floor plans that do not have rooms of a uniform size.

The values we have obtained with a detailed parameter modeling - 6 and 27 dB for the two thin and thick wall types respectively – should not be considered as the de-facto values of the influence on the signal power at the frequency 868 MHz. The values we have obtained are influenced by our model (e.g. neglection of the doors), our equipment (i.e. we did not utilize any validated RF power spectrum analyzer) and our evaluation environment (e.g. some walls are covered by the furniture). To get the standardized values for the influence of specific wall types on RSS at a specific frequency, much more elaborate experiments should be performed, for which we do not have the knowledge nor the equipment.

Table 5.1 presents the evaluation accuracy of the method when only the HomeMatic devices were used. Bigger maximal errors than in the WiFi signal case (Tbl. 4.6) are expected, as we have much less data to infer the propagation parameters. In the case of the WiFi signals, we infer the path loss exponent for each access point separately and therefore capture the influence of the AP position, scattering much more precisely due to the room size and the shape. In our setting, we have calculated four different path loss exponents, each from 3×15 measurements. In the case of HomeMatic, we had to use only one (average) path loss exponent from 3×15 measurements, as discussed previously.

Another important factor is the rate of the status packets sent by the HomeMatic devices in comparison to the rate of the beacon packets sent by the WiFi APs. The frequency of the status packets is approximately 6-times lower than the frequency of the WiFi beacon packets. This results in 2 to 3 times longer period of the measurements, taken into the account during the path loss modeling stage; thus the MFAM method is much less adaptive at the HomeMatic frequency than at the WiFi. This being said, we can still see great benefits of utilizing multiple signals in comparison to utilizing only one. At the same time both deficiencies, we have observed in the selected home automation system, could be overcome. If a manufacturer would collaborate, the devices could record and report the RSS information of the packets originating from the non-base-station devices. At the same time, the frequency of the status packets could be higher. We speculate that the impact on the battery life would be negligible, because the devices we used operate on the same set of batteries for over two years, and we predict that the electromotor that turns the valve on and off is the main consumer of the stored energy.

The comparison of the WiFi-only signals in Tbl. 4.6 and the HomeMatic signals in Tbl. 5.1 shows that the average error is worse when using the signals of 868 MHz. We can see that in both cases DS4 had the worse median errors and the largest standard deviation. The median error of DS1 is the only evaluation result where the HomeMatic evaluation was better than WiFi. We haven't utilized the 868 MHz signals, not because we have expected better results in comparison to WiFi, but because we have speculated that a fusion of both frequencies will result in an improved accuracy. That is why the accuracy at this specific frequency is not the main goal of our research.

When comparing the 868 MHz home automation results to other non-WiFi methods, we can see that our method has much higher localization accuracy than the recently published FM-based method [89] which has an error in the ranges of 15 m, 10 m and 6 m for the cases of no calibration, runtime calibration and runtime calibration aided by the path matching algorithms respectively. If we compare the single-frequency HomeMatic system to the one proposed in [86], we can see that their system got an approximately 30 % better accuracy, while utilizing 25 to 100 % more APs in a similar floor plan. Their method shows how optimization of the AP placement can greatly influence the localization accuracy. Their system has an intricate setup phase in which they begin with 39 APs and then interactively remove and reposition APs to reduce their number to 5 to 8 APs.

One of the signals often used by the authors of the non-WiFi indoor localization methods is the Bluetooth, especially with the introduction of the power-efficient Bluetooth Low Energy (BLE) specification. We can find such examples in [90] and [91]. Zhuang et al. in [90] combined the fingerprinting- and model-based approach to the BLE-based indoor localization. Their proposed method has slightly better accuracy than ours, although a fairer comparison could be made if their evaluation included rooms and not only the hallways of the building. The methods which combine the WiFi and Bluetooth signals have been researched, such as [91], although we must note that Bluetooth and 2.4 GHz WiFi work on similar carrier frequencies. Hossain et al. [91] showed that their Bluetooth-only localization has approximately the same accuracy as the combination of Bluetooth and WiFi. The reported accuracy is approximately 50 % worse than MFAM. The evaluation was done in a lecture room, where the mobile terminal and APs are in line-of-sight. We could not find any model-based method which would be using multiple signal with different signal bands, thus our method is one of the first model-based indoor localization methods utilizing multiple frequencies for the localization.

We have defined the fusion algorithm with Eq. (5.1) in which we have defined the standard deviations of the method as empirically determined. This is a deviation from our first goal of developing a method that would not need a site survey to work, but at this point, there is no method to estimate in advance the accuracy of the single-frequency method for a specific floor plan and frequency; thus we have to experimentally determine the SD_f for each frequency f. As the method still adapts to the indoor spaces, as discussed in Chapter 4, this does not mean that the method is based on the static parameters and will not work in the long term, as discussed in Section 3.1.

The results of the main topic of this chapter, the MFAM method, are presented in Tbl. 5.2. The resulting mean and median errors are outperforming both single-band methods. Since the WiFi-only evaluation is comparable to the current state-of-the-art methods, our multiple frequency evaluation of MFAM shows it can rival the best existing methods. In each DS, the multiple frequency evaluation results in higher accuracy than both single-band methods; the accuracy improvement ranges from the minimum 6.6 % (in the case of WiFi, DS2) to 40 % (in the case of HomeMatic, DS3). With multi-frequency approach, our method has achieved 18 % higher average mean accuracy, compared to the WiFi-only approach, while having 14 % lower standard deviation. It improved the HomeMatic-only approach by 33 %, while having 31 % lower average standard deviation.

The RSSI values, as the name suggests, indicate the RSS values. The RSS value of the wireless communication signals of any type in the real-world indoor setting exaggerates heavy variability due to wall reflections, multi-path effect, etc. Therefore, having four stations, which in turn means four fixed origins in the triangulation problem, results in the localization variability. The number of the WiFi points in relation to the size of the indoor area has a key influence on the accuracy. The only thing stopping us from changing the odds of this ratio is the real-world implementation and practicality. The development of the WiFi localization method with one AP in every room and the evaluation in a floor plan with many small rooms would result in small mean and median errors if we would only set the location of a mobile terminal to the center of the room from which we sense the AP with the highest RSSI. Utilizing 5 GHz WiFi which is worse at penetrating the walls than the 2.4 GHz would further improve our results. Real-world usability of the localization method is the most important limiting factor to the number of WiFi APs. Therefore, we have limited ourselves to four APs for this evaluation, which is only one more than the minimum number required for any triangulation-based localization method. Having that one extra AP enables us to correct the errors, due to the variability of the RSSI. Therefore, it is of the utmost importance to further develop the localization methods that can utilize multiple available frequencies in the "ad-hoc" manner (i.e. utilize signals that are available in the current indoor setting).

Figure 5.7 shows the direction of the errors for the MFAM method evaluation. The sizes of the arrows are proportional to the errors. The arrows are near the evaluation point and point towards the method's location estimation. Near every evaluation point, there are four arrows, which correspond to the four datasets. The comparison of Figs. 4.16 and 5.7, while acknowledging Tables 4.6 and 5.2, shows us that although the absolute values of the errors (as shown by the means and medians in the tables) have become smaller, the distribution of the sizes and the directions of the errors in space have stayed similar. Fig. 5.7 shows that we can expect smaller localization errors with our method in the center of the map. This confirms that the position of the devices transmitting or receiving the signal in the RSSI-based localization have an influence on the accuracy. A worse estimation in the vicinity of the devices has its roots in the logarithmic nature of the RSS propagation; therefore it is harder to estimate and/or sample RSS in the close proximity of the transceiver than further away.

We have shown how the usage of the multiple signal sources (in our case WiFi and HomeMatic home automation system) improved the indoor location accuracy compared to single signal methods. RSSI can be considered a normally distributed value [77]. The statistics of a normally distributed process teach us that having more samples to infer the normally distributed value lowers the variance of the result. Therefore, in our context, having more APs from which we could infer the propagation would theoretically give us better results (i.e. smaller variance). Disregarding the real-world limitation, one could increase the number of APs to, for example, 10 APs per room. This would result in more packet collisions and interferences between the signal and consequently in a worse WiFi performance. We have therefore implemented our method to the use of multiple signal frequencies, instead of increasing the number of APs, and shown that this way we have achieved considerably better accuracy. Adding a 3rd, 4th, etc. signal type would further increase the accuracy, assuming the parameters of the RSSI distribution (and consequently the single-frequency accuracy) are not significantly worse.

The fusion of multiple signals has multiple advantages; most importantly, it reduces the number of needed APs for each system, for achieving a low standard deviation of the localization errors. The beneficial side effect is less interference and collisions while using these systems. This requires a smaller investment in the deployment, particularly if other signals are already present in the buildings. This further improves the real-world applicability of our method. Furthermore, having different signals reduces the possibility of the single-point failures and thus improves the reliability of the indoor localization, which can be very important for the industrial usage.

5.7 Conclusions

We have presented MFAM, a novel indoor localization method, which utilizes different wireless frequencies to improve the localization accuracy. It reduces the number of required access points to simplify the deployment and improve the real-world applicability. It generalizes the previously presented WiFi localization method by making the method frequency- and topology-independent and by providing the method for fusing the localizations of individual frequencies.

We have first presented the evaluation of the generalized WiFi method, presented in Chapter 4, on the signals with the base frequency of 868 MHz. This frequency is completely different from the 2.4 GHz WiFi frequency, for which method was primarily designed. We have shown that our results can be comparable in the accuracy to other RF non-WiFi based localization methods.

The main goal of the MFAM was to show that the fusion of multiple frequencies for better-accuracy indoor localization is possible and beneficial. We have evaluated our method using two profoundly different networks, which differ in topology and frequency. One is the 2.4 GHz WiFi network with a peer-to-peer topology (i.e. each AP can directly communicate with other reachable APs) and the 868 MHz-based HomeMatic home automation network, with a star-based topology (i.e. APs can communicate through the gateway/base-station device). We have presented 4 independent evaluations with the average mean and median errors of approximately 2.15 m, with the standard deviation of 1.3 m. Assuming a normal distribution of the localization errors, we can expect 84 % of the localizations to have an error smaller than 3.4 m.

We have successfully retained the properties we have set for the localization method in Chapters 1 to 3 and achieved during the development of the WiFi method presented in Chapter 4. The method is therefore purely model-based and is based on the physical properties of the RF signal propagation. It does not need any fingerprinting and it does not require the devices to emit signals, which is important in the real-world deployments. MFAM features a self-calibrating operability, meaning that it can detect and adapt to the changes in the environment that have an influence on the signal propagation, which improves the accuracy and makes our method less sensitive to the changes in the indoor settings. Furthermore, our method is architecturally aware and foresees the inclusion of the floor plan into the method. This enables the localization with respect to the walls and other obstacles. Our method is widely applicable and can be implemented using simple and accessible hardware.

We had to utilize the measurements to determine the influence of the walls on the signal propagation at 868 MHz. This could be avoided if we could get credible information, as in the case of the WiFi evaluation. Similarly, in order to fuse the localizations at the two distinct frequencies, we had to take the measurements to determine the standard deviation of the results at these frequencies. Further research should be performed in the future to eliminate this step and replace the standard deviation with some other parameter. In that moment, the MFAM method will become truly model-based without the need of an advanced site-survey, similarly as our WiFi method.

6

Discussion

This section provides some additional discussion and analysis that is related to both chapters describing the method – Chapter 4 in which we focus on the WiFi and Chapter 5 of the MFAM method.

