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LOCALIZATION IN INDOOR ENVIRONMENTS USING COMMODITY OFF THE SHELF (COTS) HARDWARE

Time, Signal Property, and Particle Filtering Methods

A DOCTORAL DISSERTATION SUBMITTED

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Abstract

Localization of objects and people in indoor environments is of critical importance in applications ranging from delivering innovative positioning services, healthcare, advertising, shopping, stocking and warehousing, emergency situations such as building fires and many more. For example in hospitals, the timely access to all the necessary equipment and personnel in an emergency situation may determine a patient's survival. Locating critical resources and equipment with accuracy and speed is especially needed in cases where such assets are misplaced or not adequately organized in space. In another example, in airports and other transportation facilities where typical outdoor positioning systems do not function, indoor positioning systems based on 802.11 or similar technologies can be used for tracking valuable items. Numerous and varied uses of indoor localization range from improving the behavior of communication systems, e.g. timely planning of proactive handovers between access points or base stations leading to the improved end user's experience, locating/tracking assets for security applications, or even delivering targeted advertisements inside shopping centers. Depending on the underlying technology, various methods may be used to locate a wireless user connecting to a wireless infrastructure comprising of access points and/or base stations. These methods include techniques based on Received Signal Strength (RSS), Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA) etc.

This work examines and proposes new methods to increase localization accuracy in indoor environments through the use of 802.11 commodity off-the-shelf equipment. Multiple approaches are followed for developing optimal indoor localization techniques and systems. Firstly, existing well-known indoor localization techniques are replicated leading to a greater understanding of their advantages, drawbacks, and limitations. Subsequently current limitations are addressed aiming towards the development of new techniques and algorithms to progress beyond the current state of the art. The algorithms in this work address wireless indoor localization using off-the-shelf equipment focusing mostly on time-based localization techniques, although a novel RSSI method is also investigated and proposed. Two different approaches are presented regarding the use of the proposed algorithms in conjunction with other techniques for implementing a real-time localization system. In regards to time domain techniques, an innovative time-based localization method that utilizes the information provided by 802.11 Beacon packet data is

also presented. The advantage of this method over other time-based methods is that the Mobile Terminal (MT) overcomes the need for establishing a connection to an Access Point (AP), sending and receiving packets and clock synchronization. The method works by analyzing Beacon timestamp and MAC timestamp. The use of Beacon Interval, Beacon timestamp and Service Set Identifier (SSID) of a packet, enabled optimal processing of the collected MAC timestamps to provide a hybrid TDOA-TOA localization method. Another contribution of this work is a novel approach that is able to accelerate network packet time-based methods, based on a packet validation process. It is shown that the localization process time can be shortened without reducing positioning accuracy.

Moreover, the problem of tracking a moving target in an indoor environment using time-based methods is also addressed by utilizing a particle filtering method based on the kinematic characteristics of the target and past measurements. This method offers target trajectory information which has the potential to improve localization. The particle filter based method sequentially estimates the posterior of the target state and is able to fuse past and present measurements from multiple sensors with the target kinematic information in order to improve localization.

Although the main focus of this work is on time-based localization methods, during the research various RSS-based methods have been evaluated. Time based and RSS based localization methods are the two most popular indoor localization approaches. In order to go a step further in performance evaluation of the proposed methods, a cross comparison study between these approaches was necessary to take advantage of the best of both worlds. Following several experiments, it was found that while typical RSS methods utilize the average signal of surrounding APs recorded at stationary points, better localization results can be achieved by utilizing multiple RSS signals, e.g. over a path. It was observed that using RSS over travelled paths can improve localization accuracy and creates more accurate data-driven measurement models. This has led to the development of a new WKNN localization technique – described in a paper titled “a novel RSS-based localization method using path analysis”.

Last but not least, in this thesis the terms “Localization” and “Positioning” are used interchangeably and they refer to the same definition.

Περίληψη

Η διατριβή εξετάζει και προτείνει νέες μεθόδους για την αύξηση της ακρίβειας εντοπισμού ενός ασύρματου χρήστη σε εσωτερικούς χώρους, για την παροχή καινοτόμων υπηρεσιών εντοπισμού θέσης, μέσω της χρήσης συνηθισμένου εξοπλισμού που υποστηρίζει τεχνολογίες τύπου 802.11.

