Addressing Crucial Issues of Indoor Positioning Systems

THÈSE

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par

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Genève, le 23 novembre 2017

Le Doyen
Marcelo OLARREAGA

Impression d'après le manuscrit de l'auteur

Και γνώσεσθε τὴν ἀλήθειαν,
καὶ ἡ ἀλήθεια ἐλευθερώσει ὑμᾶς.

Ιωάννη 8:32

Acknowledgments

Initially, I would like to thank the co-directors of my Thesis, Prof. Dimitri Konstantas and Dr. Michel Deriaz, for giving me the opportunity to work on my PhD with them. I am truly grateful for the trust that they have consistently shown in me and for allowing me to direct my research freely. Having an open door for discussing my problems and difficulties has been indispensable for me in reaching the completion of this Thesis.

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Preface

Over the last decade, the proliferation of Location-Based Services offered by smartphones has created the growing need for indoor positioning systems (IPS), in an increasing number of environments. Visitors of hospitals, airports, shopping centers and museums are being guided indoors, enjoying services related to their indoor location. Location-Based Services assist users not only in orienting themselves indoors and finding their destination, but also utilize the location of users as context to support a wide range of possible services. The quasi-ubiquitous presence of position estimates indoors is offered by modern indoor positioning systems.

The goal of this Thesis is to propose novel methodologies to address crucial issues of indoor positioning systems. The problems addressed in this work are met throughout the whole life cycle of an IPS conception, realisation and operation, from designing innovative positioning methodologies to defining novel evaluation and tuning methodologies. Therefore, this Thesis initially investigates and reports the user needs and requirements concerning the wayfinding problems at a relevant and important use case: Geneva's University Hospitals (HUG). Following, it proposes innovative solutions that construct a robust indoor positioning system, along with ways of seamlessly switching from indoor to outdoor positioning. In order to strengthen the robustness of the system and reduce the required calibration effort, algorithms of automatic recalculation of the system are proposed and analyzed, addressing the problems of device and environment diversity. Moreover, well-defined methodologies of evaluating, comparing and optimally tuning positioning systems are proposed, addressing the most trending issues of the indoors positioning community. More specifically, an evaluation methodology for indoor positioning systems is proposed, as well as formal procedures for optimally tuning a positioning system, in an automatic way. Lastly, multiobjective optimization techniques are introduced in order to offer generic tunings based on a more holistic evaluation. In this way, the proposed methodologies of this Thesis define an innovative, complete roadmap for designing an innovative IPS, from designing and creating a robust indoor positioning system, to optimally tuning it in an automatic way and producing precise performance reports.

Résumé

Au cours de la dernière décennie, la prolifération des services de géolocalisation offerts par les smartphones a créé un besoin croissant de systèmes de positionnement en intérieur (IPS) dans un nombre croissant d'environnements. Les visiteurs des hôpitaux, des aéroports, des centres commerciaux et des musées sont guidés à l'intérieur, profitant des services liés à leur emplacement. Les services basés sur la position aident les utilisateurs non seulement à s'orienter à l'intérieur et à trouver leur destination, mais aussi à utiliser l'emplacement des utilisateurs comme contexte pour l'intégration d'une palette variée de services. La quasi-omniprésence d'estimations de position à l'intérieur est offerte par des systèmes de positionnement en intérieur modernes.

Le but de cette thèse est de proposer de nouvelles méthodologies pour traiter des problèmes cruciaux des systèmes de positionnement en intérieur. Les problèmes abordés dans ce travail sont rencontrés tout au long du cycle de vie de la création et de la fonction d'un IPS, de la conception de méthodologies de positionnement innovantes à la définition de nouvelles méthodologies d'évaluation et de réglage. Par conséquent, cette thèse étudie d'abord les besoins et exigences des usagers concernant les problèmes d'orientation dans un cas d'utilisation pertinent et important: les Hôpitaux Universitaires de Genève (HUG). Puis, elle propose des solutions innovantes qui construisent un système de positionnement en intérieur robuste, ainsi que des moyens de passer sans heurts du positionnement en intérieur à l'extérieur. Afin de renforcer la robustesse du système et de réduire l'effort d'étalonnage requis, des algorithmes de recalcul automatique du système sont proposés et analysés, abordant les problèmes de diversité des appareils et de l'environnement.

De plus, des méthodologies d'évaluation, de comparaison et de réglage optimal des systèmes de positionnement sont proposées, abordant ainsi les problèmes les plus importants de la communauté de positionnement en intérieur. Plus spécifiquement, une méthodologie d'évaluation pour les systèmes de positionnement en intérieur est proposée, ainsi que des procédures formelles pour optimiser un système de positionnement de façon automatique. Enfin, des techniques d'optimisation multiobjectif sont introduites afin d'offrir des réglages génériques basés sur une évaluation plus holistique.
Ainsi, les méthodologies proposées dans cette thèse définissent une feuille de route innovante et complète pour la conception d'un IPS innovant, de la conception et la réalisation d'un système de positionnement en intérieur robuste jusqu'à l'optimisation automatique et la production de rapports de performance précis.

Contents

1 Introduction

1.1 Overview

During recent years, the domain of indoor positioning has attracted great attention from both the academic community and the industry. The broad use of smartphones has familiarized the public with Location-Based Services (LBS). Most users of smart devices have had the experience of being positioned outdoors with the use of Global Navigation Satellite Systems (GNSS) like the Global Positioning System (GPS). Indoor Positioning Systems (IPS) are catching up, without having so far offered a generic solution such as the GPS.

Over the last decade, the proliferation of Location-Based Services offered by smartphones has created the growing need for indoor positioning systems, in an increasing number of environments. Commercial buildings like malls and shopping centers use indoor positioning to guide people into their premises and offer additional services using the users' location (offers, advertisements, etc.). Museums utilize IPS to offer tour guides to their visitors. Hospitals assist staff members, visitors and patients in finding their way in the often complex environments that are hospitals nowadays. Many public buildings like libraries, universities, public administration offices, etc., simplify the wayfinding experience of their users with the use of IPS.

The goal of this Thesis is to define new methodologies for addressing crucial issues of indoor positioning systems. The problems addressed are met throughout the whole lifecycle of an indoor positioning system's creation. Therefore, this Thesis initially investigates and reports the user needs and requirements concerning the wayfinding problems in a relevant and important use case: Geneva's University Hospitals (HUG). Following, it proposes innovative solutions that construct a robust indoor positioning system along with ways of seamlessly switching from indoor to outdoor positioning. In order to strengthen the robustness of the system, algorithms of positioning and automatic recalculation of the system are proposed and analyzed. Lastly, well defined methodologies of evaluating, comparing and optimally tuning positioning systems are proposed, addressing the most trending issues of the indoors positioning community.

In this way, the proposed methodologies of this Thesis define an innovative complete roadmap for designing a innovative IPS. The Thesis deals with a multivariate palette of steps of an IPS creation, from collecting users' requirements, designing and creating a robust indoor positioning system, to optimally tuning it in an automatic way and producing precise performance reports. All proposed innovations have been implemented and tested, forming the core bone of the internal module GPM (Global Positioning Module) of the TaM group (Traveling and Mobility) of the University of Geneva.

1.2 Statement of the Problems

In the domain of indoor positioning many technologies have been used, such as Wi-Fi, Bluetooth Low Energy (BLE), Radio Frequency Identification (RFID), Ultra-wideband (UWB), ultrasound, magnetic field distortion, inertial sensors, cameras, and others. These technologies are often not used isolated, but rather combined in a hybrid system, which is a solution which has gained in popularity over the last years. Moreover, modern positioning systems combine not only indoor positioning technologies among them, but also outdoor positioning technologies such as global navigation satellite systems (GNSS).

Each of the technologies used for indoor positioning has its own advantages and limitations, and the selection of one of them depends on the requirements of the application they are called to serve. Typical requirements of an indoor positioning system are: low cost, high accuracy (average performance, or worst-case performance), robustness, ease of deployment, ease of calibration, scalability of the system and compatibility with a wide range of devices.

A typical scenario met in current research projects is guiding a user to a specific room in a hospital. Initially, before proceeding to design such a system, which is to be used by many people, it is indispensable to consult the opinion of users of the hospital. Identifying the existing problems of the hospital, the technologies the users are willing to work with, and the services that they expect should be the first step before proceeding to create a positioning system.

Commonly, such a system should not only aim for a good average accuracy of position estimations but also to minimize the maximum estimation errors, restricting the area of position estimations to the area where the user is supposed to move. Of course, low cost, ease of deployment, ease of calibration and the extensibility of the system are requirements that should also be met.

As indoor positioning systems are not meant to function isolated from their surrounding environment, methodologies for automated switching between outdoor and indoor positioning are required. This switch should take place automatically, in a transparent way for the user, offering a seamless transition between environments and technologies. The logic of this switch should not only use an estimation of whether the user is indoors or outdoors in order to propose the corresponding positioning technology, but should also take into consideration the performance of each technology at each point. Specifically, the low quality of signals in boundary areas between indoor and outdoor environments could deteriorate the correct selection of the most appropriate technology. This is a limitation whose effects should be minimized.

A common problem for indoor positioning systems is the fact that deploying a system in different environments or using different devices affects its performance. Many positioning algorithms rely on a propagation model which is used to infer an estimate of the distance of a mobile device from an access point by using the signal strength of the received signal. The correctness of this estimation relies on the adequate selection of parameters of the propagation model so that it optimally models factors influencing the transmission, the propagation and the reception of the signals. Calibrating the propagation model in every environment is a tedious, costly and time consuming task, which also depends on the mobile devices used. Furthermore, it is hard to know the reception characteristics of all devices that could potentially be used. For these reasons, methods that would adjust the propagation model parameters in an automatic way, reflecting the environment and devices' characteristics, must studied.

Moreover, in order to evaluate the performance of a system, well-defined evaluation methodologies are required, as well as unambiguous, clearly defined metrics. So far, no universal standard has been established defining the ways of measuring and evaluating the performance of an indoor positioning system. This means that the performance of systems is nowadays compared using inconsistent or loosely defined methodologies. This has been identified by the indoor positioning community as a big limitation of the field, thus studies in this domain are considered vital for the field's advancement.

When deploying an IPS at a new place, a relevant question is: "What is needed to go from a non-existing system to a fully functional and optimally tuned system?". Some IPS might require the appropriate placement of hardware (such as BLE beacons), others might use existing infrastructure (Wi-Fi access points) or some might not require any infrastructure at all (magnetic field distortion methods). Nevertheless, all these systems commonly require some calibration steps so that the system is optimally tuned in a way that it adjusts to the particularities of the deployment environment or to some requirements of the application that is meant to use the system. As there exist numerous IPS technologies and a variety of evaluation techniques, there is no predominate methodology for optimally tuning indoor positioning systems. Well defined and efficient tuning methodologies that optimally tune a system reduce tuning time and effort, thus consequently reducing the cost, are a major need.

The issues discussed above are met in practice when working on indoor positioning systems and are also identified and discussed as open, unsolved issues, by the research community of the field. Detecting these issues has given us the motivation to work on this Thesis in addressing them, offering innovative solutions to the problems faced and contributing to the relevant public discussion of the field.

1.3 Contributing Publications

The content of this Thesis is based on seven published works, addressing the issues discussed above. The chapters of this Thesis are not carbon copies of the published papers, as the content of the papers has been updated, expanded and adjusted. The changes are mainly done to enrich the related work with the newest relevant publications, to integrate comments and proposals that were the fruit of the discussions in the conferences where the papers were presented, and to homogenize the flow of the Thesis. The seven publications are:

1. *'Navigational needs and requirements of hospital staff: Geneva University Hospitals case study'*, Anagnostopoulos G. G., Deriaz M., Gaspoz J.-M., Konstantas D. and Guessous I., in Proceedings of the Eighth International Conference on Indoor Positioning and Indoor Navigation (IPIN 2017), Sapporo, Japan, September 2017.

2. *'Accuracy Enhancements in Indoor Localization with the Weighted Average Technique'*, Anagnostopoulos G.G. and Deriaz M., in Proceedings of the Eighth International Conference on Sensor Technologies and Applications (SENSORCOMM 2014), Lisbon, Portugal, November 2014.

3. *'Automatic Switching Between Indoor and Outdoor Position Providers'*, Anagnostopoulos G.G. and Deriaz M., in Proceedings of the Sixth International Conference on Indoor Positioning and Indoor Navigation (IPIN 2015), Banff, Alberta, Canada, October 2015.

4. *'Online Self-Calibration of the Propagation Model for Indoor Positioning Ranging Methods'*, Anagnostopoulos G.G., Deriaz M. and Konstantas D., in Proceedings of The Seventh International Conference on Indoor Positioning and Indoor Navigation (IPIN 2016), Madrid, Spain, October 2016.

5. *'Positioning Evaluation and Ground Truth Definition for Real Life Use Cases'*, Martínez C. d. l. O., Anagnostopoulos G.G., Togneri M., Deriaz M. and Konstantas D., in Proceedings of The Seventh International Conference On Indoor Positioning and Indoor Navigation (IPIN 2016), Madrid, Spain, October 2016.

6. *'Practical Tuning Methodology for Indoor Positioning Systems'*, Anagnostopoulos G.G., Martínez C. d. l. O., Nunes T., Deriaz M. and Konstantas D., in Proceedings of The Fourth IEEE International Conference on Ubiquitous Positioning, Indoor Navigation and Location-Based Services (UPINLBS 2016), Shanghai, China, 2016.

7. *'A Multiobjective Optimization Methodology of Tuning Indoor Positioning Systems '*, Anagnostopoulos G. G., Deriaz M. and Konstantas D., in Proceedings of the Eighth International Conference on Indoor Positioning and Indoor Navigation (IPIN 2017), Sapporo, Japan, September 2017.

1.4 Thesis Structure

The goal of this Thesis is to define new methodologies for addressing crucial issues of indoor positioning systems. As discussed in the previous section, the problems addressed by this Thesis are met throughout the whole lifecycle of an indoor positioning system's creation. The proposed methodologies define a complete roadmap of an IPS creation, from designing and creating a robust indoor positioning system to optimally tuning in an automatic way and providing precise performance reports. This is achieved by proposing a robust indoor positioning system that can seamlessly switch to outdoor positioning technologies, while also handling device diversity and furthermore, by optimizing the tuning and evaluation process of the system.

Part I of this Thesis is dedicated to the identification of user needs and requirements. As indoor positioning systems are designed and created to serve people, it is indispensable to identify the needs and wishes of the future users of such systems.

- Before proceeding in presenting the algorithmic contributions of this Thesis in Parts II and III, in **Chapter 3** we study the requirements of users for the use-case of a big hospital. A questionnaire research was performed, based on factors identified through a review of the literature and with the assistance of health-care professionals, with the aim of investigating the navigational needs in the HUG (Geneva University Hospitals). The goals of the survey were to: 1) register the current situation in the HUG, understand the problems that people face when they try to find their way in the hospital and identify their repercussions in peoples' life and work 2) study the willingness of people to try a mobile application that helps them find their way in the hospital and their expectations from such an app, and finally, 3) evaluate ideas of additional services that can be built on top of the aforementioned app. The results of this research are numerous and very interesting. They may be shortly summarized by stating that getting lost in the hospital is identified as a common issue not only for visitors but for staff members as well. A substantial amount of staff working time is spent trying to find a destination or giving instructions to others, revealing an organizational problem, as a result of inefficient navigational aids. Lastly, it is evident from the results that the priorities set by users are affected by the context of the environment and the cultural background. This work has been published in [Anagnostopoulos et al., 2017b].

The creation of the positioning system itself is the content of **Part II** of this Thesis. This Part is composed of three Chapters, dealing with the presentation of the proposed positioning system (Chapter 4), the seamless handover between indoor/outdoor positioning technologies (Chapter 5), and the addressing of the device and environment diversity problem (Chapter 6).

- Initially, in **Chapter 4** an innovative design of an indoor positioning system is proposed and its advantages are extensively discussed. This Chapter is a significantly expanded version of the work [Anagnostopoulos and Deriaz, 2014]. The proposed system utilizes the weighted centroid method in order to satisfy the commonly met requirement of restricting the position estimates in the area of coverage. This requirement is often imposed by a navigation module utilizing the position estimates produced by the positioning system. In this work, we theoretically model and analyze the inherent error of the weighted centroid method, and based on this analysis, we subsequently propose the optimal value of the parameter of the number of closest beacons used for the position estimation. Moreover, we propose the idea that an advantage of the weighted centroid approach against the common multilateration approach is that it is far more resistant against device diversity and poorly calibrated values of the propagation model. We prove our claim with a sequence of extensive tests. Furthermore, we present the novelty of averaging the latest RSSI receptions in the distance domain instead of the RSS domain, elaborating on the advantage caused by the non-linear form of the propagation model. Lastly, we show the improvements that the proposed additional (Exponentially Weighted Moving Average) filtering step brings to the accuracy of the estimates, as well as to the smoothness of the resulting trajectory. Overall, the system shows a performance of ~ 1 meter in static tests, and ~ 2 meters in dynamic ones, in indoor areas (corridors, big halls, etc.). The system is characterized by its robustness against device diversity, its high accuracy, and the smoothness of its produced estimated trajectories, making it an excellent source of position estimates to be used as an input for a navigation module.

- In **Chapter 5**, an innovative algorithm of switching between positioning technologies is introduced. The algorithm offers a robust and seamless switching between indoor and outdoor positioning technologies, allowing users to continuously receive position estimates, as they move from an outdoor environment inwards (or vice versa). The switching of the technology used occurs in a way that is transparent to the users. Contrary to related works, we do not try to solve the indoor/outdoor detection problem using individual sensors as estimators, but we propose the approach of relatively comparing the reliability of each available position provider. In this way, the selection of the most reliable technology at all times is ensured. Moreover, in the context of our implementation, we propose an intuitive heuristic estimator of the claimed accuracy for the BLE positioning system used as the indoor technology. The proposed algorithm handles the trade-off of the switch being responsive (by switching quickly to the positioning technology that becomes more reliable) and stable (by minimizing the 'jumping' effect of unstable wobbling between technologies). The tests show that the algorithm always switches successfully to the most appropriate technology with a response time of a few seconds, depending on the environment characteristics. This work has been published in [Anagnostopoulos and Deriaz, 2015].

- Device and environment diversity is another issue that is addressed in this Thesis, in **Chapter 6**. A common problem for indoor positioning methods is the fact that the differences in the reception characteristics among devices may significantly deteriorate the performance of a positioning system. In this study, we present a novel, automatic, online self-calibration method which dynamically recalculates and improves relevant parameters of the model describing the propagation of signals in the environment and their reception by a device. The improvement in the model parameters fits the environment's characteristics and the reception characteristics of the device used. It is important to note that tests were done using the same raw data for comparing the positioning with and without the re-calibration algorithm, in order to guarantee the consistency of the comparisons. The algorithm shows an improvement of the mean positioning error up to 16% in the cases where the propagation model is to be corrected, while maintaining the system's performance in cases of properly tuned models. The proper tuning of the proposed self-calibration method is highlighted after extensive testing with different mobile devices and positioning algorithms. The method shows a similar performance tested with both the weighted centroid and the trilateration algorithm. The proposed method can be seen in scope of the research towards device independence, as well as in the context of facilitating calibration-free deployment in new areas. This work has been published in [Anagnostopoulos et al., 2016a].

Apart from proposing indoor positioning methods, a great share of the efforts made in the context of this Thesis was directed to addressing the relevant challenging methodological issues that concern the indoor positioning community. In this domain, there are three Chapters forming **Part III** of this Thesis:

- In **Chapter 7**, a new methodology for indoor positioning evaluation and ground truth definition is proposed, which serves most of the real life use cases of using an IPS. The lack of common ways of evaluating these technologies and of methods of defining the spatiotemporal ground truth have been identified by the community of the field as a major drawback. In this work, we propose a straightforward and inexpensive solution for tackling both of these problems. The current methodologies used in positioning competitions are either static, lacking the element of dynamic evaluation of a user moving, or only evaluate the position estimates sporadically, without evaluating the full outcome of a IPS's estimation. Our proposed method satisfies both these features, being dynamic and continuous. Two alternative ways of interpolating the ground truth information are proposed, and their relative advantages are extensively discussed. Moreover, we introduce a new metric (TDR) that evaluates the smoothness of the full estimated trajectory produced by a system, aiming to capture the degree at which the appearance of the estimated trajectory would be appealing for the user. The effectiveness of this metric is further verified in Chapter 9, where it is proven to be independent of the Euclidean distance error metrics and even complementary to them in some cases. The proposed methodology offers an unambiguous and fair way of evaluating and comparing IPSs. This work has been published in [Martinez de la Osa et al., 2016].

- A methodology for optimally tuning the parameters of an IPS based on recorded data is proposed in **Chapter 8**. The work-flow of this methodology contains the part of running the positioning algorithms offline and the part of comparing the spatiotemporal ground truth with the position estimates generated by the offline positioning algorithms, in order to eventually search for optimal settings of the positioning algorithm's parameters. A significant contribution of the formal methodology proposed is that the designer/tester of a system is exempt from the tedious task of having to revisit multiple times the deployment area to optimally tune the system. An overall advantage of the proposed method is the fact that the recorded data guarantee the repeatability of tests and allow consistent comparisons among different algorithms, creating the perspective of a testbed based on real data. A manual and an automatic way of tuning the system are proposed. The manual selection of parameters by a tester not only allows the experienced tester to quickly improve the system's performance offline, but offers them a better intuition about the effect of each parameter on the system's performance. On the other hand, the automatic optimization approach, which is the major contribution of this work, can offer directly optimal parameter tunings even under the absence of a person with experience in the functioning of the algorithm and of the system. A mobile application and a desktop platform have been created to implement the contributions of this Chapter, as well as those of Chapter 7. This work has been published in [Anagnostopoulos et al., 2016b].

- In **Chapter 9**, we present a multiobjective optimization methodology of tuning indoor positioning systems based on real data recorded onsite. Selecting the appropriate tuning for a positioning system is a challenging task which depends on many factors: the specific deployment, the devices used, the evaluation metrics and their order of significance, the user-case scenarios tested, etc. In order to handle these multiplicities we introduced the use of multiobjective optimization which allows several objectives to be simultaneously satisfied. Therefore, multiobjective optimization is introduced with the goal of strengthening the robustness of the parameter recommendations. In this way, multiple evaluation metrics can be used simultaneously, offering a more holistic evaluation, while multiple recordings reduce the danger of overfitting, allowing generic tunings that offer good performance in a variety of scenarios. The methodology proves to be a very useful tool in the hands of designers/testers who are designated to optimally tune the positioning system in various environments. A generic tuning that can be used in an unknown environment can be proposed by this method, based on running the optimization using recordings from a variety of environments. To the best of our knowledge, our work is the first that brings the principal solution concept of multiobjective optimization, *Pareto Optimality*, in addressing indoor positioning problems, based on recorded data. This work has been published in [Anagnostopoulos et al., 2017a].

1.5 Validation

Indoor positioning is applied in a variety of scenarios and it has been greatly popularized by the smart devices that are commonly used nowadays. Numerous mobile applications are utilizing the location of the user as contextual information, which allows them to offer useful services to users. There is an increasing variety of Location-based Services (LBS) that are related to several domains such as health, work assistance, personal life, entertainment, etc.

A common research direction lately has been the use of LBS in Active and Assisted Living. The goal of the use of LBS is to support services that help the elderly in ageing well at home, in the community, or at work, thus increasing their quality of life, their autonomy, their participation in social life, their skills and their employability, while reducing the costs of health and social care. Such applications, as for example assisting wayfinding in big hospitals, have been needed and popularized.

In the following subsection, we present the relevant research projects that have used and have validated the contributions of this Thesis.

Research Projects

The Active and Assisted Living (AAL) programme of the European Union is a funding activity that aims to create better conditions of life for older adults and to strengthen international industrial opportunities in the area of information and communication technology (ICT) [AAL,]. The AAL projects Virgilus, EDLAH and SmartHeat, which have co-financed the work of this Thesis, are examples of the use of ICT innovation to help society in addressing modern issues by using modern and innovative solutions. The innovative positioning solutions created by the work of this Thesis were used and validated in these projects, adjusted so as to satisfy their requirements.

The aim of the Virgilius project [Vir, 2014] was to increase independence and mobility of the elderly through the use of LBS. A main goal was to increase the autonomy and security of the elderly outside their homes with the help of specially adapted navigation tools. Using the system offered by this project, elderly users can easily orient themselves in environments that might otherwise be perceived as too challenging, such as hospitals and museums. The resulting system was deployed in the Hospital of Perugia, in Italy, where elderly users could navigate from their position outdoors to their specific destination inside the hospital. The increase in the seniors' sense of confidence, safety and well-being, is what systems like Virgilius' can offer to their users.

The EDLAH [EDL, 2015] project's aims were to provide the elderly with a greater level of independence, allowing them to live in their home independently, minimizing their need of caregivers' assistance. The project's outcome was a system accessed by the elderly through smart devices, offering several different services such as health and nutrition assistance, social networks, medicine companion and object localization.

The SmartHeat [Sma, 2017] project aims to radically change the home heating experience for the health, comfort and wellbeing of elderly people, by utilizing innovative Internet of Things (IoT) technologies. The goal is pursued via the development of a smart, secure and elderly friendly ICT system for heating monitoring and control. The contextual information of the occupancy of the rooms of a house throughout the day is used for feeding the intelligent algorithm that optimizes the heating of the house.

The innovation of the field of indoor positioning has also been encouraged and supported by Swiss national funds, such as the CTI (Commission for Technology and Innovation). The IDDASS project [IDD, 2017] is a CTI project that co-funded the work of this Thesis. IDDASS analyzes the user's behavior during a shopping session in a store. IDDASS is meant be integrated into a loyalty application running on smartphones and will combine its data with those coming from existing e-commerce statistical analysis tools.

Lastly, grants from the Faculty of Medicine and the GSEM (Geneva School of Economics and Management) of UNIGE have contributed in completing the HUGApp project. The HUGApp project [Anagnostopoulos et al., 2017b] was a result of the joined interests of HUG (Geneva University Hospitals) and the University of Geneva to report, understand and address the problems related to wayfinding difficulties in the premises of the HUG.

1.6 Summary

Despite being a domain that has much demand, indoor positioning is far from being considered a solved problem. Accurate positioning, seamless indoor-outdoor switching, efficient handling of device and environment diversity, deployment, tuning and evaluation methodologies that are fast and efficient, are some of the main issues that actively concern the community of the field. Efficient solutions to these issues are desired so that they can increase the performance of modern indoor positioning systems and reduce the cost and effort of deploying and maintaining them, making them eventually transparent to the user. The contributions of this Thesis are directed at addressing these relevant problems of the field, by offering innovative solutions with tangible repercussions in the IPS which implement them.

2 State of the Art Overview

2.1 Introduction

This chapter's aim is to offer a broad overview of the field of Indoor Positioning Systems (IPS) as reported in emblematic works that summarize the status of the field. As this Thesis is composed of studies dealing with different issues met throughout the whole lifecycle of the creation of an IPS, each chapter has a section regarding the related work linked to its narrow, specific domain. Therefore, a generic introduction to the State of the Art of the field of IPS is offered in this chapter.

Initially, the main measuring principles (ToA, RSS, etc.) are presented. Following, the main algorithmic methods of positioning are discussed (trilateration, fingerprints, etc), along with the technologies mostly used in the field (Bluetooth, Wi-Fi, etc.). Lastly, the open issues of the research in indoor positioning, as identified by studies summarizing the field, are presented.

2.2 Measuring Principles

In this section, we briefly present the dominant methods with which signals are handled and interpreted in the context of IPS, namely: Time of Arrival (ToA), Time Difference of Arrival (TDoA), Angle of Arrival (AoA) and Received Signal Strength (RSS).

Time of Arrival (ToA)

The Time of Arrival (ToA) methods (also known as Time of Flight (ToF)) measure the time that it takes for a signal to propagate from the transmitter to the receiver. This method assumes a very accurate synchronization of all receiving beacons and of the mobile devices. The distance between the transmitter and the receiver can be calculated using the speed of the signal's propagation and its Time of Flight. [Al-Ammar et al., 2014].

Methods that use ToA have high accuracy since, assuming an accurate synchronization of the clocks of all devices, the distance estimations can be very accurate. The accurate synchronization required also sets the main limitations and causes the main disadvantages of the method. The synchronization requirement has, as a result, the increased complexity and cost of the method. Often, specialized hardware is needed to offer a high synchronization accuracy. For instance, in custom mobile devices, the delays of the operating system do not facilitate the recording of the exact timestamp of the signal's arrival [Al-Ammar et al., 2014]. *'The TOA measurement with radio devices can be difficult due to extremely short time periods which need to be gathered'* and therefore, technologies with slower propagation speed, like ultrasound, prove to be easier in their use [Adler et al., 2014b].

Time Difference of Arrival (TDoA)

The TDoA method utilizes the time differences of arrival at the target of the multiple base stations to infer distance differences. Each difference of arrival produces a hyperbolic curve on which the estimated location of the target lies. A position estimate can be inferred by the crossing of these hyperbolic curves [Al-Ammar et al., 2014].

In this technology, the target is excluded from the synchronization requirement, which only the base stations must satisfy. Excluding the target from the obligation of being highly synchronized is a major advantage. Otherwise, the method shares the same pros and cons with the ToA.

Angle of Arrival (AoA)

In this category, the mobile device is responsible for measuring the angle of arrival of signal from the base stations of known locations. For 2D localization, two base stations are sufficient for inferring a position estimate. The addition of more base stations can allow a 3D localization and improve the accuracy of estimations. [Al-Ammar et al., 2014].

Specialized hardware is required for most implementations of these methods, making them less attractive for applications to be used by mobile devices.

Received Signal Strength (RSS)

The RSS methods utilize the signal strength of the received signal to infer useful information and eventually produce a position estimate. There are two main ways of utilizing the RSS: with fingerprinting algorithms or with a propagation model approach (ranging methods). Fingerprinting algorithms compare the signal strength receptions received at unknown locations where a user needs to be localized with recorded receptions at known locations, which are called fingerprints. Therefore, fingerprinting algorithms require an offline creation of a radio map, which records the fingerprints at known locations. On the other hand, methods utilizing a propagation model do not require any offline surveying phase, but only require the knowledge of the positions of the transmitters. The propagation model tries to model the way that the signal attenuates as it propagates in space. In this way, a distance estimate can be inferred by the strength of the received signal. Having distance estimates from three transmitters can offer a position estimate in 2D, using positioning algorithms as trilateration [Al-Ammar et al., 2014].

RSS methods are commonly used by Radio Frequency (RF) technologies. One disadvantage of the RSS methods is that the estimates are subject to noise. The RF signal receptions commonly fluctuate since they are affected by the signal's multiparty propagation, such as reflection or refraction, especially in indoor areas where many static and moving obstacles exist. On the other hand, RSS methods offer some crucial advantages. Most RF technologies that can utilize these methods are supported by most commercial mobile devices, making them available to the broad public without any additional hardware required. The deployment of the base stations is very simple, as no synchronization step is required. Lastly, they are of low cost and are easily scalable [Davidson and Piché, 2017].

2.3 Positioning Methods

Fingerprinting

The fingerprinting technique relies on the idea of creating a radio map of the indoor environment and determining the position of a device by comparing the RSS of signals that the device receives with those of the map [Beder and Klepal, 2012]. For the creation of the map, a tester should stand still at predefined locations on the area that is desired to be covered, recording the receptions of signals of interest (Wi-Fi, Bluetooth, etc.) that will characterize these known locations. The procedure is repeated for all predefined points. These points are usually selected with the aim of creating a grid that spans all the areas where the system should provide coverage.

A first naive approach is to determine, based on a similarity metric, the fingerprint that is closest to the reception and return the location of this fingerprint as the estimated location. A better solution is to combine the locations (with a centroid, weighted centroid, or another method) of a number of the most similar fingerprints. Many fingerprinting techniques utilize machine learning approaches to strengthen their robustness. Also, other approaches propose using the relative ranking of the base stations according to their RSS, instead of the actual RSS value received to avoid problems of device diversity [Machaj et al., 2011].

The fingerprinting techniques have the advantage that they implicitly map the particularities of the environment, as the fingerprints report the measured values of the receptions in the actual environment and not a theoretical estimation.

Nevertheless, the procedure of creating the radio map is tedious, time consuming and error prone, especially as the size of the indoor area increases. Moreover, these methods tend to be very sensitive against device diversity, thus the extensive literature trying to address the issue ([Laoudias et al., 2014, Laoudias et al., 2013a] and reference therein). Lastly, their maintainability and extensibility is problematic, as the addition of a few base stations requires the repetition of the radio map creation, at least at the areas close to the new base stations.

Ranging Methods

Ranging methods use estimates of the distances of a device from the base stations (with ToA or RSS) to infer a position estimate [Liu et al., 2007]. The distances from 3 points is sufficient to infer the location of the user, by using lateration. In lateration, each distance estimate defines a circle around the transmitter producing the signal. If the distance estimates are precise, the circles cross at a single point. As the estimates are subject to noise, it is rare that this unique crossing point exists. Therefore, methods of addressing this have been proposed, utilizing the crossing points of these circles. The final location estimate can be a linear combination of these crossing points [Will et al., 2012] or it can be the result of a least squares problem [Goswami, 2012].

Another approach of using the range estimates is to produce a position estimate as a weighted centroid of the closest base stations. In Chapter 4, we extensively discuss the advantages and disadvantages of this approach compared to lateration.

Ranging methods have a very significant advantage over the fingerprinting ones: they do not require the creation of a radio map, excluding in this way the person deploying the system form this tedious, time consuming task. Instead, it is simply the list of locations of the base stations that is required. Extensibility is favoured, as the system can be expanded in adjacent or distant areas, or the density of nodes can be increased, simply by adding the transmitters to the physical world and their location to the respective list. On the other hand, ranging methods using RSS utilize a generic propagation model which generally corresponds RSS values to distances, without taking into account the particularities of the environment as the fingerprinting techniques do. Relying on the values of the estimated distances, based on a propagation model, makes these methods subject to the problems of device and environment diversity [Mazuelas et al., 2009]. The issues of RSS methods are discussed in Chapter 6 and partially in Chapter 4 of this Thesis.

Angular Methods

In angular methods, the location of a mobile device is estimated at the intersection '*of angle direction lines, each formed by the circular radius from a base station*' to the mobile target [Liu et al., 2007]. The AoA methods used offer the advantage of requiring only 2 base stations for 2D positioning and 3 for 3D. Angular methods have the advantages and disadvantages presented in the AoA methods.

Additional Methods

Apart from the basic methods used to infer a position estimate, there are additional methods which improve the quality of the estimations under certain conditions.

Dead reckoning aims to estimate the position of the user, by using a previously determined position and advancing that position estimate based on measured or estimated speed and direction of movement of the user, using the inertial sensors of the mobile device. The estimated movements given by dead reckoning are subject to additive error through time [Harle, 2013]. '*Therefore, a conventional strap-down inertial navigation approach is not suitable for implementation because of the rapid accumulation of position, velocity and attitude errors*' [Davidson and Piché, 2017], in the case of smartphones. Nonetheless, dead reckoning can assist another positioning technology, creating a hybrid system. In this way, dead reckoning offers information in between the estimates of the other technology.

'The idea of using the building's geometry for reduction of position and heading errors in autonomous positioning systems has been exploited in the last several years' [Davidson and Piché, 2017]. Utilizing the information about where the users can or cannot move, can help minimize the estimation errors. For instance, map matching utilizes the network of the paths that a user can follow in a building and projects the position estimate to the closest point on the network. This step is an additional one to the position estimation, per se. The knowledge of the map can improve the accuracy of the system, adding though a significant overload to the system's creation and maintenance effort by requesting a detailed and contentiously up-to-date network.

Lastly, filtering methods can be used on top of pure position estimates produced by the positioning algorithm, with the goal of reducing the noise.

2.4 Technologies

In the field of indoor positioning, a large variety of technologies has been used offering different approaches, each having its own advantages and disadvantages. Wi-Fi, Bluetooth, RFID (Radio Frequency Identification), Ultra-wideband (UWB) and magnetic field distortion are the most dominant technologies of the field. We briefly present these technologies and comment on their basic characteristics, pros and cons, as identified by the literature of the field.

Wi-Fi

A technology commonly used for positioning in indoor environments is the Wi-Fi [Davidson and Piché, 2017, Mazuelas et al., 2009]. *'Wi-Fi access points (AP)broadcast beacon frames, which include the AP's media access control (MAC) address, ... to announce their presence in a certain area.'* [Davidson and Piché, 2017]. Despite not being its primary goal, Wi-Fi technology and its infrastructure can be used for indoor positioning based on the RSS measurements of the APs' transmissions on the mobile device that needs to be localized. One advantage of using Wi-Fi is that most buildings have several Wi-Fi APs for network access, so the hardware required is already installed. On the other hand, usually the mesh of access points is not dense enough nor optimally placed so as to facilitate a satisfactory accuracy of localization. Moreover, adding or rearranging the Wi-Fi APs is bound by the restriction that they should be plugged, limiting the freedom of their placement. The typical accuracy of Wi-Fi IPS ranges from 1-2 meters to a few tens of meters.

Bluetooth

Bluetooth, and specifically its recent evolution Bluetooth Low Energy (BLE), is a wireless technology used for transmitting data over short distances. BLE has a low energy consumption and low cost, while maintaining a communication range similar to that of its predecessor, Classic Bluetooth. *'The emergence of Bluetooth Low Energy (BLE) beacons opens up a new generation of indoor positioning systems that can be more accurate, reliable and efficient'* [Davidson and Piché, 2017]. The BLE standard is widely used, and is available in most modern smart devices. *'The Bluetooth Special Interest Group predicts that by 2018 more than 90 percent of Bluetooth-enabled smartphones will support the BLE standard, so this technology will become ubiquitous'* [Davidson and Piché, 2017].

Each beacon broadcasts a self-contained packet of data periodically. The packets contain an identifier of each beacon, so that the receiver can distinguish them and utilize the RSS for positioning. The RSS can be used for both fingerprinting and ranging techniques. Due to their low cost and low consumption, a dense network can be deployed, allowing an enhanced accuracy. BLE beacons are small and function with batteries, a fact that adds flexibility in the way they are deployed or reconfigured. The typical accuracy of BLE IPS ranges from 1-2 meters to a few tens of meters.

Studies [Zhao et al., 2014] have compared BLE to Wi-Fi based positioning and *'came to conclusion that BLE is superior for indoor localization for the following reasons: (a) channel hopping mechanism, (b) lower transmission power, and (c) much higher* *scan rate than WIFi. Frequent channel hopping can average out interference in a given channel or completely remove interference when BLE radios hop to the next channel. This makes the RSS less noisy. The lower transmission power of BLE can reduce the multipath effect in some scenarios. The high scan rate makes it possible to average out the occasional outliers caused by interference or multipath effect and improve the tracking accuracy'* [Davidson and Piché, 2017].

In the tests of this Thesis, we have mainly used BLE as the underlying technology. Nevertheless, as mentioned throughout the Thesis, the ideas presented are mostly generic and are simply exemplified with the use of BLE technology.

Magnetic field

'Magnetic field fingerprinting uses a map of magnetic field distribution inside buildings for indoor positioning' [Davidson and Piché, 2017]. One of the advantages of using the magnetic field is the fact that it exists in all places and therefore no pre-installed infrastructure is required. On the other hand, this technology suffers from major disadvantages [Davidson and Piché, 2017]. Firstly, the interferences can be significant, especially indoors were many appliances, wires and objects can affect the magnetic field. Secondly, magnetic fingerprints consist of a small number of parameters, a maximum of three, which in many cases can be only two or one. Moreover, the magnetic field measurements can be different on different devices. In addition, the changes of the magnetic field can be abrupt in different altitudes, having as a consequence the necessity of 3D fingerprints where high accuracy is required. The spatial ambiguity caused by this makes magnetic field methods more adequate as an assisting method to other technologies (as Wi-Fi or BLE) rather than an autonomous solution.

RFID

Radio frequency identification (RFID) is a technology that, as its name states, functions in radio frequencies having, as a main goal, the identification of objects or persons. Its main usage is the identification of objects in large systems, replacing the barcode usage in many commercial applications. An RFID system is composed of readers and tags. The RFID readers are transceivers able to emit an identification signal, but also to read a signal sent by another entity. There are two kinds of RFID tags, the passive and the active ones. The passive ones operate without a battery and have a small range of typically 1-2 meters. *'Active RFID are small transceivers, which can actively transmit their ID (or other additional data) in reply to an interrogation'* [Liu et al., 2007]. The active tags have a smaller antenna and a much larger range (typically a few tens of meters), compared to the passive ones, but are of higher cost and require a battery. *'Active tags are ideally suited for the identification of high-unit-value products moving through a harsh assembly process'* [Liu et al., 2007].

As RFID uses radio signals it is not bounded by line of sight (LOS) requirement since the signal can penetrate non-metallic objects. Similarly to other RF technologies, RFID systems can achieve a positioning accuracy of a few meters. Nevertheless, it is not integrated easily into other systems. Moreover, as it is targeted as a proximity identification technology, it does not have high communication capabilities.

UWB

Ultra-wideband is a radio technology that uses a very wide portion of the spectrum to send short, low energy pulses, transmitting large amounts of data. This technology can be used for positioning (mainly ToA or TDoA), achieving high accuracy. The use of UWB in positioning has several advantages. Initially, the UWB tags have a low consumption rate, lower than conventional RF tags. Additionally, the fact that the signal is sent in a large palette of frequencies makes the system more robust and less affected by interference. *'UWB short duration pulses are easy to filter in order* *to determine which signals are correct and which are generated from multipath*' [Liu et al., 2007]. The typical accuracy achieved by UWB positioning systems ranges on the scale of a few tens of centimeters. Moreover, interference with other RF technologies can be avoided. Metallic and liquid material cause significant interference, which could potentially be overcome with a strategic placement of the hardware [Davidson and Piché, 2017, Al-Ammar et al., 2014]. The main drop-backs of this technology is the high cost of its equipment, as well as the fact that it is not integrated in modern smart devices and therefore it needs additional hardware. It appears that if it were to become possible to integrate UWB in mobile devices, with a consequent reduction of its cost, UWB would prevail among the existing indoor positioning technologies.

Hybrid Systems

In IPS solutions, it is common to hybridize the systems by combining several existing technologies in order to improve the accuracy as well as the continuity of the production of position estimates. These systems may use one or more technologies for indoor and outdoor environments, as well as other sensors (accelerometers, gyroscopes, barometers, light sensors, etc.) that contribute to the quality of the position estimate [Davidson and Piché, 2017]. It is clear that no single technology exists nowadays which can provide continuous, reliable positioning, both indoors and outdoors. Therefore, for a ubiquitous positioning system, at least two technologies should compose the hybrid system. The addition of more technologies can help in improving specific aspects of positioning. In this direction, dead reckoning using inertial sensors can continue the production of position estimates when the main technologies are not available or produce low quality estimates, and barometers can help strengthen the robustness of the correct floor detection in a building, etc. Hybrid systems may combine the advantages of the technologies composing them, offering high accuracy in different environments, but also suffer from some drawbacks. The fact that multiple technologies are used simultaneously can increase the battery consumption of the system. This is an issue that the system should try to address, handling its trade off between ubiquitousness and accuracy.

Lastly, these systems require more effort in their deployment, their maintenance, and their adaptability with as many devices as possible.