As discussed in Section 3.2 model-based approaches usually require the same hardware for the APs if the readings from those are used to build the model. We have also indicated that one could try to extend the model in order to provide needed difference in modeled signal propagation due to different RF frontends. One option would be to add another variable to the equation 3.1 which would describe the influence of the RF frontend. This would then result in new variables in the equation 4.1 and all the following equations of Section 4.2.2. Equations of Section 4.2.3 do not have to be changed, as the result of this stage is used on a single device (the MT), therefore the influence of its RF frontend is equal across all captured signals. Theoretically extending the model is not difficult event if the difference between multiple hardware cannot be described only by a constant value for each device separately. The challenging part is how to define the values for the introduced parameters. The most naive way would be by empirical method, but this confronts with one of our main goals – to build model-based method that does not require manual setup phase. Another option would be that these values would be defined in an independent testing environment by manufacturer and we would consider them constant, but again this would be difficult and not likely to happen. Last option is that we consider these values as another unknown (similar as γ or β). Due to the variability of the RSSI we would need denser placement of the APs (we speculate detection of a signal at 3 other APs would not suffice any more). Such calculation would be theoretically possible if we would have a few different WiFi APs, but not if every device would be different from all other APs.

As already mentioned in the related work section, other model-based methods exist. In contrast to our method, many of them require a mobile terminal to emit the signals, which are picked by the APs. In our method, the mobile terminal does not need to transmit the signal and take valuable bandwidth as it determines its location by measuring the RSSI values of the signals. This is particularly important in the areas where many devices are trying to obtain the indoor location – e.g. factories, public spaces, commercial buildings, etc. To reduce the number of APs needed for the implementation of the localization in a specific location, our method uses multiple signals, which are already present in the buildings - this is the key differentiator of our work in comparison to others.

Table 6.1

Summarization of method's performance under different conditions using different signal types.

Evaluation	Mean Error [m]	Median Error [m]	Std. Deviation [m]
Office single room WiFi	2.63	2.29	1.45
Office multi room WiFi	3.22	3.48	1.58
Hallway WiFi	3.72	2.55	3.85
Residential WiFi	2.65	2.59	1.51
Residential 868 MHz	3.21	3.01	1.88
Residential 868 MHz & WiFi	2.16	2.14	1.30

For the summary of the performance of the method on multiple signal types and multiple environments, the reader can be referred to Table 6.1. The most important results are in the lower part of the table, where the results from the residential evaluations are presented. The method was developed in the office environment and then only transferred to a much more intricate floor plan of the residential building, without any changes to the system - we can see the performance is easily comparable to the best WiFi-based methods as discussed in the previous chapter. Another important observation is that the MFAM method which combines multiple signal sources has better statistical properties than any other evaluation; the mean and median errors are better than in other cases and the standard deviation is 10 to 30 % lower.

Although not common in the field of indoor localization, we have made comparison between our evaluation results and baseline values. In Tbl. 6.2 we can see columns "Baseline 1" and "Baseline 2".

To get the value of "Baseline 1" we have calculated statistical average error if in the evaluation space locations of the MT would be determined purely randomly. "Baseline 2" value was obtained by firstly determining the fore each point in the mesh of the "propagation simulation stage" the closest AP, which would theoretically have the highest RSSI value. In second step centroids of these group of points were determined. Thirdly, for each evaluation we have checked the maximal RSSI captured by the MT, then we have calculated average error of the "Baseline 2" method, as if it would output location as centroid of the AP of which MT measured maximal RSSI. For the MFAM

Table 6.2

Comparison of method's performance in different evaluation environments compared to the baseline.

Evaluation	Average evaluation error [m]	Baseline 1 [m]	Baseline 2 [m]
Office single room WiFi	2.63	3.93	2.94
Office multi room WiFi	3.22	5.86	3.79
Hallway	3.72	11.94	6.37
Residential WiFi	2.65	4.86	3.04
Residential 868 MHz	3.21	4.86	3.43
Residential 868 MHz & WiFi	2.16	4.86	-

method we could determine the value of "Baseline 2" method as absolute values of the WiFi and 868 MHz signals captured by two different wireless communication adapters cannot be compared in absolute value, therefore we could not determine the maximal value captured by the MT.

As can be seen average errors in all evaluations are better than "Baseline 1" and "Baseline 2" approach. Our method improves the most naïve baseline method ("Baseline 1") from 33% to 69%, while it results in 6% to 42% improvement compared to more sophisticated baseline approach – "Baseline 2".

It is also interesting to observe the stability of the RSSI. Therefore, in Tbl. 6.3 we present average standard deviation of all RSSI signals in a single evaluation. Values were obtained by calculating standard deviation of each AP-to-AP RSSI measurement and then averaging over each pair of measurements and also over all the evaluation points. We can see that standard deviation of a hallway environment is the smallest therefore average AP-to-AP RSSI measurement is expected to be the most stable in such environment. This is another supporting fact to the question why hallway environment is not challenging enough environment for the method to be tested in.

The parameter of the length of measurement averaging interval is difficult to determine as a set value. If RSSI at a specific distance would be constant (RSSI value at specific point would be stable and the measurements would have a very low standard deviation) this value would be simple to determine. As RSSI values between two fixed points exhibit heavy variability it would be difficult to design experiment in which we

Table 6.3

Comparison of average standard deviation of the WiFi RSSI per evaluation.

Evaluation	Average standard deviation of RSSI [dB]
Office single room	2.74
Office multi room	3.33
Hallway	2.50
Residential DB1	3.34
Residential DB2	3.43
Residential DB3	3.76
Residential DB4	3.87

would *a priori* define the window size.

Theoretically, due to the heavy variability, having little measurements would mean that estimation of the propagation parameters can be inaccurate. Therefore, we want to have as much measurements as possible to accurately determine the true value of propagation parameters, but in this case RSSI should be temporally stable (i.e. have a constant mean). In Section 3.1 we have observed that the variable RSSI does not have stable and constant mean. Therefore, in order for the method to adapt quickly to the changes of the mean of the RSSI, we would ideally want to have as little averaging window as possible, but as discussed previously having small group of samples to estimate the highly variable data results in bad estimation of the distribution of values.

In our work we have selected 15 measurements based on some preliminary testing during the development phase of our method. We have selected 15 measurements in the timeframe of 16 minutes, as explained and backed by the measurements in Section 4.3.1 (i.e. because while testing in realistic environment it can happen that sometimes some RSSI detections between two APs are missing – as shown in thesis this happens in less than 0.4 % of the surveys).

To evaluate if we have selected appropriate value of the window length one option is to check and see what results we would get if we had chosen other values. Table 6.4 presents results of such calculation. We can see all 7 WiFi evaluations we have performed (columns), rows present result of localization if we would take only last one,

Table 6.4

Average accuracy of WiFi evaluations using different window of measurements.

	Single room office	Multi room office	Residential DS1	Residential DS1	Residential DS3	Residential DS4	Hallway
1	3,36	3,98	3,18	1,90	2,48	2,82	3,70
2	3,07	3,60	2,76	1,76	2,96	2,67	3,72
3	2,91	3,66	2,66	2,37	3,04	2,69	3,72
4	2,89	3,56	2,45	2,39	3,10	2,48	3,72
5	2,86	3,70	2,53	2,24	3,05	2,49	3,73
6	2,69	3,53	2,70	1,83	2,84	2,74	3,71
7	2,62	3,31	2,62	2,32	2,82	2,83	3,71
8	2,65	3,40	2,39	2,19	2,93	2,31	4,68
9	2,58	3,39	2,42	2,22	2,79	2,31	3,71
10	2,67	3,34	2,56	2,28	2,89	2,77	3,72
11	2,63	3,35	2,42	2,19	2,87	2,70	3,72
12	2,66	3,26	2,37	2,15	2,93	2,58	3,74
13	2,67	3,30	2,37	2,18	2,96	2,73	3,72
14	2,66	3,37	2,58	2,30	2,88	2,63	3,72
15	2,63	3,22	2,50	2,43	2,89	2,77	3,72

two, three, etc. measurements for the determination of the parameters. Values in the body of the table presents average localization error during the calculation. Coloring of the cells in each column aids visually in determining the worse (red) and the best results (blue) and range of the values in-between.

Firstly, we can see that hallway environment has the most stable values. Average error is always 3.7 m, apart from one outlier. This further proves that hallways are not appropriate and realistic evaluation environments, as the signals in such environments are most stable. We can see confirmation of this fact also in Tbl. 6.3, where it is shown that hallway environment has the smallest standard deviation and therefore distribution of the data ($\sigma_{hallway} = 2.49$).

We can see that in single- and multi-room office environments the signal probably exhibited some variability but not much changes due to the changes of the mean of the RSSI. This can be concluded, because accuracy of the experiments with little measurements have biggest errors, which slowly get smaller while taking more and more measurements into account.

Last, but also most important, we can see most scattered data of the minimum and maximum errors in case of residential evaluations. This hints that residential evaluation was the most difficult, as there were many rooms, dividing walls and furniture,

Table 6.5

Amount of improvement or decline in accuracy using different window of measurements relative to selected value – WiFi signals.

	Single room office	Multi room office	Residential DS1	Residential DS1	Residential DS3	Residential DS4	Hallway	Median
1	28	24	27	-22	-14	2	-1	13
2	17	12	11	-28	2	-4	0	6
3	11	14	6	-3	5	-3	0	6
4	10	10	-2	-2	7	-10	0	3
5	9	15	1	-8	6	-10	0	3
6	2	10	8	-25	-2	-1	0	1
7	0	3	5	-5	-2	2	0	1
8	1	6	-4	-10	1	-17	26	-2
9	-2	5	-3	-9	-3	-17	0	-3
10	2	4	3	-6	0	0	0	1
11	0	4	-3	-10	-1	-2	0	-2
12	1	1	-5	-12	2	-7	0	-2
13	2	3	-5	-10	2	-1	0	0
14	1	5	3	-5	0	-5	0	0
15	0	0	0	0	0	0	0	0

therefore a lot of opportunity for multipath, interference, etc. As the apartment is in heavily populated residential neighborhood the experiments were subjected to the most disturbances.

In order to better view the difference that the number of the measurement makes, we have calculated for each evaluation environment and number of historical points improvement (negative values) and decline (positive values) in accuracy in reference to the selected 15-minute timeframe. Data is presented in Tbl. 6.5. Median column presents median value of the evaluations without the hallway. We have exempt it as we have shown that its values are most stable. As we can see there are some parameters that would in average produce better results than our selected 15-minute timeframe (e.g. 9 minute), but they are all in a range of a few percent, which is at the average errors in range 2 to 3 m in our evaluations in range of a decimeter. A decimeter change in accuracy of real-world multiroom experiments is accuracy at a level of the accuracy of the ground-truth, due to the obstacles and inaccurate vertical positioning of the mobile terminal.

Therefore, we conclude that selecting 15-minute timeframe, was correct decision which ensures that we address issues of outliers and at the same time method keeps its adaptive properties.

Similar analysis can be done for the signals of 868 MHz – results are presented in Tbl. 6.6. From the table it can be easily seen, that majority of strong colors in each column (i.e. values far from the median) are in the rows representing 1 to 8 taken measurements. Including more measurements results in more averaged propagation simulation and therefore less extreme values into positive or negative. Median values of the percentage of the improvement or decline of accuracy are all in range of a few percent, therefore in the range of accuracy of the ground truth.

Similar results can also be seen when performing similar analysis on the combination of WiFi and 868 MHz signal – the MFAM method. It can be seen that taking 8 or more measurements sufficiently stabilizes the propagation for it to become stable in the ±3 % range. Results can be seen in Tbl. 6.7.

Results of the analysis show that in average the accuracy improves by taking more than 8 measurements. Although the accuracy of the method then stabilizes and small influence of the number of the measurements is observed beyond this value. Analysis show that if selecting the ideal number of measurements, we would have the opportunity to improve the mean accuracy of the localizations for approximately 2 %, which is negligible at average errors of 2.16 m.