Για παράδειγμα, στα νοσοκομεία, η έγκαιρη πρόσβαση στο νοσοκομειακό εξοπλισμό και στο προσωπικό σε κατάσταση έκτακτης ανάγκης μπορεί να καθορίσει την επιβίωση ενός ασθενούς. Σε αεροδρόμια, εμπορικά κέντρα και άλλους εσωτερικούς χώρους, όπου τα τυπικά συστήματα εντοπισμού όπως το GPS δεν λειτουργούν, μπορούν να χρησιμοποιηθούν εσωτερικά συστήματα εντοπισμού θέσης βασισμένα σε τεχνολογίες 802.11 για σκοπούς παράδοσης στοχευόμενης διαφήμισης, εξυπηρέτησης υπηρεσιών έκτακτης ανάγκης κλπ.

Ανάλογα με την διαθέσιμη τεχνολογία, είναι δυνατό να χρησιμοποιηθούν διαφορετικές μέθοδοι για τον εντοπισμό ενός ασύρματου χρήστη. Αυτές οι μέθοδοι περιλαμβάνουν τεχνικές που βασίζονται στην ισχύ του σήματος (RSS), την ώρα άφιξης (TOA) ή τη χρονική διαφορά άφιξης (TDOA), τη γωνιά άφιξης (AOA) κ.λπ.

Αρχικά η διατριβή επικεντρώνεται κυρίως σε τεχνικές εντοπισμού που βασίζονται στο χρόνο (TOA/TDOA) και στη συνέχεια διερευνά και προτείνει μια νέα μέθοδο ραδιοεντοπισμού που στηρίζεται στην ισχύ του σήματος (RSS).

Όσον αφορά τις τεχνικές που βασίζονται στο χρόνο, η διατριβή αναπτύσσει και παρουσιάζει μια καινοτόμο μέθοδο εντοπισμού που χρησιμοποιεί τις πληροφορίες που παρέχονται στα Beacon πακέτα του 802.11. Το πλεονέκτημα αυτής της μεθόδου σε σχέση με άλλες μεθόδους που βασίζονται στο χρόνο, είναι ότι η ασύρματη συσκευή δεν απαιτείται να είναι ενωμένη στις ασύρματες συσκευές 802.11 της υποδομής (Wireless Access Points / Wireless Routers). Η μέθοδος λειτουργεί αναλύοντας το εκλαμβανόμενο timestamp ενός πακέτου. Μια άλλη συμβολή είναι η ανάλυση και παρουσίαση μια τεχνικής που μειώνει το χρόνο συλλογής των πακέτων Beacon, ώστε η διαδικασία ραδιοεντοπισμού να γίνεται σε μικρότερο χρόνο. Η διατριβή εξετάζει και αναλύει επίσης την κίνηση ενός χρηστή σε ένα εσωτερικό περιβάλλον, χρησιμοποιώντας μεθόδους που βασίζονται σε particle filtering.

Παρόλο που το επίκεντρο αυτής της εργασίας είναι οι μέθοδοι εντοπισμού με βάση το χρόνο, η διατριβή προτείνει επίσης μια νέα τεχνική ραδιοεντοπισμού βασισμένη στην ισχύ του σήματος (RSS). Η προτεινόμενη τεχνική βασίζεται στη σύγκριση του ράδιο-αποτυπώματος μιας σειράς σημείων, σε αντίθεση με άλλες μεθόδους που στηρίζονται στο ράδιο-αποτύπωμα ενός σημείου.

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Acronyms

AOA	Angle of Arrival
AP	Access Point
AZB	Angular Z-Buffer
BI	Beacon Interval
BSP	Binary Space Partitioning
DLOS	Direct Line of Sight
FDB	Fingerprinting Database
GLONASS	Globalnaya Navigazionnaya Sputnikovaya Sistema
GNSS	Global Navigation Satellite Systems
GO	Geometric Optics
GPS	Global Positioning System
GTD	Geometrical theory of Diffraction
IEEE	Institute of Electrical and Electronics Engineers
ILS	Indoor Localization System
kNN	k-Nearest Neighbors
LoBs	Lines of Bearing
LOS	Line of Sight
MAC	Media Access Control
MPDU	MAC Protocol Data Unit
MR1T	Many Synchronized Receivers and One Transmitter
MT	Mobile Terminal
MT1R	Many Synchronized Transmitters and One Receiver
NLOS	Non-Line of Sight
NTP	Network Time Protocol
OUC	Open University of Cyprus
PCB	Printed Circuit Board
PF	Particle Filter
RM	Radio Map
RMSE	Root Mean Squared Error
RSSI	Received Signal Strength Indication
RTLS	Real Time Location Systems