2.5 Open issues

The studies that summarize the advancements of the field commonly refer to the open issues of the field that need to be addressed. Recent surveys of the field [Dwiyasa and Lim, 2016, Davidson and Piché, 2017, Harle, 2013] have a consensus over important issues that need to be addressed in the future, namely: the need for consistent evaluation methodologies, the problem of device diversity and the need to minimize the effort of manual calibration with the goal of creating generic and adjustable IPS.

In their work *'A survey of selected indoor positioning methods for smartphones'* [Davidson and Piché, 2017], Danidson and Piché highlight the absence of a *'standard procedure for positioning accuracy evaluation of different algorithms'*. The authors underline the fact that tests are usually performed in controlled environments. Consequently, the accuracy reported by the tests is significantly better that the one achieved in real life use cases. They also identify device diversity as a common reason for accuracy degradation. Moreover, as they focus on fingerprinting techniques, they highlight the need to reduce the tedious task of creating the radio map required for the system to be usable.

A recent survey focusing on problems in wireless-based indoor positioning also highlights the same limitations of the field [Dwiyasa and Lim, 2016]. The authors state that papers *'attempt to quantify the accuracy of different techniques based on published technical papers. However, each technical paper tends to adopt a different testing environment and scenario; hence the comparative accuracies can often be misleading.'* Following, the authors discuss the recent effort of handling device heterogeneity, stating that it cannot be considered as a solved problem. Lastly, after reporting the limitations of all current technologies, the authors state that it is *'nearly* *impossible for an indoor positioning solution to work accurately anytime at any place and on any device without involving any calibration.'*

Another survey which focuses on inertial based indoor positioning in systems for pedestrians [Harle, 2013] similarly highlights the evaluation methodologies and sensor calibration as open research issues. The author notes that *'there is presently little consensus regarding how to evaluate PDR systems, which hinders their comparison'*. Therefore, the author identifies *'a growing need for thorough system evaluations over sustained periods with a diverse set of test subjects'*.

Lastly, in a recent work [Adler et al., 2015] the authors have studied 183 papers from conferences of the field (IPIN conferences 2010-2014) in order to examine the methods of experimental evaluation used by the community. The authors view this work as *' as a contribution on the debate on reproducibility in computer science research'*. A problem that they identify as crucial in preventing the reproducibility and the comparability of experiments is the lack of strict methodologies for defining the spatiotemporal ground truth information, jeopardizing the reliability of the reported evaluation. For this reason, the authors of this study *'appeal to authors to write about their method of ground truth data gathering in the spirit of comparison, reproducibility and explanation.'*

In this Thesis, we have tried to address these modern, challenging, crucial issues of the field of indoor positioning. In Chapter 4, the robustness of the proposed method against device diversity is compared with the state-of-the-art trilateration approach. Similarly, the self-calibration method proposed in Chapter 6 tackles the problem of device heterogeneity and removes the need of propagation model calibration in new environments. The trilogy of works of Part III of this Thesis (Chapters 7, 8, 9) is a sequence of studies in the field of positioning evaluation methodologies. On the solid base of the well defined methodology of collecting data with the goal of repeatable evaluation set in Chapters 7, 8, tuning methodologies are proposed in Chapters 8, 9 reducing (or excluding) the need of the system's calibration in new environments.

Part I

User Requirements

3 Navigational Needs and Requirements of Hospital Staff: Geneva University Hospitals Case Study

3.1 Chapter Abstract

Navigating in large hospitals is a challenging task. The consequences of difficulties faced by staff, patients and visitors in finding their way in the hospital can be multiple. The HUGApp project goals were to identify the navigational needs and requirements of people within the premises of Geneva University Hospitals (HUG) before proceeding with potential solutions, such as an indoor navigation mobile app. A questionnaire was designed based on factors identified through a review of the literature. It was distributed to staff members with the goal of understanding the current problems in wayfinding inside HUG, investigating the users' views on the creation of an indoor navigation mobile app, and specifying the user requirements for such an app. The study is based on a big sample, compared to the relevant literature of the positioning and navigation field. A total of 111 members of the primary care division of HUG answered the questionnaire, providing the insightful view of the healthcare professionals.

The survey shows that both visitors and staff members are facing difficulties in finding their destination. This is identified as a source of stress for both groups. Also, a

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considerable amount of the personnel's time is spent in assisting people finding their way. The fact that the existing material is inefficient for people that do not speak the official language (French) is clearly revealed. A similar impression is reported about the material assisting people with mobility restrictions. Overall, the participants highlighted the need for improvements with several kinds of navigational aids, and their willingness to use a potential navigational app for mobile devices. The features that are most desired by such an app are: the appearance of the trajectory on a map, the adaptation of usage for users with mobility limitations, the privacy preservation and the good accuracy in estimating the users' position.

3.2 Introduction

Finding one's way in large complex buildings, such as hospitals, has been shown to be a rather challenging task. Finding the desired destination in a hospital is identified as a difficult problem, not only for visitors/patients of a hospital, who may have zero prior exposure to this environment, but even for the staff members of the hospital, that spend a great amount of their daily time on its premises. The fact that staff members can face way-finding difficulties can lead to cost and efficiency issues, aside from potential cases of exposing patients' safety at risk. Also, if staff members face difficulties in wayfinding, it is logical that the difficulties will be greater for visitors, who will naturally stop and ask staff members for instructions. The fact that staff members are often stopped and asked for directions instructions can often be ineffective, as they might not know the answer or might be interrupted from important tasks they are supposed to be undertaking. Problems like this should be clearly identified, reported and understood before proceeding in finding appropriate solutions.

The use of modern technological solutions in the health-care domain has become more and more frequent during the last years. People are becoming familiar with modern smart devices and their use, which is not limited to leisure applications, but can assist people in their everyday problems, in their personal life or in their workplace. The term e-health (or health informatics) has been proposed to describe this convergence of health-care with modern informatics.

One of the domains that has gained great attention over the last decade is the utilization of positioning and navigation mobile applications that help people navigate in big hospitals. The HUGApp project is the result of the joint interests of HUG (Geneva University Hospitals), and the University of Geneva, to report, understand and address the problems related to wayfinding difficulties in the premises of the HUG. The HUGApp project aims to investigate the navigational needs in the HUG and provide proof of concept example of navigational aids' implementation using ambulatory care as the initial setting. The future goal, after the completion of the HUGApp, is to design a navigation aid's solution for the totality of the HUG, which will be based upon users' needs and requirements. The project relies on strong collaboration between the Division of Primary Care (Department of Community Medicine, Primary Care and Emergency Medicine, Geneva University Hospitals) and Computer Science University Centre (Centre Universitaire d'Informatique) of the University of Geneva.

3.3 Related Work

One common problem that people face in their interaction with hospitals is the difficulty in finding their way, their destination, in the premises of the complex constructions that big hospitals are nowadays. Researchers have been focusing in addressing this challenge, offering a great volume of interesting work. In their remarkable work [Hughes et al., 2015], authors from the University of Nottingham have discussed these issues in detail. The authors mention that: *...Despite the provision of an array of in-hospital navigational aids, 'getting lost' continues to be an everyday problem in these large complex environments."* [Hughes et al., 2015] In that work a series of semi-structured interviews with eleven participants was conducted to elicit information about a participant's navigation experience in the environment of a hospital, characterizing five main categories of interest: (i) The 'Impact' of poor navigation, (ii) 'Barriers' to effective navigation, (iii) 'Enhancers' for effective navigation, (iv) 'Types of Navigation Aids' and user groups with (v) 'Specific Navigational Needs'. Other works similarly discuss the problems of wayfinding in hospitals [Mollerup, 2009] or evaluate different kinds of assistance that facilitate hospital navigation [Yao Li and Blakey, 2015]. In the latter work [Yao Li and Blakey, 2015], 21 healthy volunteers were asked to navigate in publicly accessible parts of a large hospital, using three different kinds of assistance (i) written instructions, (ii) a map, and (iii) a video walk-through of the route. Completion times and observed errors were recorded for a route using the navigation aid and a return route without the navigation aid. The results showed that video users were over 30% faster than those using a map and over 40% faster than those given a written route description.

Older studies have even focused on more primitive aspects that can drastically affect a user's spatial perception, such as the floor numbering schemes [J. Carpman and Simmons, 1984]. The authors argue that the logic used to assign names in floor levels plays a crucial role in the users' correct orientation and their spatial awareness.

Regarding indoor positioning systems in hospitals using a smartphone, there is a plethora of technologies used, such as Bluetooth [Jingjing Yang and Zhang, 2015], WiFi [Pinchin et al., 2014], RFID [Calderoni et al., 2015], and others. The idea of a mobile application that can assist people in finding their way in a hospital is a solution that could possibly become commonplace during the next years. Indoor localisation systems are used, not only to assist people in finding their way, but also for more complex tasks like offering ambient assisted living to the elderly [Witrisal et al., 2016] or feeding data to task management systems [Pinchin et al., 2014]. In a relevant work [Rooke et al., 2010], the authors propose a Through-Life Management (TLM) approach to ensure that wayfinding information remains immortal throughout the long-life cycles of the building.

Works have studied the user acceptance of innovative mobile technologies that assist clinical staff of the hospital, not only in their wayfinding, but also in analyzing the tasks they undertake [Lang et al., 2015]. Some works [Brown et al., 2016], [Larkin et al., 2014] have even proposed task simulations, similar to serious video games, to assist the training of junior doctors in non-technical skills during out-of-hours shifts, showing that participants in the intervention group completed their non-urgent tasks more rapidly than the control group.

Furthermore, great importance has been given to the creation of systems that respect the equal right of all citizens to access public services. Studies have been focusing on methods of appropriate assistance for the visually impaired [Balata et al., 2014] [Balata et al., 2016], [Maly et al., 2015], [Owayjan et al., 2015], [Balata et al., 2012] [Johnson and Higgins, 2006], or for people with other mobility limitations [Balata et al., 2013].

Questionnaires form a common method to report user needs and requirements, and are vastly used to identify user requirements regarding the use of location based services. For instance, recent works linked to the MULTI-POS [MUL, 2016] network have focused on personal safety concerns [Kolomijeca et al., 2016] or generally non-technical concerns [Basiri et al., 2016]. In a broader context, travel patterns during pregnancy have been studied [Wu et al., 2013], by comparing trip duration given by Global Positioning System (GPS) tracking with the data obtained after asking pregnant women to give an estimation of their trip duration through a questionnaire.

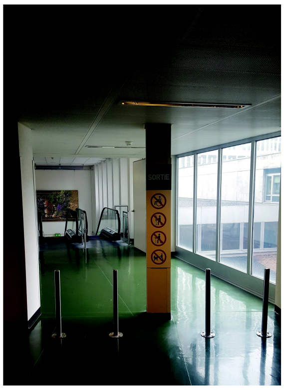
Overall, it is clear that there exists great interest in improving the experience of people in hospitals by introducing innovative solutions, and most specifically, solutions of the rather recently popularized fields of indoor positioning and indoor navigation. The experience of wayfinding in hospitals is a vastly discussed issue and working on understanding and improving this experience is a relevant and very interesting research task.

3.4 Current Status at HUG

The existing navigational aids in HUG (Geneva University Hospitals) follow the most basic standard practices used in hospitals internationally. Buildings follow consistent

(a) Each building is assigned a different color and named after a letter. Instructions are given taking into consideration the mobility capabilities of people.

(b) A sign at an office located at a crossing of several corridors, saying *'Work area. No information'*. It was one of the few signs in the building written in both English and French.



(c) Warning sign before an escalator leading to the exit, mentioning that it is not suitable for people using a cane or a wheelchair. No alternative root sign exists though.

(d) Plan of buildings of the main campus of HUG. Naming and coloring conventions become evident to the user in this map.

(e) A corridor of the ground floor is being renovated. Access to the other end of the corridor is available only by going outdoors or through another floor.

Figure 3.1: Photos related to navigational aids in HUG.

coloring and naming conventions (Figures 3.1a and 3.1d). Each building is assigned its own color and is named after a letter, while adjacent buildings are named with an alphabetic order. All elevators have detailed informative signs, highlighting the departments that can be found on each floor. Colored lines on the floor facilitate the way-finding of people towards main points of interest. Instructions like: *"... at the end of the blue line take the elevator to the second floor, and then follow the red line until the end."* can simplify wayfinding. At central cross-points of each floor a complete list of all existing rooms appears. A central reception at the main entrance of the hospital is staffed with people able to answer questions and give direction information. Similarly, the receptionists of each department can guide people, mainly within the area of the department.

Despite the fact that rooms are labelled properly and main directional information sources are available (detailed signs, building plans, colored lines on the floor, etc.), people continue to face difficulties in finding their way. The size and complexity of modern hospitals is such that makes it impossible for users to find their way from any point A to any point B, by following traditional signs only. In addition, the language barrier can be a significant source of difficulties. All directional signs are written exclusively in French, which is the official language of Geneva. Switzerland has four official languages, and in addition, English is widely used as the official working language in many workspaces (International Organizations, multinational corporations, Universities, etc.) based in Geneva. The need for the use of the English language is revealed by an informal sign met at a very centrally placed office (Figure 3.1b), informing visitors that the office is a workspace and not an information booth. Lastly, a major need appears to be the availability of tools that offer several language options, since HUG is responsible for taking care of vulnerable populations (refugees, asylum seekers), not speaking English nor French.

Signs, like the one in Figure 3.1a, guide people by taking into consideration their mobility limitations, highlighting the path that they should take according to their type of mobility. Nonetheless, in other cases (as in Figure 3.1c), certain paths are highlighted as not suitable for certain groups of people (people using a cane, a wheelchair, or carrying a stroller), without however providing information for an alternative suitable path.

Another challenging task is keeping all relevant information updated, as the hospital environment changes. Renovations or rearrangements are frequent (Figure 3.1e). In these cases, simply placing new labels on the new rooms following rearrangements is not enough, as other consequences should also be anticipated. The area where a renovation takes place may be part of a standard path (e.g, containing a colored line, leading to a destination) which becomes inaccessible. Therefore, navigation aids should have the ability to dynamically adjust to the changing environment of a hospital.

3.5 Motivation

The first goal of the HUGApp project is to identify the navigational needs of people in the Geneva University Hospitals (HUG). To do so, it is necessary to register the current situation in HUG, to understand and evaluate the problems that people face when they try to find their way in the hospital. In general, frequently-faced problems are: insufficient, confusing or outdated direction signalling, the language barrier, the lack of information material for people with reduced mobility, etc.

Apart from registering the current wayfinding problems, it was of great interest to identify their repercussions on people's life and work. The inability of a person to find their way in a hospital, whether that person be a visitor, a patient, or a staff member, can affect their stress level, and particularly for staff, their productivity and cause fatigue.

In addition to identifying the problems and their repercussions, a look towards the potential solutions should take place with close collaboration with people that interact daily with the environment of the hospital. A study of the potential navigational aids that people are willing to use needs to be conducted before they are put into action.

The technologies that could be used to improve wayfinding in the hospital, along with the desired features of these technologies should be based upon user-defined requirements. For these reasons, in this work the users were also asked to evaluate the importance of features that they would like a potential navigation mobile application to have as well as the importance of services that could be built on top of such an app.

3.6 Methodology

A questionnaire was designed by a primary care physician and an indoor positioning specialist based on factors identified in the literature review. The questionnaire was created with the tools provided by GoogleForms. It was distributed to the email list of the division at the end of 2016 (November-December), to both physicians and non-physician healthcare providers as well as to staff in administration. Out of 169 eligible collaborators, 111 (65.7%) answered the questionnaire. Among the collaborators that completed the survey, 61.3% were physicians (doctors), 56.7% of the collaborators had ≥ 5 years of work at HUG, 70.2% were female, while the mean age was 39.6 years and the standard deviation 10.3 (Table 3.1). A total of 70,1% were Swiss (persons with single and with double nationality included, so nationalities were not mutually exclusive), while 84.7% were native French speakers. The vast majority of participants reported having a smartphone that supports Location Based Services (LBS)(87.7%), while most of them mentioned a high level of familiarity with smartphones and their applications (66.7%). All data were gathered anonymously and the questionnaires were completed in French.

3.7 Results

In this section, the results of the questionnaires are presented and extensively discussed. Initially, a first list of questions helps depict a clear view of the current status of the navigational needs, the problems faced and their consequences in the environment of HUG. Following, the user requirements are described, separated into

Table 3.1: Demographics of the subjects of the study that replied to the questionnaire (N=111).

Variable	Level	n	n/N(%)
Age	Mean	**39.6**	
	Median	**37**	
	Standard deviation	**10.3**	
Gender	Female	**78**	(70.2%)
	Male	**33**	(29.7%)
Nationality	Swiss	**79**	(71.1%)
	French	**27**	(24.3%)
	Other	**11**	(9.9%)
French language level	Native	**94**	(84.7%)
	Working proficiency	**16**	(14.4%)
	Sufficient for everyday needs	**1**	(0.9%)
Occupation	Doctor	**68**	(61.3%)
	Nurse	**8**	(7.2%)
	Administration	**25**	(22.5%)
	Other health-care providers	**10**	(9%)
Years of working in HUG	Less than 6 months	**5**	(4.5%)
	6-12 months	**1**	(9.9%)
	1-2 years	**9**	(8.1%)
	2-3 years	**9**	(8.1%)
	3-5 years	**14**	(12.6%)
	5-10 years	**24**	(21.6%)
	More than 10 years	**39**	(35.1%)
Possesses smartphone supporting LBS	Yes	**97**	(87.4%)
	No	**8**	(7.2%)
	Does not know	**6**	(5.4%)
Level of familiarity with smartphones	1 (Zero knowledge)	**3**	(2.7%)
	2	**12**	(10.8%)
	3	**22**	(19.8%)
	4	**62**	(55.9%)
	5 (Expert)	**12**	(10.8%)

three subsections: (1) technologies that users are willing to work with, (2) requirements of a potential mobile app that helps people locate themselves and find their way in HUG, and lastly (3) additional services that a mobile application could offer on top of providing location information.

3.7.1 Status Report

In this section, questions regarding the current situation in the hospital are presented. Initially, the participants were asked if they had faced difficulties in finding their destination in the hospital (Figure 3.2). Only 9.9% of them answered "never" while 37.8% replied "rarely". The majority (52.3%) of the participants answered that they did actually face difficulties (36.9% occasionally; 14.4% often, 0.9% all the time). These results show that even for staff members of the hospital, not being able to find their destination on the premises of the hospital, which is their workplace, can be a recurring problem. It can be safely assumed that if people working in the hospital face these difficulties, the scale of the problem for visitors and patients will be even greater.

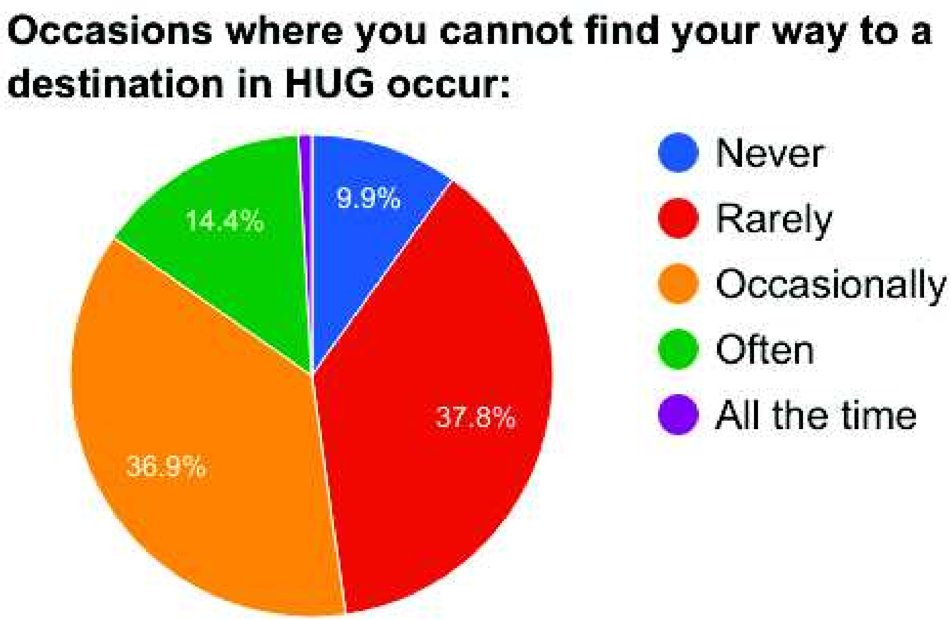


Figure 3.2

In the following Figure 3.3, we observe that more than 50% of the participants reported that they have to give direction instructions with high frequency ("often" or "all the time"), with "often" being the most popular answer (48.6%). These results undoubtedly reveal a common and significant existing problem.

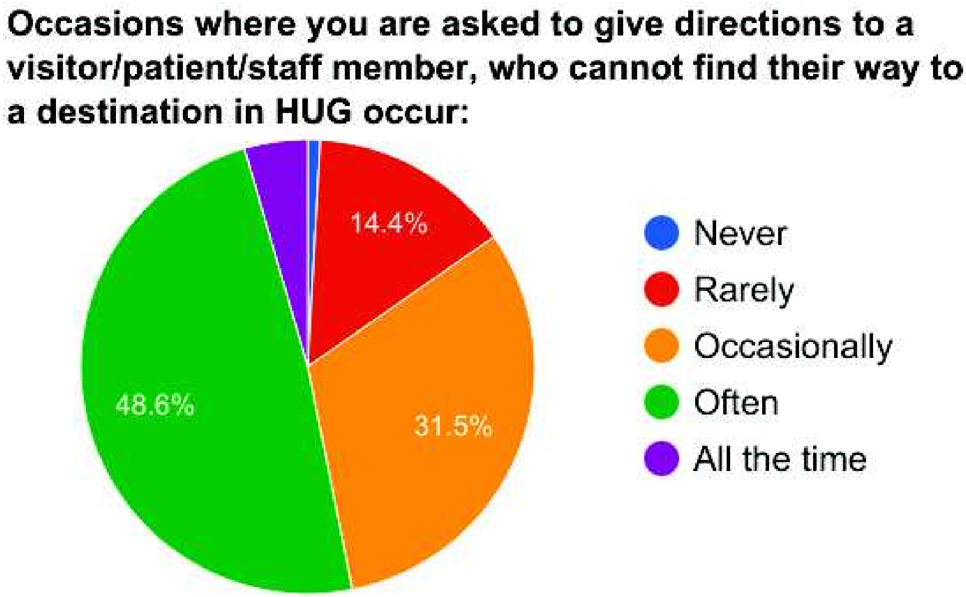


Figure 3.3

Based on the answers to the previous question, the results of the following one do not come as a surprise. The majority of the participants (52.2%), characterize the existing indications that assist people in finding their way as insufficient (6.3% characterizing them as "very insufficient" and 45.9% simply "insufficient").

The participants were asked the following question: *"How many minutes per week do you estimate that you spend on searching for your destination in HUG or answering questions of others trying to reach their destinations?"*. The average value of the answers was 11.7 minutes and the median value was 5 minutes. Considering only the replies of doctors, the average value was 8.7 minutes and the median value was still 5 minutes, indicating that doctors are similarly occupied with answering wayfinding questions, as are all other staff members. Moreover, a common problem is that staff members that are asked are often not able to answer the question so the question is repeated to other staff members.

The following two questions (Figure 3.4) intend to identify if the participants consider that the existing material that assist people in finding their way are well-adapted for non-French speaking people or for people with limited mobility. The results for the non-French speaking are impressive, as 18.9% of the participants characterized the signs to be "very badly" adjusted and 53.2% said they are simply "badly" adjusted. It is noteworthy that there were no answers for the reply "very well", which was also available. The fact that almost three quarters of the participants report the inefficiency of the information in other languages, apart from French, is a significant observation, especially for such an international city as the city of Geneva.

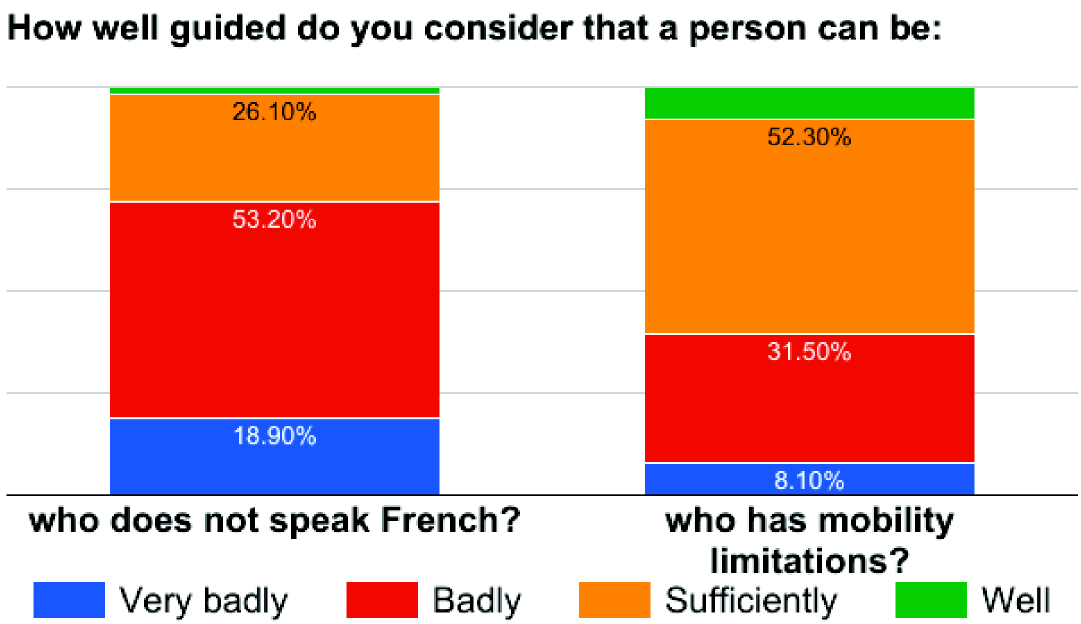


Figure 3.4

For the same question, concerning people with mobility limitations, we observe that the most frequent answer is the middle option, characterizing the signs as "sufficient" (52.3%). Nevertheless, only 8.1% express a clearly positive evaluation ("well"), while a significant amount of people (39.6%) characterize them as "bad" (31.5%) or "very bad" (8.1%). Lastly, there were no answers for the reply "very well", which was also available.

This result shows that there is space for improvement, especially as the environment at hand concerns a public hospital, were accessibility should be an equally shared right among all citizens, which is a constitutional principle of the Canton of Geneva. In the Canton's constitution, it is clearly stated that *"New buildings, accommodation places and workplaces should be accessible and adaptable to the needs of people with disabilities. In the case of renovations, the needs of the latter are taken into consideration in an appropriate manner."* (Art.207.2, Constitution de la République et canton de Genève).

In the next two questions, the participants were asked if the difficulty of finding one's way in the hospital can be a source of stress, firstly for staff members of the hospital and secondly for the visitors/patients. A total of 69.4% answered positively, concerning the staff members. Regarding the visitors/patients the results are truly impressive, as the difficulty in finding one's way in the hospital has almost unanimously (97.3%) been reported as a source of stress.

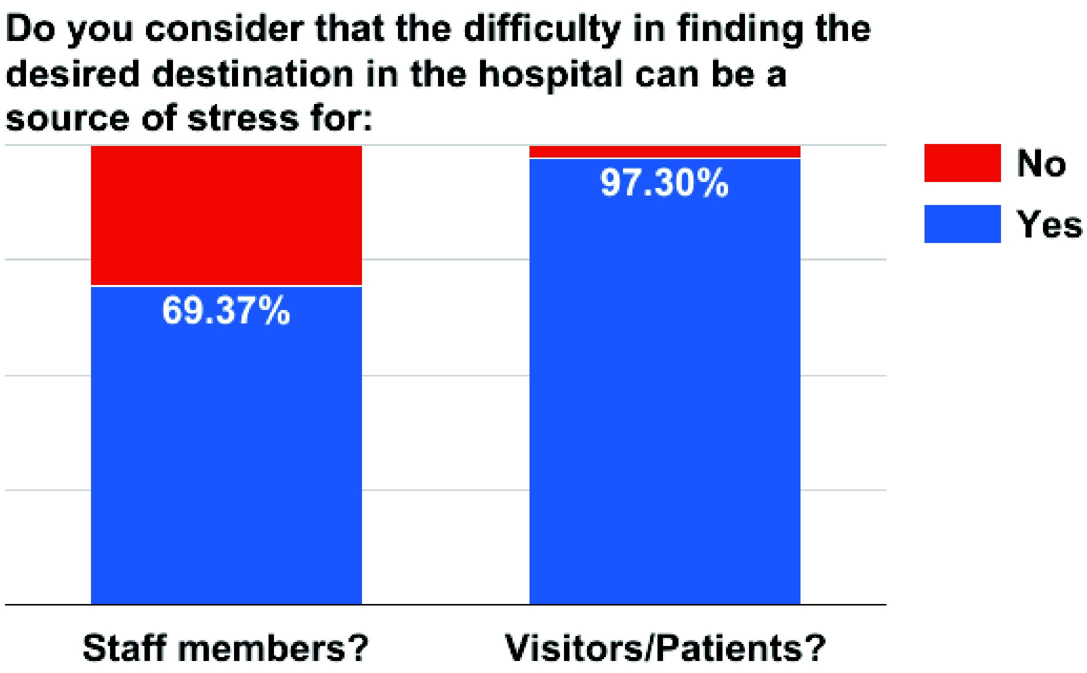


Figure 3.5

3.7.2 User Requirements

This section consists of three subsections. In the first one, the views of the participants about future solutions are reported as well as their willingness to use mobile applications for navigation. Subsequently, requirements for a potential mobile app that helps people locate themselves and find their way in HUG are reported. Lastly, a list of additional services that a mobile application could provide on top of providing location information is evaluated.

3.7.2.1 Technologies

Before proceeding to the questions that are specific to a mobile application approach, it is important to ask the participants about the way they believe that wayfinding will be improved in the future. The participants were able to make multiple choices from a list of solutions, shown in Table 3.2, while they were also given a free text option. Most mentioned that the signs should be improved (81 votes). The strategical addition of landmarks that would help differentiate similarly looking environments was the second most popular option with 59 votes, followed by the solution of interactive screens throughout the hospital that offer relevant content (maps, instructions, etc.), with 57 votes. Close to the two previous solutions comes the mobile application approach, with 54 votes. Improved colored lines on the floor, and volunteers helping people in wayfinding complete the list with 44 and 41 votes respectively. In addition, in the free text field, some interesting suggestions were given. One participant wrote: *"Editing of a colored document, personalized and handed out by hostesses (such as a Mappy or ViaMichelin or Google Map route) for people who are not used to new technologies."*. Another reasonable remark was underlining the need for: *"A 'natural' (intuitive) numbering of offices / meeting rooms / consulting offices"*. Lastly, there were suggestions indicating that, regardless of the improvements, there will always be the need for humans to accompany visitors, especially foreigners or the elderly.

The participants selected, on average, more than 3 options from the list, showing that there does not exist a single way that seems able to undoubtedly solve the wayfinding

Table 3.2: Number of answers to the multiple choice question: “In which way do you think that way-finding in hospitals can be improved in the future?”

Solution	Number of votes
Improved signs	**81**
Strategically add landmarks, such as photos or paintings, to help people identify and differentiate similarly looking environments.	**59**
Interactive screens throughout the hospital, offering location information (such as maps, instructions, etc.).	**57**
Smart mobile applications offering location information (such as maps, instructions, etc.).	**54**
Improved colored lines on the floor.	**44**
Volunteers (potentially old staff members) who help people in way-finding.	**41**

problem in hospitals. On the contrary, according to people’s feelings, the combination of several improvements seems to be the way that the problem will be handled in the future.

Having identified the need for a multifarious approach in addressing the navigational needs of people in hospitals, we proceeded to ask participants’ views regarding the creation of a relevant mobile application. The participants expressed a very positive view about the prospect of the creation of an application for mobile phones that would guide people to their destination, in HUG. On a scale from 1 to 5 (1: negatively - 5: positively), the most frequent evaluation values were 4 and 5, corresponding to positive evaluation, with 36% and 29.7% respectively (Figure 3.6). Negative evaluations (1 or 2) come from a small percentage of participants (9%). The average score was 3.85. One of the participants that gave a negative evaluation, justified it by mentioning the increased concern about people spending more and more time in public places by being totally focused on the screen of their smartphone.

The participants were asked to evaluate how likely it is for them to use such an app, on a scale from 1 to 5 (1: certain not to use it - 5: certain to use it, as seen in Figure 3.7). The most frequent answer is 5 (certain to use it) with 29.7%. Only 12.6% gave the

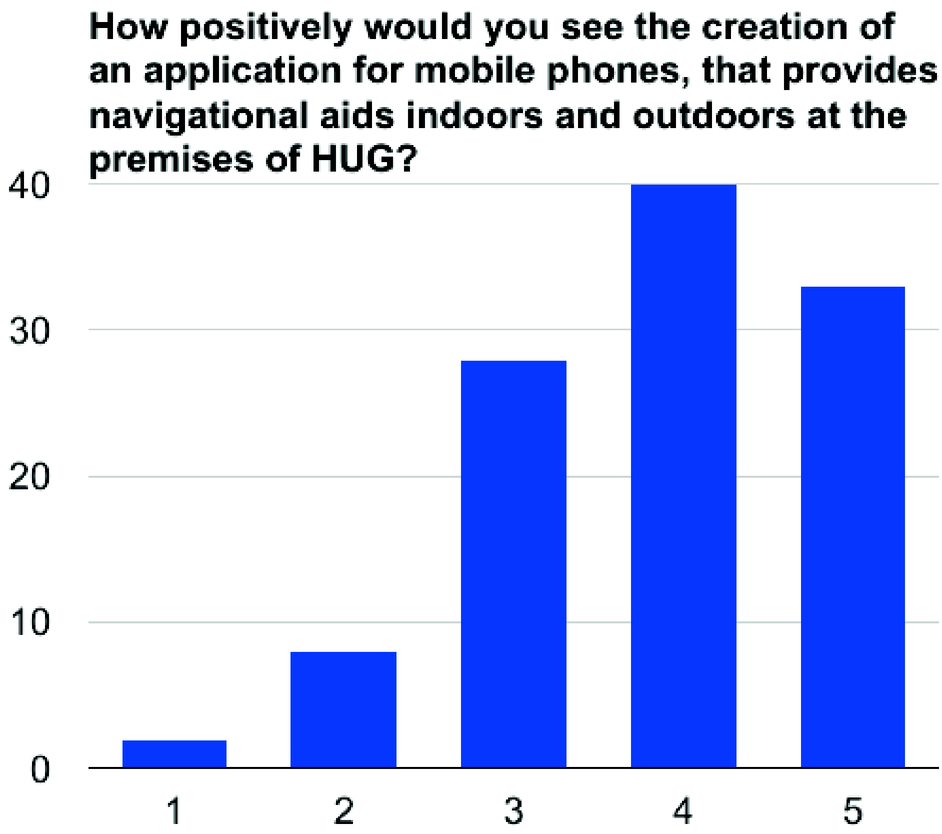


Figure 3.6: Number of evaluations per evaluation score (1: negatively - 5: positively).

lowest value 1 (certain not to use it), among whom most do not have a smartphone supporting location services, ergo their certainty. The average score was 3.42. This positive acceptance of the prospect of such an app is significant considering that the questionnaire was directed at hospital staff who are supposed to be familiar with the hospital's environment.

Combining the results of the last two questions with those of an earlier one regarding the time that the participants estimate that they spent in providing direction instructions, brings an interesting result. While the average time spent for all participants was 11.74 minutes per week, for those viewing positively (score: 4 or 5) the creation of a mobile application the average time is 15.01, while for those certain to use it (4 or 5) it is 15.92. These results show that staff members who are mostly facing the problem of people getting lost in the hospital are those that emphasize the

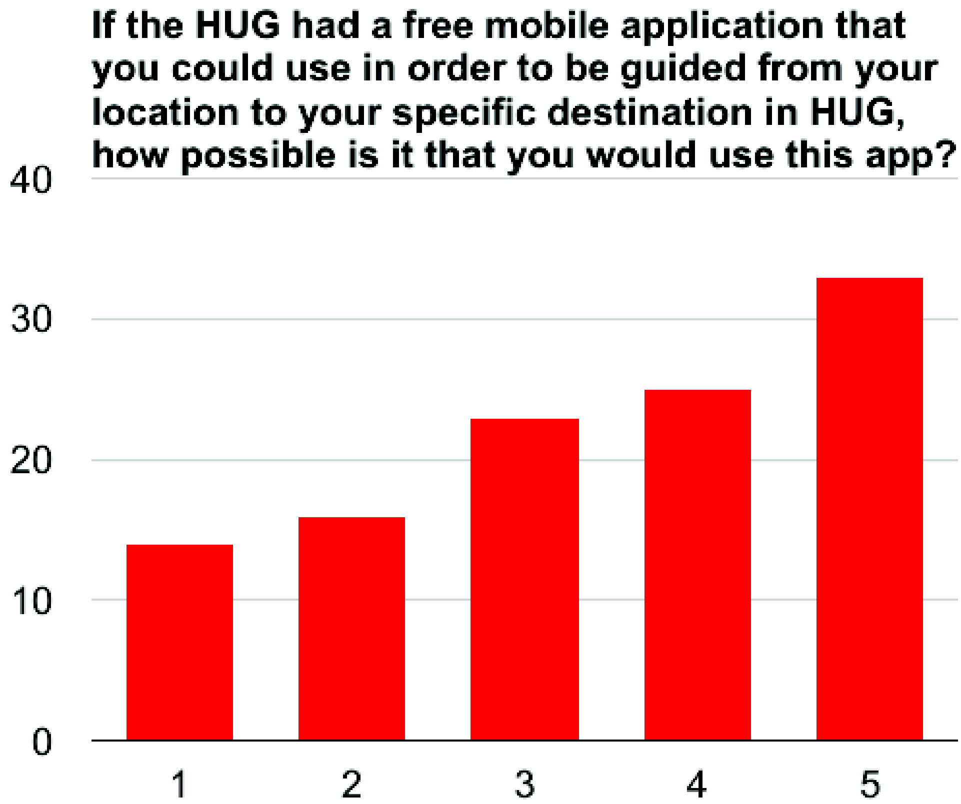


Figure 3.7: Number of evaluations per evaluation score (1: certain not to use it - 5: certain to use it).

necessity of such a navigation aid. Lastly, a result that could be characterized as counter intuitive is the fact that the average age of those certain to use the app (4 or 5) is 40.7 years, in comparison with the 39.6 years of all participants. This shows that it is not only the younger staff members that are willing to use modern technology, as the average age is slightly increased for those eager to use it.

3.7.2.2 Mobile app requirements

The participants were asked to evaluate the importance of features (on a scale from 1 to 5, with 5 being the highest importance) that they would expect a navigation application to have. In Table 3.3, we can see the average importance score that the participants gave to each of these features. In brackets, we see the relative ranking of the features in the list.

Table 3.3: Average user evaluation (and ranking) of the desired features for a navigation mobile application, on a scale of 1 to 5, with 5 indicating high importance.

Feature	Importance (Rank)
Estimating my position accurately.	**4.45** (4)
Smooth flow of position estimates (no abrupt 'jumps' of the position estimates).	**3.80** (10)
The trajectory towards my destination should appear in a map.	**4.52** (1)
Direction instructions should be given by arrows.	**3.96** (8)
Direction instructions should be given by explanatory text.	**3.37** (11)
Direction instructions should be given verbally.	**2.95** (12)
The application should be available in many languages.	**4.16** (6)
The application should be able to take into consideration the mobility capabilities of users.	**4.49** (2)
The application should not require internet connection in order to function correctly.	**4.27** (5)
The application should have low battery consumption.	**3.86** (9)
The application should protect my privacy.	**4.49** (3)
The application should combine its directions with the existing navigational aids of the hospital, as the colored lines on the floor.	**4.14** (7)

We observe that the most important feature is the one that concerns having a map on which the estimated position appears. It is true that having an interaction with a map on which their position appears is much easier and more intuitive for the users than other approaches, like simple text instructions, etc. In second place, we find the need of taking into account the mobility capabilities of the users. A navigation application that would not take into account the mobility of its users would be discriminatory and inappropriate, especially for the environment of a hospital. It is notable and quite positive that the professionals of healthcare prioritize needs that way. In third place, and not much below the rest, we find the privacy protection, which is generally highly valued when dealing with medical information. In fourth place appears the feature concerning the high accuracy of the position estimates. Having a high accuracy in the indoor positioning system is a naturally expected requirement, since the correct functioning of the application relies on this accuracy.

The features that were ranked as the least desired are the following: having direction instructions given in written text or verbally, the smoothness of the sequence of position estimates, as well as the requirement of the low battery consumption. Instructions given written or verbally can be an additional, optional feature on top of the most important features of showing the user position in a map and providing direction instructions with arrows. Moreover, the low importance that the participants gave to the low battery consumption requirement could be interpreted in the sense that people who use smartphones are familiar with the fact that location services tend to require a fair share of the battery's energy. Nevertheless, handling a trade-off between low battery consumption and good performance should be the goal of every modern mobile application.

3.7.2.3 Additional services

Lastly, the participants were asked to evaluate the importance of a variety of potential additional services that a mobile application could offer on top of providing location information. In Table 3.4, we can see the average importance score that the participants gave to each of the potential services.

From the scores given to these services, we can observe that, in general, the additional services are not characterized as important as the main desired features presented in Table 3.3. The most desired service, which has an average importance score of 3.78 is the last one, which describes the application being able to inform and guide professionals to the room where a meeting that they are supposed to attend is taking place. An appointment reminder service and a service facilitating the organization of meetings and the booking of meeting rooms received the same importance score (3.4/5). Having a messaging system or the possibility of sharing the location with others could potentially be useful, as a patient could share his location with their

Table 3.4: Average user evaluation of potentinal additional services, on a scale of 1 to 5, with 5 indicating high importance.

Service	Importance (Rank)
The application should allow users to communicate through a messaging system.	**2.15** (5)
The application should allow users to share their location with others.	**2.27** (4)
The application should provide reminders to the users when the time of an appointment is approaching and advise them when to depart, taking into account their current location.	**3.4** (3)
The application should facilitate the hospital staff in organising meetings by providing information about the vicinity and availability of meeting rooms.	**3.4** (2)
The application should be able to inform and guide professionals to the room where a meeting that they are supposed to attend is taking place.	**3.78** (1)

doctor some time before the appointment, so that the doctor knows if the patient will arrive on time. These two options though were not characterized as important by the participants, with 2.15/5 and 2.27/5 respectively.

3.8 Conclusions

The questionnaire offered a great insight concerning the identification of the navigational needs of people in HUG. The survey shows that both visitors and staff members are facing difficulties in finding their destination. This is identified as a source of stress for both groups. Also, a considerable amount of the personnel's time is spent in assisting people finding their way. The fact that the existing material is inefficient for people that do not speak the official language (French) is clearly revealed. Similarly, an imperfection is reported for the material assisting people with mobility restrictions.

The participants showed very positive feelings regarding the creation of a mobile application that can help people be guided around in the hospital. Problems that were highlighted as frequent and important, such as not taking into account the users' mobility limitations or their language preferences, are easily solved with a mobile application that can customize its function according to the user needs. Concerning the required features of the app, the results are very interesting. The ability to adjust the information according to the mobility restrictions of the users has been highlighted as a feature of very high priority. Also, people want an app that guarantees privacy protection. They expect a system that has a good accuracy in estimating the users' position and that displays their position and the direction instructions on a map.