Second time-related interval is interval of the measurement performed by the MT. To have quick and dynamic method we wanted to minimize the time needed by the MT to scan the RSSI. Lim et al. [34] presented Wi-Fi approach and as shown in Section 4.6 it performs very well also with the respect to the evaluation space. The major downside of the method in real-world evaluation is that device has to be kept stationary for 2 minutes while the MT scans the RSSIs. Our goal was to have this value as small as possible in order for the method to be usable in the real-world environment. Even more importantly, if we were able to keep this value low, this opens possibilities for future development of indoor navigation system which requires quick measurements. Due to variability of the RSSI data reported by the MT we knew that we need at least some averaging and/or filtering. After some preliminary analysis we decided that 3 samplings of which each takes approximately 5 seconds is enough. Our method

Table 6.6

Amount of improvement or decline in accuracy using different window of measurements relative to selected value – 868 MHz signals.

	DS1	DS2	DS3	DS4	Median
1	10	3	-1	-7	1
2	7	3	2	0	2
3	-10	8	-1	4	2
4	-7	-2	0	-1	-2
5	-5	-4	3	-1	-2
6	6	-4	5	2	3
7	9	-3	4	1	3
8	11	-4	1	1	1
9	4	0	1	-1	1
10	0	1	2	-1	0
11	2	0	2	-2	1
12	2	0	2	-2	1
13	1	-1	0	0	0
14	0	-1	0	0	0
15	0	0	0	0	0

Table 6.7

Amount of improvement or decline in accuracy using different window of measurements relative to selected value – WiFi & 868 MHz.

	DS1	DS2	DS3	DS4	Median
1	32	-3	10	8	9
2	16	-3	12	2	7
3	6	8	14	5	7
4	1	-2	16	1	1
5	6	-4	13	-4	1
6	14	-13	7	1	4
7	15	1	8	2	5
8	9	0	4	-10	2
9	5	4	1	-12	3
10	3	1	-2	-2	-1
11	1	-3	-2	0	-1
12	1	-1	-2	-4	-2
13	2	-1	1	-1	0
14	3	1	0	-2	0
15	0	0	0	0	0

is therefore capable of similar accuracy as method by Lim et al. while device requires only approximately 15 seconds to scan the RSSI in comparison to their method, which requires 2 minutes.

Conclusions

7

We have started this research with nothing but knowledge, ingenuity and the idea of creating the universal indoor localization method for the future IoT technologies. From the start we knew we do not want to develop a fingerprinting method, as those are not suitable for the real-world deployments. The one and only goal was to develop a method that is usable in the real-world conditions. Thus, every design step, every decision and the evaluation procedure were subjected to this goal.

On the Gartner's Hype Cycle for Emerging Technologies the IoT platform is still before the "Peak of Inflated Expectations". Therefore it is not surprising, that there is still no common IoT platform, no common set of protocols and interfaces. As the technologies for the future must be developed today, we have set on a journey of the development of an indoor localization system. We started by analyzing the limitations and deficiencies of the past research. As most of the indoor localization solutions utilize WiFi, we have chosen it as our first protocol for evaluation. In the back of our minds we have always tried to keep the method signal- and frequency-agnostic.

Our endeavor for the real-world applicability resulted in a detailed analysis of the long-term stability of the WiFi signal in real-world environments. We have explored and researched the stability of the WiFi signals in the course of 8 weeks in the real-world setting of an office building. We have also come across interesting observations which can be cues for the future research – e.g. why did we observe worse signal strength in weeks where there were less people in the offices; how does the number of the people in the room influence the stability of the signal and consequently the accuracy of localization? Pursuing the goal of the universal indoor localization, we have also presented our view on Tx methods and the reasons why we are convinced one should select a more difficult task of developing the methods that are based on the receiving of the signal at the mobile terminal. The knowledge on the emerging and future WiFi protocols further convinces us why the frequency-independent methods should be developed for the future. The fact that the majority of the methods are in our opinion not evaluated in the floor plans that represent real-world indoor locations, which are furthermore vaguely defined and described, results in an unfair comparison between the published methods.

Equipped with the described facts, we have started the development of the WiFi localization method, as presented in Chapter 4. We have thoroughly presented the development of the method with the evaluations in the office, residential and hallway environments. The presented method is self-calibrating and self-adaptive, and thus maintenance-free. It can operate for years and have the same accuracy as immediately after deployment, because no static parameters are used to define the propagation model. The model is built by using the observations of RSSIs at the APs in the short time before the localization process. The only input requirements of the method are the WiFi access point positions, and the positions and properties of the walls. We have developed and evaluated the method in the office spaces of our laboratories. The main factor which proves that the method is deployable in the real-world situations is the fact that we have transferred the equipment to the residential apartment and obtained the localization accuracy without any changes and easily comparable to the state-of-the-art methods. Evaluation in a hallway environment was performed to simplify comparison with the related methods which are often evaluated in such simplistic environments.

Afterwards we have continued the development of our method by generalizing it, in order to evaluate it on the frequencies and protocols different than WiFi. We were able to generalize the method and apply it to the 868 MHz-based home automation system already present in the evaluation apartment. Due to the reasons discussed in Chapter 5, the method expectedly performed worse in comparison to the evaluation utilizing the WiFi signals. We have also shown that its accuracy is comparable to some of the non-WiFi RF-based localization methods published recently. Utilizing the home automation signals alone was never the goal, as we wanted to use them in conjunction with the WiFi signals.

The MFAM method fused both signals and gave better results than any of the individual signals. We wanted to show that one does not have to add an impractical number of WiFi APs to achieve the needed accuracy, but instead with the MFAM method it can utilize the already present signals. The home automation devices we have used in the evaluation are part of the functioning heating system of the apartment and therefore we have not added any additional structural device (AP) to improve the average accuracy of the localization for 6 to 30 %. The only hardware-related change was enabling the mobile terminal to capture the RSS information of the packets at the selected frequency.

The scientific contribution of this work can be summarized as follows:

- a novel calibration method for the indoor WiFi-modeled approaches which continuously monitors the WiFi signal spectrum and adjusts the propagation parameters without human intervention;

- a novel self-adaptive model-based WiFi indoor localization method that accounts for the architectural aspects of the building layout;
- Multiple Frequency Adaptive Model-Based Indoor Localization Method which generalizes our WiFi method to utilize multiple signal types and then provides a fusion method that considers the accuracy of the method at each individual frequency.

7.1 Future research

It is said that every ending is the beginning of something new. Defining a new method always results in an infinite number of questions: "What if you would include...? Could that be improved by...?" In this short section, we provide some research directions one could take in the future.

Our view on the method development has always been from the viewpoint of a future IoT device. The majority of the devices in our homes are stationary, therefore it is not difficult for the device to capture RSS information needed for the localization for one minute. How would the method perform in the cases where the object is moved around? There are fusion attempts of fusing the WiFi-based localization methods with dead reckoning algorithms - would our method be suitable for that?

There are methods for the indoor localization that fuse information of the WiFi-based method with some other means of localization. What accuracy can MFAM achieve, when fused with the RFID-proximity or IMU-based indoor localizations?

MFAM is built to fuse multiple frequencies; how could a mobile terminal that includes a software-defined radio (SDR) utilize the method? What accuracy could it achieve if we used SDR-equipped APs?

Finally, can we anyhow estimate a factor representing the accuracy of the single-frequency method in order to change the fusion method, which currently utilizes the standard deviation of a pre-surveyed empirical evaluation? This would make MFAM model based, without the need of pre-surveying the environment; such methods are in our opinion the ultimate goal of the indoor localization for the future technologies of the IoT.

Implementation of the method - source code

A

In order to fully disclose the presented method, the source code of our implementation is presented in the following appendix. In the first part, the configuration object is presented, which holds information about APs, HomeMatic devices, position of the walls, etc. The source code is written in the Wolfram Mathematica language.

```
In[1]:= Config = <|
  "AP"->{<|
    "ip"->"10.1.23.250",
    "nickname"->"AP1",
    "name"->"AP1",
    "mac"->"C0:56:27:29:0E:17",
    "x"->4.0, (* x position of the AP in the map *)
    "y"->4.5, (* y position of the AP in the map *)
    "ch"->11, (* WiFi channel *)
    (* parameters used for calculation in case of omitting APs *)
    "calibrateBy"->{"C0:56:27:34:92:89","C0:56:27:29:0E:65"},
    (*direction of the normal vector of this APs wall *)
    "direction"->{1,0}
  |>,
  (* other APs *)
  },
  "HM" -> {<|
    "nickname"->"HM-kitchen",
    "mac"->"3A3F3B",
    "x"->6.65,
    "y"->0.0,
    "serial"-> "MEQ0545541",
    "ch"->99,
    "direction"->{0,1}
  |>,
  (* other HM devices *)
  },
  "HM-base"-> <|
    "nickname"->"HM-base",
    "mac"->"central",
    "x"->0.6,
    "y"->8.8,
    "serial"-> "MEQ0549946",
    "direction"->{0,-1}
  |>,
  "wall"->{
    <|"x1"->0,"y1"->3.95,"x2"->7.6,"y2"->3.95,"d"->0.2|>,
    (*other walls *)
  },
  (* other paramters *)
|>;
```

This implementation was used to obtain the results presented in this thesis.

```
In[2]:= AngleFunction[alpha_] := Module[{tmp},Return[Abs[Mod[
          If[Mod[alpha, Pi] < Pi/2,
            Mod[alpha, Pi],
            -Mod[alpha, Pi]
          ], Pi]/(Pi/2)]];
        ];

In[3]:= (*query can be ip, mac or name
          and it will return whole AP Association*)
        GetAp[Config_, query_] := Module[{ret = False, i},
          For[i = 1, i <= Length[Config[["AP"]]], i++,
            If[Config[["AP"]][[i]][["ip"]] == query ||
              Config[["AP"]][[i]][["name"]] == query ||
              Config[["AP"]][[i]][["mac"]] == query,
              ret = Config[["AP"]][[i]];
              Break[];
            ];
          ];
          If[ret == False, Throw["Unknown AP: '" <> query <> "'"]];
          Return[ret];
        ];

In[4]:= AssociationToPosition[assoc_, specification_: ""] := {
          assoc["x" <> specification], assoc["y" <> specification]
        };

In[5]:= DataFileName[Config_, position_] := FileNameJoin[{
          Config[["BasePath"]],
          Config[["ExperimentDataPath"]],
          position,
          "out.json"
        }];

In[6]:= GetExperimentPosition[Config_, position_] :=
        Module[{tmp, accessPoints, ret, i},
          Needs["GeneralUtilities`"];
          If[StringMatchQ[position, RegularExpression["^[A-D][a-e]\$"]] == False,
            Throw["Unknown position : '" <> position <> "'"];];
          tmp = Import[DataFileName[Config, position]];
          tmp = ToAssociations[tmp];
          tmp["position"] = position;
          Return[tmp];
        ];

In[7]:= (*possibility to change median filter*)
        CustomMedianFilter = MedianFilter;
```