RTS/CTS	Request to Send / Clear to Send
RTT	Round Time Trip
SIR	Sampling Importance Resampling
SSID	Service Set Identifier
SVP	Space Volumetric Partitioning
TDOA	Time Difference of Arrival
TIM	Traffic Indication Map
TOA	Time of Arrival
TOF	Time of Flight
UTD	Uniform Theory of Diffraction

Chapter 1

1 Introduction

Positioning, or localization, of wireless users refers to the process of locating or tracking wireless devices used by users and/or assets. Research on positioning of wireless users has been conducted for decades [1] attracting increased interest with the introduction of cellular services and the requirement from operators to provide the users' location information to public safety services in emergency situations [2] . Although initially employed in the service of public safety, subsequent research has led to the introduction of new commercial services that became feasible with the knowledge of mobile user's exact location including location-sensitive billing, cellular phone fraud detection, cargo tracking, navigational, yellow-pages services and etc.

Research has also examined the nature of the wireless channel in order to estimate meaningful parameters and methods that could be used for localization purposes. The most frequently employed methods are geometrical – in particular those based on the estimation of the Angle of Arrival (AOA), the Time of Arrival (TOA), the Time Difference of Arrival (TDOA), Received Signal Strength (RSS) or a combination of the above [3] [4] . Achieved localization accuracy depends on the underlying technologies, the methods used and the complexity and dynamism of the varying radio channel. The application of some of these methods in indoor environments presents an additional degree of complexity compared to the outdoor environment due to the variety of building materials [5, 6]. Furthermore, there is likely to be a non-line of sight (NLOS) between the user and the wireless infrastructure (e.g. access points, base stations) leading to decreased robustness of a RSS-based scheme. The inherent complexity of indoor environments can degrade both the accuracy of RSS-based methods as well as of methods based on timing information (e.g. TOA), especially if the delay effect of the travelled paths through the indoor environment cannot be accurately described.

1.1 Thesis Motivation and Objectives

For the past decade Global Navigation Satellite Systems (GNSS) [19] provided numerous positioning and localization opportunities around the world. Today, it is almost impossible to imagine a world without navigation and localization systems. Almost all major day to day activities such as transportation, traveling, security, banking and many more, somehow rely on GNSS. As we experience the advantages of positioning systems with technology evolution, the demand for indoor localization is in the rise. That is why the use of wireless signals for providing localization of users (terminals) and or assets in indoor environments where no GNSS signals are available has attracted significant interest in recent years [28] [42] [55] [62] [81] .

Even though research on indoor localization has been active for many years, there is still no overall solution that can provide high availability, reliable coverage area, low cost, easy to use and implementation simplicity [28, 42, 55, 62, 81]. As 802.11 becomes widely available, it provides more opportunities for implementing a low-cost, off-the-shelf indoor localization system. In this work, indoor localization problems are addressed by firstly providing a detailed problem definition including the problem constraints and specializations followed by a comprehensive investigation into ways of increasing indoor localization accuracy through the use of 802.11 equipment (e.g. WiFi). For this purpose, a number of localization techniques were implemented and their performance was evaluated using realistic data for distinguishing and selecting the most appropriate indoor localization techniques [20, 21, 25, 32, 53, 71, 75, 86, 93].

There is no doubt that time-based localization methods [55, 62] can be especially useful in dynamic environments where the usefulness of Received Signal Strength (RSS) fingerprint based methods [42, 62] can be limited. Typical off-the-shelf 802.11 network packet time-based methods tend to collect a large number of packets and apply statistical analysis in order to localize a user [23-25, 60]. This packet collection process typically lies in the range of minutes, thus turning this type of localization into a non-real time process. Moreover, the kinematic characteristics of the target and past measurements offering target trajectory information which have the potential to improve localization should be taken into account. Using a particle filtering method [16, 84] can help to address the problem of tracking a moving target in an indoor environment using off-the-shelf time-based methods. The particle filter based method sequentially estimates the posterior of the target state and is able to fuse past and present measurements from multiple sensors with the target kinematic information in order to improve localization. The localization performance can be assessed using different number of particles and different number of access points (APs). Simulations [13, 16, 107] can also allow assessing the effectiveness of the method. Another objective of this work is to pursue research on how to accelerate network packet time based techniques in an effort to have a faster time-based indoor localization using COTS hardware.