The findings of this survey encourage the prospect of proceeding with the creation of an indoor navigation mobile app that would assist visitors and staff members in finding their way in HUG.

Part II

Indoor Positioning System, Indoor-Outdoor Handover and Propagation Model Self-Calibration

4 Indoor Localization System Based on the Weighted Centroid Algorithm: Parameters Analysis, Tests and Usage

4.1 Chapter Abstract

The result of the localization procedure can be used as an input for several Location Based Services (LBS). A common use of the localization estimates is to utilize them as an input for navigation applications that guide users from their location to their destination. One of the main goals of the research in the field is to improve the achieved accuracy. Along with the accuracy, factors like easiness of deployment and reconfiguration, cost, computational complexity, device independence and the ability to tune the desired accuracy in specific areas are also important.

In this work, initially we theoretically analyze and propose the optimal selection of the number of closest beacons participating in the position estimation, based on the weighted centroid method The weighed centroid method, combined with the selection of the optimal number of closest beacons, the averaging of the received signal strength indicator (RSSI) at the distance domain and the added smooth filtering step proposed in this work, offers an accuracy down to ~ 1 meter at static measurements and ~ 2 meters at dynamic ones, depending also on the deployment configuration. A great advantage of our system, compared to common trilateration techniques, is

A shorter version of this work has been published in: *'Accuracy Enhancements in Indoor Localization with the Weighted Average Technique'*, Anagnostopoulos G.G. and Deriaz M., in Proceedings of the Eighth International Conference on Sensor Technologies and Applications (SENSORCOMM 2014), Lisbon, Portugal, November 2014.

that it restricts the position estimates in the polygon of the closest detected beacons. The notion of proportionality of RSSI measurements used by our system, as opposed to the absolute RSSI values used by the trilateration techniques, makes our system more robust against device diversity, as is shown by the extensive tests reported in this study. This feature safeguards the accuracy and the pleasant user experience by being less affected by device diversity or signal attenuation, becoming optimal as an input for the navigation module.

For the implementation and validation of this system we use the Bluetooth Low Energy (BLE) technology, which offers a low cost and is easily deployed and reconfigured. The localization system was used to feed the navigation module NaviMod, in the context of the European Ambient Assisted Living (AAL) Virgilius project, where elderly users can navigate with a smartphone. The method, after being extensively tested in the lab, was installed at the Hospital of Perugia (Italy), where end users could test it and eventually validate it, expressing their positive reception of the system.

4.2 Introduction and Related Work

Over recent last years, the field of indoor positioning has drawn increased attention among researchers. Outdoor positioning has been ahead, having reached many users through commercial applications. Nowadays, almost all new mobile devices are equipped with global positioning system (GPS) technology, which has familiarized most users with the concept of positioning. On the other hand, no indoor positioning method has been broadly recognized as a standard one, and the research in this domain has led to having multiple alternatives. This variety of alternatives satisfies different requirements, such as cost, ease of deployment, accuracy and precision, etc.

A technology commonly used for positioning in indoor environments is the Wi-Fi signal [Mazuelas et al., 2009] [Lee and Han, 2012]. One advantage of using Wi-Fi is that most buildings have several Wi-Fi access points (AP) to provide internet access so the hardware required is already installed. On the other hand, usually the access point network is not dense enough or optimally placed so as to facilitate a satisfactory accuracy of localization. Moreover, adding or rearranging the Wi-Fi APs is bound by the restriction that they should be plugged, limiting the freedom of their placement.

In this study, we work with BLE technology. BLE is a wireless technology used for transmitting data over short distances. It has low energy consumption and cost, while maintaining a communication range similar to that of its predecessor, Classic Bluetooth. As transmitters, we used BLE beacons, which are available from many manufacturers, and that comply with iBeacon technology standard, which is a widely spread protocol defined by Apple. The iBeacon protocol allows mobile applications (running on several operating systems, as iOS, Android, etc.) to periodically listen, interpret and use signals from the beacons and react accordingly. Each beacon broadcasts a self-contained packet of data periodically. The packets contain an identifier of each beacon so that the receiver can distinguish among them. The RSSI can be used to estimate the distance between the mobile device and the transmitting beacon [Mazuelas et al., 2009] [Vanheel et al., 2011] [Papamanthou et al., 2008] [Saxena et al., 2008]. Due to their low cost and low consumption, a dense network can be deployed. Having a dense deployment can lead to reliable distance estimates.

These distance estimates are used to derive an estimate of the actual position, usually by using lateration methods [Yang et al., 2010] [Lu et al., 2012] [Will et al., 2012]. These methods can have some drawbacks. For example, when the closest detected beacons are co-linear or when the estimated distances are imprecise, an estimated position that is far from the real one may be returned. Furthermore, using different mobile devices with different reception characteristics can add a systematic error to each distance estimate that will dramatically affect the lateration outcome. Thus, bad distance estimates due to noise, environmental changes (such as the movements of human bodies between the APs and the mobile device) or device diversity can result in position estimates that are far from the real position. A low accuracy of position estimates can dramatically deteriorate the performance of the navigation system, which may continuously trigger recalculations of the path to the destination according to where the noisy position estimates ‘jump around’.

In our method, we proceeded with another approach. The position prediction of the proposed method is limited to the area that is defined by the polygon that the beacons’ positions define. Therefore, we propose a placement of beacons such that the beacons surround all the area that is desired to be covered by the positioning system. Distance estimations from each beacon are inferred, not only by instantaneous receptions that are subject to noise, but by averaging the estimated distances that correspond to the latest RSSI measurements from this beacon. In this way, we partially cope with the instability of the RSSI.

Having this averaged distance estimation, we focus only on the B closest beacons. In this work, after theoretically modeling the positioning error, we propose $B = 4$ as the most appropriate setting of the parameter. We use the inverse value of the distance estimate as weight in order to perform a weighted average of the positions of the 4 closest beacons, getting this weighted centroid as the estimated position. Once a position estimate is inferred, based on the closest detected beacons, we introduce a smooth filtering step, which filters the latest position estimate using the list of the previous latest estimates. In this way, the impact of a potential wrong detection of which beacons are the closest does not have a high impact on the final position estimate. The weighted centroid method is used in works as the main positioning method or as an area/room selection first step of a bigger positioning system [Zou et al., 2013]. For instance, in this work [Zou et al., 2013] the weighted centroid method is used with the radio frequency identification (RFID) technology as an area/room selection first step before performing a server side supervised machine learning positioning method.

The lateration approach implicitly uses the assumption that distance estimates are close to accurate, which is unlikely. Our proposed method anticipates the uncertainty of this estimation, coping with the fact that the absolute values of the distance estimates might not be accurate. It firstly utilizes the fact that the expected error is smaller in short distances, and secondly, the main conceptual idea of RSSI methods, that a stronger RSSI reception from beacon a as compared to beacon b is interpreted as being closer to beacon a. The validity of this assumption can be even enhanced after averaging the list of the latest distance estimations.

The advantages of the proposed system are numerous. The Bluetooth beacons are easily deployed and rearranged in order to cover new areas of a building or to improve accuracy with a denser grid. The density can be adjusted to particularities of the areas of deployment. For example, the deployment could be denser in a corridor with many doors, where accuracy is critical, compared to a long corridor with few (or no) doors that may simply link two buildings. Another advantage is that, as a ranging technique, this method does not require the creation of a radio map [Sorour et al., 2014]. On the contrary, in fingerprinting techniques a radio map is required, where measurements of RSSI from all access points should be stored for many points of the area where the system is to be used. In the proposed system, one can reconfigure the deployment (by adding, for example, one beacon) with no need to retake any measurements for a radio map, but simply by storing the position of the new beacon(s). Our method also offers low computational and implementation complexity. Finally, as all RSSI techniques, it has the advantage that all modern smartphones can offer the RSSI of a Bluetooth reception, and thus no extra hardware or modification of the devices is required.

The rest of this chapter is organized as follows. In Section 4.3, we present the propagation model used to derive distance estimations form the RSSI values, and the assisting Android app that was designed to allow its calculation. In Section 4.4, we present in detail all parts of the proposed system. Measurements along with both theoretical and experimental results are reported and discussed in Section 4.5. The practical utilization of the positioning system that was deployed in the Hospital of Perugia in Italy, in the context of the European AAL project Virgilius, along with the user acceptance of the system is discussed in Section 4.6. Finally, conclusions drawn are presented in 4.7.

4.3 Propagation Model and its Calculation

In RSSI methods used in localization, the distance between the transmitter and the receiver can be estimated based on the received signal strength. Nevertheless, the RSSI received at a given time and space is influenced by many factors, other than the relative distance of the two devices. Even the slightest changes in position and orientation can provoke dramatic variations to the RSSI values [Zanca et al., 2008]. Moreover, the movement of people and objects in the environment often has a great effect on the signal. In general, RSSI is vulnerable to strong multipath effects especially indoors [Zanca et al., 2008]. Furthermore, factors like temperature and humidity conditions can affect the propagation of the signal [Zanca et al., 2008]. Using a set of RSSI measurements instead of a single instantaneous measurement can improve the accuracy of the distance estimations [Papamanthou et al., 2008].

The propagation model commonly used [Mazuelas et al., 2009] for the RSSI to distance correspondence, where the expected RSSI p_i in distance d_i is calculated, is the log-distance path loss model:

$$p_i = p - 10\, n \log_{10}(d_i / d_0) + X \tag{4.1}$$

In this formula, p is the received RSSI at a reference distance d_0, n is the path loss exponent which depends on the transmission channel, the transmitter and the receiver, while X is the random noise, which is assumed to have a Gaussian zero-mean distribution. Using 1 meter as reference distance, the formula is simplified to:

$$p_i = p - 10\, n \log_{10}(d_i) + X \tag{4.2}$$

From the above formula, we conclude that in order to fully describe the propagation model, two parameters are to be defined, the *path loss exponent n*, and the *received RSSI p at the reference distance*. Having a fully characterized propagation model allows the estimation of the distance between the transmitter and the receiver, based on the received signal strength. The presence of random noise though does not allow the estimations to be infallible. In order to have a more reliable distance estimation we do not use only the latest RSSI reception but a set of the latest ones. The accuracy of the distance estimation can be increased by using a considerable amount of measurements. Since the noise is assumed to have a Gaussian zero-mean distribution, the use of a plethora of measurements for each predefined distance increases the probability of reducing the average error caused by the noise.

The estimation of the propagation model for a certain deployment can be calculated by taking several measurements in known positions and then finding by regression the values of the parameters n and p of Equation 6.2.

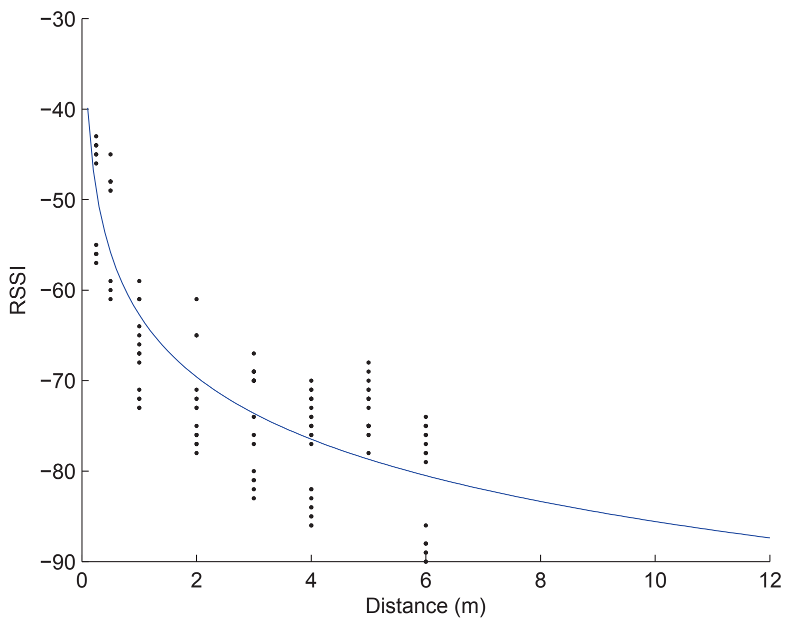


Figure 4.1: RSSI measurments at several disances (in black) and the resulting propagation model (in blue) as the best fitting curve described by Equation 6.2.

An example of the practical way of calculating the propagation model's parameters is presented below. A BLE beacon was placed at the area of the system's tests, in the corridors of the University of Geneva, and RSSI measurements were performed at several points at known distances from the beacon. These measurements were performed using a Samsung Galaxy S4 and then a regression was run in order to find the parameters of the best fitting curve described by (6.2). In Figure 4.1, we see the measured RSSI values (black dots) in several distances (at 0.25,0.5,1,2,3,4,5 and 6 meters), while with blue color the resulted propagation model as the best fitting curve is plotted. The estimated values of these parameters are $p = -62.72$ and $n = 2.2853$.

4.3.1 The 'Propagation Calculator' Android App

The *Propagation Calculator* is an Android application that was designed in the context of our system's creation in order to allow a user to calculate the parameters of the propagation model. To do so, the user has to take several measurements of a beacon's signal at several known distances. When enough measurements are taken the application can calculate the parameters of the propagation model using logarithmic regression.

Initially, the application scans the environment for beacons in range (leftmost photo of Figure 4.2). The list will show the identifier (MAC address) of each beacon or its name, if the beacon is assigned a name, defined in a dictionary file that the user may input. The dictionary is a simple text file that corresponds MAC addresses to names. The list can be filtered by typing the text in the input box on the top. Once the beacon is selected from the list, the next screen appears concerning the definition of the measurements' characteristics.

Adding a new measurement will open a dialog window (central photo of Figure 4.2) where the user should introduce the 2 parameters: *distance* and *number of samples*. The *distance* represents the distance in meters between the beacon and the device. The *number of samples* represents the amount of RSSI values that will be stored at the

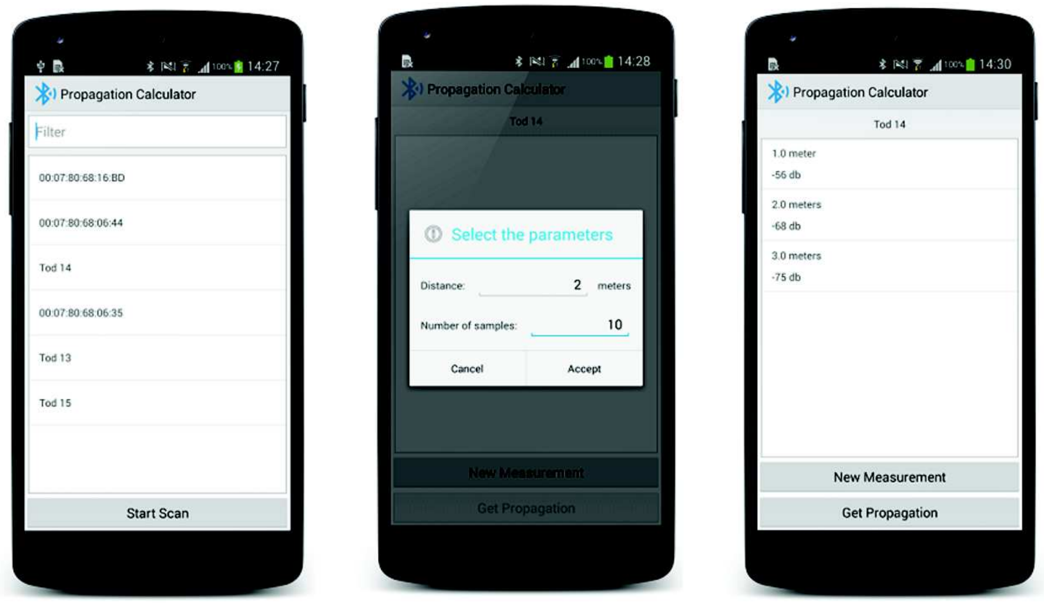


Figure 4.2: The 'Propagation Calculator' Android app

given distance for the calculation of the propagation model. Once these parameters are set, the user may start the measurements' recording. The user is informed with a progress bar regarding the advancement of the procedure. When all measurements are completed, the average RSSI and the distance appear to the user (rightmost photo of Figure 4.2).

The user has the freedom to choose at which distances the measurements will be taken and how many samples will be taken at each distance. Once all desired measurements are collected, the user receives the parameters p and n of the propagation model. The user has the option of adding or removing measurements and recalculating the parameters of the model accordingly.

4.4 The Positioning System

4.4.1 The Weighted Centroid Aproach

For an indoor localization system and its applications, it may be often desirable to constrain the prediction inside a specific area, i.e. inside a building. In the case where map matching is used to provide navigation (as in the Virgilius project [Togneri and Deriaz, 2013]), a jump of the estimation outside of a building could lead to problematic navigation. In this spirit, it is worth noting that the proposed method can give estimations of positions only inside the polygon area that is defined by the positions where the beacons are placed. Thus, in practice, to provide coverage in a rectangular room or a corridor with the proposed method, $B = 4$ is the minimum number of beacons placed inside this room to cover all its area. Later in this chapter, we discuss proposed configurations.

Having obtained an estimation about the distance of the mobile device from each beacon, we proceed to the position estimation. Due to multipath effects, it is unrealistic to claim that the distance estimations will be consistently precise. Especially in big distances, even a small difference in the RSSI values is translated to big distance differences. On the other hand, in small distances the RSSI values are quite distinguishable. We utilize this fact in the following way. From the list of beacons that are detected, we keep the 4 closest ones. The reason why the four closest beacons are selected is discussed at the next subsection 4.4.2. For a mobile device that is inside the coverage area (that is a polygon defined by the positions of the beacons), the estimated position will also be inside the quadrilateral defined by the 4 closest beacons. Let $[e_1, e_2, e_3, e_4]$ be the estimated distances from the 4 closest beacons, while $[lat_1, lat_2, lat_3, lat_4]$ and $[lon_1, lon_2, lon_3, lon_4]$, the corresponding latitude and longitude of their positions. We calculate the latitude Lat_{est} and longitude Lon_{est} of the estimated position as follows:

$$Lat_{est} = \frac{\sum_{i=1}^{4} \frac{lat_i}{e_i}}{\sum_{i=1}^{4} \frac{1}{e_i}}, \; Lon_{est} = \frac{\sum_{i=1}^{4} \frac{lon_i}{e_i}}{\sum_{i=1}^{4} \frac{1}{e_i}} \tag{4.3}$$

In Equation 4.3, we calculate the weighted centroid of the four closest beacons' positions, using as weight $1/e_i$, which is the inverse of the estimated distance from beacon i. By using this weighted centroid approach the prediction is limited inside the quadrilateral of the closest beacons. With the specific weight that is proposed the prediction is pulled towards the closest beacon, albeit allowing the rest of the beacons to contribute inversely proportionately to their estimated distance from the mobile device.

Concerning the geometrical pattern of the beacons deployment commonly used patterns are suggested for the correct function of this system. Initially, it is straightforward that all areas requiring coverage by the positioning system should be inside the polygon that the deployed beacons define. In corridors, which are the areas in which the positioning and navigation systems are mainly used, a zig zag pattern is proposed, with one beacon placed every 5 to 10 meters depending on the required accuracy. Big rooms and halls are to be covered with a zigzag or a square grid, placing at least one beacon for every 100 square meters of area. Small rooms (<70 square meters) that are adjacent to corridors with coverage can be covered with only two beacons placed at the opposite side of the room from the wall separating the room with the corridor.

4.4.2 Error Simulation and Optimal Number of Closest Beacons Selection

The minimum number of closest beacons that could be used for two-dimensional localization is 3, since 3 points define a plane. In the case where the 3 closest beacons were used, the defined area would be a triangle. In the middle area of this triangle, the estimation is slightly better compared to the case where 4 beacons are used, since the fourth beacon that is outside the triangle pulls the estimation toward its position. The drawback with the usage of only 3 closest beacons is that when the user is moving and passes from one triangle to the other, the accuracy of estimation near the common edge of the two triangles is significantly degraded. Using the 4 closest beacons offers a smooth transition from one triangle to another. In the following section, along with the system's accuracy measurements, an error analysis of these two cases is presented.

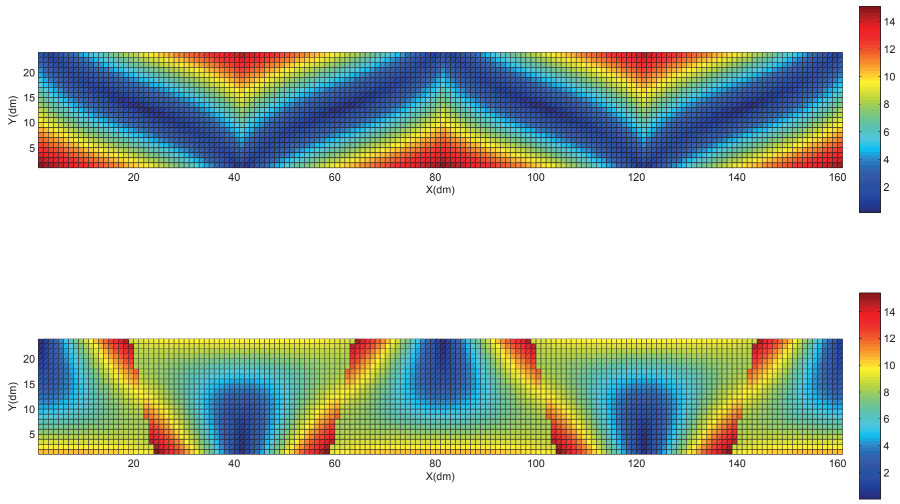


Figure 4.3: Error in decimeters (color scale) of the position estimation in a corridor at the position x,y, when using 4 (upper plot) and 3 (lower plot) closest beacons.

The weighted centroid method may have an error in the location estimations even when the distance estimates are precise. We theoretically estimate and model this error in Figure 4.3, for the cases where 4 and 3 closest beacons are used. We simulate the environment where the system is deployed and extensively tested (the corridors of the Centre Universitaire d'Informatique (CUI), of the University of Geneva). The error as it corresponds to the physical world is depicted in Figure 4.4. We observe that, in the first scenario (4 closest beacons) the error is lower at the center of the corridor where users are expected to usually move, and it slightly changes, in a smooth way, as we move along the length of the corridor. On the other hand, using just 3 beacons degrades significantly the accuracy estimation at a broader area of the triangles that the triplets of beacons define. The error increases rapidly when approaching the edges of these triangles, deteriorating the performance of the system.

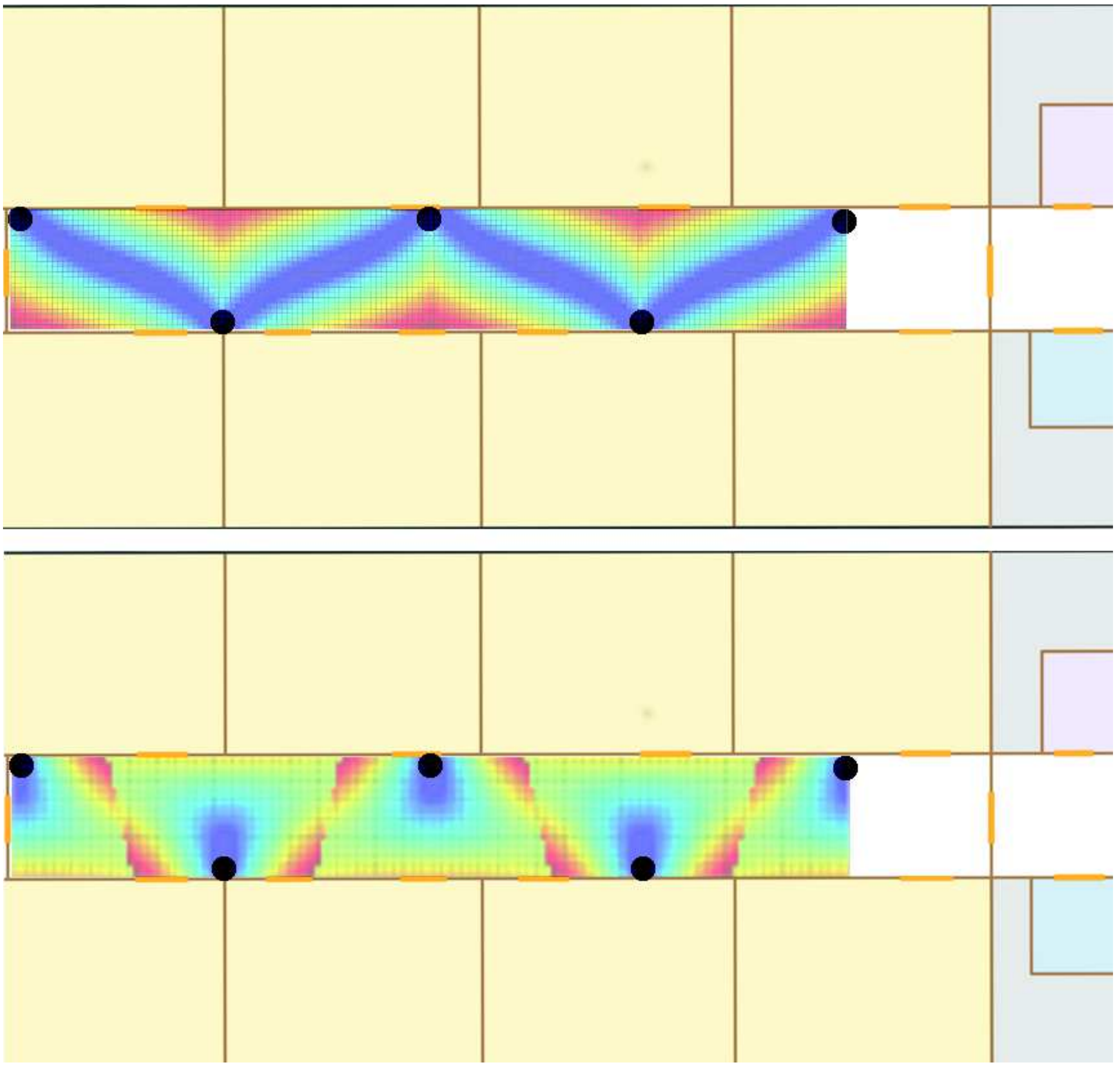


Figure 4.4: The estimated error of Figure 4.3 for 4 (upper plot) and 3 (lower plot) closest beacons, as it coresponds to the physical world's example that it models. The black dots are the beacons as they are placed in the corridors of the University of Geneva.

4.4.3 Averaging the Distance Estimations

Due to the non-linear relation between the RSSI and the estimated distance, it is important to decide if we will average the latest RSSI values and then get the distance estimation based on the averaged RSSI or if we should calculate the corresponding distance of each RSSI reception and then use the average of these distances. In Figure 4.1, we see that for distances from 0 to 5 meters, the RSSI values change significantly. On the other hand, for distances greater than 15 meters, RSSI differences are minor. Since we aim to utilize the reliability and distinguishability of the small distance measurements from the closest beacons, we direct our method to this part of the propagation model. Given that the derivative of the RSSI curve changes with the distance, averaging the RSSI values, even when assuming noiseless receptions, inserts an intrinsic error into the estimation. On the other hand, averaging distance estimates introduces no error, assuming noiseless receptions and a robust propagation model.

To state this argument we explain a simple example assuming noiseless receptions. Assume that users are moving and the RSSI measurements they receive from each beacon correspond exactly to the real distance from it at each moment. Averaging in the distance domain provides the users' average distance. On the other hand, due to the non-linear relation of distance and RSSI, averaging RSSI values first will give a distance estimation different than the average distance.

Furthermore, in the case where the measurements of the RSSI values are subject to noise, in short distances, small RSSI errors have small consequences in the distance estimations because the model's slope is very steep. On the other hand, for big distances, a small fluctuation of the RSSI values can have a dramatic consequence on the estimated distance. In the proposed method, only the RSSI values of the closest beacons are used. Because of the non-linearity of the model in this area for the model averaging in the RSSI domain would introduce a bias. For these reasons, averaging in the distance domain was selected.

4.4.4 Smooth Filtering

Apart from filtering the RSSI receptions of each AP, an additional smooth filtering step is introduced at the level of the position estimates. Even after filtering the RSSI receptions of each AP, it is possible to detect a distant AP as one of the closest ones. This would 'drag' the position estimate towards that AP. Nevertheless, by utilizing the history of estimated positions, such abrupt 'jumps' of the position estimates can be avoided.

We utilize the history of position estimates by introducing an exponential smoothing filter. The exponential filter, acts as a low pass filter keeping the low frequency changes that correspond to the trajectory of the user, reducing the effect of high frequency error caused by noise. The logic of the filter is shown in Equation 4.4. Let x_n be the n^{th} unfiltered position estimate, s_n the filtered output of this estimate and α the smoothing factor.

$$s_n = \alpha x_n + (1-\alpha)s_{n-1} \qquad s_0 = x_0 \tag{4.4}$$

The weights of old position estimates are reduced exponentially as new estimates are produced. In this way, only the latest receptions get a significant weight in the calculation. A numerical example is given bellow for $\alpha = 0.5$ and $n = 3$.

$$s_3 = 0.5x_3 + 0.25x_2 + 0.125x_1 + 0.125x_0$$

Apart from the history of the estimated positions an interesting addition is to use the history of the speed of the user as a vector expressing the advancement of the position estimate between two consecutive estimates. In Equation 4.5, we define the notion of velocity as the difference of the two latest filtered position estimates.

$$v_n = s_{n-1} - s_{n-2} \tag{4.5}$$

Averaging a number of the V latest velocities gives an estimation of how the user was moving, in which direction and how quickly. In the case where there is a back-and-forth jump of the estimate among the latest receptions, the pairs of opposite vectors even out each other, leaving the remaining velocity values to offer the estimation of the actual direction of movement.

By adding the V latest averaged velocities with a weighting factor β to the exponential filter of Equation 4.4, we get the final form of our proposed formula, in the following Equation 4.6.

$$s_{n+1} = \alpha x_n + (1-\alpha) s_{n-1} + \beta / V \sum_{i=0}^{V-1} v_{n-i} \tag{4.6}$$

The introduction of the smooth filtering improves the result not only by reducing the average error but also offering a smoother sequence of estimates. The smoothness of the the position estimates and the reduction of jumps offers a more pleasant perception to the user (as explained in the following subsection), especially considering the case when a navigation module is used on top of the positioning one. Jumps in the position estimates could trigger a recalculation of the route from the navigation system, interrupting the experience of the user and eventually degrading the efficiency of the whole system.

4.5 Measurements, Results and Discussion

4.5.1 Initial Tests - Virgilius

Before deploying our system to the Hospital of Perugia, which was the test field of Virgilius project, the system was extensively tested in the common areas of the Centre Universitaire d'Informatique (CUI) of the University of Geneva. The tests were conducted in two ways: statically and dynamically. Firstly, the static tests were done by leaving the mobile device at a specific place and recording the estimated positions that the system was provided. A second dynamic approach was to test the localization while having the mobile device moving, which better corresponds to real use cases. It is noteworthy that these initial tests were performed before the addition of the smooth filtering step.

In order to get a broad estimation of the positioning accuracy, we took 1000 measurements at three points in a corridor where the system was deployed. Two mobile devices were used for these measurements: a Samsung Galaxy S4, which was used for the creation of the propagation model (6.2) and a Samsung Galaxy Note 3. The goal was to test the adaptability of the system to different devices with different reception characteristics.

The results are represented in Table 4.1. In Figure 4.5, the beacon positions are highlighted with black color and the places that the measurements were taken with red. We placed point A at the center of the corridor, which better represents the usual usage area. In order to test the accuracy of the system at the spacial limits of its coverage area, we place point B on the wall on the side of the corridor and point C at the end of the corridor. Both points B and C lay exactly at the limit of the beacon's polygon so they theoretically represent the worst cases of the the area where coverage is provided.

TABLE 4.1. ACHIEVE ACCURACY OF TWO DEVICES AND THREE LOCATIONS

		Mean error (m)	*σ of error (m)*
Point A	S4	1.22	0.82
	Note 3	0.97	0.48
Point B	S4	3.08	0.76
	Note 3	3.18	1.09
Point C	S4	3.82	2.20
	Note 3	3.50	1.78

The position estimations are very reliable throughout the corridor, with an average accuracy of 1.22 and 0.97 meters for the two devices. The accuracy drops at the boundaries of the beacons' polygon, but remains reliable, with an average error of 3.08 (and 3.18) meters next to the wall. It is worth mentioning that the accuracy with the Note 3 is really similar to the one with the S4, which is the device used for the propagation model calculation.

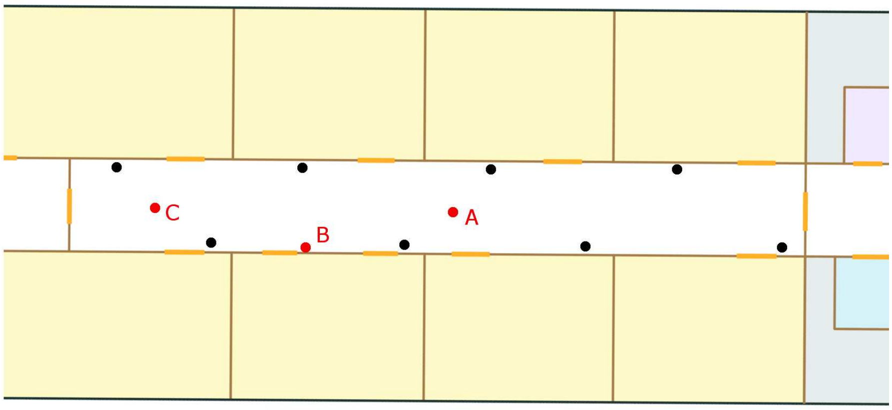


Figure 4.5. Test environment. Beacon positions are highlighted with black color, and the places that the measurements were made with red color.

Apart from the static measurements, we also performed a dynamic test in the same environment. The corridor where the dynamic tests took place was 2.5 meters wide and 25 meters long. The measurements were taken in a straight line at the center of the corridor, and at a constant pace of approximately 1 m/s. The mean value and standard deviation of the positioning error (thus the mean value of distances between the estimated and the true positions) are measured as $\mu = 2$ and $s = 1.28$ meters respectively.

The error in the dynamic version is higher than the static one, as expected. Nevertheless, a precision of 2 meters for a moving device that drops to 0.97 when the device is static, can be satisfactory for most indoor position applications. The distance measure used for calculating the error was the two-dimensional Euclidean distance. Of course, in cases where map matching is used (as is the case in the NaviMod [Togneri and Deriaz, 2013] navigation module which functions on top of the positioning at the Virgilius project) all position estimates would be projected on the axis of the corridor, reducing the error only at its length-wise component, removing the width-wise component.

4.5.2 Extensive Tests

After the completion of the Virgilius project, the system has also been used and tested in other environments. Following, we present the performance analysis in two other deployments. The first deployment environment was an underground parking lot (parking 'La Riponne' in Lausanne), where common tests with the positioning company OnYourMap were performed. The second deployment was in the office environment of the company Origammi in Zurich, which was used in the context of the CTI project IDDASS.

In both these deployments, the evaluation methodology described extensively in the later chapters of this Thesis was used [Martinez de la Osa et al., 2016, Anagnostopoulos et al., 2016b]. This methodology allows us to offer complete statistical reports.

We proceed in presenting the results in both environments, comparing the performance of the weighted centroid approach with a classic trilateration approach, for different initial tunings of the propagation model. We do so to highlight the fact that even if under a well calibrated propagation model both weighted centroid and trilateration achieve a similar performance, in cases where the model does not reflect the reception characteristics of the devices used the weighted centroid shows impressive robustness and clearly outperforms the trilateration approach.

4.5.2.1 'La Riponne' Deployment

In the following tables (Table 4.2, 4.3 and 4.4), we present the performance of the two methodologies, under different tunings of the propagation model. Three devices were used for the tests: a Samsung Galaxy S4, a Samsung Galaxy S5, and a Samsung Note 3. To offer a complete evaluation, we present the 3 quartiles of error (Q1,Q2,Q3), corresponding to the 25th the 50th and the 75th percentile of error. Moreover, the mean error and its standard deviation are also reported. Values are reported for both positioning algorithms, the weighted centroid (WC) and the trilateration (Tr). In the tables, we color the statistics of the weighted centroid method to highlight when it achieves a better (green color) or worse (red color) performance than the trilateration method.

The results show that in the vast majority of cases, the weighted centroid method clearly outperforms trilateration. In Table 4.2, the default propagation model of the system (as calibrated in previous deployments) is used. For the default values of the propagation model, the weighted centroid shows a better performance than trilateration in the two out of three devices, in all metrics (except Q1 with the S5 device). In Table 4.3, which uses the theoretical value of the path loss exponent $n = 2$ for lossless propagation in indoor environments, the weighted centroid outperforms the trilateration in all metrics for all devices used. Lastly, in Table 4.4, an unsuitable propagation model is used, providing very erroneous distance estimates. This has a major effect on trilateration's performance, as the estimation error is significantly increased. On the other hand, the weighted centroid approach shows an impressive robustness, maintaining a performance similar to the previous tests.

The robustness of the weighted centroid method, which maintains a good performance under different conditions, is due to the notion of proportionality of the RSSI that it uses in contrast to the absolute values of the distance estimates (resulting from the RSSI) that the trilateration approach uses.

TABLE 4.2. PARKING LA RIPONNE ($p = -62.72, n = 2.28$)

		Q1	*Q2*	*Q3*	*mean*	*S.D.*
S4	WC	2.57	4.46	6.50	4.71	2.66
	Tr	2.41	4.36	6.29	4.66	2.73
S5	WC	2.28	3.70	5.54	4.16	2.36
	Tr	2.16	3.76	5.62	4.23	2.69
Note 3	WC	2.77	4.82	6.71	5.00	2.77
	Tr	3.13	5.09	6.91	5.25	2.89

Considering the improvement of the performance of the system, when using the smooth filtering step, the results are impressive. In Figure 4.6, we see the ground truth path that the tester followed during the tests. In Figure 4.7, we see the estimated trajectory given by the unfiltered output (left image), and the filtered one (right image). It is visually evident that the filtered trajectory is much smoother and pleasant for the

TABLE 4.3. PARKING LA RIPONNE ($p = -60, n = 2$)

		Q1	*Q2*	*Q3*	*mean*	*S.D.*
S4	WC	2.56	4.38	6.45	4.68	2.64
	Tr	2.83	4.72	7.02	5.09	2.86
S5	WC	2.37	3.83	5.53	4.19	2.39
	Tr	3.39	4.91	6.84	5.44	2.85
Note 3	WC	2.71	4.65	6.48	4.88	2.74
	Tr	2.92	4.82	6.60	5.05	2.85

TABLE 4.4. PARKING LA RIPONNE ($p = -57, n = 1.7$)

		Q1	*Q2*	*Q3*	*mean*	*S.D.*
S4	WC	2.42	4.21	6.39	4.52	2.48
	Tr	4.35	6.62	9.36	7.01	9.36
S5	WC	3.21	5.05	7.11	5.35	2.80
	Tr	4.60	6.82	9.52	7.34	3.80
Note 3	WC	2.67	4.38	5.97	4.55	2.51
	Tr	3.66	5.46	7.70	5.97	3.10

user, as it gives a clear and consistent view of the true trajectory. This visual feeling is verified by the statistical analysis of the estimation error, presented in Table 4.5.

Figure 4.6. The predefined path followed by a tester in the parking. The area where coverage is provided is the left half side of the parking, and its dimensions are 120 by 40 m.

Figure 4.7. The estimated trajectory given by the unfiltered output (left image), and the filtered one (right image)

In Table 4.5, the statistics of the estimation error with and without filtering step clearly depict the importance of the addition of the smooth filtering step. A new metric added in the evaluation for this case is the Traveled Distance Ratio (TDR), which is equal to the ratio of the length of the estimated trajectory over the length of the true path followed. This metric, introduced here [Martinez de la Osa et al., 2016], gives an estimation of how much the estimation 'jumps around' the true path and is intended to measure the user-friendliness of the resulting estimation. An ideal estimation would give a TDR value converging to 1. In the results, we observe that while the

TABLE 4.5. COMPARATIVE ANALYSIS OF THE EFFECT OF SMOOTH FILTERING IN LA RIPONNE

		Q1	*Q2*	*Q3*	*mean*	*S.D.*	*TDR*
S4	Filtered	2.57	4.46	6.50	4.71	2.66	1.52
	Unfiltered	3.10	5.52	8.18	5.88	3.43	2.94
S5	Filtered	2.28	3.70	5.54	4.16	2.36	1.44
	Unfiltered	2.94	4.78	7.17	5.34	3.21	2.97
Note 3	Filtered	2.77	4.82	6.71	5.00	2.77	1.45
	Unfiltered	3.59	5.83	7.89	6.09	3.51	3.15

filtered output achieves a TDR of ~ 1.5, the unfiltered one is approximately double (~ 3). Thus, the improvement for the user perception (measured by the TDR) seems to be even more significant than the improvement of the euclidean error (measured with all other metrics).

4.5.2.2 Origammi Offices Deployment

Extensive tests have also taken place at the office environment of the Origammi company, based in Zurich, in the context of the CTI project IDDASS. The tests were done with two predefined paths. The first one, depicted in Figure 4.8, was a short walk-through of the environment, where a tester traversed the main accessible areas of the office. The second test was an exhaustive, repetitive walking along all accessible paths of the environment. The results of these two recordings are presented in Table 4.6.