In[8]:=
```
(* input is one of the properties by which
 AP can be found with GetAp function *)
CalculatePowerLossExponenetForAp[Config_, input_, data_] := Module[
{
  ap = GetAp[Config, input], src1, src2, src3,
  ret = <||>, i, dataX = {}, dataY = {}, tmp, timer
},
  src1 = <|"source" -> GetAp[Config, ap["calibrateBy"][[1]]]|>;
  src2 = <|"source" -> GetAp[Config, ap["calibrateBy"][[2]]]|>;

  For[i = 1, i <= Length[Config["AP"]], i++,
    If[Config["AP"][[i]]["mac"] == ap["mac"],
      Continue[];];
    If[Config["AP"][[i]]["mac"] == src1["source", "mac"],
      Continue[];];
    If[Config["AP"][[i]]["mac"] == src2["source", "mac"],
      Continue[];];

    src3 = <|"source" -> GetAp[Config, Config["AP"][[i]]["mac"]]|>;
  ];

  For[i = 1, i <= Length[data["accessPoints"]], i++,
    If[Length[data["accessPoints"][[i]]]["val"] <
      Config["Model", "numberOfHistoryPoints"],
      Throw[
        "Exptected to get '" <>
        ToString[Config["Model", "numberOfHistoryPoints"]] <>
        "' but got only '" <>
        ToString[Length[data["accessPoints"][[i]]]]["val"] <> "'"];
    ];

    If[data[["accessPoints"]][[i]]["mac"] == ap["mac"],
      If[data["accessPoints"][[i]]["ip"] == src1["source", "ip"],
        src1["measurements"] = <|
          "raw" -> Take[data["accessPoints"][[i]]["val"],
            Config["Model", "numberOfHistoryPoints"]]
        |>;
      ];

      If[data["accessPoints"][[i]]["ip"] == src2["source", "ip"],
        src2["measurements"] = <|
          "raw" ->
            Take[data["accessPoints"][[i]]["val"],
              Config["Model", "numberOfHistoryPoints"]]
        |>;
      ];

      If[data["accessPoints"][[i]]["ip"] == src3["source", "ip"],
        src3["measurements"] = <|
```

```
        "raw" ->
          Take[data["accessPoints"][[i]]["val"],
            Config["Model", "numberOfHistoryPoints"]]
      |>;
    ];
  ];
];

src1["measurements", "filtered"] = CustomMedianFilter[
  src1["measurements", "raw"],
  Config["Model", "medainFilterValue"]
];

src2["measurements", "filtered"] = CustomMedianFilter[
  src2["measurements", "raw"],
  Config["Model", "medainFilterValue"]
];

src3["measurements", "filtered"] = CustomMedianFilter[
  src3["measurements", "raw"],
  Config["Model", "medainFilterValue"]
];

ret["d1"] = EuclideanDistance[
  AssociationToPosition[ap],
  AssociationToPosition[src1["source"]]
];

ret["d2"] = EuclideanDistance[
  AssociationToPosition[ap],
  AssociationToPosition[src2["source"]]
];

ret["d3"] = EuclideanDistance[
  AssociationToPosition[ap],
  AssociationToPosition[src3["source"]]
];

ret["alpha1"] = VectorAngle[{
  src1["source", "x"] - ap["x"],
  src1["source", "y"] - ap["y"]
}, ap["direction"]];

ret["alpha2"] = VectorAngle[{
  src2["source", "x"] - ap["x"],
  src2["source", "y"] - ap["y"]
}, ap["direction"]];

ret["alpha3"] = VectorAngle[{
```

```
    src3["source", "x"] - ap["x"],
    src3["source", "y"] - ap["y"]
  }, ap["direction"]];

  If[(
    ret["d1"] > ret["d2"] &&
    Median[src1["measurements", "filtered"]] <
    Median[src2["measurements", "filtered"]]
    ||
    ret["d1"] < ret["d2"] &&
    Median[src1["measurements", "filtered"]] >
    Median[src2["measurements", "filtered"]]
    ) != True,
    Print[{"WARNING!", ret["d1"],
      N[Median[src1["measurements", "filtered"]]], ret["d2"],
      N[Median[src2["measurements", "filtered"]]],
      data["position"]}];
  ];

  For[i = 1, i <= Length[src2["measurements", "filtered"]], i++,
    AppendTo[dataY, src2["measurements", "filtered"][[i]] +
      WallCrossingsToDb[Config,
        WallCrossings[Config, AssociationToPosition[ap],
        AssociationToPosition[src2["source"]]]
      ] -
      src1["measurements", "filtered"][[i]] -
      WallCrossingsToDb[Config,
        WallCrossings[Config, AssociationToPosition[ap],
        AssociationToPosition[src1["source"]]]
      ]
    ];
    AppendTo[dataX, {
      10*Log10[ret["d1"]/ret["d2"]],
      (AngleFunction[ret["alpha1"]] - AngleFunction[ret["alpha2"]])
      *10*Log10[ret["d1"]/ret["d2"]]
    }];
  ];

  For[i = 1, i <= Length[src3["measurements", "filtered"]], i++,
    AppendTo[dataY,src3["measurements", "filtered"][[i]] +
      WallCrossingsToDb[Config,
        WallCrossings[Config, AssociationToPosition[ap],
        AssociationToPosition[src3["source"]]]
      ] -
      src1["measurements", "filtered"][[i]] -
      WallCrossingsToDb[Config,
        WallCrossings[Config, AssociationToPosition[ap],
        AssociationToPosition[src1["source"]]]
      ]
```

```
  ];
  AppendTo[dataX, {
    10*Log10[ret["d1"]/ret["d3"]],
    (AngleFunction[ret["alpha1"]] - AngleFunction[ret["alpha3"]])
    *10*Log10[ret["d1"]/ret["d3"]]
  }];
];

For[i = 1, i <= Length[src2["measurements", "filtered"]], i++,
  AppendTo[dataY,src3["measurements", "filtered"][[i]] +
    WallCrossingsToDb[Config,
      WallCrossings[Config, AssociationToPosition[ap],
      AssociationToPosition[src3["source"]]]
    ] -
    src2["measurements", "filtered"][[i]] -
    WallCrossingsToDb[Config,
      WallCrossings[Config, AssociationToPosition[ap],
      AssociationToPosition[src2["source"]]]
    ]
  ];
  AppendTo[dataX, {
    10*Log10[ret["d2"]/ret["d3"]],
    (AngleFunction[ret["alpha2"]] - AngleFunction[ret["alpha3"]])
    *10*Log10[ret["d2"]/ret["d3"]]
  }];
];

tmp = LeastSquares[dataX, dataY];

If[tmp[[1]] < Config["Model", "defaultParams" , "gamma", "minValue"],
  ret["gamma"] =
    Config["Model", "defaultParams" , "gamma", "newValue"];,
  ret["gamma"] = tmp[[1]];
];

If[ret["gamma"] >
  Config["Model", "defaultParams" , "gamma", "maxValue"],
  ret["gamma"] =
    Config["Model", "defaultParams" , "gamma", "newValue"];
];

If[tmp[[2]] < Config["Model", "defaultParams" , "beta", "minValue"],
  ret["beta"] =
    Config["Model", "defaultParams" , "beta", "newValue"];,
  ret["beta"] = tmp[[2]];
];

ret["ap"] = ap;
ret["src1"] = src1;
```

```
    ret["src2"] = src2;
    ret["r"] = Min[{ret["d1"], ret["d2"]}]/Max[{ret["d1"], ret["d2"]}];

    Return[ret];
  ];
```

In[9]:=
```
  (*
    returun Asociation of mac->gamma for all
    senced mobile Terminals in postion string
  *)
  CalculateCurrentState[Config_, positionString_] := Module[{ret = <||>, i,
    position = GetExperimentPosition[Config, positionString], tmp},

    For[i = 1, i <= Length[position["mobileTerminal"]], i++,
      tmp = CalculatePowerLossExponenetForAp[Config,
        position["mobileTerminal"][[i]]["mac"], position
      ];
      ret[position["mobileTerminal"][[i]]["mac"]] = tmp;
    ];

    Return[ret];
  ];
```

In[10]:=
```
  CalculatePowerAt[Config_, point_, ap_, properties_] := Module[
    {distance, gamma, beta, alpha},

    gamma = If[KeyExistsQ[properties, "gamma"],
      properties["gamma"],
      Throw["No 'gamma' defined"]
    ];

    beta = If[KeyExistsQ[properties, "beta"],
      properties["beta"],
      0
    ];

    distance = EuclideanDistance[
      AssociationToPosition[point],
      AssociationToPosition[ap]
    ];

    alpha = VectorAngle[
      {point["x"] - ap["x"], point["y"] - ap["y"]},
      ap["direction"]
    ];

    Return[-(
      gamma*Log10[distance] +
      20*Log10[Config["Freq", ap["ch"]]*1000] -
```

```
      27.55 +
      beta*Log10[distance]*AngleFunction[alpha] +
      WallCrossingsToDb[Config,
        WallCrossings[Config,
          AssociationToPosition[point],
          AssociationToPosition[ap]
        ]
      ]
    )];
  ];
```

In[11]:=
```
GenerateModel[Config_, positionString_] := Module[{ret = <||>, i, j, k,
  tmp, position = GetExperimentPosition[Config, positionString]},

  ret["state"] = CalculateCurrentState[Config, positionString];

  (*create mesh*)
  ret["mesh"] = <||>;
  ret["mesh", "def"] = <||>;(*definition of the mesh*)

  ret["mesh", "def", "x"] = Range[
    Config["Model", "mesh", "x", "from"],
    Config["Model", "mesh", "x", "to"],
    Config["Model", "mesh", "x", "mesh"]
  ];

  ret["mesh", "def", "y"] = Range[
    Config["Model", "mesh", "y", "from"],
    Config["Model", "mesh", "y", "to"],
    Config["Model", "mesh", "y", "mesh"]
  ];

  ret["mesh", "inst"] = <||>;(*instance of the mesh*)

  tmp = Keys[ret["state"]];
  For[i = 1, i <= Length[ret["mesh", "def", "x"]], i++,
    ret["mesh", "inst", ret["mesh", "def", "x"][[i]]] = <||>;
    For[j = 1, j <= Length[ret["mesh", "def", "y"]], j++,
      ret["mesh", "inst",
        ret["mesh", "def", "x"][[i]],
        ret["mesh", "def", "y"][[j]]
      ] = <||>;
      For[k = 1, k <= Length[tmp], k++,
        ret["mesh", "inst",
          ret["mesh", "def", "x"][[i]],
          ret["mesh", "def", "y"][[j]],
          tmp[[k]]
        ] = CalculatePowerAt[Config,
           <|
```

```
                "x" -> ret["mesh", "def", "x"][[i]],
                "y" -> ret["mesh", "def", "y"][[j]]
                |>,
               GetAp[Config, tmp[[k]]],
               ret["state", tmp[[k]]]
             ];
           ];
         ];
       ];

       Return[ret];
     ];
```

```
In[12]:= PlotModel[Config_, model_] := Module[
       {data, i, j, k, tmp, tmp2, ret = <||>, roundX, roundY},

       tmp = Keys[model["state"]];
       tmp2 = {};

       For[k = 1, k <= Length[tmp], k++,
         data = {};
         For[i = 1, i <= Length[model["mesh", "def", "x"]], i++,
           For[j = 1, j <= Length[model["mesh", "def", "y"]], j++,
             AppendTo[data, {
               model["mesh", "def", "x"][[i]],
               model["mesh", "def", "y"][[j]],
               model["mesh", "inst",
                 model["mesh", "def", "x"][[i]],
                 model["mesh", "def", "y"][[j]],
                 tmp[[k]]
               ]
             }];
           ];
         ];

         AppendTo[tmp2,
           ListPlot3D[data, PlotStyle -> Opacity[0.6],
           AxesLabel -> {"x[m]", "y[m]", "Estimated PL[dB]"},
           PlotLabel -> "Simulation of PL in space",
           BoxRatios -> Config["plotRatio"]]
         ];
       ];

       ret["allPowersSeperate"] = Row[tmp2];
       ret["allPowers"] = Show[tmp2];

       (*plot error graph*)
       If[KeyExistsQ[model, "error"],
```

```
  data = {};
  For[i = 1, i <= Length[model["mesh", "def", "x"]], i++,
    For[j = 1, j <= Length[model["mesh", "def", "y"]], j++,
      AppendTo[data, {
        model["mesh", "def", "x"][[i]],
        model["mesh", "def", "y"][[j]],
        model["error", "mesh",
          model["mesh", "def", "x"][[i]],
          model["mesh", "def", "y"][[j]]
        ]
      }];
    ];
  ];

  roundX = model["mesh", "def", "x"][[Position[
    Abs[model["mesh", "def", "x"] - model["realPoint", "x"]],
    Min[Abs[model["mesh", "def", "x"] - model["realPoint", "x"]]]
  ][[1, 1]]]] + 0.0;

  roundY = model["mesh", "def", "y"][[Position[
    Abs[model["mesh", "def", "y"] - model["realPoint", "y"]],
    Min[Abs[model["mesh", "def", "y"] - model["realPoint", "y"]]]
  ][[1, 1]]]] + 0.0;

  ret["error"] = Show[
    ListPlot3D[data, BoxRatios -> Config["plotRatio"]],
    Graphics3D[{Red, PointSize[0.1], Point[{
      model["error", "minErrorPosition", "x"],
      model["error", "minErrorPosition", "y"],
      model["error", "minError"]
    }]}],

    Graphics3D[{Blue, PointSize[0.1], Point[{
      model["realPoint", "x"],
      model["realPoint", "y"],
      model["error", "mesh", roundX, roundY]
    }]}],

    AxesLabel -> {"x[m]", "y[m]", "Error"},
    PlotLabel -> "Result from error anlysis"]
  ];
  Return[ret];
];
```