While the focus of this work is on time-based methods yet during the literature survey and replication of existing methods, many RSS methods have been evaluated [12, 32, 38, 42, 62, 89, 90] motivating some additional research. RSS methods based on off-the-shelf 802.11 equipment can be implemented with almost no modification to the existing infrastructure. They also typically have the lowest capital expenditure since 802.11 infrastructures can be used to support such activities. While current fingerprint RSS methods estimate the average RSS values at a static single point, it is possible to capture a more detailed signal behavior by utilizing the collected RSS values over an area or a short path. An indoor radio campaign and simulations were carried out to investigate if significant accuracy improvement can be achieved by using this method.

Many researchers use only simulations in order to prove a concept, however, implementations of the algorithms using real data from the environment can always provide more insights. In order to facilitate the process of real data collection, which is time consuming, a localization platform is needed to collect the packets, processes them, and plot the estimated location of the user. Such platform also helps to replicate other methods for performance comparison purposes. For this reason, this work also developed a localization platform.

1.2 Thesis contributions

This work investigates the problem of indoor localization and introduces innovative methods based on Time and RSS as means of improving the localization process.

Locating an object in an indoor environment can be a challenging task as a number of performance metrics have to be met, including accuracy, responsiveness, coverage, adaptiveness, scalability, cost and complexity. The localization scenario, that is, the nature of the actual environment, will determine which combination of these metrics constitutes a good localization technique. Locating a wireless user in indoor environment using 802.11 can be accomplished through different means including TOA, TDOA, RSS, AOA etc. [1-4, 7-13].

Most of the time-based methods rely on time synchronization. TOA/TOF methods are based on the arrival of a signal from a transmitter to one or more receivers. A packet containing transmitted timestamp travels from the transmitter to the receiver(s). By using the timestamp information, receiver calculates the transmission time delay, multiplies that by the signal speed and estimates the distance between the two nodes. Since radio waves travel at the speed of light, the transmission time delays in indoor TOA/TOF systems is in the order of nanoseconds (ns) necessitating accurate time synchronization between all nodes. Moreover, TOA/TOF systems need a time server which all nodes can use to synchronize their clocks.

Extensive research and replication of the existing COTS localization methods were followed by the identification of the limitation of those methods including ways to optimize them. New localization algorithms and techniques have been developed in both time and signal property domains including hybrid methods.

This dissertation introduces novel indoor localization methods based on IEEE 802.11 technology and inexpensive COTS hardware. As such it mostly deals with challenges that exists in COTS time-based systems. The challenge lies in that the commercial WLAN cards do not produce nanosecond timestamps which is necessary for accurate distance estimation in indoor environments. Moreover, creating customized boards and modifying the WLAN clocks to produce more accurate timestamps imposes higher costs and implementation complexity. Additionally, most of the time-based methods require bidirectional communication between base stations and Mobile Terminals (MTs). This requirement can affect both processing time and infrastructure quality of service since it requires greater data communication and generates more wireless traffic. A main contribution in this area is an innovative time-based localization method that utilizes the information provided by 802.11 Beacon packet data. Utilizing Beacon packet for localization, eliminated the need for establishing a connection between base stations and MTs. Also, the proposed method does not require any clock synchronization.

Since time-based localization methods require collection of a large number of packets, most of these methods require statistical post processing to actually localize a user. Packet collection process typically lies in the range of minutes, thus turning this type of localization into a non-real time process. Presented techniques in chapter 4, contribute on accelerating network packet time-based methods while evaluating different performance metrics. Another main contribution of this work in time domain is a particle filtering method as a means of addressing the problem of tracking a moving target in an indoor environment using off-the shelf time-based methods. Using particle filtering the kinematic characteristics of the target and past measurements offering target trajectory information which have the potential to improve localization are taken into account. The particle filter based method sequentially estimates the posterior of the target state and is able to fuse past and present measurements from multiple sensors with the target kinematic information in order to improve localization.

During the course of this thesis many signal property based methods have been replicated for evaluation and comparison purposes, which led to the development of a new WKNN localization technique [17, 18]. Signal property based methods achieve better accuracy by creating a more detailed and distinguishable Radio Map (RM). Normally the RM of an environment is created by measuring the average RSS values at static points. By utilizing the captured RSS values over a short path, a more detailed signal behavior can be recorded, resulting in the creation of a more unique RM and thus a more accurate localization process.

Novel research contributions in regards to signal property based methods can be summarized as follows:

1- Introduction of a novel kNN-based localization algorithm based on RSS captured over paths.