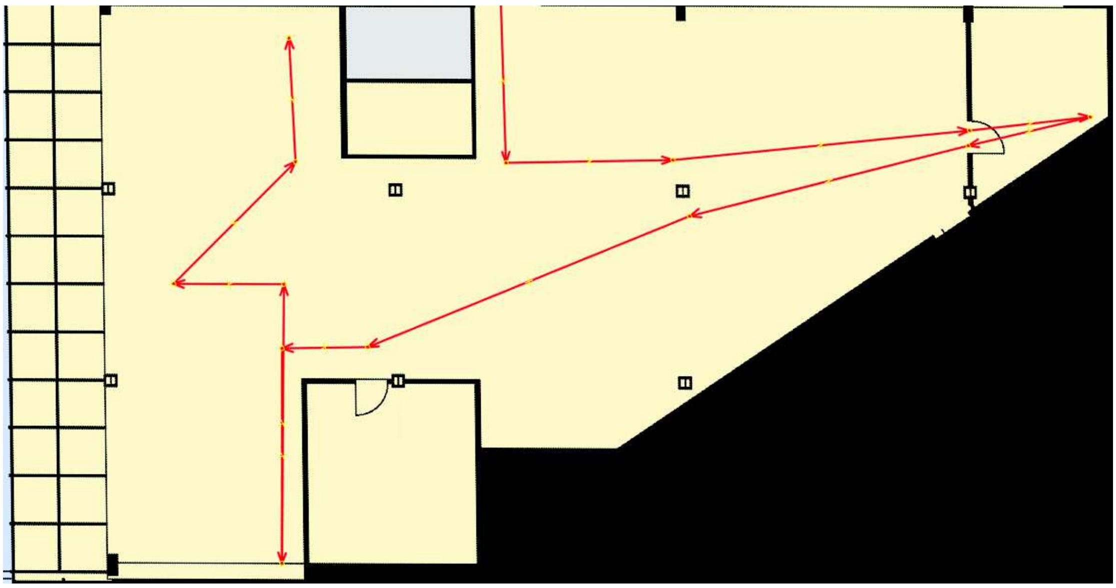


Figure 4.8. The predefined path followed by a tester in the offices of Origammi. The surface of this area is aproxximatly $450m^2$

The estimated trajectory of the short path, as calculated with and without filtering are depicted in Figures 4.10 and 4.9. From the following figures, it is visually evident that the filtering can significantly improve the visual perception of a user, regarding his trajectory. The statistics of the Euclidean error in Table 4.6 report an improvement of

TABLE 4.6. COMPARATIVE ANALYSIS OF THE EFFECT OF SMOOTH FILTERING IN ORIGAMMI

		Q1	*Q2*	*Q3*	*mean*	*S.D.*	*TDR*
Short path	Filtered	1.25	1.83	2.53	2.03	1.10	1.55
	Unfiltered	1.38	2.10	2.87	2.35	1.43	3.20
Long, repetitive path	Filtered	1.45	2.40	3.25	2.50	1.36	1.58
	Unfiltered	1.49	2.50	3.50	2.71	1.58	2.99

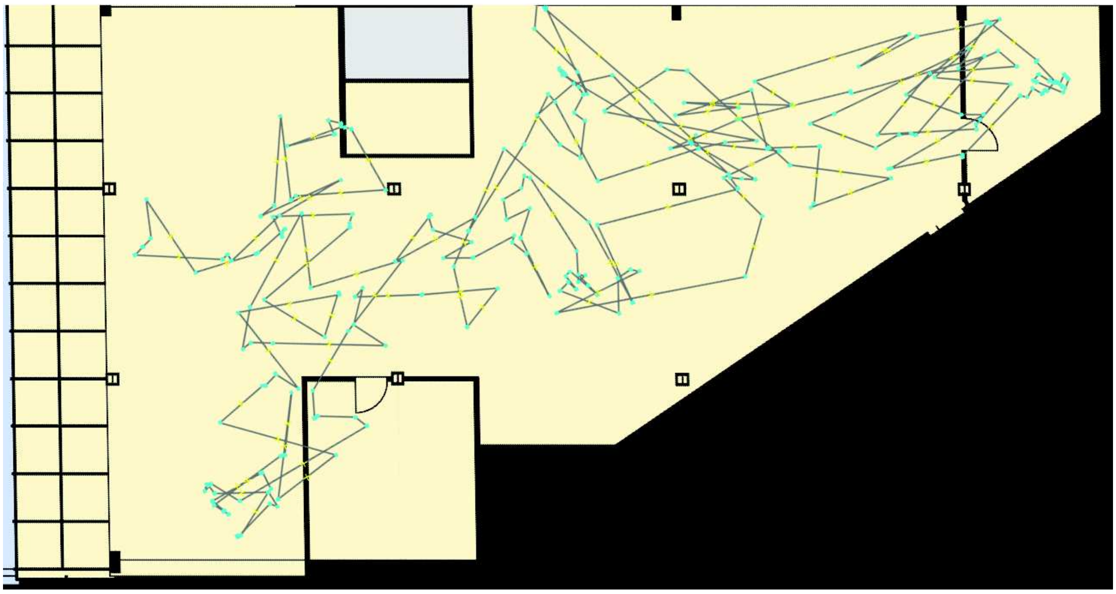


Figure 4.9. The estimated trajectory given by the unfiltered output.

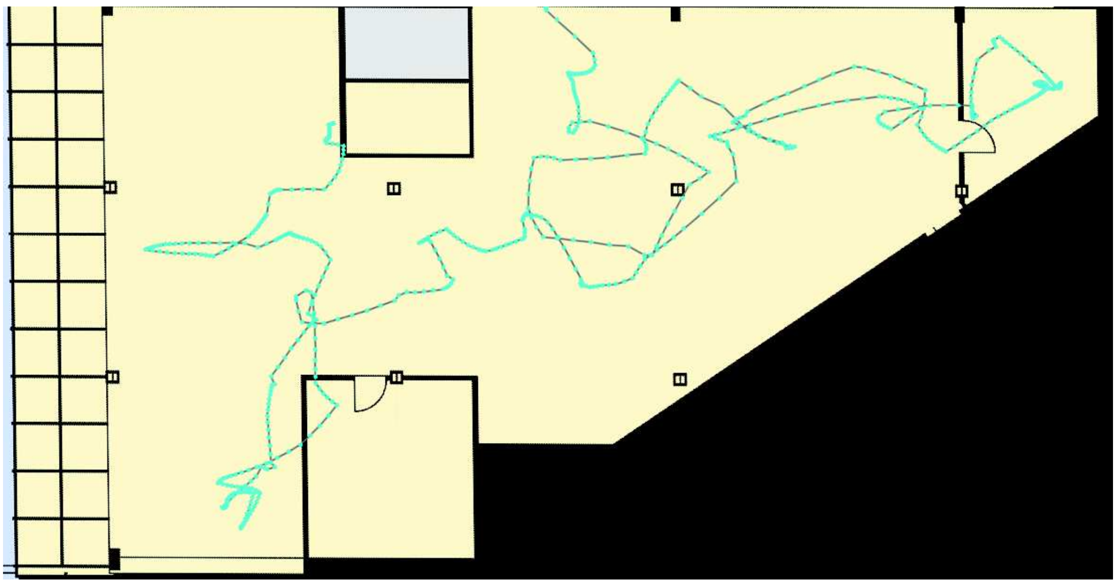


Figure 4.10. The estimated trajectory given by the filtered output.

the estimation error, on a scale of 20 – 30 cm. On the other hand, the TDR is reduced almost to its half, a fact that is visually verified in the previous figures.

4.6 End User Evaluation (Virgilius Project)

In the context of the evaluation of the Virgilius project, final users were involved throughout the progress of the project. The goal of the final user tests of the system was to test the user acceptance of the created mobile application and to evaluate the usefulness and the ease of use of the functionalities of the application. Totally, 31 elderly people participated in the final tests and in the evaluation of the mobile app that was the outcome of the Virgilius project. Most testers were in the age group 65-70 (67.7%), as seen in Table 4.7.

Table 4.7. Age distribution of the testers of the study (N=31)

Age	**%**
65-70	**67.7%**
71-75	**19.4%**
75+	**12.9%**

The users were asked to use the Virgilius app to be guided to their destination inside the hospital. In order to guide people in the hospital, two independent modules work in the background: the positioning module and the navigation module [Togneri and Deriaz, 2013]. Nevertheless, the function of two independent entities is transparent to the user since their estimated position appears on a map together with the direction instructions towards their destination. As this distinction is not intuitive (and not important) for the elderly final user, the evaluation concerns inevitably the positioning module (the system presented in this chapter) and the navigation module [Togneri and Deriaz, 2013] combined.

Initially, the users were asked about how 'user friendly' each of the features of the app was for them. In Table 4.9 we present the results for all the features related to our positioning/navigation system. We see that most users evaluate the system positively, as most of them managed to easily reach the final destination. This shows that the positioning/navigation part of the app is intuitive to use, even for elderly users. The only feature that seems to be less trivial than the rest is the creation and management of the route to the destination, which requires more actions by the users.

TABLE 4.8. EVALUATION OF EASE OF USE OF THE NAVIGATIONAL FEATURES OF THE VIRGILIUS APP.

Feature evaluation	Simple	Normal	Difficult
Navigation functionality	61.3%	35.5%	3.2%
Final destination reachability	67.7%	29.0%	3.2%
Route creation and management	54.4%	32.3%	12.9%

Following, the users were asked if they considered the features related to the positioning/navigation module to be useful. They almost unanimously agreed on the usefulness of the indoor positioning/navigation module as well as of the potential tracking option, where caregivers could be informed about the position of an elderly person in cases of emergency.

TABLE 4.9. EVALUATION OF THE USEFULNESS OF THE NAVIGATIONAL FEATURES OF THE VIRGILIUS APP.

Feature's usefulness	Useful	Indifferent
Indoor Navigation	96.8%	3.2%
Remote tracking by the caregivers	96.8%	3.2%

In the overall evaluation of the Virgilius app, 96.8% of the users found the app useful, 93.5% mentioned that they would use the app, while 87.1% considered the app to be easy to use.

4.7 Conclusions

A complete, robust and innovative indoor positioning system is presented in this chapter. The wireless technology used is BLE, which has low cost, and offers ease of deployment. It does not require the creation of a radio map nor a calibration stage, but simply the awareness of the positions where the beacons were deployed. The requirement of limiting the estimation error that was set by the navigation module in the context of the Virgilius project is fully satisfied as the system shows remarkable robustness compared with the commonly used trilateration approach. Thus, in cases of an uncalibrated propagation model, a new deployment or when using devices with significant differences in their reception characteristics, the weighed centroid proves to be more fault tolerant against poor distance estimates.

The system offers an accuracy that satisfies most use cases of LBS, indoors. For a moving user, the achieved accuracy is ~ 2m, which is considered the order of magnitude that the BLE technology is bound to. The mean error of a static device in a corridor is ~ 1m. These accuracy values certainly allow a user to be guided to a specific room, and in most cases, to be able to differentiate between two adjacent doors without even having to read the room label in the physical world. In big halls, the accuracy remains at the level of ~ 2m, allowing the users to orientate themselves properly. Similarly, a potential navigation system that utilizes the position estimates of the presented positioning system in order to guide users to their destination, can offer them a very pleasant user experience of navigation. The system is adaptable according to the use case. For instance, when installed at an underground parking lot, an accuracy of ~ 4m, which corresponds to the approximate size of a car, satisfies the use case for which the system is intended: to be guided from and to one's car. For use cases like this, a sparser mesh of beacons, compared to common in-building cases, can be deployed to achieve the desired accuracy in such a challenging environment.

5 Seamless Switching Between Indoor and Outdoor Position Technologies

5.1 Chapter Abstract

In which way may an application switch quickly and reliably between an indoor and an outdoor positioning technology as a user enters and exits buildings? In this work, we present a robust switching algorithm, utilizing the dynamic accuracy estimation of each position provider as a reliability indication. Contrary to related works, we do not aim to solve the indoor/outdoor detection problem using individual sensors as estimators, but we relatively compare the reliability of each available position provider. In this way, we ensure the selection of the most reliable technology at all times. The focus of the proposed algorithm has been on the robustness of the switching, aiming to minimizing the 'jumping' effect of unstably wobbling between technologies, while maintaining a fast switching. Avoiding these instabilities is indispensable firstly for the pleasantness of the user experience but also for the stability and the correct functioning of a potential navigation module using the position estimates produced.

Our algorithm offers a fast, robust, automatic switching between indoor and outdoor providers, which occurs in a transparent way for the user. We demonstrate an implementation of the proposed algorithm and present experimental results, using GPS outdoors and a Bluetooth provider indoors. In the context of our

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implementation, we present an intuitive heuristic estimator of the claimed accuracy of the BLE position provider. The proposed switching technique has been extensively tested in our lab and was afterwards installed at the Hospital of Perugia (Italy), in the context of the Ambient Assisted Living (AAL) Virgilius project. Using the proposed method, users could navigate with a smartphone, and be guided from their location outdoors, to their destination in the hospital.

5.2 Introduction and Related Work

Indoor positioning is a topic that has gained great attention over the last years. Numerous mobile applications are utilising the location of the user. Outdoors positioning has been ahead, with GPS (Global Positioning System) being the dominant technology of the field. On the other hand, no universal standard has dominated the field of indoor positioning, where a substantial variety of alternatives has been proposed.

A technology which has been widely used during the last years is the Bluetooth Low Energy (BLE) technology. It has low energy consumption, while maintaining a communication range similar to that of its predecessor, Classic Bluetooth. Several manufacturers produce Bluetooth beacons that can be used for location applications among their other utilities. Bluetooth beacons function with batteries and are small in size, thus they offer flexibility in the way they can be deployed in a building. Each beacon broadcasts a self-contained packet of data periodically. The packets contain an identifier of each beacon so that the receiver can distinguish them. The Received Signal Strength Indicator (RSSI) can be used to estimate the distance between the mobile device and the transmitting beacon [Vanheel et al., 2011] [Papamanthou et al., 2008] [Saxena et al., 2008]. Due to their low cost and low consumption a dense network can be deployed. Having a dense deployment can lead to reliable distance estimations from, at least, the closest beacons.

An important challenge for applications that need to offer positioning globally, both indoors and outdoors, is to have an efficient mechanism of switching between positioning technologies. An example scenario can be the task to navigate a user to a hospital with GPS, and automatically switch to BLE when the user enters the building in order to guide him to the specific room he wishes to go to, as in the Virgilius project. Another scenario may be to navigate users in University campuses or conference centres, where both indoor and outdoor positioning is required. In these scenarios, the outcome of the positioning module may be used to feed a navigation module, whose results rely on the accuracy and the responsiveness of the position estimations, regardless of the changes of environment (indoors/outdoors). Moreover, localizing a user accurately can assist other modules, such as the object localization module [Ionescu et al., 2014] created in the context of the of EDLAH project. The goal of this module is to assist older persons to locate an object that they might have lost such as keys or glasses, in their house. A BLE beacon is attached to these objects, from which the distance to the user can be inferred, as described in [Ionescu et al., 2014]. As users move inside their house or in their yard, their estimated positions and the estimated distance from the beacons are used to infer the location of the lost object.

Lately, several studies [Wang et al., 2012] [Ravindranath et al., 2011] [Saengwongwanich et al., 2014] [Radu et al., 2014] [Zhou et al., 2012] [Lipowezky and Vol, 2010] have focused on the $Indoor/Outdoor$ (IO) $detection$ problem. This problem is studied not only specifically to select the most appropriate technology for positioning but also to serve in a broader domain of context-aware applications. One of the existing techniques for IO detection is to use GPS and its drop in confidence or inability to obtain a fix in order to conclude that the user is indoors, as in [Wang et al., 2012] [Ravindranath et al., 2011].

The use of GPS quality has also been used for a positioning provider switching study [Saengwongwanich et al., 2014]. In their work, Saengwongwanich et al. [Saengwongwanich et al., 2014], present an indoor/outdoor switching methodology which utilizes the fact that receptions of at least four GPS satellites are needed in order to calculate the user's position in three dimensions. The algorithm uses the GPS position estimations when 4 or more satellites are visible, whereas the indoor provider (WiFi in their work) is trusted otherwise.

Another method is to use the light sensor of the mobile device (as in [Radu et al., 2014], [Zhou et al., 2012]) alongside other signals such as the cell signal and magnetic intensity and utilize the difference in luminosity of indoor and outdoor environments, for IO detection. Lastly, IO detection utilizing embedded digital cameras in mobile phones and image processing techniques has also been proposed [Lipowezky and Vol, 2010].

The rest of this work is organized as follows. In Section 5.3, we briefly present the indoor positioning method that was used for the experimental part of this work. In Section 5.4, we present the idea of the proposed switching algorithm. Measurements and experimental results are reported and discussed in Section 5.5. Finally, conclusions drawn are presented in Section 5.6.

5.3 Indoor Positioning Method

The switching logic that is presented in this work (and detailed in a following chapter) is generic, and technology independent. Nevertheless, for the testing implementation and the measurements of this study, the BLE technology, and more specifically, the algorithm presented in [Anagnostopoulos and Deriaz, 2014] is utilized as an indoor positioning provider. Also, GPS technology is used as the outdoor positioning provider. Following, we briefly present the indoor positioning provider that is used.

For the indoor BLE provider, Bluetooth beacons are used. Each beacon periodically transmits a packet containing its identity. The mobile device that is to be localized receives these packets from the beacons in range. From the RSSI received from each beacon a distance estimation can be inferred.

Having obtained an estimation of the distance of the mobile device from each beacon, we proceed to the position estimation. From the list of beacons that are detected, only a set of the closest beacons are used for the calculation. In [Anagnostopoulos and Deriaz, 2014], it is shown that keeping the four closest beacons minimizes the estimation error.

Assuming that the mobile device is inside the coverage area (inside the outer polygon defined by the beacons' placement), the estimated position will also be inside the quadrilateral defined by the four closest beacons. Let $[e_1, e_2, e_3, e_4]$ be the estimated distances from the 4 closest beacons, while $[lat_1, lat_2, lat_3, lat_4]$ and $[lon_1, lon_2, lon_3, lon_4]$, the corresponding latitude and longitude of their positions. The latitude Lat_{est} and longitude Lon_{est} of the estimated position are calculated as follows:

$$Lat_{est} = \frac{\sum_{i=1}^{4} \frac{lat_i}{e_i}}{\sum_{i=1}^{4} \frac{1}{e_i}}, \; Lon_{est} = \frac{\sum_{i=1}^{4} \frac{lon_i}{e_i}}{\sum_{i=1}^{4} \frac{1}{e_i}} \tag{5.1}$$

The inverse value of the distance estimation from each beacon is used as a weight in order to perform a weighted average of the positions of the closest beacons, which will give the estimated position. In order to have a more reliable distance estimation, we average the latest estimated distances from each beacon. In this way, we partially cope with the instability of the RSSI.

The position prediction is limited to the area that is defined by the polygon that the beacons' positions define. Thus, it is indispensable for this positioning algorithm that beacons be placed in such a way as to surround all the area that is required to be covered. For the deployment of this study and in order to record the experimental results that are later presented, common areas of the building of Centre Universitaire d'Informatique of the University of Geneva were used. A zigzag pattern was used to place the beacons in corridors and big halls. The same logic was used at the deployment of the Hospital in Perugia.

5.4 Switching Methodology

The algorithm proposed in this study is intended to be used with any indoor or outdoor provider. The experimental implementation for this study uses GPS as an outdoor provider and Bluetooth as the indoor one, since these were the technologies selected for the final deployment at the Hospital of Perugia. It is noteworthy that the same logic may support a multi-provider approach. Thus, the logic may support cases where several indoor areas use different indoor technologies (BLE, WiFi, etc.), or if it is desired not to restrict the outdoor provider to GPS, but also use others, such as the Cell-ID. Nevertheless, in our implementation a single provider was used for each environment (indoors and outdoors).

The crucial parameter of the switching algorithm is the dynamic accuracy estimation that each provider should offer. This claimed accuracy of each provider is utilised in order to compare the providers' reliability. The position estimations from the GPS provider contain an estimation of the accuracy, which can be used as the level of confidence of this estimation. On the other hand, in the following subsection the dynamic accuracy estimation concerning the indoor provider used is discussed before proceeding to the detailed presentation of the algorithmic logic of switching.

5.4.1 Dynamic Accuracy Estimation

The field of calculating a dynamic accuracy estimation for indoor positioning techniques is very challenging. Studies using probabilistic fingerprinting [Kontkanen et al., 2004] have proposed the utilization of the variance-covariance matrix to infer an 'uncertainty eclipse'. The authors of that study mention that drawing an ellipse centered at the expected location so that the orientation and size of the ellipse describes the uncertainty of the location estimate as well as possible. Although the

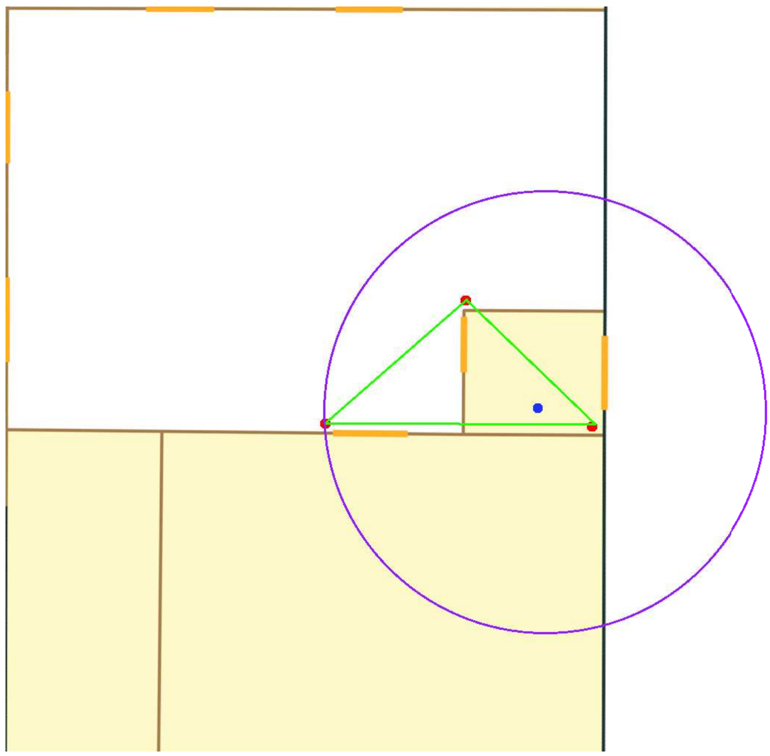

Figure 5.1. Position of the user (in blue) inside the beacon area (in green), and accuracy circle (in purple), as infered from the estimated distance from the 3 closest beacons (in red)

purpose of the ellipse is to visualize the uncertainty, a unique metric expressing this uncertainty can be extracted by the linear combination of the two axes of the ellipse.

There have been studies [Lin et al., 2010] [LaMarca et al., 2005] that use an observed correlation between the positioning error and the number of visible access points in order to provide dynamically an estimation about the certainty of the estimated position. Nevertheless, these approaches do not refer to a dense indoor deployment, such as the indoor provider used in the experimental part of this study, but refer to public WiFi access points that can provide a rough position estimation (indoors or outdoors) with a precision of a few tens of meters. Thus, to have a more representative dynamic accuracy estimation, a heuristic method is used, which is presented below.

A heuristic method was used to estimate the certainty about a position estimation, for the Bluetooth positioning method proposed in [Anagnostopoulos and Deriaz, 2014]. As described in [Anagnostopoulos and Deriaz, 2014], the beacons are deployed in a

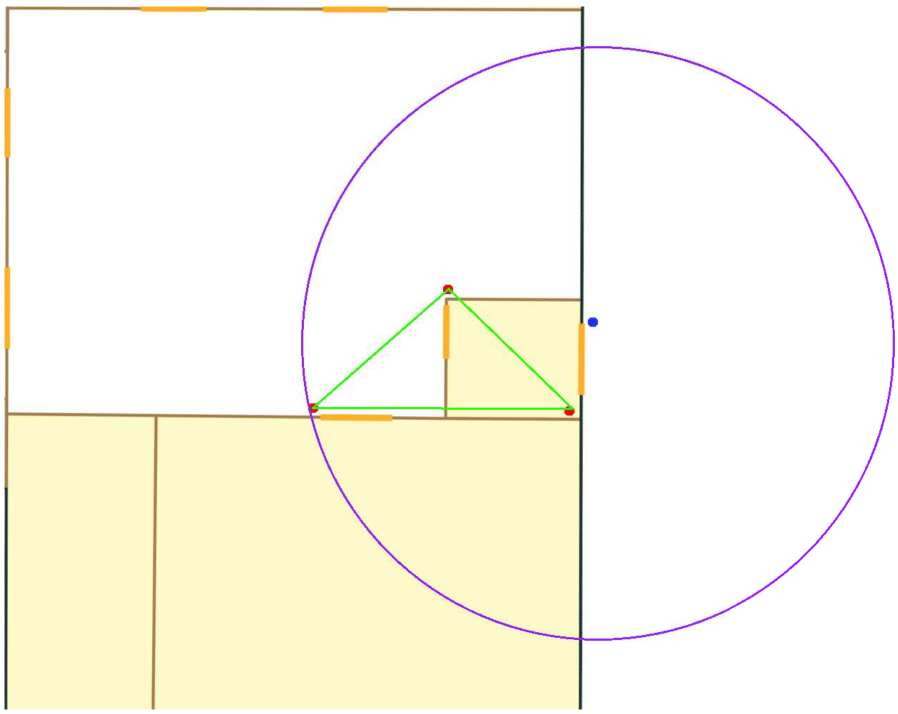

Figure 5.2. Position of the user (in blue) outside the beacon area (in green), and accuracy circle (in purple), as infered from the estimated distance from the 3 closest beacons (in red)

zigzag pattern. We chose the distance estimation from the third closest beacon to be the value of the claimed accuracy of the estimated position. A user that moves inside the area that the beacons define will be inside the triangle that the three closest beacons define (assuming a correct ordering of the beacons based on the RSSI). A circle having as center the estimated position and as radius the distance to the third beacon will include the triangle of the three closest beacons, as in Figure 5.1. When the user goes outside the area that the beacons define, as in Figure 5.2, the distance estimation from the third beacon will give a rough approximation of how far the user is from the beacon area. Even when the user exits the building, thus the beacons' area the position estimations remain inside this area, since the way the positions are estimated is by averaging the positions of beacons. Nevertheless, the estimations of the distance from each beacon will get high values, and thus, the claimed accuracy (distance from the third closest beacon) will indicate the poor quality of the estimation as the user moves away from the beacon area.

5.4.2 Behaviour of Indoor and Outdoor Providers and Switching Requirements

The dynamic accuracy estimation of the indoor positioning provider, as introduced with a heuristic estimation in the above subsection, is needed in this work in order to have a measure of comparison against the accuracy estimation of the outdoor positioning provider (GPS in the tests of this study). The accuracy of GPS takes small values (meaning that the accuracy is good) in open spaces outdoors, while it has really big values inside buildings. Using the distance estimation from a beacon (the third closest in our case), we get the inverse behaviour, that is having small values when the users move indoors among the beacons and big values as they leave the building. These measures form indications about being indoors or outdoors. The crucial step is the creation of a robust algorithm that switches quickly and reliably from one provider to the other requirements.

It is worth mentioning at this point some challenges of the task of switching. Initially, it is worth investigating the behaviour of the position estimations and of the dynamic accuracy estimation at the border regions of indoor/outdoor areas. In order to be able to exemplify this, we mention in the following example BLE as the indoor provider and GPS as the outdoor one.

When a user moves outdoors, towards the entrance of a building, the GPS accuracy may start degrading and the user may start receiving Bluetooth signal receptions. In cases like this, if the positioning application receives position estimations from both providers, and simply returns to the user the one with the best claimed accuracy, the result may be a totally inconsistent series of positions. This happens because the most reliable provider (according to its claimed accuracy) can change continuously between Bluetooth and GPS, in these border regions. A continuous switching, back and forth, between providers can significantly deteriorate the user experience and all functionalities that might be related with the location estimation. For example, a recalculation of the trip in a navigation module may be triggered continuously if the provider selection is unstable and the position estimates 'jumps in and out' of the building. On the other hand, it is desirable that the switch occurs quickly, yet still reliably. With this view, we now present the switching algorithm.

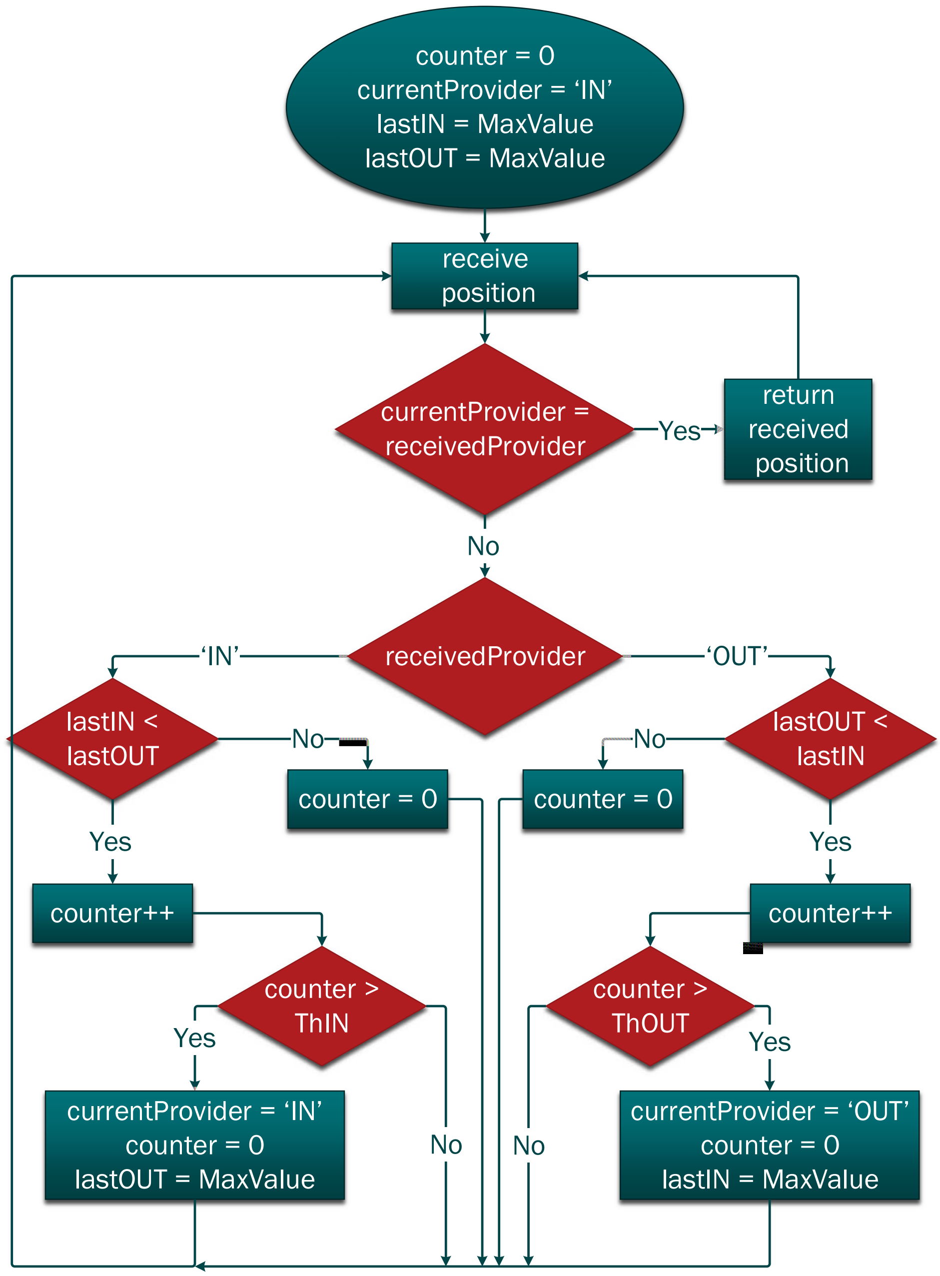

Figure 5.3. Flow chart of switching algorithm

5.4.3 Switching Algorithm

In this subsection, the switching algorithmic logic is presented with the assistance of the flow chart of Figure 5.3. We assume that position estimates from both indoor and outdoor positioning providers are available to the application. The algorithm uses the flag $currentProvider$, which stores the provider that is trusted at each moment. Without loss of generality, we present a generic solution for two providers. Let IN and OUT be these two providers, which implies that the $currentProvider$ may receive these two values. Moreover, the application stores the accuracies of the last position received from each provider namely $lastIN$ and $lastOUT$ (an implied action in Figure 5.3). At each new position estimation received from the current provider, the position is returned to the application. When the received position estimation is not from the current provider, the last accuracies of each provider ($lastIN$ and $lastOUT$) are compared. If the current provider's accuracy is worse than the accuracy of the other provider, then a $counter$ is incremented by one, otherwise the $counter$ is set to zero. When the counter reaches a threshold value, the $currentProvider$ changes value, from IN to OUT or inversely. The counter reaching a threshold signifies that several consecutive position estimates of the $currentProvider$ were less reliable than those given by the other provider. Requesting a number of good receptions greater than a threshold guarantees that the new provider is reliably better than the previous one. If there are not several consecutive good readings but sporadically a few, the $currentProvider$ remains unchanged.

The specific values of the thresholds used should be appropriately tuned according to several factors. Firstly, the frequency that position estimations are given from the indoor provider is an important factor. Commenting on our experimental experience, we note that the indoor Bluetooth provider returns one position approximately every one second. This frequency is similar to the frequency with which positions are normally obtained by GPS. Furthermore, the density of the deployment and the range of the beacons influence the threshold selection. Lastly, there is a trade-off in selecting the threshold values, between the level of certainty with which a switch should be triggered and how quickly a switch should occur.

Apart from the main algorithmic logic presented in the flow chart (Figure 5.3), more details should be carefully examined. The algorithm should not stay blocked to a provider at any point. For example, consider a scenario $IN = BLE$ and $OUT = GPS$, in which a user exits a building having BLE as $currentProvider$. Assume that the accuracy of GPS position estimations that it receives outdoors is consistently bad (due to environmental conditions). In this case, if the last Bluetooth position estimation received has a better claimed accuracy than what GPS can achieve under these circumstances, $currentProvider$ will stay blocked to BLE, and no position estimate will be returned to the application from that point on. To avoid this deadlock, we propose an additional mechanism that checks the number of consecutive position estimations that are not provided by the current provider, and that changes the $currentProvider$ when these consecutive receptions exceed a threshold.

As mentioned before, in cases where the two providers have distinct frequencies of providing position estimations, the threshold values of the described algorithm as well as the threshold of consecutive position estimations from a provider of the above mentioned additional mechanism, should be carefully tuned.

5.5 Measurements

The switching algorithm was tested in the building of the Centre Universitaire d'Informatique of the University of Geneva. Initially, in Figure 5.4, we present an example of the way the claimed accuracy of the two providers changes as a user moves, exiting from a building. As the user starts indoors, s/he moves close to the beacons and thus we observe that the estimated accuracy of the Bluetooth provider gets low values (good accuracy). As the user approaches the exit of the building, s/he starts receiving some GPS readings that have poor accuracy. At the border regions of indoor/outdoor areas, the accuracy may fluctuate until the user distances him/herself from the building. When the user passes to the outdoor area (after the red dashed line), the GPS accuracy improves and, at the same time, the accuracy of Bluetooth degrades. We observe that it takes a few seconds to receive a number of reliable readings (equal to the set threshold) from the new provider before the $currentProvider$ changes (brown dashed line). This time depends on the threshold of new reliable readings that has been set. This threshold tunes the trade-off between the delay of switching and the robustness of switching. The generic comparison of different settings of threshold values is out of the scope of this study, as it depends on many factors, such as the technologies used, the environment and the preferences of the user over the trade-off previously mentioned.

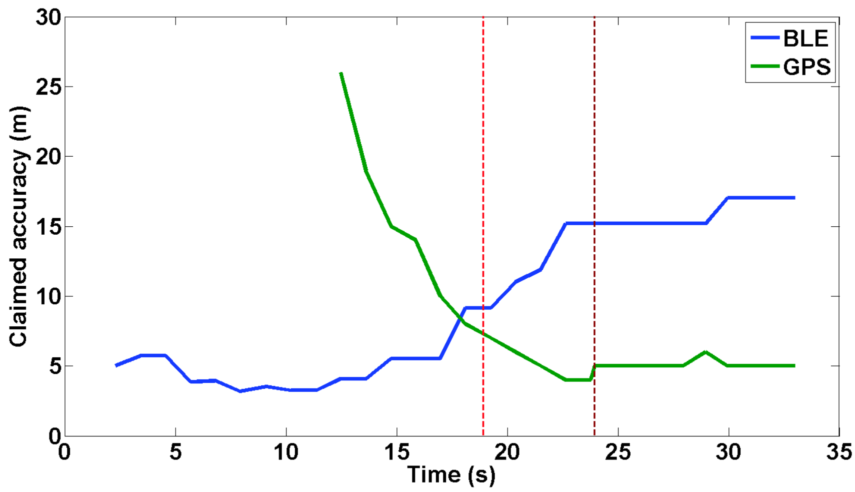

Figure 5.4. Claimed accuracies of Bluetooth (blue line) and GPS (green line), during a movement from indoor to outdoor environment. The dashed lines indicate the moment that the user went outdoors (red dashed line), and the moment the provider switched (brown dashed line).

In Figure 5.5, we present the position estimates that an application will receive, using the proposed algorithm. The grey segments represent the true trajectory of the user. From checkpoints 1 to 3, the user moves inside the building. From checkpoints 3 to 5, the user is outside the building, but under a rain shelter highlighted in light purple. In accordance with the related bibliography [Radu et al., 2014] [Zhou et al., 2012], we refer to this segment of the path as semi-outdoor part. The fact that in semi-outdoor environments the area above the user is covered, significantly degrades the position estimations given by GPS, and consequently, its claimed accuracy. For this reason, when we make a binary distinction (indoors/outdoors) in this work, we will only include the truly open spaces as outdoor environments, and not the covered areas (semi-outdoor). As a consequence, we only consider the path from checkpoints 5 to 7 to be outdoors.

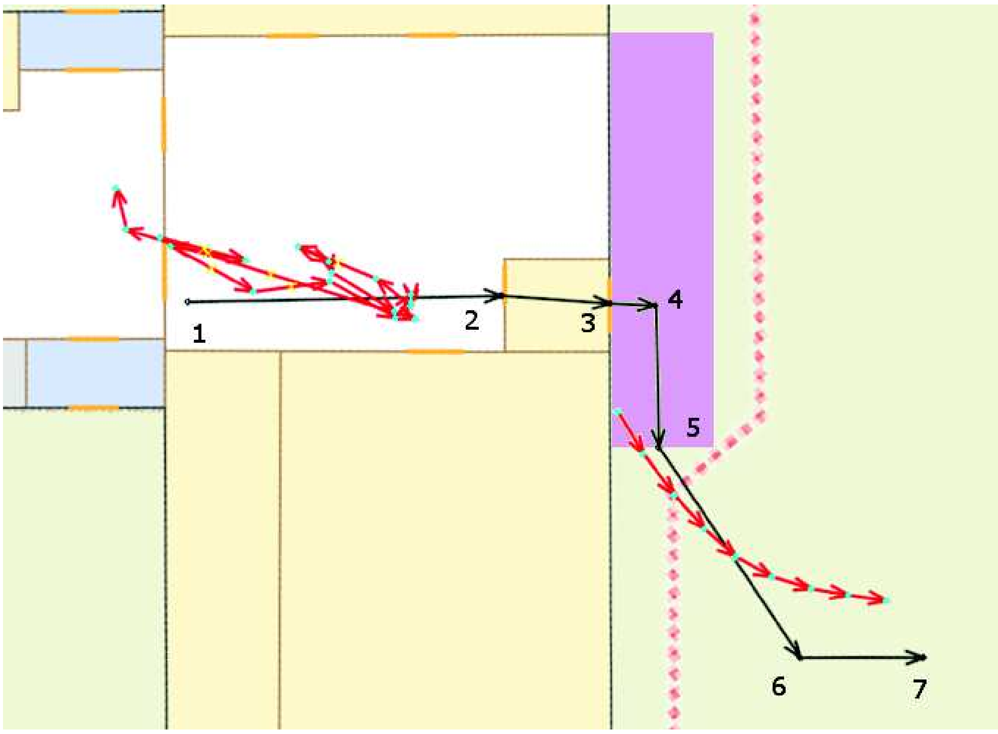

Figure 5.5. Estimated positions using the switching algorithm, are shown in red (indoors and outdoors). The true trajectory of the user appears in grey.

With the trajectories in red color, we see the estimated positions that the user receives using the automatic switching. Initially, when the user is indoors, the Bluetooth provider gives position estimates that suggest a trajectory towards the exit of the building. When the user moves into the semi-outdoor area that is not equipped with beacons, the estimated positions remain inside the building. This happens because the Bluetooth provider gives position estimates only inside the area where beacons are deployed. When the user passes checkpoint 5, GPS estimations start becoming much more accurate. At the same time, as the user distances him/herself from the beacons of the building, the claimed accuracy of Bluetooth worsens. The moment that the automatic switching occurs, indicating GPS as the *currentProvider*, the position estimations of GPS are provided to the user, as seen by the red trajectory at the outdoor part.

The distance from checkpoint 1 to 7 (outwards) and from 7 to 1 (inwards) was covered 10 times in order to report an average behaviour. In Table 5.1, the delay with which the switching occurs is reported. For the outward trip, we report the mean difference in time between the moment the user passes from checkpoint 5 and the moment that the *currentProvider* changes, as well as the standard deviation. Similarly, we provide the same statistics for the inward trip, measuring on this occasion the time difference not only regarding passing checkpoint 5 (entering the semi-outdoor area), but also passing checkpoint 3 (entering the building), since this is when the user enters the beacons' area. It should be mentioned that the algorithm's threshold of requested consecutive good readings was set to 5. In our test, the correct switch always occurs and has a very low delay. Considering that 5 good readings are requested, and that the Bluetooth provider has an update frequency of one second, we see in the values of Table 5.1 that the switching is very responsive.

Table 5.1. Delay of provider switching

	Mean switch delay (s)	*σ of delay (s)*
Outwards	6.72	2.1
Inwards (checkpoint 5)	9.04	0.95
Inwards (checkpoint 3)	3.43	1.05

To offer a better understanding of the behaviour of the claimed accuracies and of the challenges of the proposed switching algorithm, we conducted the following experiment of a border case scenario. A user moved from checkpoint 1 to checkpoint 5 (referring to the checkpoints, as they appear in Figure 5.5), and then stayed at checkpoint 5, which is the limit of indoor/outdoor areas, for 10 minutes. The measurements were taken at the premises of the University of Geneva, during the lunch break time, with crowds of people passing by, influencing the receptions as in a real life scenario. In Figure 5.6, we can observe the fluctuation of the claimed accuracies of the two providers through time. In green, we see the GPS accuracy. The

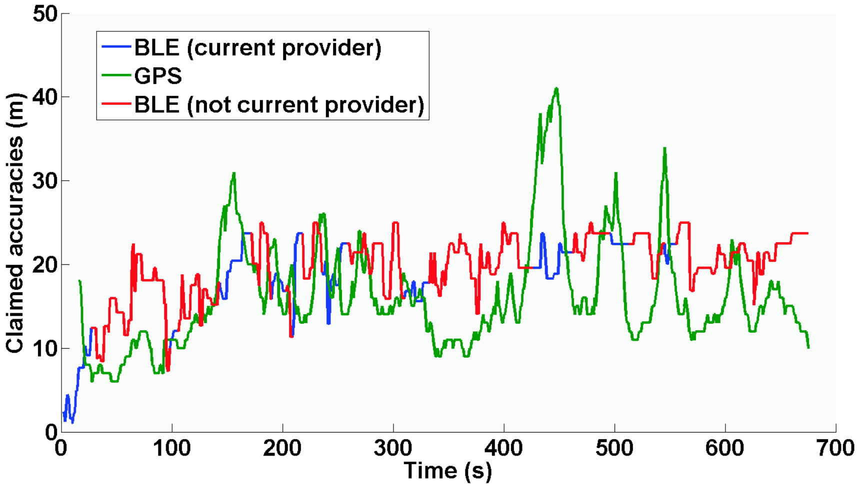

Figure 5.6. Claimed accuracies of GPS (green line) and BLE (blue when BLE is the current provider, red otherwise), received at the limit of indoor/outdoor areas.

accuracy of Bluetooth appears in blue when Bluetooth is the *currentProvider*, and in red otherwise. It can be easily observed that the claimed accuracies of the providers significantly fluctuate at the limit of indoor/outdoor areas. During this experiment, the *currentProvider* changed 19 times. We see that instant jumps from one provider to the other are avoided, and the median time of staying at the same provider is 20 seconds. On the other hand, if only the latest claimed accuracy were used, the *currentProvider* would have changed 40 times, and it would often switch back and forth between the two providers, at consecutive seconds.