In[13]:=
```
(*
  point is array of <|mac->XXX,
  values-> {}|> senced at some point,
  model is the return of GenerateModel
*)
```

```
FindPointInModel[Config_, point_, model_] := Module[{
  pointForCalculation, i, j, k, ret = <||>, tmp, error,
  maximalPoint, ipOrMac, valOrValues},

  pointForCalculation = <||>;

  If[point[[1]]["mac"] == "homegear",
    ipOrMac = "ip"; valOrValues = "val";,
    ipOrMac = "mac"; valOrValues = "values";
  ];

  For[i = 1, i <= Length[point], i++,
    pointForCalculation[point[[i]][ipOrMac]] =
      Mean[point[[i]][valOrValues]];
  ];

  ret["mesh"] = <||>;(*instance of the mesh*)
  ret["minError"] = False;
  ret["minErrorPosition"] = <||>;

  ret["maximalPoint"] = <|"mac" -> False, "value" -> False|>;

  tmp = Keys[pointForCalculation];

  For[k = 1, k <= Length[tmp], k++,
    If[ret["maximalPoint", "value"] == False ||
      ret["maximalPoint", "value"] < pointForCalculation[tmp[[k]]],
      ret["maximalPoint"] = <|
        "mac" -> tmp[[k]],
        "value" -> pointForCalculation[tmp[[k]]]
      |>;
    ];
  ];


  For[i = 1, i <= Length[model["mesh", "def", "x"]], i++,
    ret["mesh", model["mesh", "def", "x"][[i]]] = <||>;
    For[j = 1, j <= Length[model["mesh", "def", "y"]], j++,
      error = 0;
      For[k = 1, k <= Length[tmp], k++,
        error = error + (
          (
           model["mesh", "inst",
             model["mesh", "def", "x"][[i]],
             model["mesh", "def", "y"][[j]],
             tmp[[k]]
           ] -
           model["mesh", "inst",
             model["mesh", "def", "x"][[i]],
```

```
              model["mesh", "def", "y"][[j]],
              ret["maximalPoint", "mac"]]
          ) (*relative value to maximum*)
          -
          (
            pointForCalculation[tmp[[k]]] -
            pointForCalculation[
              ret["maximalPoint",
              "mac"]
            ]
          )(*relative value to maximum*)
        )^2
      ];
      error = Sqrt[error];
      ret["mesh",
        model["mesh", "def", "x"][[i]],
        model["mesh", "def", "y"][[j]]
      ] = error;
      If[ret["minError"] == False || ret["minError"] > error,
        ret["minError"] = error;
        ret["minErrorPosition", "x"] = model["mesh", "def", "x"][[i]];
        ret["minErrorPosition", "y"] = model["mesh", "def", "y"][[j]];
      ];
    ];
  ];

  Return[ret];
];
```

```
In[14]:= DetermineRealPosition[Config_, point_] := Module[{ret = <||>},

  If[StringMatchQ[point, RegularExpression["^[A-D][a-e]\$"]] == False,
    Throw["I dont undertand point definition."]
  ];

  Return[
    ret = <|
      "x" -> Config["DataX", StringTake[point, 1]] + 0.0,
      "y" -> Config["DataY", StringTake[point, -1]] + 0.0|>
  ];
];
```

```
In[15]:= (*Full error calculation*)
FullErorCalc[
  Config_,
  WifiNotHomematic_: True,
  TestOnlyInnerPoints_: False
] := Module[{
```

```
    errorAnalysis = {}, dataX, dataY, i, j, tmp, tmpPoint, model, error,
    ret = <||>, vectorPlot = {}, progressBarValue = 0, timer
  },

    dataX = Keys[Config["DataX"]];
    dataY = Keys[Config["DataY"]];

    Print[ProgressIndicator[
      Dynamic[progressBarValue], {1, Length[dataX]*Length[dataY]}
    ]];

    ret["allStates"] = <||>;
    ret["allModels"] = <||>;

    For[i = 1, i <= Length[dataX], i++,
      For[j = 1, j <= Length[dataY], j++,
        progressBarValue = progressBarValue + 1;
        tmpPoint = dataX[[i]] <> dataY[[j]];

        If[
          TestOnlyInnerPoints &&
          Not[MemberQ[
            Config["InnerPoints", If[WifiNotHomematic, "WiFi", "HM"]],
            tmpPoint
          ]],
          Continue[];
        ];

        If[FileExistsQ[DataFileName[Config, tmpPoint]],
          If[WifiNotHomematic,
            model = GenerateModel[Config, tmpPoint];,
            model = GenerateModelHomematic[Config, tmpPoint];
          ];
          model["realPoint"] = DetermineRealPosition[Config, tmpPoint];

          If[WifiNotHomematic,
            model["error"] = FindPointInModel[Config,
              GetExperimentPosition[Config, tmpPoint]["mobileTerminal"],
              model
            ];,

            model["error"] = FindPointInModel[Config,
              GetExperimentPosition[Config, tmpPoint]["homeGear"], model];
          ];

          ret["allModels", tmpPoint] = model;
          ret["allStates", tmpPoint] = model["state"];

          error = EuclideanDistance[
```

```
          AssociationToPosition[model["error", "minErrorPosition"]],
          AssociationToPosition[model["realPoint"]]
        ];

        AppendTo[errorAnalysis, {
          Config["DataX", dataX[[i]]],
          Config["DataY", dataY[[j]]],
          error
        }];

        AppendTo[vectorPlot, {
          AssociationToPosition[model["realPoint"]],
          AssociationToPosition[model["error", "minErrorPosition"]] -
            AssociationToPosition[model["realPoint"]]
        }];
      ];
    ];
  ];

  ret["data"] = errorAnalysis;

  tmp = Sort[ret["data"][[All, 3]]];
  ret["cfd"] = Transpose[{tmp, Range[Length[tmp]]/Length[tmp]}];

  ret["plot"] = ListPlot3D[errorAnalysis,
    AxesLabel -> {"x[m]", "y[m]", "Error [m]"},
    PlotLabel -> "Error in m for each point of evaluation",
    BoxRatios -> Config["plotRatio"]
  ];

  ret["errorCFD"] = ListPlot[ret["cfd"],
    AxesLabel -> {"Error [m]", "CDF"}
  ];

  If[\$MachineName == "desktop-caqngev",
    ret["vectorErrorPlotList"] = vectorPlot;
    ret["vectorErrorPlot"] = ListVectorPlot[vectorPlot,
      PlotLabel ->
        "Direction of error, size of arrows proportional to error",
      FrameLabel -> {"x[m]", "y[m]"},
      VectorPoints -> All
    ];,
    ret["vectorErrorPlot"] = vectorPlot;
  ];

  Return[ret];
];
```

In[16]:=

```
HistogramOfParamter[Config_, model_, paramteter_, round_] := Module[
```

```
    {out, legend, ii, tmp, A, tmp2, dataX, dataY, i, j, a = {}},

    out = {};
    legend = {};
    For[ii = 1, ii <= 4, ii++,
      tmp = {};
      tmp2 = {};

      A[x_] := AppendTo[tmp,
        Round[x[Config["AP"][[ii]]["mac"], paramteter], round]
      ];

      Map[A, model["allStates"]];
      AppendTo[out, tmp];
      Print[Histogram[tmp]];
      Print[ListPlot[tmp,
          FrameLabel -> {"measurement number", "gamma"}
      ]];

      dataX = Keys[Config["DataX"]];
      dataY = Keys[Config["DataY"]];

      For[i = 1, i <= Length[dataX], i++,
        For[j = 1, j <= Length[dataY], j++,
          AppendTo[a, {
            Config["DataX", dataX[[i]]],
            Config["DataY", dataY[[j]]],
            model["allStates",
              dataX[[i]] <> dataY[[j]],
              Config["AP"][[ii]]["mac"],
              paramteter
            ]
          }];
        ];
      ];

      Print[ListPlot3D[a, AxesLabel -> {"x[m]", "y[m]", "gamma"}]];
      AppendTo[legend, Config["AP"][[ii]]["nickname"]];
    ];

    Histogram[out,
      ChartLegends -> legend,
      AxesLabel -> {"gamma value", "Number of occuraces"}
    ]
  ];
```

```
In[17]:= WallCrossings[Config_, pointA_, pointB_] := Module[
    {i, ret = <||>, w1, w2},
    For[i = 1, i <= Length[Config["wall"]], i++,
```

```
      w1 = {Config["wall"][[i]]["x1"], Config["wall"][[i]]["y1"]};
      w2 = {Config["wall"][[i]]["x2"], Config["wall"][[i]]["y2"]};

      If[Length[Solve[
        Element[{x, y}, RegionIntersection[
          Line[{w1, w2}],
          Line[{pointA, pointB}]
        ], {x, y}]] > 0,
        ret[Config["wall"][[i]]["d"]] = If[
          KeyExistsQ[ret, Config["wall"][[i]]["d"]],
          Config["wall"][[i]]["d"] + 1,
          1
        ];
      ];
    ];
    Return[ret];
  ];
```

```
In[18]:= WallCrossingsToDb[Config_, wallCrossings_] := Module[
    {i, sum = 0, keys},
    keys = Keys[wallCrossings];
    For[i = 1, i <= Length[keys], i++,
      sum = sum +
        wallCrossings[keys[[i]]]*Config["wallEffects", keys[[i]]];
    ];
    Return[sum];
  ];
```

```
In[19]:= CalculateCurrentStateHomematic[Config_, positionString_] := Module[
    {ret = <||>, position = GetExperimentPosition[Config, positionString],
      data = <||>, dataX = {}, dataY = {}, i, j, k, tmp},

    For[i = 1, i <= Length[position["accessPoints"]], i++,
      For[j = 1, j <= Length[Config["HM"]], j++,
        If[position[["accessPoints"]][[i]]["mac"] == "central",

          (*check points*)

          If[Length[position["accessPoints"][[i]]]["val"] <
            Config["Model", "numberOfHistoryPoints"],
            Throw["Exptected to get '" <>
              ToString[Config["Model", "numberOfHistoryPoints"]] <>
              "' but got only '" <>
              ToString[Length[position["accessPoints"][[i]]]]["val"] <>
              "'"
            ];
          ];

          If[position["accessPoints"][[i]]["ip"] ==
```

```
                Config["HM"][[j]]["mac"],

                data[position["accessPoints"][[i]]["ip"]] = <|
                  "raw" -> Take[
                    position["accessPoints"][[i]]["val"],
                    Config["Model", "numberOfHistoryPoints"]
                  ]
                |>;

                data[position["accessPoints"][[i]]["ip"]]["filtered"] =
                  CustomMedianFilter[
                    data[position["accessPoints"][[i]]["ip"]]["raw"],
                    Config["Model", "medainFilterValue"]
                ];

                data[position["accessPoints"][[i]]["ip"]]["position"] =
                  AssociationToPosition[Config["HM"][[j]]];

                data[position["accessPoints"][[i]]["ip"]]["d"] =
                  EuclideanDistance[
                    AssociationToPosition[Config["HM"][[j]]],
                    AssociationToPosition[Config["HM-base"]]
                  ];

                data[position["accessPoints"][[i]]["ip"]]["alpha"] =
                  VectorAngle[
                    Config["HM"][[j]]["direction"],
                    Config["HM-base", "direction"]
                ];
              ];
            ];
          ];
        ];

        For[i = 1, i <= Length[data], i++,
          For[j = 1, j <= Length[data], j++,

            (*do not calcluate for two exactly the same iot devices*)
            If[i == j, Continue[];];

            For[k = 1, k <= Config["Model", "numberOfHistoryPoints"], k++,

              AppendTo[dataY,
                data[[i]]["filtered"][[k]] +
                WallCrossingsToDb[Config, WallCrossings[Config,
                  AssociationToPosition[Config["HM-base"]],
                  data[[i]]["position"]
                ]]
                - data[[j]]["filtered"][[k]] -
```

```
          WallCrossingsToDb[Config, WallCrossings[Config,
            AssociationToPosition[Config["HM-base"]],
            data[[j]]["position"]]
        ]];

        AppendTo[dataX, {
          10*Log10[data[[j]]["d"]/data[[i]]["d"]],(
            AngleFunction[data[[j]]["alpha"]] -
            AngleFunction[data[[i]]["alpha"]]
          )*10*Log10[data[[j]]["d"]/data[[i]]["d"]]
        }];
      ];
    ];
  ];

  tmp = LeastSquares[dataX, dataY];

  ret["gamma"] = tmp[[1]];
  ret["beta"] = tmp[[2]];
  Return[ret];
];
```