2- Analysis of k selection impact on kNN algorithms and the proposed method.

3- Investigation of the impact on the performance of the proposed method in the case of device diversity, as well as the effect of a variable captured RSS sample number for various user walking speeds.

All of the developed methods were tested using real data collected from an actual indoor environment. Simulated data based on ray tracing was also generated for comparison purposes.

Last but not least, in the course of this thesis the following papers were published and some are prepared for submission and publications:

- Gholoobi, A; Stavrou, S., "A hybrid TDoA-ToA localization method," Telecommunications (ICT), 2013 20th International Conference on., pp.1-4, May 2013.
- Gholoobi and S. Stavrou, “Accelerating toa/tdoa packet based localization methods,” in Wireless Sensors (ICWiSE), 2014 IEEE Conference on, Oct 2014, pp. 31–35.
- Gholoobi, I. Kyriakides and S. Stavrou, “Indoor Target Tracking Based on Time Difference of Arrival and Particle Filtering,” in Computers and Communication (ISCC), 20th IEEE Symposium on, Jul 2015, pp. 974-977.
- Gholoobi and S. Stavrou, "RSS Based Localization Using a New WKNN Approach," Computational Intelligence, Communication Systems and Networks (CICSyN), 2015 7th International Conference on, Riga, 2015, pp. 27-30.
- Gholoobi and S. Stavrou, "A New WKNN Localization Approach," International Journal of Simulation Systems, Science & Technology (IJSSST), Dec 2015, Vol. 16, No. 6.
- “PathLoc: A Path-Based Indoor Localization Method”, (About to submit it to an IEEE Journal)

1.3 Overview of the thesis structure

The remainder of the work is organized as follows. Chapter 2 provides an introduction to wireless positioning systems, localization algorithms and a brief introduction into the basic radio propagation modelling techniques. It summarizes localization activities based on different methods. In addition, the chapter gives an introduction to indoor localization methods and highlights the important methods used for location applications in indoor environment used today. Moreover, a literature review and initial experiments are also presented in this chapter in an effort to distinguish the most suited methods comparison in line with the research work objectives. Chapter 3 presents an overview of time-based localization methods and algorithms. In particular, it focuses on lateration approaches that use TOA and TDOA to estimate the location including a presentation of a basic approach to each, as well as to some of the other well-known techniques. Finally, a new time-based localization method is presented and its performance is compared with the existing methods. This work is presented in [14]. Chapter 4, introduces methods on how to accelerate network packet time based techniques. This work is presented in [15]. Chapter 5 presents a particle filtering method to address the problem of tracking a moving target in an indoor environment using off-the-shelf equipment and time-based methods. It discusses the kinematic characteristics of the target and past measurements to offer target trajectory information which have the potential to improve localization. Part of this work is presented in [16]. Chapter 6 presents signal property based localization methods. It emphasizes on a new RSS localization method based on path analysis which utilizes the captured RSS values over a short path in an effort to capture a more detailed signal behavior, when compared to typical RSS methods. This work is presented in [17, 18]. Chapter 7 presents the localization platform developed and used for automation and testing of all the proposed methods in this work. Finally, chapter 8 presents the conclusions and future research direction.

Chapter 2

2 Wireless Positioning Systems and Location Algorithms

2.1 Introduction

Localization activities can be classified into different categories depending on the area of use, performance metrics and detection techniques. As shown in Figure 2-1, positioning systems fall into three categories:

1. Based on Environment
2. Based on Cooperation
3. Based on Technology

In regards to the environment, localization can be categorized into:

1. Indoor
2. Outdoor

Location-aware applications can rely on GPS, GLONASS and GALILEO [19] for outdoor localization, whereas a terminal in an indoor environment requires usage of other technologies. An indoor localization system is either a Self-Positioning System or a Remote/Cooperative Positioning System. Using self-positioning, a mobile terminal is able to locate itself with respect to static/known points in the indoor environment. Remote or cooperative positioning refers to techniques that allow mobile terminals or infrastructures to locate other terminals in their coverage area.