5.6 Conclusions

A simple and effective algorithm for automatic switching between indoor and outdoor positioning providers was presented. The algorithm can be tuned according to the properties of the technologies used and the requirements of the application. The experimental results highlight the robustness of the switching logic and its impressive response speed. The fact that the algorithm does not allow the position estimates to unstably wobble between indoor and outdoor technologies‘ offers the necessary stability required. This stability is indispensable not only for a pleasant user perception, but also for the correct functioning of a navigation module using these position estimates.

For battery saving reasons, geofencing can be used to activate and deactivate providers. For example, when a user is outdoors, the BLE could be inactive until the user enters an area around the building that supports a BLE positioning provider. Thus, it is only next to the building that both providers will be active. In this way, the proposed responsive automatic switch occurs when the user actually enters the building, and also, battery life is increased as both providers stay active only in areas where a switch may occur.

The current study works as a solid base for the rest of the research modules of the two European projects, EDLAH and Virgilius. The robustness and responsiveness of the selection of the most appropriate provider improves the quality of position estimates that are fed to the object localisation module of EDLAH. Furthermore, a fast and automatic switching between indoor and outdoor providers facilitates the goal of Virgilius towards a continuous user-friendly navigation, in any environment.

6 Online Self-Calibration of the Propagation Model for Indoor Positioning Ranging Methods

6.1 Chapter Abstract

A common problem for indoor positioning methods is the fact that the differences in the reception characteristics among devices or the different characteristics of the environments in which a positioning system can be deployed may significantly deteriorate the performance of a positioning system. Ranging algorithms for positioning rely on the accuracy of the parameters of the propagation model. This model is used to infer an estimate of the distance of a mobile device from each access point with the use of the Received Signal Strength Indicator (RSSI). In this study, we propose an algorithm which dynamically recalculates the propagation model, as the system is being used. The improvement of the model parameters fits the environment's characteristics and, more importantly, the reception characteristics of the device used. The proposed algorithm is tested with different devices at an indoor deployment covering a large area where Bluetooth Low Energy (BLE) technology is used. The experimental results show that the proposed method offers a significant accuracy improvement to less properly tuned devices while it slightly improves the performance of those that are more properly tuned.

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6.2 Introduction

One of the most common techniques in the field of indoor positioning is the utilization of the Received Signal Strength (RSS). One popular RSS approach is the RSS fingerprinting which requires an off-line phase in which a radiomap of the localization area needs to be created. During this procedure, a reference device is used to record fingerprints of specific locations. The fingerprint of a location is the set of RSS receptions from each access point at said location. In the online phase, the new receptions from all access points are compared with the recorded one, called fingerprints. An estimated position is inferred based on a similarity measure between the receptions at a certain time, and the recorded fingerprints.

Another way of utilizing the RSS is by inferring a distance estimate. Having a distance estimate from each access point, a position estimate can be calculated, with the use of ranging methods like multilateration [Mazuelas et al., 2009] or weighted centroid [Anagnostopoulos and Deriaz, 2014]. The knowledge of the exact location of the access points is needed for these methods, along with a propagation model which allows corresponding RSS values to distance estimates. An advantage of these methods is that they do not require an off-line surveying phase, which can be very time consuming. Another advantage is that a potential displacement of an AP or the addition of new ones, only brings the obligation of adding the new APs' positions in the list of known APs, whereas in RSS fingerprinting such a change would require the repetition of the off-line phase.

A common problem for both fingerprinting and ranging methods that rely on signal strength is that they suffer from fluctuations of RSS receptions. Fingerprinting techniques commonly use a reference device to record the fingerprints. The fact that these fingerprints will be used by other devices, with different reception characteristics, may lead to a degradation of the performance of the positioning accuracy on those devices. Moreover, ranging methods use a propagation model whose parameters rely on many factors such as the environment and the devices used. Subsequently, a specific setting of the propagation model's parameters may be adequate for a reference device with which the positioning system is tested but it may also be faulty for another device with different reception characteristics.

In this chapter, we present a novel approach to recalculating on-line the propagation model parameters, in ranging positioning methods. With the proposed method, a device, whose reception characteristics may differ from the ones used to create the propagation model, uses the initial range estimates along with the position estimates to gradually correct the propagation model. The experimental testing of the method is very promising, since an accuracy improvement above 13% was achieved with a mobile device that is different from the one used for the creation of the propagation model. It is noteworthy that not only were several mobile devices used for the tests, but also the beacons used at the test environment were different from those that were used for the initial calculation of the propagation model's parameters, which took place at a different environment. The performance of the mobile device used to create the propagation model also showed slight improvements. The presented method contributes to the recurrent research with the goal of device independence in indoor positioning systems. It also makes it possible to omit the propagation model calculation when a system is deployed in a new environment, with a different kind of beacon.

The rest of this chapter is organized as follows. After commenting on the related work in Section 6.3, and introducing some preliminaries in Section 6.4, in Section 6.5 the proposed method is extensively presented. In Section 6.6, we analyse and discuss the results of the experimental measurements from a real deployment. Lastly, drawn conclusions along with future directions are discussed in Section 6.7.

6.3 Related Work

During recent years, research towards propagation model correction and device independence for indoor positioning techniques has blossomed. Many studies have focused on this goal for both surveying (fingerprinting) and ranging positioning techniques.

An early work in this domain by Mazuelas et al. [Mazuelas et al., 2009] tunes the path loss exponent parameter of the propagation model characterizing each AP on a wireless local area network (WLAN). The motivation of that work is mainly directed towards eliminating the necessity of the propagation model calibration step and not device independence per se. The tuning is done by finding the set of path loss exponent values that solve a least square optimization problem concerning the distance of the estimated position from the radical axes of the range estimates. The proposed solution is elegant and appealing, though quite complex, and relies on an assumption that parameter p (received RSS at a reference distance) can be considered a constant, which is a rather optimistic assumption when working with several devices.

In another study [Balata et al., 2013], the authors adjust the propagation model by utilizing contextual knowledge of where the walls are in a building in order to properly tune the model's parameters of each AP. They do so by introducing an attenuation factor for every wall between said AP and the estimated position, which requires a procedure of defining the areas where walls exist and estimate the level of attenuation that the walls introduce. This approach requires the contextual information of the room in which the user is located to be known, either by another system or by the positioning system itself without the use of the wall attenuation factor. Also, the task of estimating the attenuation of each wall and the precise reporting of the walls' locations on a map is a tedious task that is also required. Recent studies [Xu et al., 2014], [Gholami et al., 2013], tackle the problem of RSS-based localization when the channel parameters are considered unknown, providing however only simulations and no experimental results. An advantage of the second work [Gholami et al., 2013] is that it describes algorithms that deal with determining three problems: defining the path loss exponent n, the transmit power at the reference distance p, or both said parameters.

In fingerprinting techniques, the recorded RSS values at known positions are usually taken with a single reference device. As other devices will report different RSS values at the same positions, due to different reception characteristics (apart from the random noise), a calibration that attains a good mapping between the reference and the user device is needed. Extensive literature exists dealing with the impact of device diversity on fingerprint positioning techniques.

Inspiring solutions have been proposed by these studies, including among others, signal strength histogram equalization [Laoudias et al., 2012], [Laoudias et al., 2013a], spatial mean normalization [Wang et al., 2013], signal strength ratio utilization [Kjærgaard, 2011], differential fingerprinting [Laoudias et al., 2014], fusing of crowd-sourced RSS data into usable radiomaps of differential fingerprints [Laoudias et al., 2013b], and ranking of RSS values from a set of APs from high to low [Machaj et al., 2011], since ranking is device independent.

At a sequence of two interesting works [Laoudias et al., 2012], [Laoudias et al., 2013a], the authors utilize the histograms of the RSS receptions of the user device, and those of the fingerprints, in order to map their relation. The histogram of the RSS receptions of the fingerprints taken with the reference device are available at each user device, which is meant to use them for the positioning system. When a user enters a building, the device uses the received RSSIs, comparing them to the fingerprints taken by the reference device, to infer position estimates. At the same time, the observed RSS values are recorded simultaneously in the background to create and update the histogram of the user's device. The proposed method attempts to fit the RSS histogram of the user's device to the one of the reference device, with a linear mapping between the two.

The idea of shifting the fingerprinting method from comparing absolute RSS values to a relative approach is often met in the literature. For instance, M. Kjærgaard proposed an aproach of hyperbolic location fingerprinting, which records fingerprints as signal strength ratios between pairs of base stations instead of absolute signal strength values. [Kjærgaard, 2011]. In the same vein, a spatial mean normalization aproach has also been proposed in an intresting work [Wang et al., 2013], in which the authors propose the removal of the spatial mean of the RSS values in order to compensate for the shift effect resulting from device diversity. The effectiveness of this method is demonstrated with experimental results on an indoor Wi-Fi environment, where realistic RSS measurements were collected through heterogeneous laptops and smart phones. A similar approach of differential fingerprinting has been proposed [Laoudias et al., 2014], offering though a methodology that requires fewer differences of pairs of values, significantly reducing the computation time due to its reduced fingerprint dimension. As a continuation of this work, the group from the University of Cyprus has utilized differential fingerprinting in order to homogenize crowd-sourced fingerprints [Laoudias et al., 2013b]. Initially, the authors prove both with simulations and experimental results the inappropriateness of using the traditional RSS values approach with crowd-sourced data, before demonstrating the efficiency of their proposed method. The complete system called Anyplace is presented in this work [Georgiou et al., 2015], which summarizes the system's architecture of the Crowd-sourced Indoor Information Service. Lastly, another interesting approach has been proposed [Machaj et al., 2011] that consists of ranking the RSS values from a set of APs from high to low. Since RSS rank is invariant to bias and scaling, it offers an interesting alternative in addressing device heterogeneity.

From the volume of the relevant work of this rather recent field, it is evident that methods of automatic self-calibration or re-calibration as well as calibration-free methods are a trending topic. Numerous studies that address device heterogeneity have been discussed above for both ranging and fingerprinting techniques. Comparing these two approaches (ranging and fingerprinting) in terms of manual tasks needed before having a system that is ready to be used, it is evident that the fingerprinting methods (contrary to the ranging ones) need a manual surveying phase of recording the fingerprints and creating a radio map (whether this process be done either by an expert or be crowd-sourced). Thus, ranging methods that include a self-calibration method which adjusts the propagation model characteristics can offer positioning systems that should be ready for a plug-and-play kind of use.

Before proceeding to the presentation of the self-calibration method, the explanation of some preliminary elements is in order.

6.4 Preliminaries

6.4.1 Propagation Model

For ranging indoor positioning techniques an estimation of the distance from the APs is necessary. More specifically, when using RSS methods, a propagation model is used to infer a distance estimate from a value of the Received Signal Strength Indicator (RSSI). The propagation model commonly used for indoor positioning is the log-distance path loss model, presented in Equation 6.1. The propagation model, with which the expected received power p_i in distance d_i is calculated, is characterized as:

$$p_i = p - 10\, n\, log_{10}(d_i / d_0) + X \tag{6.1}$$

In this formula, p is the received RSSI at a reference distance d_0, and n is the path loss exponent which depends on the transmission channel. The path loss exponent n can be considered as also influenced by the way the transmitter and the receiver are made (for example, different device packaging materials alter the channel) or placed (since the transmission is not uniform towards all directions). Theoretically, $n = 2$ for no attenuation in power, whereas in actual indoor deployments values of $n > 2$ better describe the power loss, while values $n < 2$ are suitable if the signal is enhanced by the environment. Lastly, X is a random noise, which is assumed to have a Gaussian zero-mean distribution. Using 1 meter as reference distance ($d_0 = 1$), the formula is simplified to:

$$p_i = p - 10\, n\, log_{10}(d_i) + X \tag{6.2}$$

In order to translate an RSSI reception to a distance estimate, the parameters p and n need to be defined. Usually, the determination of these parameters requires a calibration step. This calibration can be completed with a straightforward procedure: several receptions are recorded at predefined distances from the emitting beacon. The best fitting curve describing these measurements, obtained by regression, provides the p and n values that optimally describe the RSSI-distance relation in Equation 6.2. The accuracy of this method can be increased by using a large number of measurements. This is because the noise is assumed to have a Gaussian zero-mean distribution, thus, using a plethora of measurements for each predefined distance increases the probability of reducing the average error.

However, this method has some clear limitations. Firstly, the parameters inferred rely on the environment of the calibration. Performing the calibration with one beacon at a certain location, and using the obtained parameters for all the beacons of the same type that are placed at a deployment may be convenient, but does not describe the particularities of the environment around each beacon, like possible reflections and Non-Line of Sight (NLOS) cases. On the other hand, calibrating the propagation model of each beacon after it is placed may require a considerable effort and it can be a great restriction for big deployments with many beacons. Secondly, apart from the transmitter (the beacon) and the channel (the environment between the beacon and the area where users move), the parameters also depend on the receiver's (the mobile device's) characteristics. If the calibration procedure is repeated with other mobile devices, with different reception characteristics, the resulting estimates of the propagation model parameters will differ among them. Thus, using a propagation model inferred by a single device introduces an inherent error when the model is used by another device.

6.4.2 Positioning Algorithms Used

With the use of the propagation model, a distance estimate can be inferred from the RSSI received from each beacon. Having obtained an estimate of the distance of the mobile device from each beacon, we proceed to the position estimation. In this study, we use two positioning algorithms, the weighted centroid algorithm [Anagnostopoulos and Deriaz, 2014], and a multilateration algorithm [Will et al., 2012]. In both algorithms, only the N beacons that are detected as being closer to the mobile device are used. In [Anagnostopoulos and Deriaz, 2014], it is shown that keeping the $N = 4$ closest beacons minimizes the expected estimation error, and thus this value is used in the experiments of this work.

The weighted centroid algorithm is a simple, straightforward positioning method, with very low computational complexity. Let d_i be the estimated distance from the i_{th} closest beacon, and (x_i, y_i) the beacon's position. The estimated position is given as the weighted centroid of the positions of the $N = 4$ closest beacons, using as weight $w_i = 1/d_1$ the inverse of the distance estimate from this beacon.

$$x^{est} = \frac{\sum_{i=1}^{N} \frac{x_i}{d_i}}{\sum_{i=1}^{N} \frac{1}{d_i}}, \; y^{est} = \frac{\sum_{i=1}^{N} \frac{y_i}{d_i}}{\sum_{i=1}^{N} \frac{1}{d_i}} \tag{6.3}$$

In order to get a more reliable distance estimate, the latest estimated distances from each beacon are averaged. In this way, we partially cope with the instability of the RSSI.

A notable property of this method is that it restricts the position prediction inside the area that the positions of the beacons define, making it impossible to give a position estimate outside this area. Thus, it is indispensable for this positioning algorithm that beacons be placed in a way that they surround all the area that is required to be covered. When working with a badly tuned propagation model, limiting the estimates inside the area of the surrounding beacons can be a desirable property, in order to limit the area of the potential positioning error.

The other approach used is a multilateration method. Four circles are drawn, using each beacon's position (x_i, y_i) as the center, and the corresponding estimated distance d_i of the mobile device from the i^{th} beacon as radius. If the distance estimates are correct, all circles will intersect at a single point. As the distance estimates are subject to noise, while also the propagation model might be imperfect, a single intersection is unlikely. Therefore, all the crossing points of each pair of circles are stored. Then, from each pair of circles the point closer to the position estimate is selected with the following logic: If the two first circles intersect, the method keeps the intersection point closest to the third circle. Lastly, we characterize each intersection point with a weight equal to the inverse value of the smallest radius of the two circles in which the point belongs. Then, the weighted centroid of all the stored intersection points is the estimated position.

6.5 Self-Calibration Method

6.5.1 Presentation of Self-Calibration Method

The proposed self-calibration method acts dynamically as the user moves and receives position estimates. Let M be the path loss model used (defined in Equation 6.2), characterized by the two parameters:

$$M = [p, n] \tag{6.4}$$

Initially, a set of default values of the parameters p and n is used. The position estimates received are used for gradually adjusting the values of the parameters. Before proceeding to details, some definitions are in place. Let:

$$d^{est} = [d_1^{est}, d_2^{est}, \ldots, d_N^{est}] \tag{6.5}$$

be the set of distance estimates from each of the N closest beacons used for positioning, as inferred by using the propagation model defined in Equation 6.1. These estimated distances are used in order to infer a position estimate (x^{est}, y^{est}). Furthermore, let:

$$d^{pos} = [d_1^{pos}, d_2^{pos}, \ldots, d_N^{pos}] \tag{6.6}$$

be the set of the distances of the position estimate (x^{est}, y^{est}) from each of the N closest beacons. Therefore, we have two kinds of distances: d^{est} which is the distance estimates from each beacon as inferred by using the propagation model defined in Equation 6.1 and the RSSI values, and d^{pos} which is the distance of the position estimate resulting from the positioning algorithm from each of the access points. Ideally, d^{est} and d^{pos} should be the same but due to noise and the inaccuracy of the model used, they tend to differ.

The proposed method consists of two steps that are both performed after each position estimation: an *optimization step* and an *update step*.

At the *first optimization step*, the optimization problem presented in Equation 8.2 needs to be solved for each of the N closest scanned beacons.

$$M^* = \underset{M}{\arg\min} \left| d^{pos} - d^{est}_{(M)} \right| \tag{6.7}$$

The model M^* resulting from this step is the one that minimizes the difference between the two distances: d^{pos}, that is the distance from the beacon to the estimated position as calculated before the optimization step, and $d^{est}_{(M)}$, that is the estimated distance of the mobile device from the beacon as inferred from the received RSSI, by using the model in search M, which is the tunable argument. We will refer to M^* as the optimal model for the consistency of the latest reception.

Since the algorithm updates the parameters of the model at each reception, we will refer to the state of the model at time t as $M[t]$.

At the *second updating step*, the current model $M[t]$ is updated with the result of the optimization step ($M^*[t]$) based on the latest reception, providing the model $M[t+1]$ to be used at the next reception, at time $t+1$. The update is made with the following logic:

$$M[t+1] = \alpha M^*[t] + (1-\alpha)M[t] \quad , \quad \alpha \in [0,1] \tag{6.8}$$

The update rate α in Equation 6.8 determines the level of influence of the optimal model for the consistency of the latest reception $M^*[t]$ in updating the model used for the next step $M[t+1]$. This step can be described as *exponential smoothing*, in which the parameter α is referred to as the *smoothing factor*. The tuning of the update rate as well as other issues regarding the optimal setting of the self-calibration method are discussed in the following subsection.

6.5.2 Tuning of the Self-Calibration Method

The proposed method contains several settings that need to be tuned. One of the challenges in finding the best settings for this method is selecting the optimization algorithm for the first step (Equation 8.2). One option would be to perform a Brute Force search at the space of possible solutions (the search space in this case is the space of all acceptable values of the pair of parameters p and n of the model M). This option has the evident drawback of being computationally expensive. Thus, the alternative of using a heuristic algorithm could reduce the computational cost. Furthermore, the method starts with a set of default values for the model's parameters so there exists a meaningful starting point for a local search algorithm, as for instance the Hill-Climbing algorithm. In addition, the parameters in question are expected to be relatively close to their default values rather than at the limits of the search space. For this reason, a local search algorithm is more likely to avoid some extreme values at the limits of the search space that could be provided due to a potential noisy reception. The efficiency and the computational cost of these two approaches are discussed in Section 6.6.

Regarding the optimization algorithm, there are some important parameters to be set. Initially, the limits of the search space should be defined ($n_{MIN} \leq n \leq n_{MAX}$, $p_{MIN} \leq p \leq p_{MAX}$). Furthermore, the granularity of the search algorithm should be defined, for both dimensions of search (p and n). Let p_{step} and n_{step} be the step size for each respective dimension.

Lastly, a crucial decision to be taken is the value of the update rate α. Choosing a large value for α, which would be close to 1, would mean that there is a big danger of overfitting the model in cases of noisy receptions. Using this completely wrong model at a following positioning step could deteriorate the quality of the position estimations, and eventually lead to diverging from the optimal model. On the other hand, a small value of α, close to 0, offers the opportunity of reducing the influence of occasional outliers, or even evening out their effect smoothly. A low update rate however should be carefully chosen in a way that would allow the model to change with a pace that is sufficient enough to improve the overall positioning system.

The following Section contains a detailed practical examination of all the above presented aspects of the self-calibration method.

6.6 Results of Experimental Measurements

For the evaluation of the proposed self-calibration method, both simulation results as well as results from an actual deployment of positioning system were used. The simulation results, apart from verifying the improvement of the accuracy of the system with the self-calibration method, offer the opportunity to observe the change in the results by tuning the level of the noise of the simulation. In this way, the results of a noiseless simulated environment can be compared with those of a noisy alternative. Such a comparison, having full control over the level of noise of the system, can only be made in a simulated environment. For the rest of the comparisons, the results of the real deployment are used, analyzed and commented on.

For the evaluation of the proposed self-calibration method, measurements from an actual deployment of a positioning system were used. A broad area (120 * 40 m) of an underground parking lot was used as the test environment (left half part of Figure 6.1). In this area, 40 BLE beacons were placed at a rhombus grid pattern by a partner of our Lab, the company OnYourMap (http://www.oym.co/). The density of beacons is close slightly lower (1 beacon per 120 m^2) than what the company usually recommends (1 beacon per 100 m^2). Thus, the density of deployment is a representative use-case scenario.

The path shown in Figure 6.1 was followed by a user holding three different mobile devices: a Samsung Galaxy S5, a Samsung Galaxy S4, and a Samsung Galaxy Note 3. During this path, each device recorded all the necessary information of the received signals (RSSI, timestamp, beacon ID), as well as the spatio-temporal ground truth,to enable us to run the positioning algorithm later off-line and evaluate its performance. Using the recorded raw data (RSSI, timestamp, beacon ID), position estimates can be calculated off-line either with or without the proposed self-calibration method. It was chosen to record and use the raw data in order to have a consistent comparison over the same dataset.

Moreover, the user holding the devices informed the recording application at every moment that passed by each one of the 50 predefined checkpoints of the path (the nodes of the path in Figure 6.1). Thus, not only do signal receptions have their exact timestamps, but also the 50 checkpoints of the path are linked to the exact time that the user was there. In this way, assuming that the user was moving at a steady pace between two consecutive checkpoints, the real position (ground truth) of the user

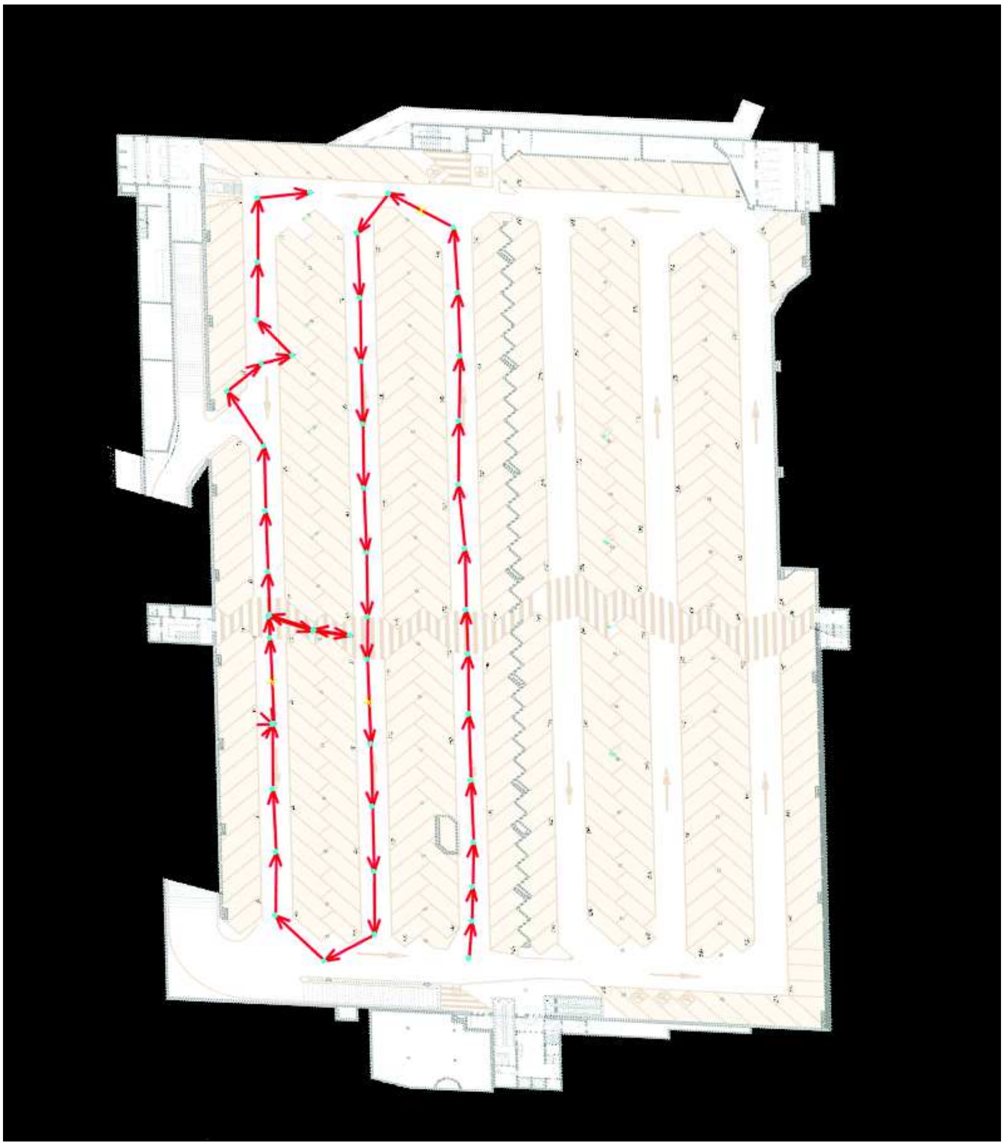

Figure 6.1. The predefined path followed by a tester in the carpark. The area where coverage is provided is the left half side of the parking lot, and its dimensions are 120 by 40 m.

can be inferred at any moment during the path. Consequently, after obtaining the position estimates from the raw data by a positioning algorithm, the error of each position estimate at any moment can be precisely calculated. The methodology of recording the spatio-temporal ground truth of the user and the raw data in order to run off-line positioning algorithms and evaluate them is extensively explained in the Chapters 7, 8 of this Thesis.

It was chosen to use as default values of the model, the values of an old deployment, in a different environment (corridors of the University of Geneva) with a different brand of beacons (the beacons' brand 'tod') than those of the current deployment in the carpark (the beacons' brand 'kontakt'), which were estimated using a Samsung Galaxy S4. These default values were calibrated to be p=−62.72 and n=2.28. Also, regarding the tuning of the parameters presented in Section 6.5.2, the following values were chosen empirically: the values n_{MIN}=1, n_{MAX}=3, p_{MIN}=-45 and p_{MAX}=-75 set the limits of the search space, while p_{step}=1 and n_{step}=0.02 determine the step size of the search.

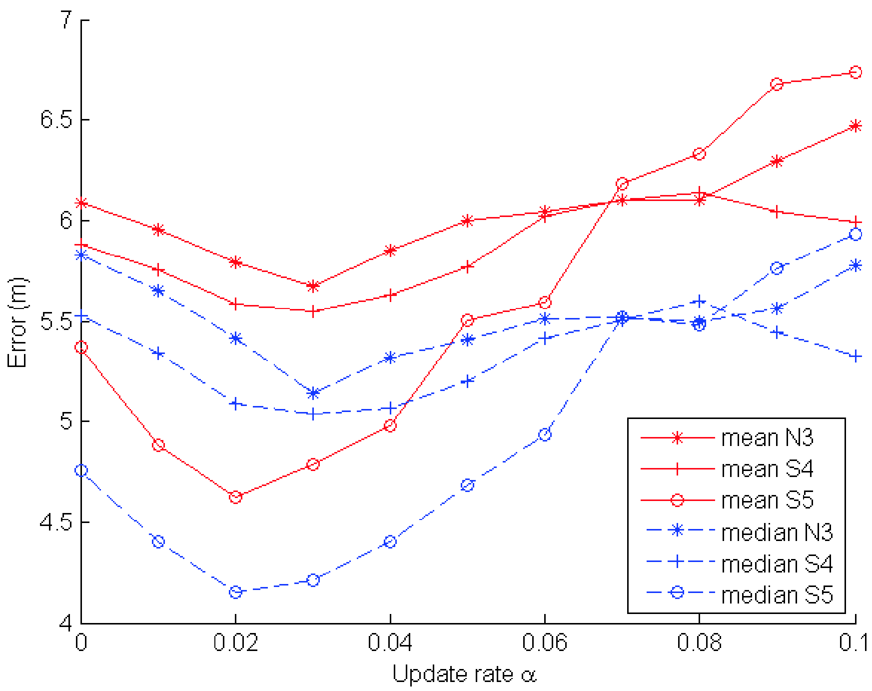

Figure 6.2. Mean and median values of the positioning error of the three devices used, for several values of the update rate α.

In Figure 6.2, we see the statistics of the achieved positioning accuracy with the three devices (Samsung Galaxy S5, S4, Note 3), for several values of the update rate α. In Figure 6.3, the box plot characterizing the accuracy of one device (Samsung Galaxy S5) highlights the median value of the positioning error with the red line inside each box. The limits of each box represent the 25th and the 75th percentile of the error. Apart from the box plot, the black stars connected with a black line show the mean value of the error of each case. The positioning algorithm used for these tests was the weighted centroid algorithm. Similar results were achieved also with the multilateration approach, as will be shown later on.

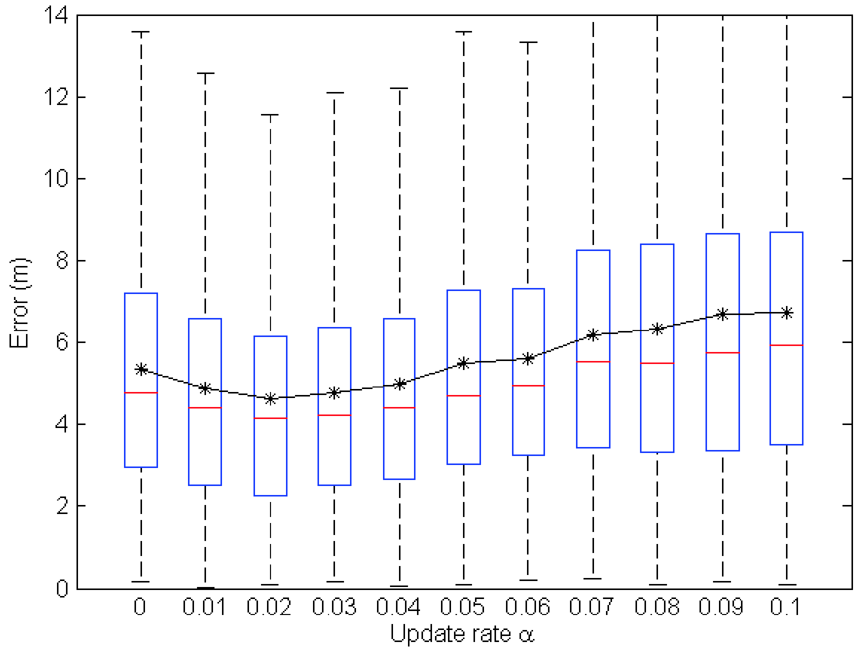

Figure 6.3. Box plot and mean values (black line) of the positioning error for several values of the update rate α, using a Samsung Galaxy S5.

For α=0, the statistics concern the pure positioning algorithm without the self-calibration method. For low values of α in the range $0.01 \le \alpha \le 0.04$, we see that all devices achieved an improvement in accuracy. In Figure 6.2, we see that the S5 device had the greatest improvement in accuracy among the devices, going from a mean value of 5.37 m for $\alpha = 0$ to 4.62 for $\alpha = 0.02$ (13.96% improvement). For greater values of α, it is evident that the accuracy degrades. In addition, the other two devices have a less impressive but still satisfactory performance. Both S4 and Note 3 achieved a ~5% improvement for $\alpha = 0.02$.

An important desired feature for the self-calibration method is that it not only improves the accuracy when this is possible, but also that it does not degrade the system's performance when the conditions (high noise, very imprecise default model) do not allow the convergence to a more appropriate model. After performing multiple tests, we have empirically concluded that a value of $\alpha = 0.02$ handles a satisfactory trade-off of these two attributes. The good performance of this value can also be observed in the two last Figures (Figure 6.2 and Figure 6.3).

In Table 6.1, the mean error before and after introducing the self-calibration is presented for several pairs of initial values of the propagation model parameters. The data collected with the S5 device are used. The first value of each cell is the mean error of pure positioning, while the second value is the mean error when using the self-calibration method with $\alpha = 0.02$. Lastly, the percentage change of the mean error appears in the brackets.

Table 6.1. Mean error before and after the self-calibration

p	n=2	n=2.3	n=2.6
-50	9.78 - 9.74 (-0.4%)	8.41 - 7.91 (-5.9%)	6.78 - 6.04 (-10%)
-55	8.30 - 7.65 (-7.8%)	6.68 - 6.05 (-9.4%)	5.23 - 5.14 (-1.7%)
-60	6.56 - 5.51 (-16%)	5.19 - 4.77 (-8.0%)	5.36 - 4.72 (-12%)
-65	5.26 - 4.73 (-10%)	5.34 - 4.92 (-7.8%)	5.36 - 5.37 (+0.1%)
-70	5.31 - 5.14 (-3.2%)	5.34 - 5.82 (+8.9%)	5.36 - 6.43 (+19%)

Having a very bad initial estimation of the propagation model parameters, far from the optimal one, significantly deteriorates the position estimates, which are used in the self-calibration method. Thus, in these cases of bad initial estimations, as for example with (p,n)=$(-50,2)$ or with (p,n)=$(-65,2.6)$, we observe that the self-calibration method has a similar performance to the calibration-free case. In most of the cases of Table 6.1 the method improves the average performance at a level of approximately ~10%. Only in the two extreme cases, for (p,n)=$(-70,2.3)$ and (p,n)=$(-70,2.6)$, does the low quality of the initial estimations disallows the method to improve the accuracy, but also results in a drop of the achieved accuracy.

In Figure 6.4, accuracy statistics of the two positioning methods are reported. Both multilateration and weighted centroid (which was used for the previous experiments) achieve similar patterns of improvement in accuracy for the presented values of α.

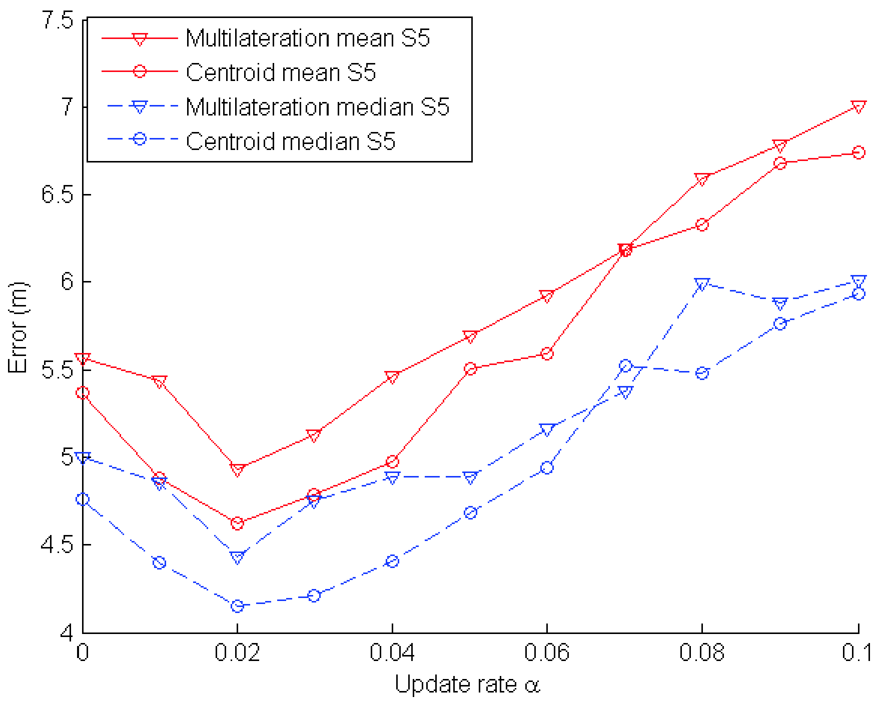

Figure 6.4. Mean and median values of the positioning error using multilateration and weighted centroid, for several values of the update rate α, using a Samsung Galaxy S5.

Lastly, it is worth comparing the two algorithms used for the optimization step, Brute Force and Hill-Climbing. Both algorithms have a very similar performance for all values of the update rate α. Similarly to Hill-Climbing, Brute Force has the best performance for low values of the update rate and more specifically, for α=0.02. In terms of computational effort though, Hill Climbing clearly outperforms Brute Force, as expected. In order to compare their performance, the execution time of the off-line positioning algorithm running the data collected during the path of Figure 6.1 was measured. The average time for estimating the position estimates of this path over 1000 repetitions was 82 ms for Hill Climbing and 342 ms for the Brute Force search. Since the algorithm is to be used on-line, on mobile devices, it is indispensable to minimize the computational effort, especially when this is possible without any impact on the performance. For this reason, the use of the Hill Climbing is recommended when reduced computational effort is desired.

6.7 Conclusions

A simple and effective algorithm for automatic self-calibration of the propagation model in ranging positioning techniques is introduced in this study. At every new deployment of a positioning system, a potential calibration procedure that tries to model the propagation characteristics, apart from being time consuming, cannot predict the reception characteristics of any mobile device that could use the positioning system. To cope with this issue, the proposed method offers a robust way of correcting the propagation model. It offers a significant improvement to the less properly tuned devices (tests showing a 13.88% improvement of mean error for the Samsung Galaxy S5) while it slightly improves the performance of those that are more properly tuned (a ~5% improvement for the Samsung Galaxy S4, and the Samsung Galaxy Note 3). The proposed method can be seen in the scope of the research towards device independence as well as in the context of facilitating calibration-free deployment in new areas.

Part III

Evaluation and Tuning Methodologies for Indoor Positioning Systems

7 Positioning Evaluation and Ground Truth Definition for Real Life Use Cases

7.1 Chapter Abstract

Evaluating indoor positioning systems has become a matter of heated debate in the indoor positioning community over the course of the last years. There is no clear standard on how these technologies should be evaluated and no predominant solution for defining the spatiotemporal ground truth with which the position estimates may be compared. In this study, we propose a simple and inexpensive solution for tackling both of these problems in real life use cases. With the proposed methodology, it is possible to measure the performance of positioning systems by creating a predefined path composed by checkpoints. Then a tester walking over them, indicates when the device was over the aforementioned checkpoints. Using this information, this study proposes ways to evaluate the estimates by comparing them with interpolated points of the ground truth trajectory. Two methods are proposed for performing such interpolation. Finally, in order to evaluate the performance of the positioning system as well as the perceived utility of the position estimates from the end user's point of view, a series of statistical parameters is discussed. Lastly, a parameter (TDR) that measures the occurrence of abrupt changes in the position estimates is proposed, in the context of approximating an evaluation of the perceived utility by an end user.

This work has been published in: *'Positioning Evaluation and Ground Truth Definition for Real Life Use Cases'*, Martínez C. d. l. O., Anagnostopoulos G.G., Togneri M., Deriaz M. and Konstantas D., in Proceedings of The Seventh International Conference On Indoor Positioning and Indoor Navigation (IPIN 2016), Madrid, Spain, October 2016.

7.2 Introduction and Related Work

In recent years, the indoor positioning field has experienced very notable progress. The rise of technologies such as Bluetooth, Near Field Communication (NFC) or ultrasound has allowed deployment costs to be reduced, increasing the research related to this field. At the same time, the way that these positioning systems are evaluated has gained more importance.

In this work, we describe a methodology for evaluating positioning systems in a predefined path and gathering the spatiotemporal ground truth data which is used as reference for the evaluation. The motivation of this work comes from the identified necessity of evaluating the performance of our positioning systems when utilized by moving end users.

Before the current study, the characteristics of the positioning systems of our research group have been measured using "static evaluation". This method consists of determining a point with known coordinates such as the spatiotemporal ground truth, and comparing it with the position estimates obtained with the positioning system at that location, without moving. It is commonly used in some indoor positioning competitions [Lymberopoulos et al., 2015]. Also, an improved version of this concept is used at the Indoor Positioning and Indoor Navigation (IPIN) conference competition [IPI,]. In the work described by Pulkkinnen and Verwijnen [Pulkkinen and Verwijnen, 2015], the authors discuss this method and propose some metrics to improve the scientific value of the evaluations, introducing interesting parameters like "environment-normalized error" or "shortest path error".

The work presented by Schwartz, et al. [Schwartz et al., 2012] introduces three categories for the evaluation methods:

1. *Static evaluation:* described in the previous paragraph. This evaluation method can also be achieved with our proposed recording methodology, although it is not the main goal.

2. *Dynamic evaluation with predefined geometrical paths:* specific paths are defined in advance in a test field, and then followed by a person using the positioning system under evaluation. We will refer to this person as the tester during the rest of this study, to make a distinction between such a tester, and the (final) user(s) of the positioning system.

3. *Dynamic evaluation using a reference positioning system:* a positioning system with higher accuracy is used as a reference for the evaluation of the target system.

The third kind of evaluation methodology is widely used for outdoors positioning systems, using as a reference the Global Positioning System (GPS) which already presents errors, typically, between 1 and 15 metres, depending on the quality of the system used and the place of measurement, or Differential GPS (DGPS) for more accurate measurements, around tens of centimetres. This method is also used indoors [Schwartz et al., 2012, Becker et al., 2015, Das et al., 2005], although it is generally difficult or expensive to deploy. Such a use can be found in the work proposed by Schmitt, et al. [Schmitt et al., 2012], where the authors use off-the-shelf components to build a robot capable of gathering the ground truth data necessary for the evaluation of a positioning system. This solution, nevertheless, presents some limitations as the robot cannot move on all surfaces and it is not able to climb stairs, or it might not be practical to use as a deployment step in commercial applications.

The work described in this study lies under the second category, *dynamic evaluation with predefined geometrical paths*. A tester will define the spatiotemporal ground truth from a predefined path, while, at the same time, recording the sequence of position estimates given by the positioning system. This type of measuring offers the possibility of introducing some metrics about the trajectory, or the overall shape of the route of a moving target, as mentioned in [Pulkkinen and Verwijnen, 2015]. Improving these values could result in a more natural tracking behaviour in the positioning system for the end users.

Additionally, in this study we also discuss the way to evaluate the positioning systems, once the data has been gathered. Many studies have focused on this topic, with interesting benchmarks proposed like the EVARILOS benchmarking platform [Van Haute et al., 2015]. The parameters mentioned in these studies can be measured with our methodology. In another interesting work about Benchmarking Radio Frequency (RF)-based indoor localization [Lemic et al., 2014], the authors focus on the reproducibility by controlling the RF interference and using a robot as a tester. Some other efforts in this direction can be found in the work done by Adler, et al. [Adler et al., 2013], where the authors offer an open virtual testbed for indoor localization.

Finally, in this work, the intention to measure the perceived utility from the end user's point of view is also highlighted. For this purpose, a new metric comparing the predefined and the estimated paths is proposed. Furthermore, we pay special attention to a parameter also considered crucial for the end user's perception of the system, which is the claimed accuracy of the position estimates. While outdoor position providers, like the GPS, provide a claimed accuracy of the position estimates, the concept is not so often discussed in indoor positioning and the related research. It is important to evaluate positioning providers not only by the quality of the positions estimates that they give, but also by how representative the accuracy that they claim for each position estimate is. This parameter is extremely important in heterogeneous positioning systems which try to use the best technology available [Anagnostopoulos and Deriaz, 2015], [Martinez de la Osa et al., 2015].