In[20]:=
```
GenerateModelHomematic[Config_, positionString_] := Module[
  {ret = <||>, i, j, k, tmp,
    position = GetExperimentPosition[Config, positionString]},

  ret["state"] = CalculateCurrentStateHomematic[Config, positionString];

  (*create mesh*)
  ret["mesh"] = <||>;
  ret["mesh", "def"] = <||>;(*definition of the mesh*)

  ret["mesh", "def", "x"] = Range[
    Config["Model", "mesh", "x", "from"],
    Config["Model", "mesh", "x", "to"],
    Config["Model", "mesh", "x", "mesh"]
  ];

  ret["mesh", "def", "y"] = Range[
    Config["Model", "mesh", "y", "from"],
    Config["Model", "mesh", "y", "to"],
    Config["Model", "mesh", "y", "mesh"]
  ];

  ret["mesh", "inst"] = <||>;(*instance of the mesh*)

  tmp = Config["HM"];
  For[i = 1, i <= Length[ret["mesh", "def", "x"]], i++,
    ret["mesh", "inst", ret["mesh", "def", "x"][[i]]] = <||>;
```

```
        For[j = 1, j <= Length[ret["mesh", "def", "y"]], j++,
          ret["mesh", "inst",
            ret["mesh", "def", "x"][[i]],
            ret["mesh", "def", "y"][[j]]
          ] = <||>;
          For[k = 1, k <= Length[tmp], k++,
            ret["mesh", "inst",
              ret["mesh", "def", "x"][[i]],
              ret["mesh", "def", "y"][[j]],
              tmp[[k]]["mac"]
            ] = CalculatePowerAt[Config,
              <|
                "x" -> ret["mesh", "def", "x"][[i]],
                "y" -> ret["mesh", "def", "y"][[j]]
              |>,
              tmp[[k]],
              ret["state"]
            ];
          ];
        ];
      ];
    Return[ret];
  ];
```

In[21]:=
```
JoinModels[wifiFullErrrorCalc_,hmFullErrrorCalc_]:=Module[
{out=<||>,points,i,joinedPoint,tmp,stdWifi,stdHm,wWifi,wHm},

   wWifi=1/stdWifi;
   wHm=1/stdHm;

   points=Intersection[
     Keys[wifiFullErrrorCalc["allModels"]],
     Keys[hmFullErrrorCalc["allModels"]]
     ];
   out["joinedPoints"] = <||>;
   out["errors"] = <||>;
   out["errorsVector"] = {};
   For[i=1,i<= Length[points],i++,
    joinedPoint = (
       wWifi*AssociationToPosition[
wifiFullErrrorCalc["allModels",points[[i]], "error","minErrorPosition"]
]
        +
        wHm*AssociationToPosition[
hmFullErrrorCalc["allModels",points[[i]], "error","minErrorPosition"]
]
       )/(wWifi+wHm)
    ;
```

```
 out["joinedPoints", points[[i]]] = joinedPoint;
 tmp= EuclideanDistance[
     joinedPoint,
     AssociationToPosition[
             wifiFullErrrorCalc["allModels",points[[i]], "realPoint"]
     ]
   ];
 out["errors", points[[i]]] = tmp;
 AppendTo[out["errorsVector"],tmp];
 ];
Return[out];
];
```

Razširjeni povzetek

B

B.1 Uvod

V modernem svetu se srečujemo s tehnologijo na vsakem koraku. S koncepti, kot so pametne hiše, internet stvari (ang. Internet of things, IoT) in Industrija 4.0, vpeljujemo digitalne senzorje in aktuatorje v naša življenja. Že danes so na trgu na voljo sistemi za pametne hiše, kjer lahko preko centralnega nadzornega sistema krmilimo vsak električni porabnik našega doma. V prihodnjem desetletju se bodo ti sistemi še bolj razvili in postali cenovno bolj dosegljivi končnim uporabnikom. Domovi in stanovanjske zgradbe pa niso edina okolja, ki bodo pridobila z vpeljavo IoT. Paradigma Industrije 4.0 je trenutni trend v industrijski proizvodnji, ki se fokusira na komunikacijo in izmenjavo podatkov tako med napravami kot tudi med napravami in ljudmi, ki so udeleženi v proizvodnem procesu. Za najboljše krmiljenje moramo tem sistemom preko senzorjev zagotoviti ustrezne informacije, na podlagi katerih lahko sistem krmili porabnike.

Tako v viziji IoT kot tudi v viziji Industrije 4.0 je informacija o lokaciji ljudi, naprav in senzorjev znotraj prostorov zelo zaželena. Glede na to, da v sodobnem svetu nosimo mobilni telefon vedno s seboj, bi sposobnost lociranja mobilnega telefona omogočala pametnim hišam lociranje uporabnikov znotraj stavbe in posledično npr. samodejno prilagajanje osvetlitve in avdiovizualnih sistemov željam specifičnega uporabnika. V industrijski proizvodnji je že leta odprt problem lociranja; implementacija sodobnih transportnih sistemov v proizvodnji je pogojena z možnostjo lociranja, prav tako bi lociranje omogočalo boljšo spremljanje učinkovitosti delavcev in sledenje produktom tekom proizvodnega procesa.

Pričujoče besedilo povzema doktorsko nalogo, v kateri smo razvili metodo za določanje položaja v prostoru na osnovi signalov in modela zgradbe. Primarno smo razvili metodo z uporabo WiFi signalov, v drugem delu pa smo metodo razširili za večfrekvenčno lokalizacijo. Naš glavni cilj je bil razvoj metode, ki bi bila primerna za uporabo v realnem okolju hkrati pa bi se po natančnosti merila z najboljšimi trenutnimi metodami. Želeli smo ustrezno nasloviti težavne kalibracijske procedure, uporabo statičnih parametrov propagacijskih modelov in strojne zahteve obstoječih metod. Naš razvoj je temeljil na naslednjih predpogojih.

- *WiFi signali* - WiFi je dandanes ena najbolj pogosto uporabljenih tehnologij brezžične komunikacije, zato ne čudi dejstvo, da je na raziskovalnem področju lokalizacije na podlagi brezžičnih signalov najpogosteje uporabljena tehnologija.

Kljub temu je bil razvoj celoten čas podrejen želji, da bi metoda delovala tudi na drugih frekvencah.

- *Modelni pristop* - V grobem delimo WiFi metode na tiste, ki bazirajo na podlagi prstnega odtisa (tj. statičnih meritev) in tiste, ki bazirajo na podlagi modeliranja širjenja signala po prostoru. Prve navadno niso sposobne prilagajanja realnim variacijam signala, zato za dolgoročno natančnost potrebujejo pogoste kalibracije. Modeliranje širjenja signala ponuja izgradnjo sistema, neodvisnega od statičnih meritev, in s tem dolgoročno stabilne sisteme.

- *Upoštevanje notranjih sten* - Le ena izmed 17 metod, ki smo jih primerjali v dizertaciji, je bila evalvirana v stanovanjskem okolju. Metode so praviloma evalvirane v okoljih raziskovalnih inštitutov in fakultet, kjer navadno najdemo velike prostore z malo predelnimi stenami. Vpliv sten na natančnost je veliko večji v stanovanjskem okolju, kjer so navadno prostori manjši, kar pa moramo upoštevati pri razvoju univerzalne metode.

- *Nizke strojne zahteve* - Uporaba namenske in drage strojne opreme zmanjšuje univerzalnost in uporabnost metode; npr. z laserskimi sistemi lahko določimo relativne pozicije na milimetre natančno, vendar je cena takšnega sistema visoka. Zadali smo si cilj, da želimo razviti metodo, ki bo sposobna določiti lokacijo vsake WiFi povezane naprave.

B.1.1 Znanstveni doprinosi

Glavni obseg tega dela je nova metoda za določanje položaja v prostoru. Metoda je bila primarno razvita za uporabo WiFi signalov, kasneje pa razširjena za večfrekvenčno delovanje. Znanstvene doprinose lahko povzamemo kot:

- *Nova metoda kalibracije za modelne pristope, temelječe na signalih WiFi.* Predstavljena metoda implementira metodo za neprekinjeno spremljanje širjenje signala po prostoru in prilagajanje propagacijskega modela. Ta pristop k sprotni ocenitvi parametrov propagacije se lahko uporabi pri številnih drugih metodah, ki vsebujejo statično določene izhodiščne parametre.

- *Nova prilagodljiva metoda za določanje položaja v prostoru na osnovi signalov WiFi in modela zgradbe.* Z uporabo razvite kalibracijske metode smo razvili metodo za določanje pozicije znotraj stavb, ki upošteva postavitev sten med prostori, določa propagacijski model na podlagi sprotnih meritev, za dolgoročno stabilno delovanje ne potrebuje ročnih posegov, ne potrebuje nobene dodatne strojne opreme poleg dostopnih točk (ang. access point, AP) in ne zahteva, da terminal (naprava, ki jo želimo locirati) oddaja signale. Metoda je bila uspešno evalvirana tako v stanovanjskem in v pisarniškem okolju kot tudi v dolgem hodniku, ki je velikokrat uporabljeno evalvacijsko okolje pri sorodnih metodah.

- *MFAM metoda: metoda za določanje položaja v prostoru na podlagi signalov več frekvenc*. Tekom razvoja metode za določanje lokacije se nismo z ničemer omejili na signale WiFi. Zato smo v nadaljnjem delu razširili metodo za uporabo na več frekvencah. Metodo za določanje položaja smo uspešno aplicirali na frekvenco 868 MHz, ki jo uporablja sistem za avtomatizacijo doma v izbranem elevacijskem okolju. Definirali smo metodo za fuzijo obeh frekvenc in pokazali, da kombinacija signalov WiFi in 868 MHz daje boljšo natančnost kot uporaba posameznih frekvenc.