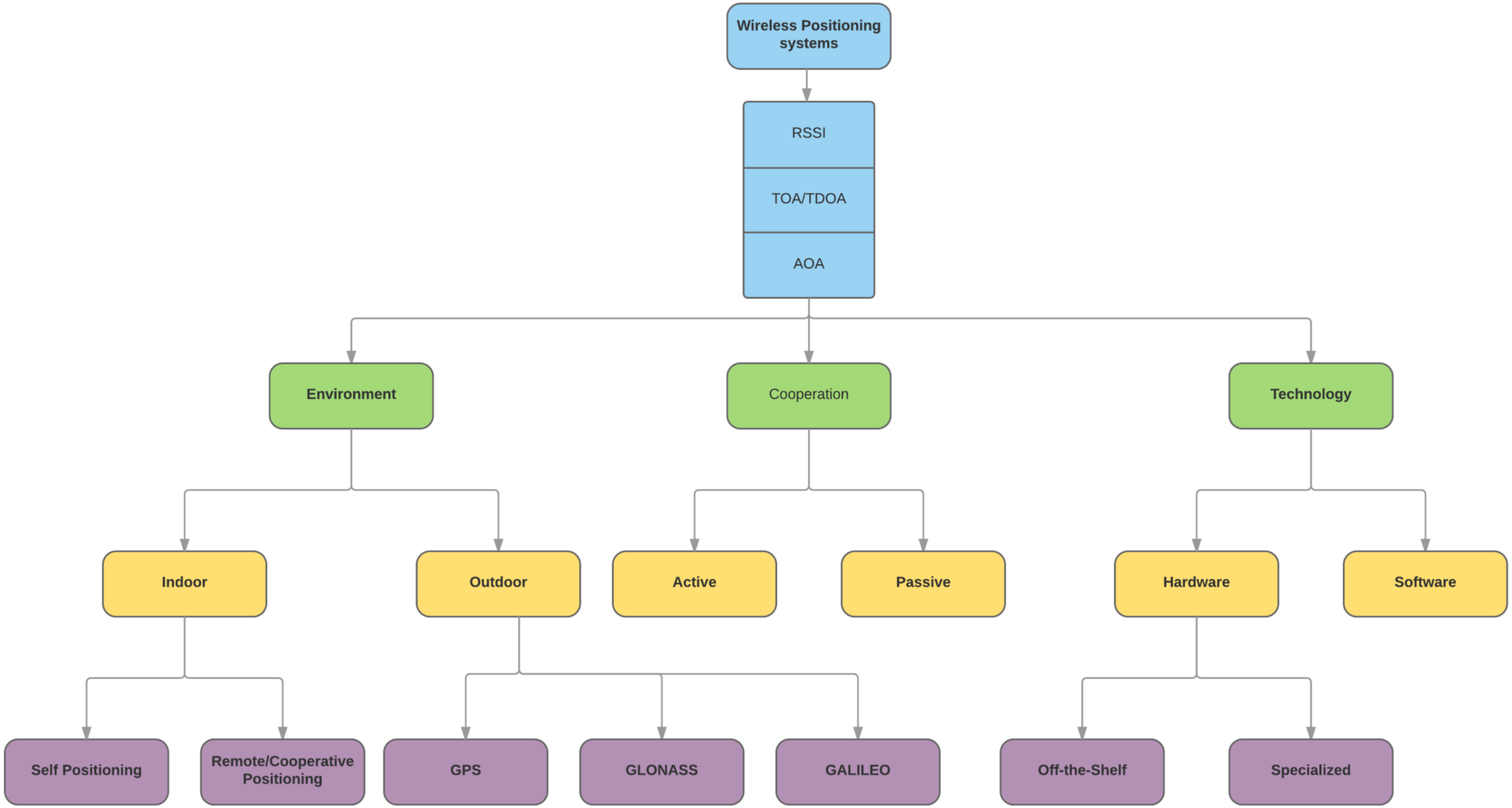

Figure 2-1: Wireless Positioning Systems Classification

Moreover, indoor localization methods can be implemented as Active or Passive. Unlike passive methods, active methods require active communication between the Mobile Terminal (MT) and the infrastructure. An active method example can be a user positioning himself and finding his way through the environment. Passive methods can be used for localization scenarios involving equipment or other resources in hospitals, factories, companies or other similar environments.

Based on methodology and use of technology, indoor localization methods can be divided into two main categories:

1. Hardware-based localization
2. Software-based localization

The first category refers to localization methods that use customized or modified hardware for localization purposes [20-22]. The second category is based on localization methods which are purely software-based requiring no specialized hardware or hardware modifications [14, 23-27]. Software-based methods utilize different types of packets such as RTS-CTS, Ping, Beacon and custom-made packets. A correct packet type and an optimum packet generation technique can improve the speed and accuracy of distance estimation in software-based localization.