In a very useful survey done by Adler, et al. [Adler et al., 2015], the authors state that a high percentage of the authors, from the last five IPIN conferences, describe their methods of ground truth data gathering poorly or they do not describe them at all. One of the main goals of the current work is to offer a clear view of the evaluation methods utilized in our lab so that it can be used as a reference in future works in order to back up the presented results

The rest of this chapter is organized as follows. In Section II, we present the ground truth definition methodology, explaining the path creation and data recording. The position estimate evaluation is shown in Section III. In Section IV, we illustrate the proposed methodology with a detailed example. Finally, conclusions drawn are presented in Section V.

7.3 Ground Truth Definition

The first part of the proposed methodology consists of defining how the ground truth data are gathered. These are later used as a reference to evaluate the position estimates.

As discussed in the introduction, our method lies inside the category of *dynamic evaluation with a predefined geometrical path*. One of the important characteristics of the proposed method is the addition of predefined checkpoints along the path in order to be precise with the time that the user walked over each stretch of the route. A high density of checkpoints makes the methodology more accurate in defining the exact time of each position over which the user passed.

Once the procedure of defining the path is finished, the user will travel the path, recording the position estimates received, and indicating the moment he steps over every checkpoint. After gathering the estimates and the ground truth data, an evaluation of the positioning system will be possible.

7.3.1 Path Creation

The first step is to create a path which simulates the route in a typical usage scenario. The creation of the paths should be done with the intention of exploring most of the coverage area of the positioning system. Each path consists of a list of positions, as real world coordinates (latitude and longitude) which will be followed one after the other walking the linear segment connecting them, and will serve as checkpoints for the testers. In order to avoid errors at this point, it is indispensable that the maps used to create the path and to estimate the position of the users have the same geographic calibration.

The minimum required fields for a checkpoint are latitude and longitude. Apart from these, the checkpoint can be enriched by adding other parameters that describe a position, such as altitude, floor, room, etc., with more detail.

7.3.2 Data Recording

The second step required, prior to the evaluation, is to record the positioning system data along the predefined path.

The mobile application needed for this purpose is very simple. It has, as an input, the list with the checkpoints created in the previous step. Besides, it has access to the position providers that we want to evaluate, defining a position provider as the logic that transforms raw sensor data into position estimates. Finally, it should offer a way to enable the tester to indicate the moment he is passing over a checkpoint.

Before starting the recording, the tester should clearly identify the predefined path in the real world, with clear landmarks. If these landmarks are not precise enough to be identified, the tester should measure the distances in the reference maps and in the real life scenario and place signs for every checkpoint, such as clear numbered labels on the ground.

In order to start recording the data, the tester must be placed over the first checkpoint. Then, he should indicate it to the application and start walking towards the second checkpoint. At the same time, the system logs the time the user began the path and starts recording the position estimates coming from the different positioning providers which the tester selected to record, also storing the timestamp of each estimate. Consecutively, the application will continue logging these estimates while the user is moving, with the data being recorded at all times, not only at the checkpoints. The tester should indicate to the application the time he steps over each checkpoint, in order to store the time when he walked over each of them until he reaches the end of the path where the application will stop gathering information.

In between two consecutive checkpoints the tester should walk at a steady pace over the line that links both checkpoints in order to maximize the accuracy of the method. This pace can be different during different stretches of the path as long as it remains constant in every stretch.

Evidently, this method for defining the ground truth may introduce some errors. First of all, as commented earlier in this study, the maps used along the process (those used to define the location of the access points or the fingerprints and the checkpoints) have to be calibrated the same way, and not doing so would introduce a systematic error. Secondly, another source of error can be the discordance between the checkpoints created in the reference maps, and the ones used in real life, if they are not properly indicated. Lastly, the user can introduce some error when executing the process if he is not precise enough pressing the button when going over all the checkpoints or if he distances himself from the lines defined by the path or if he does not maintain a steady pace in between checkpoints.

A recent interesting study [Popleteev, 2016] has focused on measuring the error introduced by people when they are called to statically place a hand-held device over predefined points, defined by floor or ceiling markers or even defined relatively to landmarks of the environment. People unfamiliar with the process participating as a test group, achieved in all three cases (floor markers, ceiling markers and landmarks) a median error lower than $10cm$. In the floor markers case, which is the one commonly used in competitions, the median error was only $7.1cm$, and the 95th percentile of the error $15cm$. The authors also present the accuracy of a series of benchmarks that use high accuracy positioning systems (as reported in the relevant publications), ranging between 6.7 and $25cm$. The results indicate a similar accuracy between the human defined ground truth and the commonly used reference systems.

7.3.3 Procedure Example

An example of a path can be seen in Figure 7.1, where we have created a path going from the inside of the building Battelle A in the University of Geneva to a point outside, in the park. The intention behind the creation of such a path was to evaluate not only the indoor positioning provider, but also the seamless switching to the outdoor provider used.

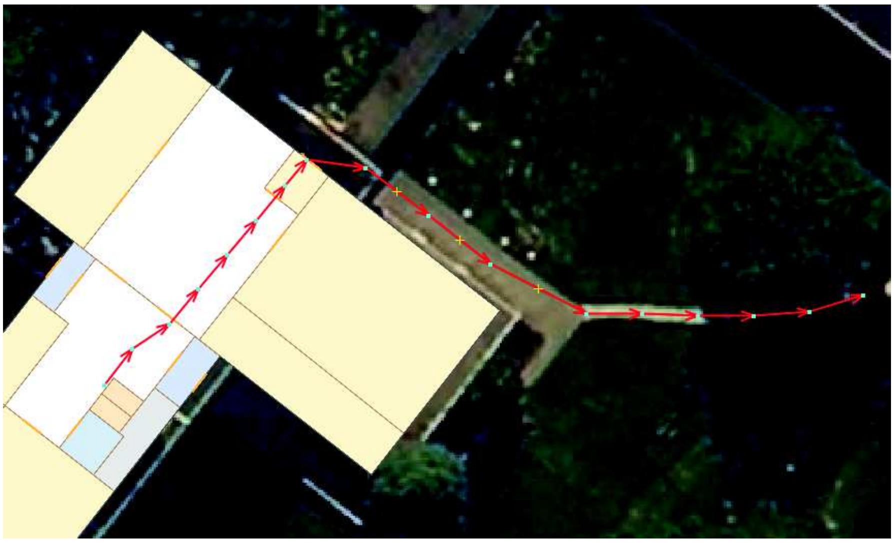

Figure 7.1. Example of a predefined path

We wanted to measure positioning algorithms programmed for Android mobile devices so we created an Android application with two simple screens, as seen in Figure 7.2. In the first one, on the left, the tester can select the position providers he wants to record. Following, he will select the file containing the predefined path he wants to follow. Finally, the main interface is a screen with a single button indicating the number of the next checkpoint, as shown in the right side of Figure 7.2.

7.4 Position Estimate Evaluation

Once the spatiotemporal ground truth data has been gathered along with the position estimates, the evaluation of the results can be made. In this section, the different

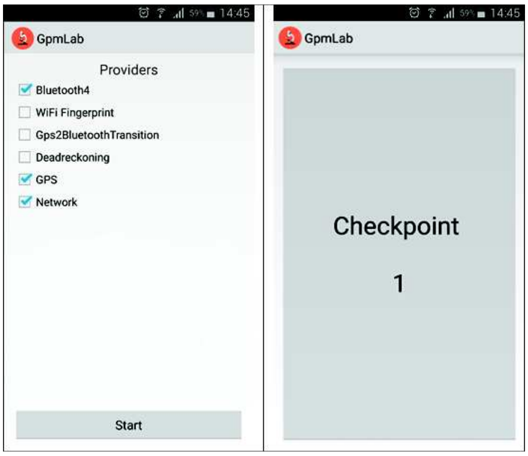

Figure 7.2. Two screenshots of our Android recording application

attributes of a position estimate will be described as well as two methods to evaluate them, along with different parameters that can be evaluated with our procedure.

7.4.1 Position Estimate

To begin with, it is necessary to establish the attributes that a position estimate must have in order to be suitable for evaluation. Therefore, they are expected to be recorded by the position providers. These are:

- Latitude
- Longitude
- Provider name
- Timestamp

The two basic parameters that a position must have are the latitude and longitude coordinates as they allow the identification of a specific point in the geographic coordinate system. Moreover, the name of the provider that estimated the position must be delivered in order to give the user and the system information about the technology used. Finally, the timestamp is crucial as it allows us to compare the estimated positions at a given time with the spatiotemporal ground truth.

On top of this, a highly recommended parameter to calculate in a position provider is the claimed accuracy of the position estimate. As the calculated position is an estimate, we need to have an idea of the claimed quality (or the level of certainty) of that estimate.

Additionally, the position estimate might also contain information about the altitude, the bearing of the user, etc. Recording the room and the floor estimated by the position provider can provide very useful information as the accuracy with which these are calculated can be measured. A more detailed description of the convenient properties that a position estimate can possess can be found in the work presented by Bekkelien and Deriaz [Bekkelien and Deriaz, 2012].

7.4.2 Ground Truth Linear Interpolation

In order to evaluate a position provider, the position estimates will be compared with the spatiotemporal ground truth data acquired. For this purpose, both data need to be known at any particular point in time. As it is highly improbable that checkpoints of the ground truth and position estimates coincide exactly in time, interpolations from one or the other must be created. To this end, two solutions are proposed. In both cases, the assumption made is that, when defining the ground truth using the application, the user was moving in a straight line at a steady pace between every two consecutive checkpoints.

7.4.2.1 Interpolation per Estimation Update

The first solution proposed will calculate an interpolated point in the ground truth path whenever a new position estimate is received. In order to do this, every time the algorithm processes a position estimate update, it checks its timestamp and calculates the corresponding interpolated point in the ground truth path for this timestamp. This pair of points will later be compared in the evaluation phase. An example is shown in Figure 7.3, where the blue dots show the checkpoints and the time when the tester crossed them. The black triangles are the position estimates given by the position provider. Using the timestamps of those estimates, the interpolated checkpoints are created, shown as green squares, assuming a straight line and a steady pace between the two checkpoints. In this example, at the evaluation phase, the position estimates will be compared with the interpolated checkpoints created for that specific time.

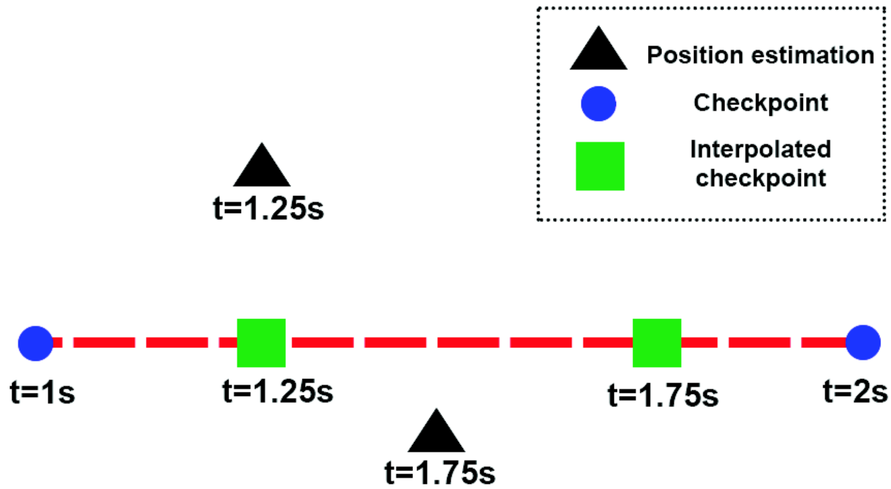

Figure 7.3. Linear interpolation example by estimate updates in a two-dimensional map

This approach is useful for evaluating each position estimate at the moment they are created, and checking the logic of the algorithm that calculates the position is accurate. On the other hand, there exists a drawback with this technique. In cases where a position provider is updating the position estimates with a very low frequency, only these few position estimates will be taken into account for the statistical analysis, which will not be representative of the quality of the information that a user would receive throughout the whole path. To illustrate this argument, we briefly present a simple example. Assume that a tester starts recording a path which is one kilometer long, and that the provider only gives two position estimates, one at the very beginning and another one at the very end of the path, both of them very accurate. Using this method, the evaluation will conclude that the provider is very accurate, while for most of the duration no position estimate updates were provided. Thus, for the whole kilometer of the path the user would only see the estimate produced at the beginning of the path that was (at the time it was produced) accurate.

One way to cope with this problem is to simply accompany the result of this interpolation method with information concerning the frequency with which the system produces new position estimates. An alternative way which may implicitly integrate the information of the frequency of position updates is presented in the second interpolation method, presented below.

7.4.2.2 Periodical Interpolation

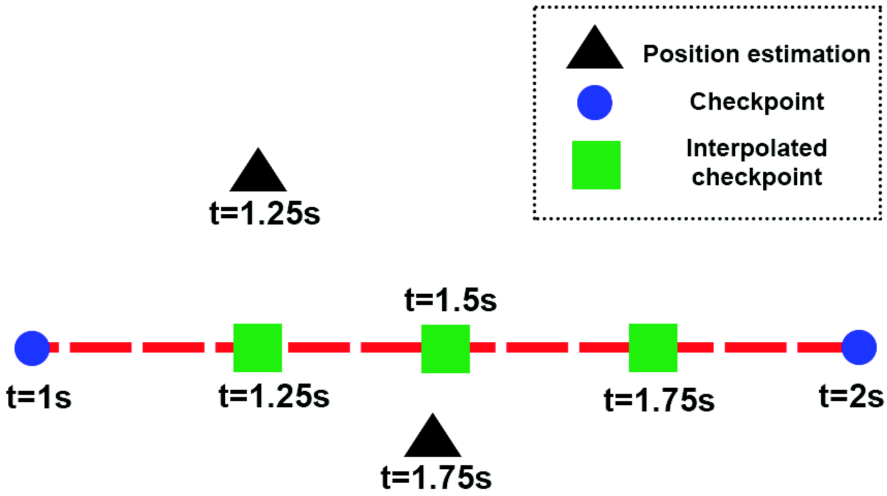

Figure 7.4. Linear interpolation example using fixed time interval in a two-dimensional map

In order to better evaluate the end user's perception of the positioning provider, a different interpolation method is proposed. In this case, the tester will choose a fixed time interval (T). Then, the system will create an interpolated point in the ground truth periodically every T (0,T,2T, 3T...), including the beginning and the end of the path. These points will be compared to the most recent position estimate received right at the corresponding timestamp. The shorter this time interval is, the more precise the evaluation will be, proportionally incrementing the processing time though. This method copes with the limitation of the first interpolation method as it compares the real position of the tester with the estimates, very frequently. Figure 7.4 shows an example of this procedure. As in the previous Figure, the blue dots indicate the checkpoints and the time when they were created. The black triangles are the position estimates given by the position provider. The green squares are the interpolated checkpoints created every T=0.25s, assuming a straight line and a steady pace between checkpoints. In this case, the interpolated checkpoints at t=1.25s and t=1.5 will be compared with the position estimate at t=1.25, while the interpolated checkpoint at t=1.75s and the checkpoint at t=2s will be compared with the estimate at t=1.75s.

7.4.3 Data Evaluation

Finally, regardless of the interpolation method used, some parameters must be chosen for the evaluation of a given provider. Keeping in mind the evaluation of the end user experience we have chosen the following:

Euclidean Distance Error

The most popular way to evaluate a positioning system is stating the average error committed between the estimated position and the real one. Using the proposed methodology, the errors are calculated individually for every interpolated checkpoint. Therefore, many common statistical parameters can be calculated with this procedure, such as:

- Mean
- Median
- Quartiles Q_1 and Q_3
- 95th percentile
- Standard deviation

- Cumulative Distribution Function (CDF)

Another possibility is to represent these errors chronologically, for the purpose of extracting some useful data. For example, Figure 7.5 shows a plot indicating the error of a Bluetooth position provider along a predefined path. It allows us to infer the different areas where the technology has coverage or not since the error increases significantly when the coverage is lost.

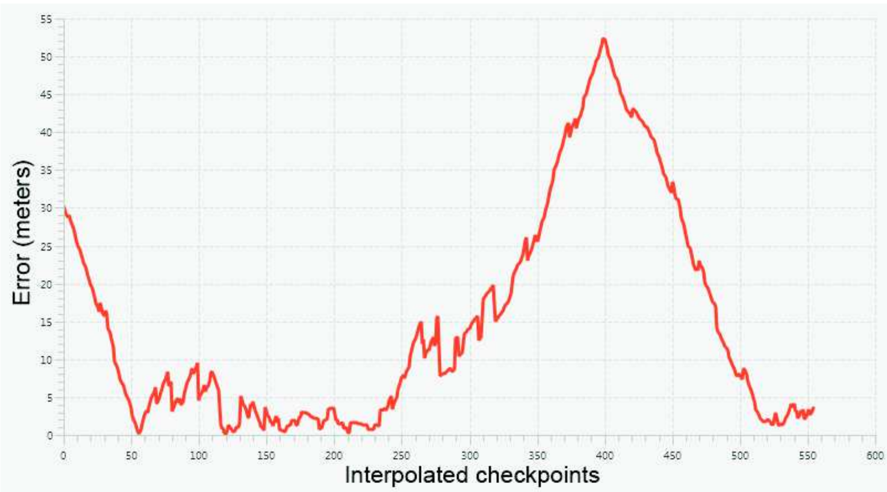

Figure 7.5. Error of a Bluetooth position provider along a path, as it changes over time

Floor Accuracy

Floor accuracy is given by the ratio between the number of correct detections of the floor in the position estimates divided by the total number of estimates. Similarly to the room accuracy, a position provider can estimate the altitude or the floor of the position evaluation, analysing the accuracy of this estimation can allow the end user to trust the veracity of this information or not.

Room Accuracy

Room accuracy is given by the ratio between the number of correct detections of the room by the position estimates divided by the total number of estimates. Indoor positioning providers are able to estimate the room in which the end user is. If the room parameter is included when defining the ground truth path, the accuracy of the provider in estimating the room can be calculated.

Time to First Fix

It is also important to indicate the time it takes for a position provider to give the first position estimate from its initialisation.

Frequency of Position Estimates

Reporting the frequency with which the system produces new position estimates can be a very descriptive metric for the quality of the system. This information can be given with several statistics concerning the time intervals between the consecutive estimates. Apart from the average time interval, the worst and the best case (shortest and largest time intervals) can also be very informative.

Claimed Accuracy Estimation Evaluation

The claimed accuracy estimation (CAE) is another key parameter for perceived utility of the position estimates by the end user. This value can be described as the radius of p% confidence of the position, where p should be described by each provider. As an example, this value is claimed to be 68% in Android position providers, while in many GPS cases it is common to utilize 95%. In other words, if a circle centred at the position estimate's latitude and longitude is drawn, and with a radius equal to the accuracy estimation, then there is a p% probability that the true position is inside the circle. The accuracy estimation provides to the end user a degree of certainty over the position estimate received.

In the method presented in this study we attempt to have a better characterisation of the accuracy estimation by evaluating its precision during the recorded path. Using the proposed methodology, we can empirically measure p by calculating the percentage of ground truth positions inside the radius indicated by the accuracy estimation.

Travelled Distance Ratio

One of the most unpleasant effects for an end user when utilising a positioning system is visualising constant abrupt changes in the estimated position, as it does not transmit a feeling of continuity when walking. In order to evaluate this effect, we introduce the concept of travelled distance ratio (TDR), which is defined as the ratio of the total distance from the estimated path, divided by the distance defined by the predefined path.

Ideally, this ratio should be one if the estimates were exact, as both distances would be the same. However, when abrupt changes appear, they generally deviate from the line followed by the user or go back and forward from the real position. This makes the total distance travelled by the estimated route longer than the ground truth one and, therefore, the TDR is higher than one. We consider the positioning system provides a better user experience when this ratio is closer to one. Figure 7.6 shows an example of a real path, in the upper part in red, and an estimated path, lower part in blue. In this case, the estimated path is twice as long as the real path, therefore the TDR would be 2.

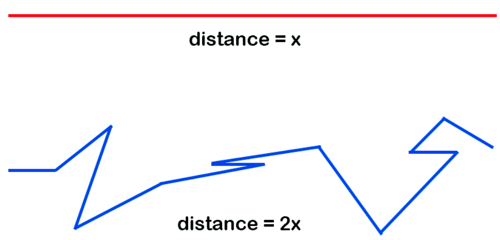

Figure 7.6. Example of a real path (up) and a estimated path (down)

7.5 Use Case Example

In this section, we show an example of the full process using the proposed methodology in a real life scenario, where we wanted to evaluate our positioning system in an already deployed infrastructure of Bluetooth low energy beacons, in an underground parking area. The logic of the position provider is described in the work presented by Anagnostopoulos et al. [Anagnostopoulos and Deriaz, 2014].

As described, the first step is to geolocalise the map of the area and create a predefined path for the tester to follow. The path is created trying to imitate how the positioning system could be used or trying to explore a certain behaviour of it in a specific situation. As landmarks we use the lines painted on the ground for the parking spaces. The result of this procedure is shown in Figure 7.7.

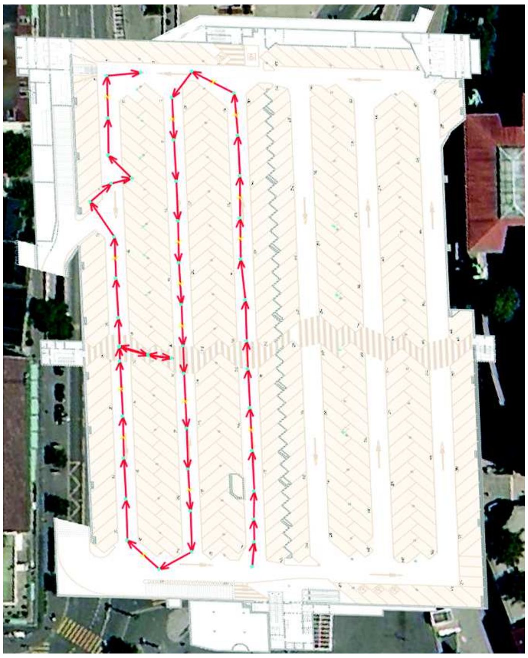

Figure 7.7. Predefined path used as ground truth

The following step is to walk over the checkpoints, trying to maintain a steady pace at each segment and reach the end of the predefined path. At the same time, the position estimates given by the Bluetooth position provider are recorded. The estimated path is shown in Figure 7.8.

In order to better exemplify the meaning of the statistical parameters, we also recorded, at the same time, an additional version of the same position provider. This provider performs a filter over the position estimates. In this way, it smoothes the variations of

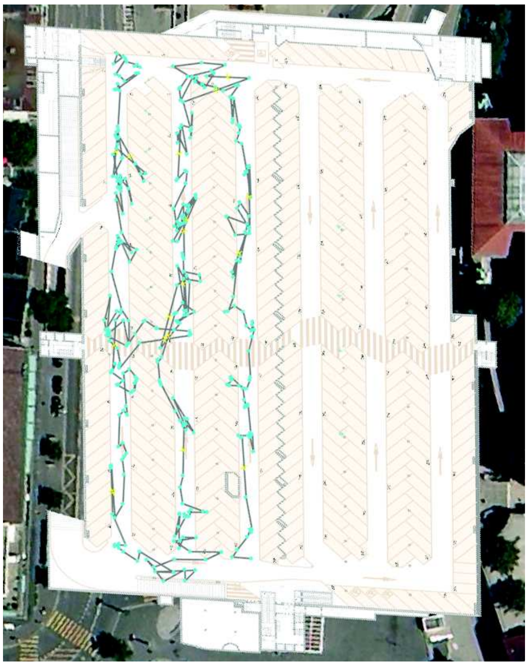

Figure 7.8. Estimated path by the position provider

the position estimates in order to offer a better experience to the end user. The result of this recording is shown in Figure 7.9.

Once the recording step is completed, we proceed to the evaluation. For this purpose, we need to obtain the pairs of interpolated ground truth positions and position estimates for specific timestamps. In this case, we have used the fixed time interval method with a value of 250 ms.

Finally, we analyse the data recorded to extract some of the statistical parameters described in Section III. These data are shown in Table 7.1.

TABLE 7.1. STATISTICAL PARAMETERS FOR TWO POSITION PROVIDERS

	Bluetooth LE	*Bluetooth LE Filtered*
Mean error	5.88 m	4.71 m
Median error	5.525 m	4.468 m
Time to first fix	1.5 s	1.5 s
AE p%	86.99%	93.84%
TDR	2.94 m	1.52 m

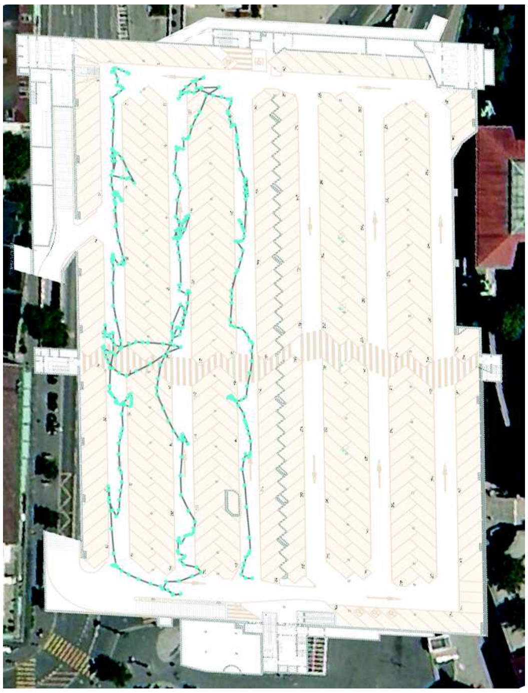

Figure 7.9. Estimated path by the position provider with filtering

It can be observed how the travelled distance ratio has a value much closer to 1 in the case of the position provider that uses filtering techniques, and avoids abrupt changes in the position estimates. It is hard to predict the end user's feelings over their experience as they certainly are subjective. In our experience, a TDR closer to 1 corresponds to a better perceived utility of the positioning system for the end user. A clear example can be seen comparing Figures 7.8 and 7.9. The estimated trajectories clearly show how the accuracy of the filtered provider is better than the unfiltered one. In this case, better accuracy coincides with a better value for the TDR but this does not necessarily imply a correlation between the two. For example, there might exist the case where the position estimates are continuously calculated with the same error, higher than with another provider, but this error is always constant and in the same direction, so that it still gives a pleasant experience to the end user.

We can also see how the accuracy estimation $p\%$ is higher in the provider using the filter. This fact allows the final user to be more certain that the position estimate he is receiving lays inside the radius given by the accuracy estimation.

In this scenario, the room or floor accuracy mentioned in Section III were not considered as all the positioning system was deployed in one big area in the same floor.

7.6 Conclusions

In this work, we have presented a methodology for evaluating positioning systems and defining the spatiotemporal ground truth for such evaluation. The lack of use of standardised evaluation procedures is a common issue in the indoor positioning community [Adler et al., 2015]. We covered this need with the proposed methodology, which we have extensively tested in some existing deployments, as the example presented in this work. The method is based on creating a predefined path marking checkpoints on a map where the positioning system is deployed. After doing so, a tester records the position estimates at the same time as s/he walks over the checkpoints and records, by indicating to an application, the moment s/he steps over them. The paths can simulate many different usage scenarios and the more checkpoints used, the more precise the ground truth definition will be.

Following the data gathering, two methods of interpolating the points from the reference path are introduced, indicating the advantages of both of them, remarking that if it is desired to better evaluate the experience of an end user, a fixed time interval interpolation is recommended.

Finally, several statistical parameters are recommended for use in evaluating the performance of the positioning system as well as the experience of an end user. In this aspect, we propose the parameter TDR, which indicates if the position estimates change abruptly. This parameter is calculated by dividing the length of the estimated path by the length of the real one. The closer to 1 this value is, the better we predict that the perceived utility of the system will be for the end user.

One of the main goals achieved in this work was to propose a simple and inexpensive procedure, aiming to contribute to the positioning community. Additionally, we offer a precise definition of the evaluation methods used in our lab, for use as reference by future works. By using this reference, we can improve the value and credibility of the scientific process when presenting positioning research studies.

8 Practical Tuning Methodology for Indoor Positioning Systems

8.1 Chapter Abstract

How do we evaluate the performance of an indoor positioning system? How can we make consistent comparisons of different settings of the same system or of different systems in a robust and efficient way? In addition, in which way can an indoor positioning system be optimally tuned for a certain environment? These are the questions addressed in this study. We propose a practical, cost efficient methodology for evaluating and tuning indoor positioning systems. The methodology has two main phases. In the first online recording phase, the ground truth information is gathered, and raw signals are recorded. In the second phase, offline positioning algorithms utilize the recorded information to infer position estimations which can then be precisely evaluated. An automatic parameter optimization methodology, which recommends optimal tunings for the positioning algorithm, is presented as a key utility of this work. An overall advantage of the proposed method is the fact that the recorded data guarantee the repeatability of tests, and allow consistent comparisons among different algorithms, creating the perspective of a testbed based on real data. Additionally, these consistent tests over the same data exempt the tester from the tedious task of having to revisit multiple times the deployment area to tune the system,

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as they are performed offline. The implementation of the methodology is exemplified with the presentation of the GpmLab Android application and the GpmStudio desktop platform, tools which assist our main positioning framework, the Global Positioning Module (GPM).

8.2 Introduction

In recent years, the domain of indoor positioning has attracted a lot of attention in both the academic community and the industry. So far, no universal standard has been established defining the way of measuring and evaluating the performance of a positioning system.

Having a consistent way of measuring the performance of positioning systems is indispensable. It is evident that a reliable evaluation methodology allows a research group to share with the community the performance of their positioning system. Moreover, it provides the group with the possibility of having a continuous overview of the impact of the improvements that they aim for in the existing methods, as well as evaluating new algorithms and comparing them with others.

One of the main challenging issues in the evaluation procedure is the ground truth acquisition. In a relevant recent study [Adler et al., 2015], the authors studied the publications from five recent indoor positioning conferences, and found that a high percentage of the authors describe their methods of ground truth data gathering poorly or do not describe them at all. Furthermore, they express their concern about the reproducibility of the experiments of the field. Given the above, we believe that a discussion on the ways that we test, measure and evaluate indoor positioning systems is indispensable.

An interesting study in this domain [Schwartz et al., 2012] describes the evaluation methods by grouping them in three categories. The first method is (i) *Static evaluation*, in which a device is left at a specific location for a sufficient amount of time. Then, the evaluation is made by analysing the position estimates that the System Under Test

(SUT) provided during this time. A major drawback of this category is that it does not reflect most real use cases, which are expected to be more dynamic. This requirement is addressed by the other two categories: (ii) *Dynamic evaluation using a reference positioning system* and (iii) *Dynamic evaluation with predefined geometrical paths*. Category (ii) methods use a positioning system with high accuracy in order to evaluate the SUT. The need to use another system may imply significant additional deployment effort and cost. In the third category (iii), specific paths are defined in advance at a test field, and then followed by a person that records the estimations of the SUT. The method presented in this study belongs in this category, which combines many advantages, such as realistic capture of real-life usage scenarios, ease of deployment, and cost efficiency.

Furthermore, apart from the evaluation methodologies that have started to attract significant attention by the indoor positioning community, the methodologies of optimally tuning a system is also a domain worth discussing, sharing ideas on and improving. Assume a positioning expert called to deploy a positioning system, to tune it properly, to present it and to evaluate its performance. It is common in the community to discuss the parts of deploying and its requirements, the positioning methods, as well as the ways of evaluating the system's performance. However, it is not uncommon that the step of how the system is tuned accordingly is left unclear, mentioning for example an empirical selection of the appropriate settings. The question of how to tune a positioning system at a new deployment has drawn our interest. Investigating this issue gave rise to the present work. This study is the natural continuation and a significant expansion of the previous work of Chapter 7, where we focused on ground truth definition and position evaluation of online positioning solutions. In the current study, we present a practical evaluation and tuning methodology, which simplifies the procedure of optimally tuning a positioning system at a new deployment. A more detailed description is given at the end of the following section, where after presenting the related work we proceed to explain the contributions of the current work.

The rest of this chapter is organized as follows. In Section 8.3, the related work is discussed, along with the contributions of this study. After presenting the proposed method theoretically in Section 8.4, the implementation of the method with the related software tools are shown in Section 8.5. Lastly, in Section 8.6, we conclude the work by providing an overview of the use cases of the methodology and discussing its particularities.

8.3 Related Work

The definition of the ground truth information used to evaluate positioning systems is a crucial subject for the indoor positioning community. As mentioned earlier, a recent study [Adler et al., 2015] expresses the concern of its authors about the lack of strictly defined procedures of ground truth acquisition. Furthermore, during their analysis, the authors of that work found several studies that refer only to the spatial information of the ground truth, reducing the precision of their evaluation methodology. Hence, they highlight that the temporal information about both the ground truth and the position estimates is also indispensable.

There are studies [Sharp et al., 2012] that try to simplify the procedure of evaluating positioning systems, by defining the ground truth only with spatial (and not temporal) information, aiming to approximate the cumulative statistics of the positional error. Nevertheless, even to achieve this approximation, strict requirements are set concerning the symmetry of the deployed access points and the form of the path followed for the recording. More precisely, it is required that all base stations are deployed symmetrically, so that the cross-track and along-track errors can be considered statistically independent. Then, an approximation of the statistical distribution of the overall positioning error is given, based on the cross-track error (vertical deviation from the predefined path).

Recent indoor positioning competitions, like the Microsoft Indoor Localisation Competition [Lymberopoulos et al., 2015] (performed in the context of the ACM IPSN conferences), and the EvAAL competition [Barsocchi et al., 2013] (in the context of the IPIN conferences) define strict methodologies of evaluating positioning systems. In IPSN, a list of specific evaluation points is defined in the test area. A tester carries a device above each of the evaluation points, waits for a couple of seconds at that point, and records the location reported by the SUT. This methodology evaluates precisely the accuracy of position estimates statically, as discrete points, though it does not aim to evaluate the continuous dynamic movement of users.

The competition of IPIN defines a dynamic way of evaluation, aiming to cover this aspect. Again, a list of specific evaluation points is defined in the test area. The tester follows the path defined by a sequence of evaluation points at a natural pace, and without performing an artificial pause at the evaluation points. The tester records on the device the timestamp of the moment he passed by each evaluation point, so that the most recent position estimate is compared to the position of the evaluation point. This methodology covers the more realistic use cases of moving users, as all measurements are taken dynamically. It is noteworthy though, that in contrast with the IPSN competition, the ground truth position and the position estimate are not taken simultaneously, introducing implicitly as a factor in the evaluation, the frequency of production of position estimates. Thus, this method has the feature of dynamic recording, and the feature of evaluating at random moments of the walk (when passing by an evaluation point) the latest position estimate that a user of the SUT would see on his screen.

An impressive contribution in the direction of benchmarking of indoor positioning systems has been the work performed in the context of the EVARILOS project [Van Haute et al., 2015], [Van Haute et al., 2013]. This project identifies the pitfall of reproducing research results of indoor localization in real life scenarios, as they suffer from uncontrolled RF interference and from the weakness of numerous published solutions being evaluated under individual, incomparable and repeatable conditions. EVARILOS, as well as other works [Schwartz et al., 2012, Becker et al., 2015, Das et al., 2005, Schmitt et al., 2012] perform their evaluation with the use of another system of high accuracy, such as a robot or cameras, as a reference system. Using a precise robotic system as reference is a valuable solution for strictly measuring and evaluating systems in controlled test areas. Nevertheless, this approach has some limitations, such as the cost, the speed with which a broad area can be measured, and its mobility limitations (obstacles, stairs, etc.). Furthermore, it might be much less complex for a human tester to perform the task in the case where an evaluation is needed in the context of tuning a positioning system, when deploying it in a crowded public space (like a shopping mall), which might also have the above mentioned limitations. Nevertheless, when focusing purely on a precise evaluation, methods that utilise high accuracy reference systems are precious.

Apart from the definition of the ground truth by traversing the predefined path, recording simultaneously the raw data received from the technologies used for positioning is of high importance. Having this information combined (ground truth and raw data) facilitates the reproducibility of tests since using the same data allows consistent comparisons among systems. In an influential sequence of publications [Schmitt et al., 2012], [Adler et al., 2013], [Adler et al., 2014c], [Adler et al., 2014d], [Adler et al., 2014a], the authors from the Free University of Berlin have worked in this direction. After defining a reference system for indoor localisation systems [Schmitt et al., 2012], they present the concept of a visual testbed [Adler et al., 2013], in which a robot spans an area recording both the raw signals and the ground truth information throughout the area. These data are offered for use as a testbed for positioning systems. Following, they perform several experimental evaluations of systems [Adler et al., 2014c], [Adler et al., 2014d], [Adler et al., 2014a], using their robotic reference system.

In the current work, we have tried to address most of the problems discussed above. Similarly to both the above mentioned competitions (IPSN and IPIN), the proposed methodology utilizes a predefined path in which a tester passes through predefined checkpoints. As our intention was to evaluate the continuous performance of the SUT, the evaluation is not limited only to the checkpoints, but concerns the continuous production of estimations of the system (as opposed to the aforementioned competitions). The continuous evaluation is achieved through two alternative ways of interpolating the ground truth information, introduced in the previous Chapter 7. Furthermore, contrary to the IPIN competition, the ground truth position and the position estimate are simultaneous, without having to perform the artificial stop required in the IPSN competition. In addition, since the data collected with the proposed methodology can be repeatedly used to test offline positioning algorithms and evaluate their performance, the perspective of a testbed is created. Lastly and most importantly, in this study we introduce the perspective of utilizing the above discussed steps to create a tuning tool that facilitates the task of optimally tuning a system. This tuning methodology is extensively discussed and exemplified throughout this study.

8.4 Proposed Method

In this section, we present the proposed methodology in its full extent. Firstly, we offer an overview of the global architecture. Then, we proceed with a detailed presentation of the online data recording method, followed by the off-line positioning and evaluation part. Lastly, we analyse the procedure of optimally tuning the positioning algorithm.

8.4.1 Architecture

In this subsection, we describe the workflow of our proposed methodology. It consists of two main phases: an online recording phase which takes place in the environment of the deployment, and an offline phase. The workflow is summarized in Figure 8.1. During the first online phase, the spatio-temporal ground truth information is gathered (the spatial information (x, y), plus the time t), along with the received raw signals (the signal s, at time t). In the second phase, an offline positioning algorithm is used to infer position estimates (the spatial information (x, y), along with the time t), using the recorded raw data. Different settings of the parameters of the tested

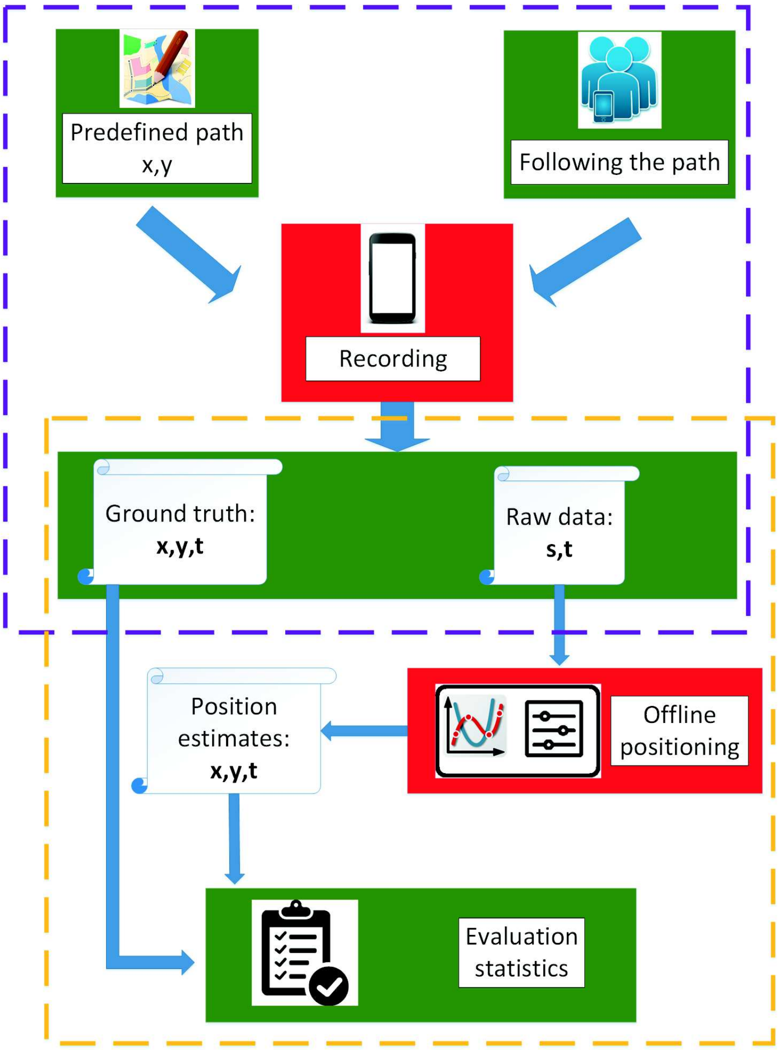

Figure 8.1. The overall workflow of the proposed methodology. The purple box highlights the online part, while the yellow one indicates the offline part.

algorithm, result in different lists of position estimates (containing spatial information (x, y), plus the time t) which can be directly compared with the ground truth information, and evaluated. By comparing the position estimates of the offline positioning algorithm with the ground truth, the parameters of the positioning algorithm can also be properly tuned, and its performance can be optimized.

8.4.2 Online Data Recording

For the online phase, a predefined path needs to be designed. This path consists of a list of positions that will be followed, one after the other, by a tester and will serve as checkpoints. The tester will have to follow this predefined path, holding the mobile device that will continuously record all the raw signals that it receives throughout the length of the path, along with the timestamp of each reception. The tester has simply to indicate to the recording application the moment at which he passes over each checkpoint. In this way, every predefined checkpoint is marked with the exact timestamp indicating when the tester passes by it. The tester should move on the path, which is composed of the straight linear segments that connect these checkpoints, at a steady pace. Note that the pace should be steady during a linear segment connecting two checkpoints, but it is not required to be the same among different segments.

With this procedure, the exact time that each checkpoint was crossed was recorded. The spatio-temporal ground truth information for every moment between the crossing of two checkpoints can be inferred with linear interpolation. Under the assumption of a steady pace between consecutive checkpoints, the result of the linear interpolation is the accurate ground truth. The density of the checkpoints handles a trade-off between minimising the effort included in the recording procedure and minimising the interpolation error. Having dense checkpoints allows the user to frequently inform the recording application about his true position, reducing the length of the segments in which the interpolation is done. In this way, the error introduced by the interpolation is minimized. On the other hand, a sparser placement of checkpoints simplifies the procedure, with the risk of introducing a higher error due to interpolating over bigger segments.