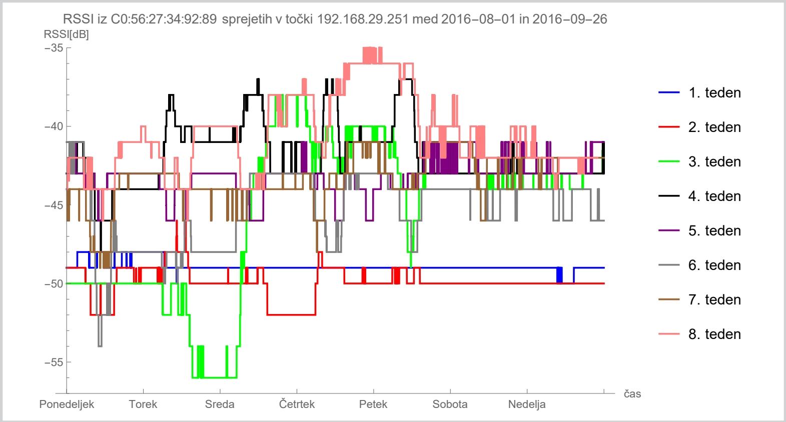
B.2 Določanje položaja v prostoru

Določanje lokacije naprav znotraj prostorov je že dolgo raziskovan problem, ki zadnje čase postaja tudi industrijsko in komercialno zanimiv, kar rezultira v veliko preglednih člankih [7–9, 27, 33]. Večina del se osredotoča na WiFi signale, gledano širše pa Yassin et al. [7] razdelijo algoritme za določanje lokacije na triangulacijske algoritme, algoritme, ki delujejo na podlagi analize prostora, in tiste, ki delujejo na podlagi zaznave bližine. Kot že omenjeno v uvodu, WiFi metode v grobem ločimo v dve skupini. Med triangulacijske lahko umestimo večino modelnih pristopov za določanje lokacije, medtem ko metode, delujoče na principu prstnega odtisa, umeščamo med metode analize prostora.

V literaturi se pojavlja veliko pristopov, ki poskušajo vpeljati dodatne informacije v proces določanja lokacije, da na ta način zmanjšajo vpliv variacije WiFi signalov. Taki primeri so metode, ki uporabljajo inercijske senzorje poleg signalov WiFi. Take pristope najdemo tako v skupini metod, temelječih na prstnih odtisih [42, 43], kot tudi v skupini modelnih pristopov [57]. Velika pomanjkljivost teh metod je, da se zanašajo na gibanje človeka, ki napravo nosi v žepu. Zato niso primerne za industrijsko proizvodnjo in razmeroma statične naprave v prostoru. Nekateri raziskovalci iščejo bolj stabilne značilke propagacije signala [44, 45, 58, 60], vendar za uporabo le-teh potrebujemo naprednejšo in posledično dražjo opremo, kar pa zmanjša univerzalnost razvite metode.

Pri razvoju metode, ki deluje na podlagi moči signala, je njuno razumevanje definicije moči signala. RSS je kratica, ki označuje moč prejetega signala (ang. received signal strength). V klasičnih napravah WiFi dostopa do tega podatka nimamo, niti ga naprave ne merijo. Specifikacija WiFi standarda [68] določa količino RSSI kot indikator količine RSS (ang. received signal strength indicator). Standard eksplicitno ne določa, kako je definiran RSSI, zato je implementacija prepuščena izdelovalcu strojne opreme. To je glavni razlog, zakaj moramo biti pri razvoju metod za določanje lokacije na podlagi RSS/RSSI pozorni na različnost meritve pri uporabi različne opreme. Definicija standarda le določa, da je to 8-bitna vrednost, ki je rezultat monotono naraščajoče funkcije prejete moči. Problem RSSI pa je, da navadno ni direktno dostopen. Operacijski sistem navadno implementira nivoje abstrakcije nad to informacijo, ki jo nato preslika z neko funkcijo v logaritemsko (decibelno) skalo. Že standard opozarja, da je ta vrednost navadno povprečena preko daljše časovne periode.

Glavna slabost sodobnih pristopov za določanje lokacije je predpostavka, da se nekatere statistične vrednosti signala na dolgi rok ne spreminjajo. V nalogi pokažemo rezultate eksperimenta, pri katerem smo 8 tednov vsako minuto merili moč signala med parom dostopnih točk v istem prostoru. Analiza vseh meritev je dala pričakovano



Slika B.1

RSSI vrednosti v času 8-ih tednov.

naravno porazdelitev s povprečno vrednostjo $\mu = -45\,\mathrm{dB}$ in standardnim odklonom $\sigma = 4{,}7$. Podrobnejša analiza podatkov je pokazala, da lahko najdemo časovna obdobja, ko je moč signala $-50\,\mathrm{dB}$ in na drugi strani časovna obdobja, ko je bila moč signala $-36\,\mathrm{dB}$. Rezultate analize lahko vidimo na sliki B.1, kjer smo signale filtrirali z mediano z oknom 2 uri. Iz tega je razvidno, da metode, ki bazirajo na statičnih odčitkih vrednosti (npr.: metode na podlagi prstnih odtisov), ne morejo dobro delovati v daljšem časovnem obdobju brez ponavljajočih kalibraciji. S stališča dolgoročne stabilnosti so problematične tudi modelne metode, ki gradijo svoj model propagacije na podlagi nekih statičnih odčitkov – npr. eksperimentalno določena vrednost za pričakovan upad moči na določeni razdalji od oddajnika.

Modelne pristope, ki ustrezno naslovijo probleme različnih implementacij RSSI vrednosti in ustrezno naslovijo težave dolgoročne stabilnosti signala, je relativno trivialno zgraditi, v kolikor uporabimo za določanje lokacije signale, ki jih oddaja terminal. Te metode bazirajo na oddanih signalih s strani naprave, na drugi strani pa so metode, kjer te naprave analizirajo signale, prejete s strani dostopnih točk. Pri razvoju smo se odločili za drugi način, saj prvi ni primeren za prostore, kjer želi veliko ljudi določiti svojo pozicijo hkrati (npr. javne prireditve, stadioni, nakupovalni centri). V tem primeru naprave zapolnijo komunikacijske frekvence in tako onemogočijo osnovno nalogo Wi-Fi, to je zagotavljanje povezljivosti, prav tako pa konstantno oddajanje signala poveča zahteve po energiji.

Utemeljitev odločitve, da razvijemo metodo, ki bo neodvisna od frekvence signala in ne bo omejena samo na signale WiFi, najdemo v predvidenem razvoju WiFi. V začetku leta 2017 je bil objavljen dodatek k WiFi standardu, ki definira protokol 802.11ah. Ta bo deloval na frekvencah 900 MHz in bo namenjen napravam IoT. Dolgovalovni signali so manj občutljivi na pregrade, njihova slabost pa je nižja možna hitrost. V kolikor bo standard 802.11ah doživel široko uporabo, želimo, da bo naša metoda sposobna uporabiti nove signale.

Področje metod za določanje lokacije znotraj prostorov je specifično, ker je rezultat močno odvisen od testnega okolja. Poleg tega je zaradi narave metod (npr. strojne zahteve) navadno zelo oteženo testiranje različnih metod v istem okolju. Posledično je standardni način primerjave metod analiza statistike napak, ki so jih dosegle metode v različnih testnih okoljih. Zaradi velike razlike med zgradbami so take primerjave zelo težavne in dopuščajo, da raziskovalci izvajajo evalvacije v okolju, ki najbolj ustreza njihovi metodi. Z evalvacijo predlagane metode v treh zelo različnih okoljih – pisarniško, stanovanjsko in hodnik – smo nakazali univerzalnost metode in njeno neodvisnost od okolja.

B.3 Nova metoda za določanje položaja v prostoru na osnovi signalov WiFi in modela zgradbe

Osnovno predlagano WiFi metodo razdelimo na štiri faze: faza pridobivanja podatkov, faza modeliranja upada moči, faza simulacije propagacije in faza določanja lokacije.

V *fazi pridobivanja podatkov* metoda spremlja propagacijo signala z beleženjem RSS/RSSI informacij na posameznih APjih. Ko beležimo moč signala, prejetega v dostopni točki AP_j, ki izhaja iz dostopne točke AP_i, dobimo informacijo o trenutni propagaciji signala, v katerega so zajeti dejavniki prostora. Faza pridobivanja podatkov neprenehoma teče v ozadju in pridobiva podatke, iz katerih v naslednjih fazah matematično definiramo trenutno stanje signala v prostoru.

V *fazi modeliranja upada moči* uporabimo razširjen model logaritemskega upada moči širjenja signala. Osnovni model propagacije smo razširili s faktorji, ki popisujejo število sten med dvema dostopnima točkama in količino, ki vključuje odvisnost smeri odboja signala od stene z nameščenim oddajnikom. Z meritvami smo pokazali [11], da je širjenje signala vzporedno s steno z nameščenim oddajnikom slabše kot širjenje signala pravokotno na steno; predvidevamo, da je zaznani efekt posledica delovanja stene, ki deluje kot antenski reflektor.

$$\begin{aligned}\left(RSSI_{m,i} - W_{m,i}\right) - \left(RSSI_{n,i} - W_{n,i}\right) &= \\ &= 10\gamma_i \log_{10} \frac{d_{i,m}}{d_{i,n}} + 10\beta_i \log_{10} \frac{d_{i,m}}{d_{i,n}} \times \left(\alpha_{i,m} - \alpha_{i,n}\right) \qquad \text{(B.1)}\end{aligned}$$

Enačba (B.1) opisuje model širjenja signala, ki ga implementira naša metoda. V enačbi $RSSI_{m,i}$ označuje RSSI signala, ki izvira iz točke AP_i in je bil sprejet v točki AP_m. $W_{m,i}$ označuje vpliv sten med AP_i in točko m, $d_{m,i}$ označuje razdaljo med točkama, γ_i označuje eksponentni upad moči za dostopno točko AP_i, vrednosti β_i in $\alpha_{i,m}$ označujeta vpliv kota širjenja signala skladno s formulo (B.2). $\alpha_{i,m}$ je kot, ki ga tvorita normala n_i na steno, ob kateri je postavljena dostopna točka AP_i, in vektor direktne poti $s_{i,m}$ med točkama AP_i in m, v radianih deljen s $\pi/2$. Vrednost $W_{m,i}$ izračunamo kot vsoto števila posameznih tipov sten, pomnoženih z njihovim vplivom na širjenje signala.

$$\alpha_{i,m} = \frac{\sphericalangle\left(n_i, s_{i,m}\right)}{\pi/2} \tag{B.2}$$

V tej fazi uporabimo odčitke iz faze pridobivanja podatkov v zadnjih 15 minutah pred procesom določanja lokacije. Znane (npr. razdalje med dostopnimi točkami, število sten, α vrednosti) in izmerjene količine ($RSSI$) rezultirajo v predeterminiranemu sistemu enačb, iz katerega določimo vrednosti γ_i in β_i za vsako izmed dostopnih točk AP_i.

V *fazi simulacije propagacije* uporabimo ITU model [82], ki smo ga podobno razširili s količinami za popis vpliva sten in parametrom β, da simuliramo propagacijo signala v prostoru in tako dobimo virtualni zemljevid propagacije. Parametri razdelitve prostora morajo biti določeni skladno z velikostjo prostora, računsko zmogljivostjo in sprejemljivo napako.

V *fazi določanja lokacije* naprava, ki želi določiti svojo pozicijo, opravi tri iskanja WiFi dostopnih točk v okolici. Uporaba srednje vrednost treh meritev za vsako dostopno točko zagotovi filtriranje meritve. Zajete vrednosti in vrednosti v virtualnem zemljevidu normaliziramo glede na najmočnejši signal, ki ga je zajela naprava, da delno naslovimo problem različnosti strojne opreme. Točka, katere vektor tako izračunanih vrednosti je najbolj podoben vektorju, ki smo ga dobili iz zajetih signalov na napravi, določa rezultat metode.

Metodo smo evalvirali v dveh zelo različnih okoljih. V pisarniškem okolju smo metodo preizkusili v scenarijih enega prostora in dveh prostorov z vmesno steno. Nato pa smo metodo preizkusili še v modernem stanovanju s šestimi različnimi prostori in dvema različnima tipoma sten – predelne stene iz mavčnih plošč in stene iz opeke. Tabela B.1 povzema statistiko napak, ki smo jih dobili pri 52-ih oziroma 24-ih poizkusih, opravljenih v pisarni v primeru enega oziroma dveh prostorov. Rezultat za stanovanjsko evalvacijo bazira na 4-ih neodvisnih setih meritev, opravljenih v 17-ih različnih točkah stanovanja.