2.2 Radio Propagation Modeling

Radio propagation modelling refers to the analysis of radio propagation in wireless scenarios which can lead to the prediction of the received field (or power) or other element parameters at all the visible/possible receiver locations. Typically, propagation models are classified into three categories based on the way they calculate path loss or the received signal strength. These can be empirical, semi-empirical and deterministic (or site-specific) models. This section presents these three categories and describes their potential advantages and disadvantages.

2.2.1 Path loss

Path loss is an essential information for determining the radio coverage of a transmitting antenna (Base Station or access point) [108] . It is defined as the ratio of the received power P_r to the transmitted power P_t, usually expressed in dB [109] .

$$L(dB) = 10\log\left(\frac{P_r}{P_t}\right) \tag{2.1}$$

In free space, where there is a Line of Sight between the transmitting and receiving antennas, the path loss is considered to follow an inverse square law with respect to the distance travelled by the waves [113] . It also depends on the frequency of transmission. Therefore the free space loss can be written as:

$$L_{free}(dB) = 10\log\left(\frac{G_t G_r \lambda^2}{(4\pi)^2 R^2}\right) \tag{2.2}$$

Where G_t and G_r are the gains of the transmitter and the receiver antennas respectively, λ is the wavelength and R is the distance away from the transmitter. For G_t and G_r equal to unity the above equation can also be written as [110] ,

$$L_{free}(dB) = 32.4 + 20\log R_{Km} + 20\log F_{MHz} \tag{2.3}$$

which clearly shows that by doubling either the distance or the frequency, the free space loss increases by 6dB (inverse square law).

2.2.2 Empirical and Semi-Empirical Models

Empirical Models are described by a set of equations fitted to the results obtained from extensive number of path loss measurements [110] [112] . They are simple and efficient (fast) to use since the estimation is usually calculated from this set of equations. They are relatively accurate for environments which have the same characteristics as the one where the measurements were originally performed but error standard deviation tends to be large. The input parameters for such models are usually qualitative and not so specific. Their main disadvantage is that they are not applicable for different environments without modifications and may be considered as non-applicable for indoor environments [108] due to their inability to provide accurate results for disparate scenarios (in other words they are hard to generalise). They do not provide any physical insight into the propagation mechanisms and this could lead to wrong predictions when the environmental clutter becomes increasingly complex (indoor environments).

Semi-Empirical Models are based on equations derived from partly the application of deterministic methods [112] . These equations are based on the characteristics surrounding the transmitter and the environmental characteristics of a particular scenario. They require more detailed information about the environment than empirical models but less than deterministic ones. Again, as for empirical models, it is hard to use these kinds of models for different scenarios.

Empirical and Semi-Empirical Models are more or less environment and frequency range specific. Some of the better known ones are:

- Okumura-Hata Model [114] . This is a fully empirical model, which is based on an extensive series of measurements carried out in Tokyo city between 150MHz-1.5GHz. The predictions are made through a series of graphs, the most important of which have been approximated by Hata [115] . These model can be used for open, urban and suburban area predictions.
- Ibrahim and Parsons Model [116] is intended as a first step in quantifying urban propagation loss. It is based upon measurements made around London, UK.
- Allsebrook and Parsons Model [117] is a semi-empirical model for suburban predictions. It is based on measurements made in three British cities (Bradford, Bath and Birmingham) at 86, 167 and 441MHz.
- Ikegami Model [118] is a semi-deterministic model which attempts to produce deterministic predictions at specific points. It uses a detailed description of the environment and calculates only reflections from the surrounding clutter with the reflection loss being constant at a fixed value. Diffraction is calculated using single edge approximation.
- Walfish-Bertoni Model [119] is a semi-deterministic model which can be used to predict multiple diffraction over building rooftops.
- Cost-231-Hata model [120] is an extension of the Okumura-Hata Model to cover the 1500-2000MHz band.
- Lee Model [121] is an empirical power law model with path loss exponents derived from measurements at 900MHz. It can be also applied for other frequencies if correction factors are used.

All the above models deal with outdoor propagation predictions. In fact, empirical and semi-empirical models exist for indoor or outdoor-indoor propagation. COST231 LOS and NLOS [110] , [120] models can be used for predicting indoor radio propagation in floors and between floors, and ITU-R P.1238-2 can be used for predicting indoor radio communication in the frequency range 900MHz-100GHz. Nevertheless, for increased accuracy, deterministic or site-specific models should be employed.