There are different approaches that utilize a predefined path. A common method used (for example by the IPSN competition) is the one in which the tester has to follow a path with checkpoints, at which he is called to halt for a couple of seconds in order to receive a position estimate, and then continue the path. Even if the SUT can continuously utilize information received between the checkpoints (such as inertial sensor data), the evaluation is actually a static one, as the tester stops to take a measurement. On the other hand, there exist more dynamic evaluation methods (as the one performed at the IPIN competition), where the user follows a path without stopping at the checkpoints. However, even if the measuring procedure has the element of a continuously moving user, the evaluation of the SUT is not continuous, but sporadic since only a sampling of the most recent estimations at the checkpoints is evaluated. Therefore, despite being dynamic, the method does not fully capture the experience of a user that would actually follow the path while receiving position estimates.

In this work, we discuss two methods of interpolating the recorded checkpoint indications of the tester to obtain the spatiotemporal ground truth information, and based on this, to evaluate the position estimates. These methods are discussed in the following subsection.

8.4.3 Offline Positioning and Ground Truth Interpolation

In the preceding online phase, all the necessary data needed for feeding an offline positioning algorithm were recorded. The collected raw data are utilized by the offline positioning algorithms, which produce position estimates from the recorded raw signals. Thus, for any signal s received at time t, a position estimate x, y is inferred. The same data can feed different positioning algorithms, or the same algorithm with several different settings of its parameters, resulting in different position estimates.

As a simple verification method of the correct functioning of the implementation of the methodology, apart from recording only the raw data that feed an offline positioning algorithm, it is recommended to also run the online version of the algorithms, and record the position estimates. The results of the online and the offline algorithms should be identical, under the same parameter tuning and the same data.

The spatiotemporal information of the position estimates inferred can be compared with the ground truth, in order to evaluate the accuracy of the estimation. To be able to evaluate an estimate x, y for the time t, the ground truth position at time t is needed. The ground truth information available from the offline phase is limited to the positions of the checkpoints and the corresponding time the tester was there. On the other hand, as the signal recording was continuous, the position estimates will have timestamps that chronologically lay between the timestamps of two consecutive checkpoints. In order to infer the true position of the user at a time between two consecutive checkpoints, we have proposed from an earlier work [Martinez de la Osa et al., 2016] two interpolation approaches, which are presented bellow.

8.4.3.1 Interpolation per Estimation Update

This first solution is the most intuitive approach, which is to calculate an interpolated ground truth point in the path, at the time that every new position estimate was received. In order to do this, every time the algorithm processes a position estimation update, it checks its timestamp, and calculates the corresponding interpolated point in the ground truth path for this timestamp. For example, assume that a tester was at checkpoint A at time $t_A = 0$ and at checkpoint B at time $t_B = 10$. If he receives a position estimate at time $t = 1$, his ground truth position is inferred by linear interpolation, and is assumed to be at the 10% of the distance of the linear segment linking A to B.

This approach is useful for evaluating each position estimate individually, and checking if the logic of the algorithm that calculates the position estimates is accurate. On the other hand, there is a drawback to this technique in the case where a position provider is updating the position estimates with a very low frequency. In these cases, only a few points will be taken into account for the statistical analysis. A substantial time lapse between consecutive position estimates can significantly deteriorate the perceived utility for the user, who will have the feeling that the estimations are lagging, and thus, the estimates will not be representative for the whole path. For example, assume a scenario where a tester starts recording a path which is one kilometer long, and he receives only two position estimates, one at the very beginning and another one at the very end of the path, both of them are very accurate estimates.

Using this method, the evaluation will later conclude that the position provider is very accurate, despite the fact that during the whole path the latest position estimate was the first one, placing the user at the beginning of the path. With this motivation, we proceed to discuss the second interpolation method.

8.4.3.2 Periodical Interpolation

In order to better evaluate the end user's perception of the positioning provider, a different interpolation method is proposed. In this case, the tester will choose a fixed time interval, the period T_i. Then, the system creates an interpolated ground truth point in the path periodically every T_i time units $(0, T_i, 2T_i, 3T_i, \ldots)$. These points will be compared to the most recent position estimate received at the corresponding timestamp. In this way, we have a periodical evaluation of how close the estimation that would appear on the user's screen to the true position is. The shorter the time interval T_i is, the more representative of the continuous user experience the evaluation will be, increasing though proportionally the processing time. Let T_p be the expected period with which the position provider offers its position estimates. Thus, selecting a $T_i \ll T_p$ is recommended. This method copes with the limitation of the first algorithm, as it very frequently compares the position of the tester with the estimates. On the other hand, it misses the advantage of evaluating the estimates created against the ground truth at the exact time of their creation.

8.4.4 Evaluation

After the interpolation process, pairs of simultaneous ground truth positions (x_g, y_g) and position estimates (x_e, y_e) will have been created, regardless of which interpolation method was selected. With this information, the evaluation of the positioning algorithm can take place. The most popular way of evaluating positioning systems is by utilizing the 2D Euclidean distance error d_e (Equation 8.1), and the relative statistics that can be inferred based on it.

$$d_e = \sqrt{(x_g - x_e)^2 + (y_g - y_e)^2} \tag{8.1}$$

It is common in evaluating positioning systems to present the Cumulative Distribution Function (CDF) of the error, and report basic statistical metrics like: the mean, the median, the 75th percentile and the standard deviation. All these metrics can be easily calculated from the recorded data. According to the kind of information that are included in a position estimate, other metrics can be also added. For example, if the position estimate and the corresponding ground truth include extra information like: room, floor, building, etc., this allows an estimation of room accuracy, floor accuracy, and building accuracy as a ratio of correct detection. Furthermore, other metrics regarding the smoothness of the estimated path, based on the full sequence of position estimates of a moving tester (as discussed in [Martinez de la Osa et al., 2016], [Pulkkinen and Verwijnen, 2015]), could also be used. Potential metrics that may be used have been extensively discussed in relevant studies [Van Haute et al., 2015], [Pulkkinen and Verwijnen, 2015].

The tester can use the metric of his choice in order to evaluate the performance of the positioning SUTs, according to his needs. The key point of the evaluation with the proposed method is that the results of different algorithms, or different tunings of the same algorithm, can be consistently compared as they are produced by the same raw data recordings.

8.4.5 Tuning and Optimization

The tuning of the positioning algorithm can be done either manually, by a person that is experienced in the particularities of the positioning algorithm, or automatically by using optimization techniques. The logic of the tuning procedure is presented in Figure 8.2.

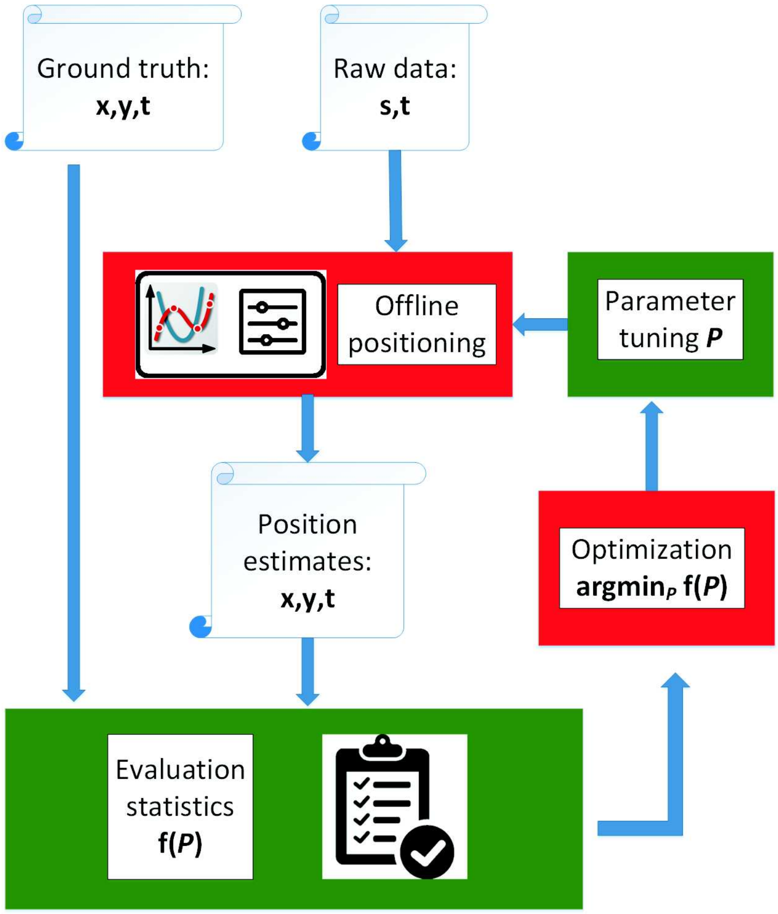

Figure 8.2. The workflow for the optimization of the parameter tuning P that determines the positioning algorithm's performance.

Initially, the offline positioning module receives as input the recorded raw signals with their timestamp (s, t), and based on some setting P of its algorithm's parameters, the module produces its outcome: a list of position estimates with their corresponding timestamp (x_e, y_e, t_e). Then, by comparing the estimates to the ground truth (x_g, y_g, t_g), the tester can characterise the performance of the setting P, using a statistical metric $f(P)$ (e.g. mean error, median error, etc.) that evaluates the outcome of the estimation. This procedure can be repeated for several parameter settings P, obtaining an evaluation for each of them, in search of the optimal one P^*.

$$P^* = \underset{P}{\arg\min} f(P) \tag{8.2}$$

Without the possibility of running the positioning algorithms offline and comparing it against the spatio-temporal ground truth information, the tuning of a positioning system can become a very tedious task. The tester would need to repeatedly traverse the environment with an online positioning application. The performance of the online positioning algorithm should be evaluated for many candidate parameter settings. In this case, one formal solution would be to repeat this procedure many times, and to record the position estimates every time, while also gathering ground truth information. The complexity of this task can increase exponentially with the number of parameters, due to the possible combinations. Furthermore, the environmental conditions can change in the different recordings, introducing a potential bias in the selection of the optimal setting and making the comparisons to be inconsistent.

A less formal, but undeniably existing method in practical deployments, is the approach of testing-and-setting with visual evaluation, in which an experienced engineer empirically tries several parameter settings, evaluating the position estimations visually, in real time. The sketchiness of this method is evident, but due to lack of formal, efficient and low cost evaluation and tuning methodologies, it is often met.

With the proposed method, the search for the optimal setting P^*, can be done offsite either manually or automatically.

Manual Parameter Tuning

In the manual approach, the tester can run the offline algorithms, trying several candidate settings, one by one. For each setting, all the evaluation metrics characterising the performance of the estimation (as discussed in Section 8.4.4) can be calculated. Also, the tester can visualize the estimated path in order to obtain a visual feeling, similar to the one a user would have while using the system. In this way, a tester can find the most appropriate tuning for a specific deployment. Moreover, evaluating several parameter settings without any effort, may offer the tester an insight of the practical effect of each parameter to the algorithm. A thorough analysis like this, may enrich the intuition of the tester concerning the algorithm under test or even inspire him about how to improve the algorithm itself.

Automatic Parameter Optimization

The procedure of the automatic optimization approach is straightforward. An optimization algorithm that runs offline tries to solve the optimization problem defined in Equation 8.2. The tester needs to choose four elements:

- (i) the recorded data over which the optimization will take place
- (ii) the evaluation metric $f(P)$ (the objective function, as mentioned in the optimization terminology)
- (iii) the optimization algorithm
- (iv) the search space

The elements (i) and (ii) that concern the recorded data and the evaluation metric have been discussed earlier in this work. The optimization algorithm (iii) can be chosen by the tester according to the problem's characteristics. For example, a full search algorithm would evaluate all valid candidate solutions P, in order to provide the optimal one. This approach though is computationally expensive. Therefore, heuristic optimization algorithms could be useful in the case of significant computational complexity. The search space (iv) is the area of all valid values of the parameter tuning P, in the context of the optimization problem. Each parameter of the algorithm that needs to be properly tuned can be one of the dimensions of the multidimensional search space. The set of valid values for each parameter/dimension should be defined. The search space will have as many dimensions as the number of the parameters to be optimized.

8.5 Implementation

In this section, we present the software tools which allow the execution of the presented workflow. Firstly, we introduce the mobile application GpmLab with which we perform the raw data recording along with the ground truth gathering. An early version of this application, without the raw data recording option, is also discussed in our previous work [Martinez de la Osa et al., 2016]. Furthermore, we present the GpmStudio platform which runs the offline positioning and offers evaluation and tuning capabilities. Both GpmLab and GpmStudio tools assist the main positioning framework of our team, the Global Positioning Module (GPM) [Bekkelien and Deriaz, 2012].

8.5.1 GpmLab: Recording Application

As it has been explained during the presentation of the method, the recording procedure has one prerequisite, that is the definition of the path to be followed by the tester. This path consists of a list of positions, that will be followed one after the other, and will serve as checkpoints for the tester. The minimum required fields for a checkpoint are the 2D coordinates of its position. Apart from these, the checkpoint can be enriched by adding other fields that describe a position with more detail, such as altitude, floor, room, etc. This predefined path is the only input required by the GpmLab application. An example of a predefined path is shown in Figure 8.3.

Figure 8.3. An example of a predefined path.

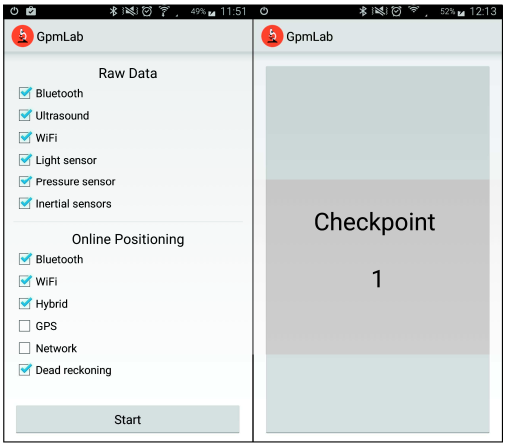

Figure 8.4. The two main screens of the recording application GpmLab.

Before proceeding to the recording, the tester should clearly mark in the physical world the predefined path with clear landmarks or added signs. If it is not possible to precisely determine the checkpoints' positions with landmarks, the tester should measure the distances in the reference maps and place in the physical world signs for every checkpoint, such as stickers on the ground with clear numbered labels.

The GpmLab application has a very simple and straightforward interface with two simple screens (Figure 8.4). Initially, the user has to select the kind of signal readings that he wishes to record, such as Bluetooth, Ultrasound, WiFi, sensor data, etc., as seen in the left screen of Figure 8.4. Apart from the raw data, recording the estimations provided by online positioning algorithms is also possible. It is noted though that in the context of this work, the online positioning does not participate in the proposed methodology. As mentioned earlier, recording the estimations of the online position providers could potentially be useful to verify the consistency between the online and the offline providers. After selecting the information to be recorded, by pressing start, the second screen appears (right side of Figure 8.4), which facilitates the synchronisation of the the raw data recording with the ground truth gathering. In this screen, there is a single big button indicating the number of the next checkpoint to be reached.

In order to start recording the data, the tester must be placed over the first checkpoint. Then, he should indicate it to the application by clicking the unique button of the interface and start walking towards the second checkpoint. The system logs the time the user begins the path and starts recording the raw signals of all selected sources, marking them with the timestamp of each reception. The application will continuously log these data throughout the whole path, and not only at the checkpoints. Every time the tester steps over a checkpoint, he should indicate it again by pressing the unique button (on which the number of the checkpoint will be indicated), so as to to mark the checkpoint with a timestamp, until he reaches the end of the path. At the moment of arrival at the last checkpoint (an event indicated by the user), the application will stop gathering information.

8.5.2 GpmStudio: Offline Evaluation and Tuning Platform

The GpmStudio platform is an offline positioning tool suite that utilizes the recordings obtained by the application GpmLab. The interface of GpmStudio is shown in Figure 8.5.

On the left panel, there is a menu where all available recordings are listed in a structured way. The tester can select the recording which he wishes to process.

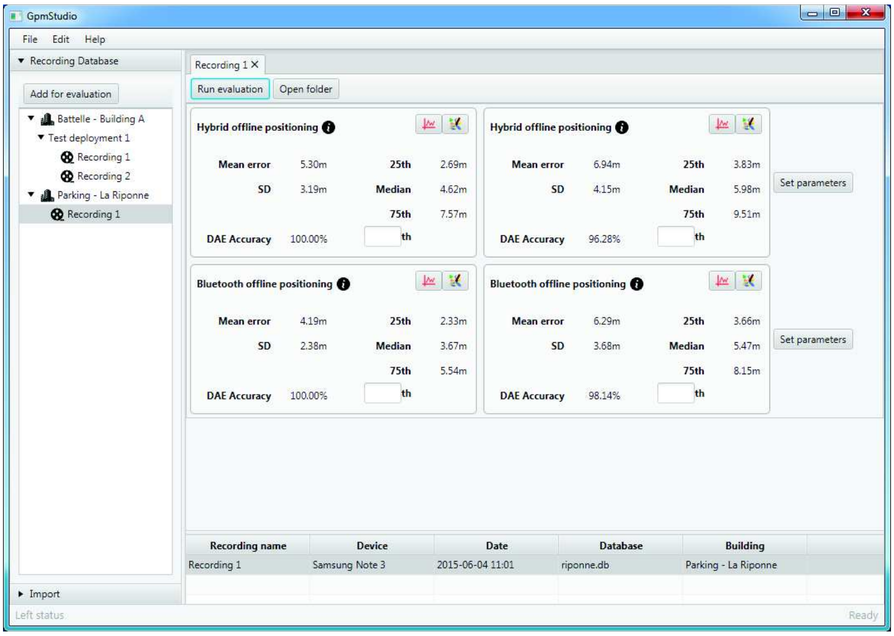

Figure 8.5. The interface of the GpmStudio tool suite.

According to the source type of the recorded raw data, the corresponding offline position providers that can utilize these data are used, running their offline positioning algorithms with their default parameter settings. At the same time, the evaluation of the performance of each provider is done, as the spatio-temporal ground truth information for each recording is available. The default interpolation method is the *interpolation per estimation update* (presented in Section 8.4.3.1), though the tester can choose the desired one.

The results of the evaluations are presented in the large central panel of the interface. The evaluation of each position provider is included in a box, highlighting the main statistical metrics of the error (mean, standard deviation, 25th, 50th and 75th percentile). Moreover, links to the visualization of the estimated path on a map (Figure 8.6), and plotting options of the cumulative distribution function of the estimation's error (Figure 8.7) are offered.

The presented scenario intends to exemplify the features of the evaluation platform. For clarity, we specify that a broad area (120 * 40 m) of an underground parking

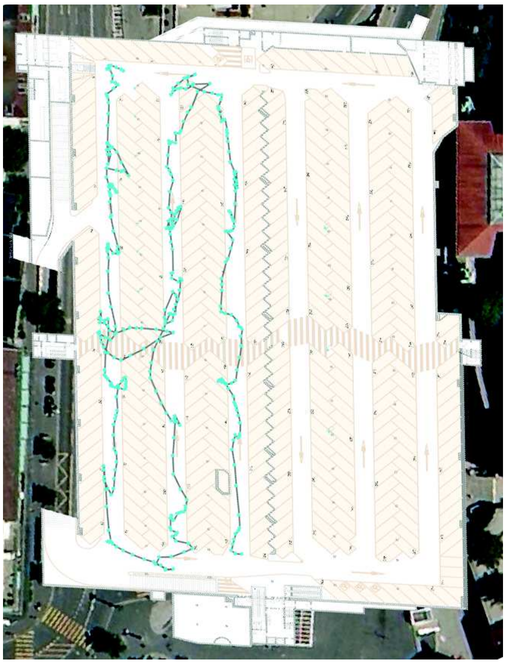

Figure 8.6. The visualisation of an estimated path, produced by the offline positioning functionality of the GpmStudio.

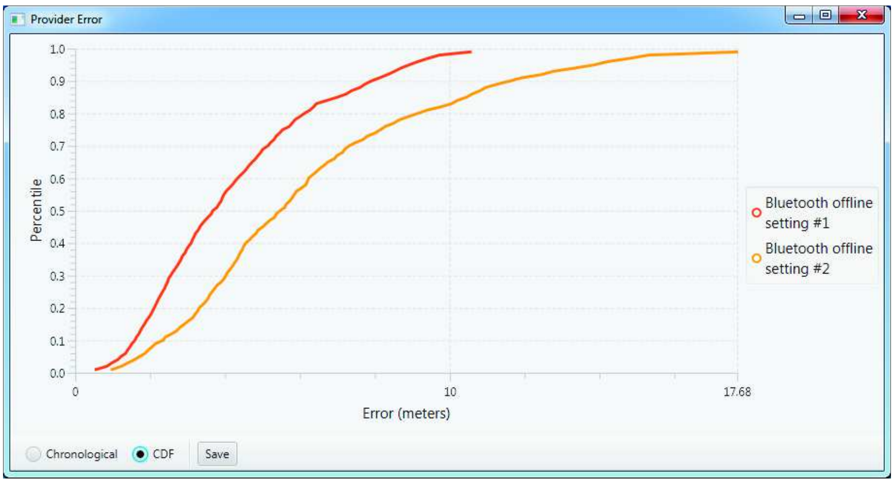

Figure 8.7. The CDF of the positioning error with two different parameter tunings, produced by GpmStudio.

lot was used as the test environment (left half part of Figures 8.3 and 8.6). In this area, 40 BLE beacons were placed on a rhombus grid pattern, and a filtered weighted centroid algorithm was used [Anagnostopoulos and Deriaz, 2014]. As explained in

Section 8.4.2, the distance between the checkpoints is a designer's choice. In this example, the distance between consecutive checkpoints is approximately 8-10m.

8.5.2.1 Manual Parameter Tuning

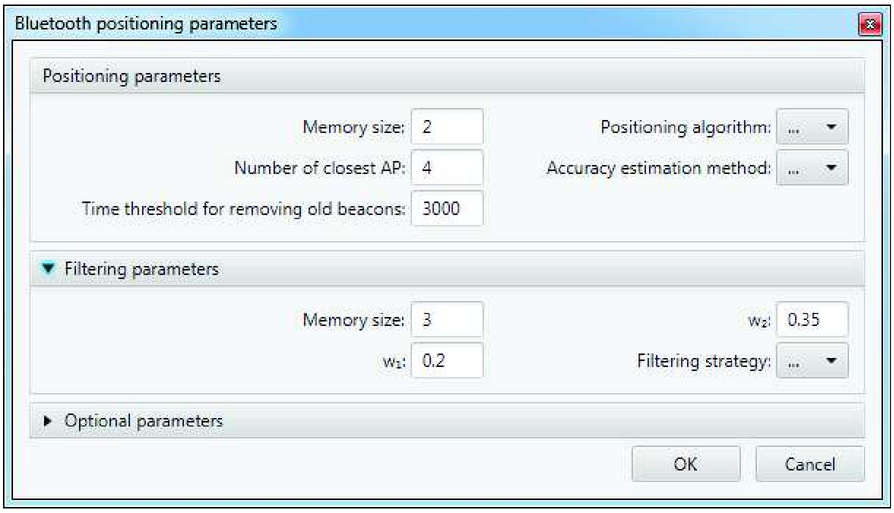

Figure 8.8. A parameter selection window of the GpmStudio tool suite.

So far, the evaluating capabilities of GpmStudio platform have been presented. The main power of this platform however lays on its tuning features. The tester who has an insight of the system under test, is offered the possibility of adjusting all tunable parameters of each positioning algorithm, re-evaluating each time, and comparing the change in performance. This difference in performance can be evaluated by comparing the statistical metrics, comparing the respective CDF's, and by examining the estimated paths on a map. Figure 8.7 exemplifies the difference in performance between two different parameter settings of the same algorithm, while in Figure 8.5 the corresponding statistical metrics are reported.

In Figure 8.8, an example of a parameter selection window that is offered to the tester is shown. Using a tool like this, the designer (or the tester) of a positioning algorithm, has the possibility of testing the immediate impact of each parameter on his algorithm's performance.

This tuning option has proven to significantly facilitate the deployment procedure for our team. Following this methodology in cases where we had a new deployment in a new environment, simplified the task of tuning the positioning system. An experienced person was able to quickly tune the algorithm, adjusting its parameters accordingly.

8.5.2.2 Automatic Parameter Optimization

The GpmStudio tool suite contains a module for automatic parameter optimization. The goal of this module is to find those parameter settings that optimize the performance of positioning algorithms, based on the recorded data. To proceed with the optimization, the tester needs to choose four elements:

- (i) the recorded data
- (ii) the objective function $f(P)$
- (iii) the optimization algorithm
- (iv) the search space

The user can select (i) the recorded data of the path that he wishes to process, selecting from the available recorded files. The selection of (ii) the objective function and (iii) the optimization algorithm is done by choosing from a list of available options. Defining (iv) the search space is the most delicate action to be performed. The tester should select the dimensions of the search space. Each parameter chosen to be included in the optimization problem is one of the dimensions of the search space. For each dimension, the tester needs to define its set of valid values. Assuming numerical parameters, the tester should define the minimum and maximum value of the parameter as well as the granularity of the search, i.e. the distance between two consecutive values of the parameter.

In Figure 8.9, an exemplification of the form of an optimization problem is given. The search space of this problem has two dimensions and the objective function is the mean error. The first parameter is the number of the closest access points used for ranging methods. The selected range of values is $[1, 10]$, with a step of 1 which is an intuitive selection for an integer parameter. The second parameter is the number of the latest RSSI receptions from each access point that are used in the calculations (the memory size of a list), which similarly has a range of valid values $[1, 10]$, with a step of 1. The best value of the objective function (5.7 meters) is achieved at the point corresponding to 4 access points, and to a memory size of 2.

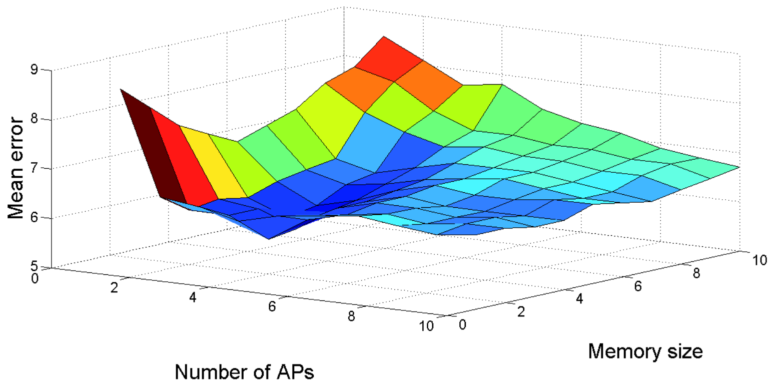

Figure 8.9. Mean positional error for 100 combinations of parameter settings, exemplifying the perspective of an optimization problem.

Evidently, the problem presented above is a simple case, with a very limited search space. A full search algorithm can quickly evaluate all the points of the search space (100 points in this case), and produce the data for the plot of Figure 8.9. For practical needs of our group, the full search algorithm has been used, providing results in most cases within a time-frame of a few minutes, or on rare occasions where many parameters were used, a few hours.

The complexity of the problem increases as more dimensions are added or with a high granularity of non-integer parameters. By imagining a hybrid system, utilizing information from many sources, each of which has several parameters, while also adding a filtering step or other processes with their own parameters, it becomes evident how enormous the search space can become. For cases like these, meta-heuristic algorithms can be very useful. When the search of the whole search space is not possible, local minima could provide a near optimal solution. In this context, the hill climbing algorithm (which is a local search method) has been used in this optimization module. The hill climbing algorithm requires a starting point in the search space. Naturally, the default values of all parameters, as they are set, are used to define the starting point. The intuition behind this selection is that a local minimum close to the default values is more likely to be near-optimal than other local minima close to a random starting point in the search space. Nevertheless, the tester has the freedom to define the starting point.

The outcome of the optimization is a list with the best solutions, sorted by their objective value. Each solution is a point in the search space, thus it is a set of values for the parameters that were chosen to participate in the optimization. Since many points in the search space might have very similar evaluation scores, the tester can observe the values of the parameters of each point among the best ones, and select accordingly. Blindly selecting the parameter setting that gives the best evaluation score, based on a single recording, might be quite misleading as there is the danger of overfitting. A single recording might contain particularities that do not reflect all use cases. Factors that can play a role are: the speed of the tester while he is recording the path, the noise level of the environment during the recording, the device used, the chosen path (which parts of the area of the deployment the path covers and how equally it covers them), etc. To address these issues up to a certain extent, we are proposing a multi-objective optimization approach, which will allow the combined usage of several recordings.

8.6 Usage Overview and Conclusions

In this work, we presented a straightforward methodology for evaluating and tuning positioning systems. The methodology includes a dynamic way of recording the ground truth information and the received raw signals. The subsequent offline phase offers the possibility of tuning the positioning algorithm in order to improve the system's performance. The tuning can take place either manually by an expert, or in an automatic way, by an optimization module of the offline evaluation platform.

The proposed methodology has several applications. A usual scenario that a positioning expert has to face is deploying in a new environment, in which the need to calibrate the positioning algorithm appears. A simple approach is using a test-and-set method. With this first approach, for every different tuning of the system, the tester has to revisit the deployment area, and either visually evaluate the performance or actually record the position estimates and the ground truth each time. This tedious task is completely overcome with the proposed methodology. In this way, the time needed at the deployment area is minimized. Also, the consistency of the test with different parameter settings is guaranteed, as the test utilises the same data.

Moreover, each recording of a path is an addition enriching the bank of collected data. Increasing the number of collected recorded paths offers the possibility of making consistent comparisons through time over a variety of environments. The possibility of crowd-sourcing recorded paths creates the perspective of a testbed based on real data.

Furthermore, having recorded all the data needed for an offline positioning algorithm, by following a precisely described methodology, can significantly facilitate the reproducibility of experiments for indoor positioning publications. Making the recorded data publicly available (raw data and ground truth), and mentioning the exact methodology of collecting these data, removes any ambiguity over the presented experiments of a publication. In this way, issues such as the ones presented in [Adler et al., 2015], and discussed earlier in this work, can be efficiently overcome. As emphasized at the published conclusions from the IPSN 2014 competition [Lymberopoulos et al., 2015], in order to ensure that all systems are evaluated under identical environmental conditions (i.e., number of people in the room, interference etc.), all systems should be simultaneously evaluated at a given evaluation point. Generally, using results of another work as a baseline, requires a consistent comparison, with similar conditions. Using the same recorded data, guarantees the consistency of the comparison.

Lastly, this study proposed two ways of optimizing the system's tuning. The manual selection of parameters by a tester, not only allows the experienced tester to quickly improve the system's performance offline, but offers them a better intuition about the effect of each parameter on the system performance. The ability to compare the result of each parameter change consistently can help the tester/designer of the system to better understand the role of the parameters in the resulting performance. Moreover, this understanding may inspire the tester/designer of the system how to evolve and potentially improve the algorithm used. On the other hand, the automatic optimization approach directly offers optimal parameters tunings, even in the absence of a person with experience in the functioning of the algorithm and the system. For cases that the spanning of the whole search space is feasible in reasonable time frames, a full search is proposed. On the contrary, in cases where the computational complexity is high, heuristic algorithms prove to be very useful. Local search algorithms, like the one presented in the tests of this study, are an appropriate solution assuming that a reasonable starting point is known. Since existing systems have a default parameter setting, this setting forms a perfect candidate for a starting point. For problems with a very big search space of high dimensionality, meta-heuristic algorithms (such as genetic algorithms) that offer better diversification can be used.

9 A Multiobjective Optimization Methodology of Tuning Indoor Positioning Systems

9.1 Chapter Abstract

How can the collected data from testing an indoor positioning deployment be transformed into information concerning the optimal tuning of a positioning system in this deployment? How can such a kind of accumulated information from several deployments be transformed into more generic knowledge regarding the system's performance, with respect to several performance goals? In this work, we address these issues by presenting a multiobjective optimization methodology of tuning indoor positioning systems, based on real data recorded onsite. Selecting the appropriate tuning for a positioning system is a challenging task, which depends on many factors: the specific deployment, the devices used, the evaluation metrics and their order of significance, the user-case scenarios tested, etc. In order to handle these multiplicities, we introduce the use of multiobjective optimization which allows several objectives to be simultaneously satisfied. We exemplify the methodology performing tests with the GpmStudio platform, a desktop tuning and evaluation platform that supports our Global Positioning Module (GPM). The methodology proves to be a very useful tool in the hands of testers who are designated to optimally tune the positioning system in a variety of scenarios.

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9.2 Introduction

In recent last years, the indoor positioning community has identified the need to establish well defined methodologies of evaluating the performance of indoor positioning systems [Adler et al., 2015]. A series of works [Martinez de la Osa et al., 2016, Lemic et al., 2015, Torres-Sospedra et al., 2017, Barsocchi et al., 2013, Lymberopoulos et al., 2015], has offered several well defined alternatives, some of which are the formal ways of performing indoor positioning competitions, like the ones held in the IPIN [Torres-Sospedra et al., 2017, Barsocchi et al., 2013] and the IPSN [Lymberopoulos et al., 2015] conferences.

Furthermore, apart from the evaluation methodologies that have started to draw significant attention from the indoor positioning community, the methodologies of optimally tuning a system also form a domain worth discussing, sharing ideas on and improving. Assume a positioning expert called to deploy a positioning system, tune it properly, present it and report its performance. While the part of the evaluation and its relevant methodologies have started to be extensively discussed, the step of how the system is tuned accordingly does not appear to have gained the same popularity. It is not uncommon that, regarding the optimal tuning of the system, an empirical selection of the appropriate tuning is mentioned, or a manual test-and-set procedure.

The question of how to tune a positioning system at a new deployment has drawn our interest. We have approached the domain of evaluating and tuning positioning systems with a trilogy of works. In the first work of this trilogy (Chapter 7), we established a methodology of ground truth definition and position evaluation of online positioning solutions. In the second work (Chapter 8), we presented an offline tuning and evaluation methodology based on recorded data. In that work, by presenting our offline parameter optimization platform (GpmStudio), the way that the methodology exempts the tester from the obligation of repeatedly revisiting the deployment environment to test-and-set the Indoor Positioning System's (IPS) parameters was exemplified. The current study concludes the trilogy with the introduction of multiobjective optimization techniques.

The broad goal of optimally tuning a positioning algorithm may be composed of a multitude of objectives to be satisfied. This multitude of objectives may concern different kinds of multiplicities. It is generally accepted [Lymberopoulos et al., 2015] that it is very hard to fully capture the effectiveness of an indoor localization algorithm with a single metric. Using a unique metric might not be representative of a system's performance and could be unfair when used for comparisons. A more holistic evaluation would be an appealing field of research. Thus, one kind of multiplicity is the use of several evaluation metrics as different objectives to be satisfied. This approach can provide a more complete evaluation of the performance of a system under test.

Moreover, selecting a parameter tuning based on a single recording introduces the risk of overfitting. Combining several recordings (with each recording being another objective) of the same deployment could minimize this danger by strengthening the robustness of the parameter setting suggestion. Lastly, using recordings from a variety of environments to infer a parameter setting that handles a good trade-off in all of them could lead to a good selection of the default setting of the system to be deployed in an unknown environment.

The rest of this chapter is organized as follows. In Section 9.3, we introduce preliminary information, necessary for the rest of the work. In Section 9.4, the related work is discussed, along with the contributions of this study. The proposed methodology is theoretically presented in Section 9.5, along with the implementation of the method with the related software tools. The experimental results based on a multitude of recorded data are presented and discussed in Section 9.6. Lastly, conclusions drawn are discussed in Section 9.7.

9.3 Preliminaries

9.3.1 Multiobjective Optimization

The goal of mathematical optimization is the selection of the best element from a set of available alternatives, with regard to an accurately defined criterion. The function which evaluates the suitability of each candidate solution is called *objective function*. The space of feasible solutions is called *search space* or *decision space*. Many real life problems (in engineering, economics, operational research, logistics, etc.) contain more than one objective that needs to be satisfied. Multiobjective optimization is the domain that is applied where optimal decisions need to be taken, in the presence of more than one objectives. In multiobjective optimization, the evaluation of a candidate solution is a vector in a space with a number of dimensions equal to the number of objectives. This space is called the *objective space*.

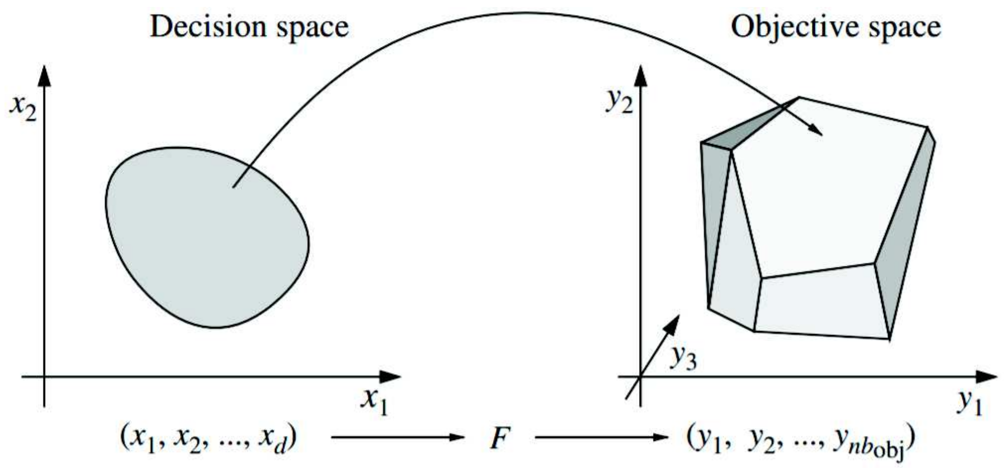

Figure 9.1. The decision space and the objective space in a multiobjective optimization problem (Image from [Talbi, 2009]).

In this category of problems, these multiple objectives can often be contradictory. Therefore, a trade-off among all relevant objectives is usually needed. The preferences concerning all objectives (their relative significance, their importance ranking, constrains, etc.) might often be unclear when stating the problem.

The principle solution concept used in multiobjective optimization is the notion of *Pareto Optimality*. With this solution concept, a small optimal subset is selected from the set of all candidate solutions. A solution A is said to *Pareto-dominate* another solution B, if A is better (or equal) than B in all objectives. A solution A belongs to the *Pareto Optimal Set* if there exists no other feasible solution that Pareto-dominates A. The image of the *Pareto Optimal Set* in the *objective space* is referred to as the *Pareto Front*. Each candidate solution of the population can be assigned with a *Pareto Rank*. All solutions of the *Pareto Front* form the first rank. Excluding the first rank from the population, and recalculating the *Pareto Front*, provides the solutions of rank two. All following ranks are calculated with the same procedure.

There is a plethora of algorithms and solution concepts that may use the notion of *Pareto Optimality* or not. A simplistic approach is to transform the problem into a single objective problem, by defining a linear combination of the multiple objectives as the unique objective function. This simple, practical and straightforward method has significant limitations. Initially, it might be unclear to the designer how to relatively weigh all objectives, in a precise way. Moreover, the objectives might be non-commensurable (the units of each objective may be incomparable among them), and an effort of normalizing them in order to combine them might not be practical, feasible or desired.

The result provided by the solution concept of the *Pareto Optimality* is a set of non-dominated solutions that are considered optimal. The selection of a unique solution among the *Pareto Optimal Set* (in case one is needed to be selected) is left to the discretion of a Decision Maker (DM), who chooses according to the current needs, and based on their own criteria [Coello, 2000, Rachmawati and Srinivasan, 2006].

Overall, a variety of algorithmic approaches allows the designer to decide and precisely define how the trade-off among conflicting objectives can be handled in order to arrive at a unique, optimal solution. The designer is free to define priorities, relative weights or restrictions among the objectives. Furthermore, it is also possible that a small list of optimal solutions is calculated (*Pareto Optimal Set*), which can then be given to a

DM who has the expertise to select the most preferable of these few optimal solutions. Decision support systems aim to facilitate the DM in the final selection of a unique solution. The flexibility in the ways of defining preferences regarding the structure of the problem and the characteristics of the desired optimal solution is a key element of multi-objective optimization.

9.3.2 Data Gathering

In contrast to works that are based on a simulation of a deployment's environment, this work is based on real data collected in IPS deployments. The data that need to be collected are of two main types:

- the timestamped measurements of raw signal receptions
- the spatiotemporal ground truth

The first category, concerning raw signals, is to be used as an input of offline positioning algorithms that output timestamped position estimates. These estimates are compared with the spatiotemporal ground truth in order evaluate the performance of the system. In our previous works [Martinez de la Osa et al., 2016], [Anagnostopoulos et al., 2016b], we have fully characterized a dynamic data gathering methodology. Here, we briefly describe this method, mentioning also other similar methods that are broadly used, as in the positioning competition of the Indoor Positioning and Indoor Navigation (IPIN) [IPI,] conference, and could also be used to feed the tuning methodology of this work. Both our proposed method and the one used in the IPIN competition belong to the category of dynamic evaluation (e.g. a moving tester) with predefined geometrical paths.

In these methods, a predefined path needs to be specified. This path consists of a list of positions that will be followed, one after the other, by a tester and will serve as checkpoints. A tester has to follow this predefined path, holding the mobile device that will continuously record all the raw signals that it receives during the path (and/or the position estimates that the positioning system produces), along with the timestamp of each reception. The tester should move on the path, which is composed of the straight linear segments that connect these checkpoints, at a steady pace. The tester has simply to indicate to the recording application the moment at which he passes over each checkpoint. In this way, every predefined checkpoint is marked with the exact timestamp indicating when the tester passed over it. These methods are subject to a small error that is introduced by the human factor (imprecision of the time or the location of clicking).

At the IPIN competition, the estimates that are evaluated are the most recent estimates obtained before each checkpoint. In our previous works [Martinez de la Osa et al., 2016], [Anagnostopoulos et al., 2016b], we proposed a continuous evaluation of all received position estimates. This is achieved by interpolating the ground truth between checkpoints to obtain the true position of the user for the time of the reception of each position estimate. Assuming a steady pace of the tester throughout the linear segment connecting two checkpoints, the interpolation would introduce no error. It is noteworthy that the tester is not required to maintain the same pace among different segments, but only during each segment.

This method has the disadvantage of adding to the human error the one that the tester may introduce by the imprecision in the time or the location of clicking (which is an inherent disadvantage of all similar methods), the interpolation error when not maintaining an actual steady pace between two checkpoints. The range of this possible error can be reduced by a dense checkpoint placement. Overall, despite this minor error addition, the benefits of this method are important for certain use cases. For instance, this continuous evaluation method can fully capture the experience of a user that would actually follow the path while receiving position estimates, since the complete trajectory estimation produced is evaluated. Also, it can provide metrics that concern the totality of the estimated trajectory. These metrics may evaluate the smoothness of the estimated trajectory, offering an indication of how pleasant the produced outcome may be to a user.

Nonetheless, the rest of this work makes no assumption about the method used to collect the data, as long as a spatiotemporal ground truth and timestamped raw signal measurements are present. The tests of this work were done with our methodology previously discussed in [Martinez de la Osa et al., 2016], [Anagnostopoulos et al., 2016b]. It is left to the discretion of the designer though to use the data gathering method that suits their needs and preferences.