Glede na to, da smo metodo razvijali v pisarniškem okolju fakultete in jo nato nespremenjeno prenesli v stanovanjsko okolje, je najpomembnejši rezultat pridobljen v stanovanjskem okolju. Povprečna napaka med 2 in $3\,\mathrm{m}$ je primerljiva z najboljšimi poznanimi metodami. Hkrati naša metoda zagotavlja prilagajanje spremembam v prostoru in dolgoročno stabilnost, saj po definiciji metode vplivajo na rezultat le meritve, pridobljene v časovnem oknu $15\,\mathrm{min}$ pred določanjem lokacije. Poleg tega ima

Tabela B.1

Povzetek statistike napak metode WiFi.

Evalvacija	Povprečna napaka [m]	Mediana napake [m]	Odklon [m]
Pisarna en prostor	2,63	2,29	1,45
Pisarna dva prostora	3,22	3,48	1,58
Stanovanje	2,65	2,59	1,51
Hodnik	3,72	2,55	3,85

naša metoda najmanjše možne strojne zahteve za metodo, ki temelji na signalih WiFi – poleg dostopnih točk potrebujemo le napravo, ki je sposobna poročati RSS/RSSI vrednosti dostopnih točk v okolici. Skladno s predhodno diskusijo metoda deluje na podlagi prejetih signalov na terminalu, zato ni potrebno, da bi naprava delovala v načinu dostopne točke.

V eksperimentalnem delu smo zaznali tudi anomalije, ko so dostopne točke, ki so bile oddaljene dlje od izvora signala, poročale o močnejšem signalu kot dostopne točke bližje izvora. Matematično to pomeni, da se signal s potovanjem od izvora krepi, kar pa je fizikalno nemogoče. Takšne anomalije so posledice variacije RSSI vrednosti, poročanih s strani dostopnih točk. V nalogi pokažemo, kako implementacija posebne procedure za primere, ko je γ_i negativen, poskrbi, da tudi v takšnih primerih metoda vrača pričakovane rezultate. Poleg tega tudi pokažemo, kakšni so rezultati, v kolikor takih primerov ne predvidimo.

Tekom eksperimentov smo prišli do potrditve teze, da postavitev dostopnih točk močno vpliva na natančnost WiFi metod. V obeh primerih večsobnih preizkusov smo uporabili neoptimalno postavitev dostopnih točk in na ta način postavili težji izziv svoji metodi. Glede na to, da si na tem raziskovalnem področju vsak raziskovalec določi svoje evalvacijsko okolje, to ponovno potrdi tezo, da bi za resnično realno primerjavo metod morali različne metode evalvirati v istem okolju.

B.4 MFAM: Večfrekvenčna razširitev metode

Radi bi poudarili, da smo si zadali cilj razviti metodo, ki bi bila neodvisna od frekvenc in ne bi bila primerna izključno za WiFi signale. Zato smo razvili metodo MFAM, ki osnovno WiFi metodo nadgradi za večfrekvenčno uporabo. Eden izmed razlogov so že predhodno omenjeni prihajajoči WiFi standardi, ki vpeljujejo nove frekvence in lahko pokrivajo veliko večja področja. Ker strojne opreme, ki bi podpirala te frekvence in standard, še ni na tržišču, smo morali v eksperimentih uporabiti druge tipe signalov. V stanovanjskem okolju, v katerem smo ocenjevali WiFi metodo, smo imeli na voljo brezžično omrežje za avtomatizacijo doma.

Različni sistemi za avtomatizacijo doma (ang. home automation systems) postajajo vse popularnejši, saj prinašajo možnost krmiljenja luči, ogrevanja, ventilacije ipd. preko telefona in drugih naprav. Večina teh sistemov deluje brezžično in s pomočjo baterijskega napajanja, kar olajša implementacijo teh sistemov v obstoječe objekte. V stanovanju, kjer smo izvajali testiranje WiFi metode, je implementiran sistem za avtomatizacijo doma, ki krmili posamezne radiatorje po sobah in skladno s potrebo po toploti vklaplja in izklaplja etažno peč. Sistem komunicira preko zaprtega protokola na frekvenci 868 MHz, kar je relativno zelo blizu frekvenc, na katerih bo deloval protokol 802.11ah.

Glavna razlika med WiFi in različnimi protokoli za avtomatizacijo doma je v topologiji omrežij. V slednjih je največkrat dosegljiva samo 1 naprava iz TCP/IP omrežja, komunikacija s preostalimi napravami pa je onemogočena. Skladno s tem je bilo treba prilagoditi nekaj podrobnosti v fazah pridobivanja podatkov, modeliranja upada moči in simulacije propagacije. Ker se omrežji razlikujeta v topologiji in v teh omrežjih naprave direktno med seboj ne komunicirajo, je glavna razlika v tem, da imamo v tem primeru na voljo manj meritev, iz katerih lahko ocenjujemo parametre γ_i in β_i. Zato v primeru omrežja za avtomatizacijo doma ne določamo parametrov γ_i in β_i za vsako izmed dostopnih točk posebej, ampak le en skupen set parametrov γ in β. Glede na manjšo količino podatkov, iz katerih lahko izračunamo parametre, ne pričakujemo, da bo natančnost ob uporabi izključno omrežja za avtomatizacijo doma boljša od uporabe WiFi. Nadejamo pa se boljšega rezultata ob upoštevanju obeh tipov signalov.

V dodatni 5. fazi MFAM metode delamo fuzijo lokacije posameznih frekvenc. Določili smo način fuzije, ki ga definira enačba (B.3). V enačbi $\left(x,y\right)_{MFAM}$ predstavlja rezultat MFAM metode, f frekvenco, pri kateri poteka evalvacija, SD_f standardni odklon napake, ki jo metoda naredi pri frekvenci f. $\left(x,y\right)_f$ predstavlja lokacijo, ki jo

Tabela B.2

Primerjava natančnost metod ob uporabi različnih signalov.

Uporabljeni signali	Povprečna napaka [m]	Mediana napake [m]	Odklon [m]
WiFi	2,65	2,59	1,51
868 MHz	3,21	3,01	1,88
868 MHz & WiFi	2,16	2,14	1,30

določi metoda pri frekvenci f.

$$\left(x,y\right)_{MFAM} = \frac{1}{\sum_f \frac{1}{SD_f}} \left(\sum_f \frac{1}{SD_f} \left(x,y\right)_f \right) \tag{B.3}$$

Tabela B.2 primerja statistiko napak ob uporabi različnih tipov signalov pri evalvaciji v stanovanjskem okolju. Evalvacija je bila razdeljena na 4 neodvisne sete meritev, ki smo jih opravili na 17-ih različnih lokacijah. Iz tabele je razvidno, da je kombinacija omrežja za avtomatizacijo doma in WiFi signalov s stališča natančnosti najboljša, saj rezultate WiFi metode izboljša za 18 %.

B.5 Zaključki

Na Gartnerjevem ciklu prihajajočih tehnologij je IoT platforma še vedno pred vrhuncem napihnjenih pričakovanj. Kljub temu da trg še vedno ni realno definiral področja IoT, pa se raziskovalci trudimo razvijati potrebne tehnologije. Naš cilj doseči uporabnost metode v realnih razmerah nas je vodil preko analize obstoječih metod, identifikacije slabosti, dolgoročne analize RSSI in nam določil robne pogoje za razvoj.

Skladno z željami in cilji smo razvili metodo, ki implementira algoritme za neprenehno prilagajanje parametrov modela spremembam v okolici brez človeškega posredovanja. Metoda je zasnovana brez uporabe statičnih parametrov, zato je po definiciji enako natančna tik po zagonu in mesece ter leta kasneje. Pomembna lastnost metode je neuporaba statičnih parametrov, vezanih na prostor, kar obljublja uporabnost ne glede na prostor. To smo dokazali z evalvacijo v dveh različnih okoljih, edina vhodna parametra metode so pozicije dostopnih točk in pozicije in materiali pregradnih sten.

V evalvaciji v pisarniškem in stanovanjskem okolju je metoda dosegla povprečno napako 2 do 3 m, kar metodo dela primerljivo s trenutno najboljšimi sorodnimi metodami. Dokaz, da prostor ne vpliva na našo metodo, je viden v tem, da je velikost napake v obeh evalvacijskih okoljih podobna. V nalogi pokažemo, kako so evalvacije metod velikokrat pomanjkljive in prostori nereprezentativni, hkrati so metode navadno evalvirane le v okolju, v katerem so bile razvite. V nalogi podajamo tudi primerjavo metod z ozirom na površino evalvacijskega okolja in številom naprav, saj oba parametra močno vplivata na povprečno napako.

Uspešna evalvacija WiFi metode nam je dala zagon za nadaljnje raziskovalno delo, v katerem smo razvili metodo MFAM, ki omogoča določanje lokacije na podlagi različnih frekvenc. Metodo smo aplicirali na 2,4 GHz signale WiFi in na 868 MHz signale sistema za avtomatizacijo doma. MFAM metoda je v eksperimentih dosegla boljše rezultate kot WiFi metoda. Povprečna vrednost napak se je gibala med 2 in 2,3 m in hkrati izkazala povprečni standardni odklon 1,3 m. MFAM metoda je v posameznih evalvacijah izboljšala povprečno napako za 6 do 30 % v primerjavi z evalvacijami ene frekvence.

Tekom raziskovalnega dela smo razvili metodo za lokalizacijo znotraj prostorov, katere glavno vodilo je bila uporabnost v realnem okolju. Razvili smo WiFi metodo in posplošeno MFAM metodo za večfrekvenčno uporabo, ki dosegata natančnosti, primerljive z najboljšimi metodami, hkrati pa poenostavljata implementacijo ter vzdrževanje dolgoročne natančnosti. Znanstvene doprinose našega dela lahko strnemo kot:

- metoda za neprekinjeno spremljanje propagacije signala in kalibracijo modela propagacije, primerna za številne modelne pristope, ki delujejo na podlagi RSS/RSSI;
- nova prilagodljiva metoda za določanje položaja v prostoru na osnovi signalov WiFi in modela zgradbe, ki močno poenostavlja implementacijo in vzdrževanje pri realni uporabi, medtem ko zagotavlja natančnost, primerljivo s trenutno najboljšimi metodami;
- MFAM metoda, ki generalizira WiFi metodo in omogoča določanje položaja v prostoru na podlagi več frekvenc.

Vsak zaključek nekega poglavja odpira nova vprašanja za prihodnost. Tako se ob zaključku tega dela ponuja nekaj iztočnic za delo v prihodnosti. Večina naprav v naših domovih je pretežno stacionarna, zanimivo bi bilo raziskati, kako se metoda obnaša v primerih, ko se naprava premika. Veliko metod, ki temeljijo na brezžičnih signalih, so raziskovalci združili z metodami, baziranimi na inercijskih senzorjih, in raznimi metodami za zaznavo bližine. Kako dobre rezultate lahko predlagani WiFi in MFAM metodi dosežeta v povezavi s podobnimi sistemi? Najzanimivejše področje dela v prihodnosti se kaže v povezavi MFAM metode s programsko določenimi radijskimi sprejemniki (ang. software defined radio, SDR). Kakšno natančnost lahko dosežemo s SDR moduli, ki bi delovali kot dostopne točke in mobilni terminali? Bi znali določiti frekvence, ki bi dale optimalne rezultate? In nenazadnje vprašanje kako določiti uteži v zadnjem koraku MFAM metode brez empiričnega poizkusa. V kolikor bi našli odgovor na ta problem, bi tudi MFAM metoda postala metoda, ki ne potrebuje kalibracijske evalvacije za svoje delovanje. Razvoj takšnih metod je po našem mnenju končni cilj raziskovalcev metod za določanje lokacije znotraj stavb za prihodnje tehnologije IoT.

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