9.4 Related Work

The field of IPS evaluation has attracted the attention of researchers in the field over the last years. Indoor positioning competitions have started becoming popular in relevant conferences [Torres-Sospedra et al., 2017, Barsocchi et al., 2013, Lymberopoulos et al., 2015, Torres-Sospedra et al., 2017]. Works have proposed methodologies where a robot replaces the human tester to traverse the test environment defining the ground truth and collecting data [Lemic et al., 2015, Adler et al., 2013, Adler et al., 2014d]. Such robots are equipped with a high accuracy positioning system, whose accuracy is higher by at least one order of magnitude compared to the system under test. A recent interesting study [Popleteev, 2016] has focused on measuring the error introduced by humans when they are called to statically place a hand-held device over predefined points, defined by floor or ceiling markers or even defined relatively to landmarks in the environment. People unfamiliar with the process participated as a test group, achieving in all three cases (floor markers, ceiling markers and landmarks) a median error lower than $10cm$. In the floor markers case, which is the one commonly used in competitions, the median error was only $7.1cm$, and the 95th percentile of the error $15cm$. The authors also present the accuracy of a series of benchmarks that use high accuracy positioning systems (as reported in the relevant publications), ranging between 6.7 and $25cm$. The results indicate a similar accuracy between the human defined ground truth and the commonly used reference systems.

Apart from the evaluation methodologies, the creation of testbeds has gained popularity over the last years. In [Adler et al., 2013], a visual testbed is introduced, in which a robot spans an area recording both the raw signals and the ground truth information throughout the area. These data are offered for use as a testbed for positioning systems. Moreover, the creators of the IndoorLoc Platform [Sansano et al., 2016], present a testbed based on data collected by humans. This method is used for the offsite track of the IPIN competitions, where the IPSs of different teams compete by running positioning algorithms offline, based on recorded data that they receive.

The metrics used to evaluate positioning systems can be numerous. The statistics of the Euclidean error (mean, median, percentiles, standard deviation, etc.) are the most commonly used. Other metrics, such as the room, floor, or building hit rate [Torres-Sospedra et al., 2017], the latency of estimation [Lemic et al., 2015] or the smoothness of the estimated trajectory [Martinez de la Osa et al., 2016, Pulkkinen and Verwijnen, 2015] are also used. It is not uncommon that these metrics are combined in a unique final score [Lemic et al., 2015, Torres-Sospedra et al., 2017] based on subjective criteria, introducing a simple case of multiple objective handling.

It is common in the community to discuss the parts of deploying and its requirements, the positioning methods, as well as the ways of evaluating the system's performance. It is not uncommon though that the step of how the system is tuned accordingly is left undescribed, mentioning for example an empirical selection of the appropriate settings. For instance, among the five competing teams in the offline track of the 2016 IPIN competition [Torres-Sospedra et al., 2017], only one focuses on explaining the procedure of optimizing the parameters of their system, according to several objectives. The BlockDox team [Torres-Sospedra et al., 2017], chose to optimize the hyper parameters of their algorithm hierarchically and greedily, by firstly optimizing the parameters of the floor classification, and only then the location parameters. In this way, when the optimum of each parameter was found, it was turned into a constraint and the optimization procedure continued to optimize the next parameter.

So far, advanced multiobjective optimization techniques have not been extensively used in the field of indoor positioning. In a very interesting sequence of works [Domingo-Perez et al., 2014, Domingo-Perez et al., 2016a, Domingo-Perez et al., 2016b, Martín-Gorostiza et al., 2016], Domingo-Perez et al. and Martin-Gorostiza et al. introduce multiobjective optimization techniques to solve the optimal sensor placement problem. An adaptation of the state of the art NSGA-II algorithm [Deb et al., 2002] is used to infer the *Pareto Optimal Set* of sensor placements, from which a decision maker can choose. Contrary to our current work, these studies concern a pre-deployment task, and therefore are based on simulations of the resulting deployment. To the best of our knowledge, our work is the first that brings the principal solution concept of multiobjective optimization, the *Pareto Optimality*, in indoor positioning problems based on real recorded data.

In the last decades, Multiobjective Optimization Evolutionary Algorithms (MOEA) have been greatly studied. State of the art algorithms, such as SPEA2 [Zitzler et al., 2001], NSGA-II [Deb et al., 2002] and recently its evolvement NSGA-III [Deb and Jain, 2014, Jain and Deb, 2014], have been widely used in problems with many objectives, in search of the *Pareto Optimal Set*. The goal of such algorithms is finding the *Pareto Optimal Set* of non-dominated solutions, among which a decision maker should choose one according to their preferences [Coello, 2000, Rachmawati and Srinivasan, 2006]. In this approach, preferences are expressed *a posteriori*. On the other hand, in *a priori* methods the decision maker expresses preferences regarding the objectives in advance and in a formal way. For instance, in some cases the tester is able to combine the objectives *a priori* into a single objective function, or may define a desired reference point in the objective space [Yang, 2000]. Lastly, *interactive methods* allow the DM to intervene during the search, steering the development of the search, as for instance by responding to comparisons of pairs of candidate solutions [Malakooti, 1988].

According to relevant surveys [Coello, 2000, Zio and Bazzo, 2011], the *a posteriori* methods are the most used ones. Recent works in the field, have tried to facilitate the task that remains for the DM, i.e. choosing a final solution among the optimal set of non-dominated solutions. Efficient visualization techniques for *Pareto Front and Set* analysis have been proposed to help DMs in the selection task [Zio and

Bazzo, 2011], [Blasco et al., 2008]. Moreover, methodologies to reduce the number of members in the *Pareto Front* have been proposed to help the DM identify their preferred solution [Zio and Bazzo, 2011].

9.5 Proposed Methodology and its Implementation

9.5.1 Concept

In our previous work [Anagnostopoulos et al., 2016b], we presented a methodology that allows the tester to make consistent comparisons of parameter settings, or even of different positioning algorithms, by running positioning algorithms offline based on the same recorded data. In this way, a tester is exempt from the tedious task of repeatedly traversing the environment in order to tune the parameters of the positioning system. Furthermore, the offline running of optimization algorithms provided the parameter tuning that gives the best performance of the selected evaluation metric based on a specific recording.

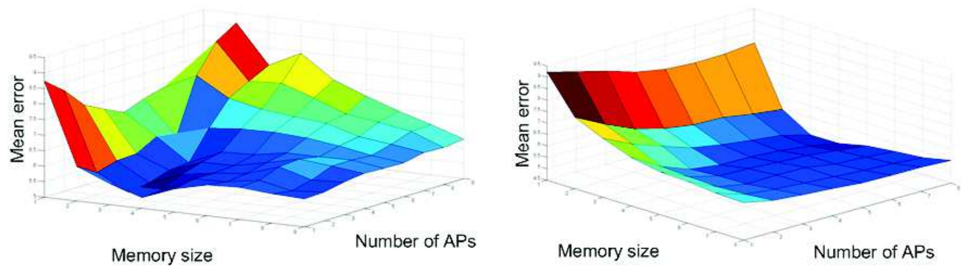

Figure 9.2. Average positioning error, depending on two parameters, based on recordings in two different environments.

The goal of this work is to move further on, by doing the extra step of combining different kinds of multiplicities, and providing a result that efficiently handles a trade-off of multiple objectives. These multiplicities may concern multiple recordings in the same environment, multiple mobile devices, multiple environments, etc. In Figure 9.2, we see the performance of an IPS in two environments. It is evident that the best performance for each environment (the lowest mean error in this case) is not achieved by the same parameter values. How should the designer of the system choose from a big variety of parameter settings? This problem becomes even harder when considering hybrid systems, where apart from the parameters that serve the positioning algorithm of each technology used, additional parameters concerning the hybridization of the technologies also need to be properly tuned. To address these issues, we propose the introduction of multiobjective optimization techniques, to optimally tune an indoor positioning system.

A first approach is to use the simplistic method of reducing the problem to a single objective one, where the final single objective is a linear combination of the objectives. In cases where the units of the objectives can easily be combined, and that the designer is certain about the relative relevance of the objectives, this method may be an appropriate way to approach the problem. On the other hand, when combining many objectives, or non-commensurable objectives, the solution concept of the *Pareto Optimal Set* is more appropriate. The notion of *Pareto Dominance* excludes all dominated solutions from the *Pareto Optimal Set*, as it would be irrational to choose them. From the resulting optimal set, the designers/decision makers are free to choose according to their preferences.

Sum of Ranking at Each Objective

In many cases, a supporting system to the final decision making process is required, either to help the DM or to replace them in case the process of selecting a parameter tuning needs to be automated. As a supporting system, we propose a sum of the rankings of each solution according to each objective. The candidate solutions of the optimal set are sorted according to their performance in each objective, and are assigned a ranking at each objective accordingly. Adding the rankings of a solution in all objectives, can give a unitless impression of how well the solution performs in all objectives. Weights can be introduced to the sum of rankings, in order to express a potential difference of importance among the objectives.

9.5.2 Implementation

The GpmStudio platform, presented in our previous work [Anagnostopoulos et al., 2016b], is a desktop application that allows a tester who interacts with a user friendly GUI to access a database of recorded data and manually tune the IPS or run optimization algorithms which calculate optimal parameter settings for the positioning algorithms used. In this work, GpmStudio has been enriched with the addition of the mutliobjective optimization module. The mutliobjective optimization module of GpmStudio supports several algorithms and solution concepts. The main solution concepts of multiobjective optimization and relevant decision support methods discussed in this work (*Pareto Optimality*, *Linear Combination of Objectives*, *Sum of Ranking at Each Objective*) are implemented and supported by GpmStudio.

In the following Section 9.6, we present the results of tests performed with the mutliobjective optimization module of GpmStudio. Several recordings from different test environments are used along with different evaluation metrics. Each recording contains all receptions throughout a predefined path that traverses all accessible areas of each test environment. All tests are performed utilizing Bluetooth Low Energy (BLE) receptions. The Received Signal Strength (RSS) is used by a weighted centroid algorithm, used and discussed in previous works [Anagnostopoulos and Deriaz, 2015], [Anagnostopoulos et al., 2016a].

The focus of our tests is not on the specific positioning algorithm used and its parameters, but rather on the method with which the performance of the candidate solutions in multiple objectives is handled. Thus, our analysis focuses on the *objective space* and the relevant analysis therein, which holds in any other relevant context without loss of generality, rather than focusing on the *search space* which is bound to the specific example. For the sake of completeness, we mention that the *search space* of the tests of this work is composed of the valid values of the main parameters of the RSS positioning algorithm used. Such parameters are the number of closest APs included in the position estimation calculation, the memory size of the buffer storing the latest RSS, as well as parameters of the filtering used to smooth the sequence of position estimates. Regardless of the specific algorithm and its parameters, in the following section we proceed with a generic exemplification of the proposed methodology, focusing on the tester's selection options regarding the objectives to be used and the relevant analysis in the *objective space*.

9.6 Experimental Results

In this section, the results of a variety of tests exemplifying the proposed methodology are presented. In each test, more than one objectives are set to be satisfied. The differences among the objectives can be the different evaluation metrics chosen to evaluate the system, the different recorded data that the offline algorithms utilize, or a combination of them. Concerning the evaluation metrics, usual statistics of the estimation error are used (mean, median, percentiles, etc.). Moreover, a metric concerning the smoothness of the estimated trajectory was desired. As such, the Travelled Distance Ratio (TDR), which was discussed here [Martinez de la Osa et al., 2016], is used. In short, the TDR is equal to the ratio of the length of the estimated path over the length of the ground truth path. A value close to 1 indicates a smooth trajectory, while a higher value implies that the trajectory suffers from abrupt changes.

As a first simple exemplification of our method we present a problem with two objectives. The two objectives are two evaluation metrics: the mean error and the TDR. The recorded data used for both objectives are the same, recorded at an underground parking environment of a size 120 by 40 meters. In Figure 9.3, the first ten *Pareto Ranks* are presented in the objective space of the problem. The *Pareto Front* is the set of solutions in the first rank. We see in this plot that the solutions of the first two ranks are quite distinguishable from the next ranks, though really close to each other. The leftmost solutions of Figure 9.3 have a mean error of $3.2-3.3m$, while the solutions of the third rank are mostly above $3.5m$. At the same time, all TDR values in the range of $1-1.1$ can be considered very satisfactory, setting the leftmost solutions of the *Pareto Front* eligible and appealing for the decision maker. Having this result, the DM may either choose from the front based on the objective values

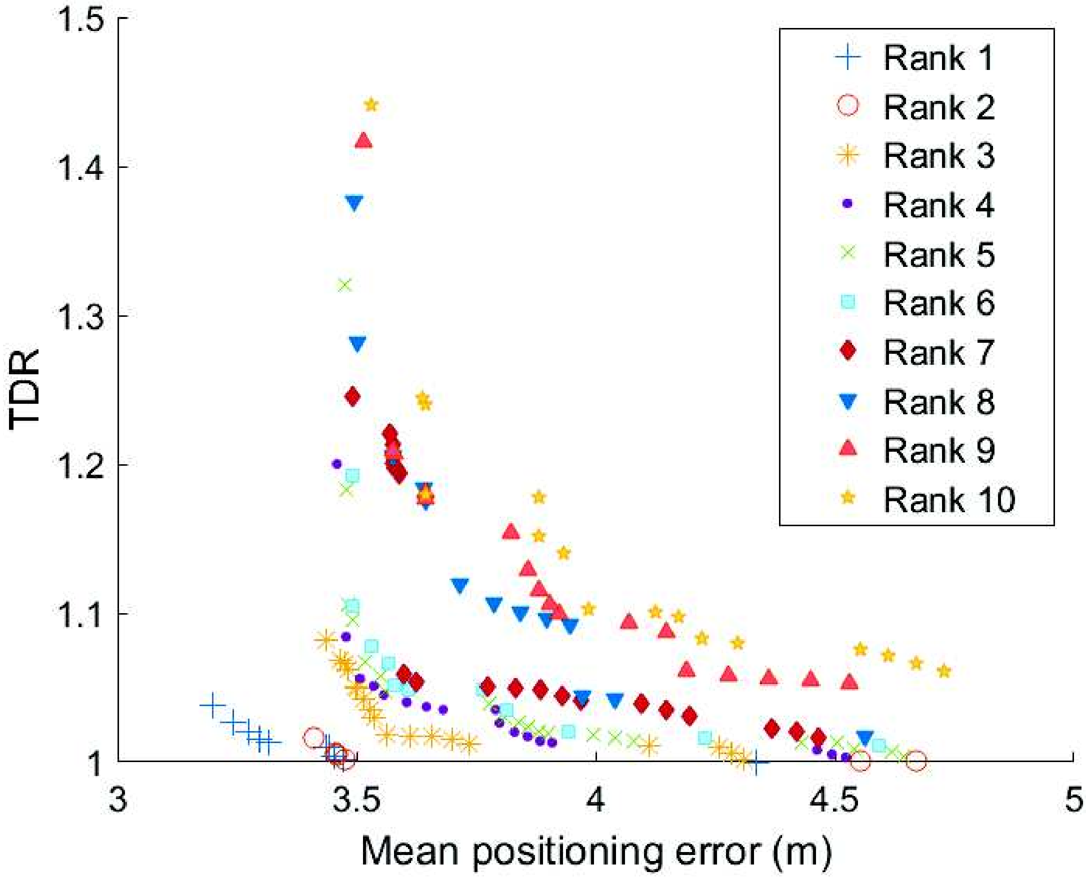

Figure 9.3. The 10 first Pareto Ranks of a 2-objective problem.

and the relevant preferences or repeat the test adding more objectives to obtain a more holistic view before selecting a solution.

For some applications, apart from the mean performance of the system, the worst case performance might also be crucial. For this reason, a third objective is added to the previous test: the 95th percentile of error. This objective adds to the calculation the notion of a 'worst case performance'. In Figure 9.4, the fronts of this 3-objective problem are presented. It is visually clear that two of the objectives (mean, 95th percentile) seem to have a strong correlation. Nevertheless, the addition of this objective can help the decision maker to potentially reject some solutions. For instance, those members of the *Pareto Front* that seem to have a significantly higher

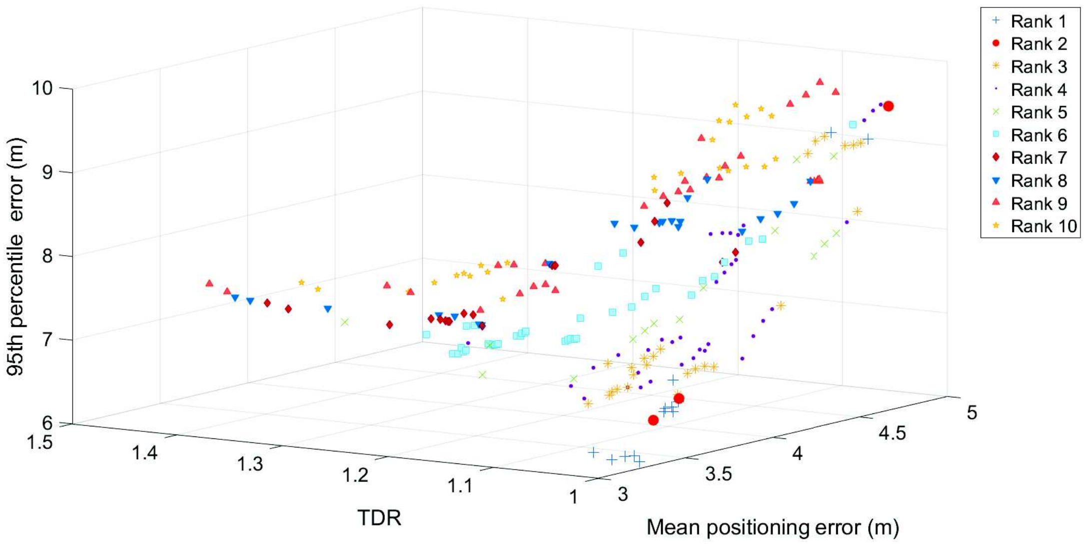

Figure 9.4. The 10 first Pareto Ranks of a 3-objective problem.

error at the 95th percentile ($> 9m$) than others ($\sim 6m$) could be excluded by the DM from the set of candidate solutions, simplifying his decision making.

Another interesting task is to comparatively evaluate the performance of the parameter settings in different environments. In Figure 9.5, we see the mean positioning error in three test environments: an underground parking lot of $\sim 4800m^2$ with a sparse access point (AP) deployment, an office environment of a $\sim 450m^2$ common space and a house environment of $\sim 60m^2$. The elements of rank 1 appear spread out in the plot. Using the *Sum of ranking at each objective* method discussed in Subsection 9.5.1, the rightmost solution of Figure 9.5 is proposed, which achieves $(3.2m, 2.1m, 1.4m)$ in the three respective objectives, having the lowest sum (equal to 18) among the solutions of the *Pareto Front*. Moreover, the linear combination of objectives is possible in this case, as the objectives are commensurable. Using a simple average of the three objective scores as a unique objective, the same solution results having the lowest value among the solutions of the Pareto Front. It is noteworthy that the same solution, meaning the same parameter setting, appears in the Pareto Front of the two previous problems (Figures 9.3 and 9.4).

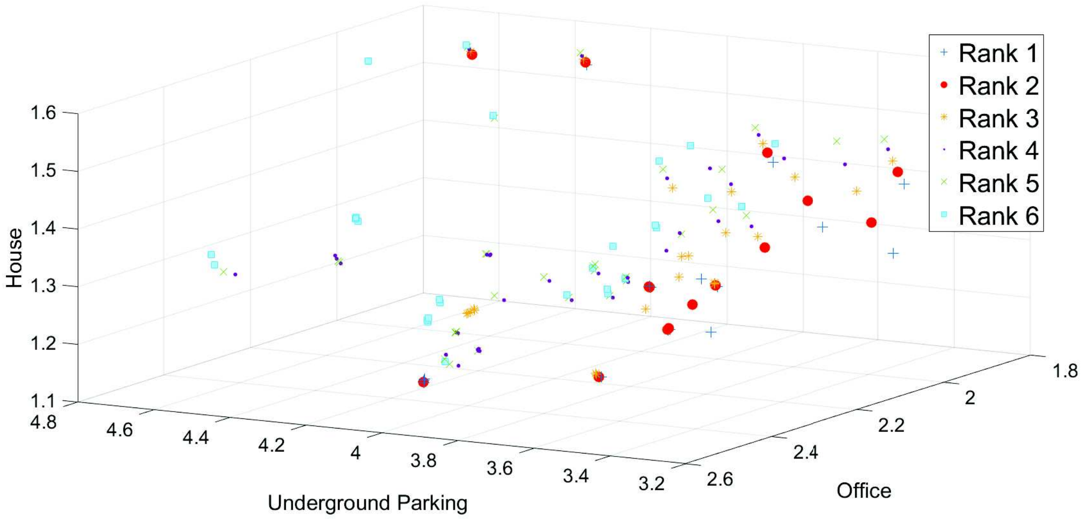

Figure 9.5. The 6 first Pareto Ranks of the mean error at 3 deployments.

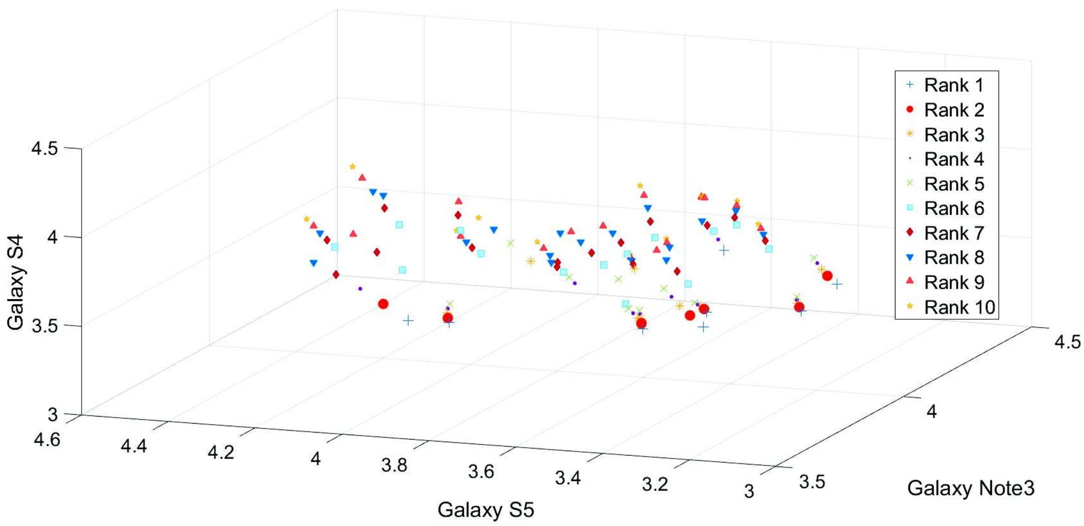

Figure 9.6. The 10 first Pareto Ranks of the mean error with 3 devices.

Several tests were executed either by combining pairs and triads of objectives or by combining many objectives. For instance, three different devices were used to record data in the environment of the underground parking lot. The mean error values of the three objectives formed another test that was performed. In Figure 9.6, the *objective space* of this problem is presented, along with the ten first Pareto ranks. The solutions, especially those of the *Pareto Front*, are much less spread out in the *objective space*, when compared with Figure 9.5, since the recordings of three devices in the same environment seem to be less contradictory objectives, compared to recordings in three environments with very different characteristics.

When combining all the objectives of all previous tests in a single problem, the nature of the problem changes drastically. In problems with more than three dimensions, a graphical representation is possible only for a subspace of the multidimensional objective space, disallowing a reliable visual overview to the decision maker. Moreover, the number of solutions appearing in the *Pareto Front* increase drastically. The four problems of Figures 9.3-9.6, have $10, 13, 17$ and 8 members in their *Pareto Fronts* respectively. On the other hand, when running the problem with 18 objectives, produced by combining 3 evaluation metrics (mean, $95th$ percentile, TDR) with 6 recordings (3 devices at the parking lot, 2 at the office and 1 at the house environment) the results are not really helpful for the DM. Out of 1125 possible solutions defined as the search space of the problem, 843 appear in the *Pareto Front*, offering no significant information to the DM. Similarly, the problem with 6 objectives (the mean error of the 6 recordings) has 72 members in its *Pareto Front*.

On the other hand, instead of putting all objectives in a single problem and selecting a solution from the resulting list, a solution that appears in the Pareto Fronts of all (or of most of the) smaller tested problems that have $2-3$ objectives, can be a solution to choose, as it efficiently handles the trade-off. For instance, there is only one solution appearing in the *Pareto Fronts* of all four problems previously presented (Figures 9.3-9.6). This fact sets this parameter setting as a perfect candidate for the default tuning of the tested system. It is also noteworthy that the parameter values of the above mentioned solution that appears in the Pareto Fronts of all four problems are close to the ones empirically selected as the default one for our system. More specifically, the proposed number of closest beacons to be used for the position estimations is 4. This forms an experimental confirmation of the theoretical characterization of this number of closest beacons as optimal, in chapter 4.

9.7 Conclusions

In this work, a complete formal workflow of a tuning methodology for indoor positioning systems using multiobjective optimization has been presented. The first step to be performed is the recording of the required data (spatiotemporal ground truth and timestamped raw signal receptions) in the test environment. Having collected those data, the tester can make consistent comparisons of different parameter settings, by running offline positioning algorithms. In this way, the tester is exempt from the tedious task of traversing repeatedly the test environment to test different settings of the system. In addition, contrary to the repetitive online testing procedure where the conditions of the test cannot be fully controlled (the noise level, the environment conditions, etc.), running offline positioning algorithms over the same recorded data guarantees the consistency of the tests.

The innovative step forward of this work is the ability to combine many objectives to be simultaneously optimized, offered by the introduction of multiobjective optimization techniques. With this approach, multiple evaluation metrics, several recordings in the same environment, different environments or devices, and other kinds of multiplicities can be combined in the effort to find a more holistic evaluation to optimize the system's performance.

Data recordings collected from three test environments with different devices, have been used to centrally perform tests and extract information in a formal way regarding the optimal parameter selection for an IPS under test. In the absence of methodologies such as the proposed one, this procedure is usually simplified to being the outcome of an empirical parameter selection by the system's expert. With the proposed methodology, new algorithms can be quickly tuned based on existing recorded data, while the empirically selected default parameter setting of existing algorithms can be evaluated and potentially improved. The trade-off of different evaluation metrics can be efficiently handled by selecting solutions from the resulting

Pareto Optimal Set. Similarly, trade-offs among different environments or devices used can be also efficiently addressed.

To facilitate the decision maker in choosing a unique solution from the resulting optimal set, we have tested two support systems: the *linear combination of objectives* for commensurable objectives and our proposed *Sum of ranking at each objective*. When combining a large number of objectives (> 4) in a single problem, the number of solutions appearing in the *Pareto Optimal Set* increases significantly. To simplify such cases, the big problem can be decomposed into smaller ones, with fewer objectives each. The final selection can be done by choosing solutions that appear in the *Pareto Fronts* of all (or most) smaller problems.

In order to further utilize the methodology proposed in this work to its full extent, we intend to systematically collect data from all new environments where we deploy positioning systems and use efficient ways of handling 'big data' in a unique problem. Moreover, we are investigating the potential use of crowdsourced data, and evaluating the feasibility of utilizing existing data from crowdsourcing platforms [Sansano et al., 2016, Georgiou et al., 2015] with our methodology.

So far, we have been collecting in our recordings all types of data that could be useful for a hybrid provider. Apart from the BLE receptions utilized for the tests of this work, sensor data (accelerometer, barometer, light sensor, etc.), as well as Wi-Fi and GPS recordings were stored. GpmStudio is therefore able to integrate hybrid providers in the calculations of its multiobjective optimization module.

In problems that the whole *search space* can be searched in feasible time frames, the *Linear combination of objectives* and the *Pareto Optimal Set* can be calculated by a full spanning of the whole search space. For very big problems, heuristic approaches come to address the issues of computational complexity. The commonly used *NSGA-II* algorithm [Deb et al., 2002] is implemented in GpmSudio, with a view to addressing computationally challenging scenarios. All tests performed in this work had a computational complexity that makes the full search of the search space feasible. Nevertheless, as the search space may increase in the future with the addition of hybrid algorithms, state of the art heuristic methods should prove efficient in providing good approximations of the *Pareto Optimal Set*.

Lastly, in an earlier chapter 4 where we theoretically modelled the intrinsic error of the indoor positioning method used in this work, we theoretically concluded that the optimal number of closest beacons to be used by this method is 4. The practical tests of this study came to experimentally verify that theoretical claim, by proposing the same value for that parameter.

Part IV

Conclusions

10 Conclusions

The goal of this Thesis has been to propose novel methodologies to address crucial issues of indoor positioning systems. The problems addressed are met throughout the life cycle of an IPS creation, from the design of innovative positioning methodologies to defining novel evaluation and tuning methodologies. All issues that the Thesis addresses with the proposed innovations had been identified by the scientific community as open problems that needed to be addressed. The proposed innovations have been published, passing peer review of experts in the field, at the most important conferences of the domain of IPS, and have been validated via implementation in national and international projects. In this chapter, we conclude the Thesis by discussing the contributions, their results and their importance, organizing them in the Parts that structure this Thesis.

Users Requirements

Since indoor positioning systems are designed and created to serve people's needs, it is indispensable that these needs are identified and taken into consideration in the way the system is planned and created. For this reason, identifying the needs and requirements of users is in order, before the start of the designing or the implementation part. Serving this direction, a questionnaire research was performed, aiming to investigate the navigational needs in the HUG (Geneva University Hospitals). The questionnaire offered great insight concerning the identification of the navigational needs of people in HUG.

The results of the survey, presented in Chapter 3 show that both visitors and staff are facing difficulties in finding their destination in the premises of the hospital. This is identified as a source of stress for both groups. Moreover, a significant amount of personnel time is spent in assisting people find their way. The survey results revealed that the existing assisting material is inefficient for people that do not speak the official language (French). A similar impression is reported for the material assisting people with mobility restrictions.

Apart from identifying the problems faced by and the needs of the users, the expectations and the requirements of the users from candidate solutions were also studied. The participants showed very positive feelings regarding the creation and the use of a mobile application that can help people find their way in the hospital. Some main problems that were highlighted as frequent and important, such as not taking into account the users' mobility limitations or their language preferences, are easily solved with a mobile application that can customize its function according to the user needs. The features that the users chose as the most significant were the appearance of the direction instructions as an intuitive trajectory in a map, the high accuracy of the position estimates, the consideration of users with mobility limitations and privacy protection.

From the results, it is evident that the priorities set by users are affected by the context of the environment and their cultural background. The importance given to the accessibility for people with mobility limitations is in accordance with the relevant sensitivity of health care providers on this issue as well as with the values of the Canton of Geneva. Similarly, privacy protection is highly valued in Switzerland, especially concerning health related information.

Indoor Positioning System, Indoor-Outdoor Handover and Propagation Model Self-Calibration

There are three subjects of research in Part I of this Thesis, concerning the core of a positioning system, that were presented in Chapters 4,5, and 6.

In Chapter 4, an innovative design of an indoor positioning system was proposed and its advantages were extensively discussed. The proposed system utilizes the weighted centroid method to satisfy the commonly met requirement of restricting the position estimates in the area of coverage. After theoretically analyzing and modeling the inherent error of the weighted centroid method, we show that the optimal selection of the parameter of the number of closest beacons used is 4. This theoretical estimation of the optimal selection of the number of closest beacons was later verified by the practical tests of the tuning methodology of Chapter 9. Moreover, we also proved our claim that an additional advantage of the weighted centroid approach, against the common multilateration approach, is that it is far more resistant against device diversity and poorly calibrated values of the propagation model. The practical tests in a challenging environment (an underground carpark) showed that even if the two algorithms have a similar performance (4∼ 5 meters) under a proper propagation model, when unsuitable propagation model parameter values are set, the weighed centroid maintains a similar performance while trilateration degrades offering an accuracy of above 7 meters. Moreover, we have presented the novelty of averaging the latest RSSI receptions in the distance domain instead of the RSS domain, elaborating on the advantage caused by the non-linear form of the propagation model. Lastly, we have shown the improvements that the additional filtering step brings to the accuracy of the estimates as well as to the smoothness of the resulting trajectory. The system showed a performance of ∼ 1 meter in static tests, and ∼ 2 meters in dynamic ones, in indoor building areas (corridors, big halls, etc.).

In Chapter 5, an innovative algorithm of switching between positioning technologies was introduced. The switching algorithm allows ubiquitous positioning with a seamless switching between indoor and outdoor areas and among their corresponding positioning technologies. Contrary to related works, we did not try to solve the indoor/outdoor detection problem using individual sensors as estimators, but we relatively compare the reliability of each available position provider. In this way, we ensure the selection of the most reliable technology at all times. In the context of our implementation, we proposed an intuitive heuristic estimator of the claimed accuracy for the BLE positioning system. The proposed algorithm handles the trade-off of the switch being responsive (by switching quickly to the positioning technology that becomes more reliable) and stable (by minimizing the 'jumping' effect of unstably wobbling between technologies). The algorithm's parameters allow the designer to adjust the system in accordance with the application's requirements, favoring either a quicker or a more robust switch. The experimental results of the tests, with a BLE indoor positioning system and the GPS as the outdoor technology, showed that the switching is robust, successfully occurring in all tests, maintaining an impressive average response time of 3-7 seconds.

A novel, automatic, online self-calibration method, which corrects the parameter values of the propagation model, was presented in Chapter 6. The improvement of the model parameters fits the environment's characteristics and, more importantly, the reception characteristics of the device used. In a series of tests, we showed the effectiveness of the method for both badly tuned and more properly tuned devices. The tests were done using the same raw data to compare the positioning with and without the re-calibration algorithm in order to guarantee the consistency of the comparisons. The algorithm showed a significant improvement of the mean positioning error, up to 16%, when the propagation model is to be corrected, while maintaining the system's performance in cases of properly tuned models. The proper tuning of the proposed self-calibration method is highlighted after extensive testing with different mobile devices and positioning algorithms. The method shows a similar performance in both the weighted centroid and the trilateration algorithm. The proposed method can be seen in the scope of research towards device independence, as well as in the context of facilitating calibration-free deployment in new areas.

Evaluation and Tuning Methodologies for Indoor Positioning Systems

The methods of evaluating indoor positioning systems has become a matter of heated debate in the indoor positioning community over the last years. The lack of common ways of how these technologies should be evaluated and how the spatiotemporal ground truth is to be defined has been identified by the community in the field. In Chapter 7, a simple and inexpensive solution is presented to tackle both of these problems in real life use cases. The current methodologies used in positioning competitions are either static, lacking the element of dynamic evaluation of a user moving (as in most realistic use cases), or only evaluate the position estimates sporadically, without evaluating the full outcome of an IPS's estimation. Our proposed method satisfies both these features, being both continuous and dynamic. Two alternative ways of interpolating the ground truth information are proposed and their relative advantages are extensively discussed. Moreover, we introduce a metric (TDR) that evaluates the smoothness of the full estimated trajectory produced by a system, aiming to capture the degree at which the appearance of the estimated trajectory would be appealing for the user. The effectiveness of this metric is further verified in Chapter 9, where it is proven to be independent of the Euclidean distance error metrics, and even complementary to them in some cases.

In Chapter 8, we proposed a practical, cost efficient methodology to evaluate and tune indoor positioning systems. The proposed methodology exempts the designer/tester of the system from the tedious task of having to revisit multiple times the deployment area for optimally tuning the system. As the tuning tests are performed offline based on the same recorded data, consistent comparisons of different settings of the same system or of different systems can be made in a robust and efficient way. The tuning of the system can take place either manually by an expert, or in an automatic way, by an optimization module of the offline evaluation platform (such as the GpmStudio platform that implements the proposed methodology), which constitutes a major utility of this work. A prospect that the proposed methodology creates is that of a testbed based on real data, especially considering the possibility of crowd-sourcing recorded paths. Furthermore, having recorded all the data needed for an offline positioning algorithm, by following a precisely described methodology, can significantly facilitate the reproducibility of experiments for indoor positioning publications. Making the recorded data publicly available (raw data and ground truth), and mentioning the exact methodology of collecting these data, removes any ambiguity over the presented experiments of a publication. Lastly, the manual selection of parameters by a tester, not only allows the experienced tester to quickly improve the system's performance offline, but offers them a better intuition about the effect of each parameter on the system's performance. On the other hand, the automatic optimization approach offers optimal parameters tunings directly, even in the absence of a person with experience in the functioning of the algorithm and the system.

In the last Chapter of this Thesis (Chapter 9), we presented an innovative multiobjective optimization methodology of tuning indoor positioning systems, based on real data recorded onsite. To the best of our knowledge, this is the first work proposing the use of multiobjective optimization for optimally tuning positioning systems based on real data. While the part of the evaluation and its relevant methodologies have started to be extensively discussed in the literature of the field, the step of how a system is tuned accordingly does not appear to have gained the same popularity. It is not uncommon that, regarding the optimal tuning of the system, an empirical selection of the appropriate tuning is mentioned, or a manual test-and-set procedure. Selecting the appropriate tuning for a positioning system is a challenging task which depends on many factors: the specific deployment, the devices used, the evaluation metrics and their order of significance, the user-case scenarios tested, etc. In order to handle these multiplicities, we introduced the use of multiobjective optimization which allows several objectives to be simultaneously satisfied. Using more than one evaluation metric can offer a more representative evaluation of a system's performance. Our extensive tests showed how this methodology can propose parameter tunings that efficiently handle the trade off between complementary evaluation metrics. Moreover, the use of multiple recordings minimizes the danger of overfitting, strengthening the robustness of the parameter setting suggestion. Furthermore, using recordings from a variety of environments allows the selection of the default setting of the system that can achieve good performance when deployed in an unknown environment. The methodology proves to be a very useful tool in the hands of testers who are designated to optimally tune the positioning system in a variety of scenarios. A practical result of the proposed methodology is that the usual empirical parameter selection of an IPS by the system's expert can be evaluated and potentially improved, with no effort nor extra cost.

Future developments

The tuning and evaluation methodologies that have been presented in Part III have been implemented with the creation of the GpmStudio platform and data have been collected from some test environments. The usefulness of this implementation thought as well as its power, lies in the continuation of collection of data from diverse environments and in their usage for a comparison of different positioning algorithms and technologies. In the future, the goal is to systematically collect data from all new environments where positioning systems are deployed. Moreover, the potential use of crowdsourced data, as the existing crowdsourcing platforms [Sansano et al., 2016], [Georgiou et al., 2015] do, could facilitate the combined use of data from diverse environments and create a public testbed based on real data.

Concerning the directions that are trending in the field of positioning, we briefly discuss those appearing to be the most promising ones. Therefore, in the following paragraphs, we elaborate on the high accuracy of UWB solutions, on the ubiquitousness of the hybrid systems, discussing particularly the Tango project of Google, and on the use of GNSS indoors with the goal of achieving more efficient emergency response times. Lastly, we describe the expected potential of the millimeter-wave technology that is currently under investigation for 5G communications systems.

The Ultra wideband (UWB) technology is broadly recognized as the most accurate RF technology commonly used for indoor positioning. The typical accuracy achieved by UWB positioning systems ranges on the scale of a few tens of centimeters. There are two main drawbacks of this technology: the high cost of its equipment, and the fact that it is not integrated in modern smart devices and therefore it requires additional hardware. In indoor positioning applications that are not restricted to the use of personal smart devices, and where the use of custom tags is acceptable, UWB by far exceeds other RF solutions. UWB has gained popularity over recent years, and a potential reduction of the price of its hardware could make its use even more frequent. It appears that if it were to become possible to integrate UWB in mobile devices, with a consequent reduction of its cost, UWB would prevail among the existing indoor positioning technologies.

A direction that has gained in popularity over the last few years is the approach of hybridizing positioning technologies. Inputs from multiple sensors of mobile devices are utilized to strengthen the robustness of the position estimations. As no single technology appears to clearly predominate the field of indoor positioning, and since modern smart devices include multiple sensors that can be utilized, hybrid systems become more and more common as the preferred solution. They achieve high accuracy in areas where technologies with high accuracy provide coverage, while in other places technologies like Dead Reckoning take over, offering position estimates ubiquitously. Each of the available sensors can have a contribution to the improvement of the overall system. For instance, sensors like the barometer, assist the altitude/floor detection, while light sensors can be used for the indoor/outdoor detection. Using as many of the available sources of information as possible appears to be a trend that will be followed in future years, in the absence of a unique solution that would clearly outperform all others.

Project Tango is an augmented reality platform powered by Google. It uses stereoscopic computer vision and sensors of mobile devices to infer the device's position. Having created a 3D map of the environment, indoor navigation can be provided, with high accuracy. The platform uses augmented reality to provide a diverse palette of services, such as gaming, educational or tourist applications. Most of these service use the inferred location offered by the underlying indoor positioning technology. A drawback of using this technology is that it requires specific hardware on the mobile device. Since the initial release of the project in 2014, the number of devices supporting its requirements remains low, and its use has not attained mainstream usage so far. Nevertheless, the high accuracy of project Tango, and the fact that it is supported by a big company like Google, could allow its broader acceptance as a main approach for indoor positioning services.

It is not uncommon that in emergency calls, practical difficulties do not allow the accurate localization of the place where help is needed. An automated localization of the device used to make an emergency call has been, for several years, a goal of authorities, internationally. As no current positioning technology functions completely ubiquitously, in all environments, solutions using GNSS are used as the best available solution. The European Galileo GNSS system, which is nowadays functional and its full functionality is expected for 2020, is designed to include the option of forwarding an automatic distress alert and receive a return alert service that informs the sender that their message has been received. Galileo, combined with other GNSS like GPS and GLONASS, has been measured as having significant accuracy improvements, compared against the accuracy of a single system. These systems combined, can offer a satisfying accuracy of position estimations for emergency call localization, even in indoor environments, worldwide. Its improved accuracy will have a profound impact not only in situations like emergency calls, but in numerous sectors of daily life.

The fifth generation (5G) of the mobile networks technology, which is currently under investigation, brings great expectations concerning its capabilities in being applied in indoor positioning. More spesifically, it is stated that the 5G technology *'will be able to provide centimeter (cm)-accuracy indoor localization in a robust manner'* [Witrisal et al., 2016]. Achieving such a performance without requiring the installation of additional hardware at the deployment area would truly revolutionize the field of indoor positioning.

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Abbreviations

AAL	Active and Assisted Living
AoA	Angle of Arrival
AP	Access Point
BLE	Bluetooth Low Energy
CAE	Claimed Accuracy Estimation
CDF	Cumulative Distribution Function
CTI	Commission for Technology and Innovation
CUI	Centre Universitaire d'Informatique
DGPS	Differential Global Positioning System
DM	Decision Maker
GNSS	Global Navigation Satellite Systems
GPM	Global Positioning Module
GPS	Global Positioning System
GSEM	Geneva School of Economics and Management
HUG	Hôpitaux Universitaires de Genève
ICT	Information and Communication Technology
IO	Indoor/Outdoor
IoT	Internet of Things
IPS	Indoor Positioning System
LBS	Location Based Services
LOS	Line Of Sight
MAC	Media Access Control
MOEA	Multiobjective Optimization Evolutionary Algorithms

NFC Near Field Communication
NLOS Non-Line Of Sight

RF Radio Frequency
RFID Radio Frequency Identification
RSS Received Signal Strength
RSSI Received Signal Strength Indicator

SUT System Under Test

TaM Traveling and Mobility
TDoA Time Difference of Arrival
TDR Traveled Distance Ratio
TLM Through-Life Management
ToA Time of Arrival
ToF Time of Flight
Tr Trilateration

UNIGE University of Geneva
UWB Ultra-wideband

WC Weighted Centroid
WLAN Wireless Local Area Network