2.2.3 Deterministic or Site-Specific Models

Deterministic or Site-specific Models are based on the application of well-known electromagnetic techniques and numerical methods (such as Ray Tracing) to a site-specific environmental description which is obtained from the particular environment (building) database [112] or the finite-difference-time-domain (FDTD) method. The main advantage of these models is that they are generic for arbitrary environments. For a given environmental description they use electromagnetic theory to estimate the field strength at every possible receiver location. They provide the ability to the engineer to define the two-dimensional or three-dimensional geometry of the environment by means of facets specifying the location of the buildings' walls, the electrical properties of these walls (constitutive parameters such as permittivity and conductivity), the transmitter location, the antenna patterns and polarisations and the frequency of transmission. Considering all these properties of deterministic models, it can be concluded that they are very well suited for indoor environments since they can provide relatively highly accurate predictions. The main drawback of this way of modelling is the large computational overhead required which effectively high computational power is required.

2.3 Deterministic Modelling using Ray Tracing

Ray Tracing is the dominant deterministic technique used to predict propagation effects in mobile and personal communication environments. It is based on Geometrical Optics (GO), which is an approximate method for predicting a high-frequency electromagnetic field. Ray Tracing is used to identify all the possible ray paths between the transmitter and possible receiver locations and uses high-frequency electromagnetic theory to calculate the amplitude, phase, delay and polarisation of each ray. Two main algorithms exist for the implementation of Ray-Tracing; the ray launching and the image method.

This chapter presents the basic principles and algorithms of Ray Tracing, and the high frequency methods used to reduce the complexity of the electromagnetic problem to be solved (Geometrical Optics GO and its extensions: Geometrical theory of Diffraction GTD and Uniform Theory of Diffraction UTD).

2.3.1 Geometric Optics (GO)

As already mentioned, Geometric Optics represent a simple way for predicting approximately the electric field at any possible receiver location. It assumes an infinite frequency for the propagating signal in such as way as to consider all the propagating energy to be contained inside very thin tubes, called rays [122] . Using this theory the reflected and transmitted fields can be determined. However, this theory is subject to the following assumptions [110] :

- Waves are locally plane to the points of interaction
- Wavelength is small compared to the distance between the source and the first interactions along each ray path and the distance between individual interactions.
- Surfaces are large compared to the wavelength of transmission
- Curvature of Surfaces is small compared to the wavelength.

The first step of GO is to calculate all the important ray paths (based on predefined criteria) between the transmitter and all the possible receiver locations, which are consistent with Snell's Laws of Reflection and Transmission. This step usually requires high computational costs in order to identify all the possible rays. For these reason only the rays that have the highest impact on the overall result are considered; these are usually the rays that suffer less interactions between the transmitter and the field points. Once the most important ray paths have been identified, electromagnetic theory is used to calculate the Fresnel's coefficients at each interaction point as if incident waves were plane and boundaries were plane and infinite [110] . Thirdly, the amplitude of each ray path should be corrected to account for the wavefront curvature from the source and the curvature of the boundaries. Finally all ray paths are summed up with regard to phase and amplitude. The following equation is used to formulate this procedure.

$$E = \sum_{i} E_o \, A_i \left[\prod_{j=1}^{N_{Ri}} R_{i,j} \prod_{m=1}^{N_{Ti}} T_{i,m} \right] e^{-jkr_i} \tag{2.4}$$

where N_{Ri} , N_{Ti} are the number of reflections and transmissions of each ray path i respectively. $R_{i,j}$ and $T_{i,m}$ are the corresponding reflection and transmission coefficients. r_i is the total path length and the factor A_i accounts for the wavefront curvature as well as the curvature of the reflection and transmission boundaries (i.e. walls) also known as *spreading factor*. E_o is the reference field at the transmitter. Finally the exponential term corresponds to the phase difference due to propagation delay of each ray. It needs to be noted that for grazing incidence (i.e. 90^o degrees) the reflected component grazes the surfaces and GO will fail to provide a sufficient solution for the Reflection coefficient and therefore this case needs to be treated separately [111] .

By utilising the Geometric Optics theory it becomes impossible to predict diffraction over obstructions because it ignores that energy does propagate into the shadowing region. For this reason the method has included to the Geometrical Theory of Diffraction (GTD) in order to include diffraction.

2.3.2 GTD and UTD

Geometrical Theory of Diffraction (GTD) which was developed by Keller [123] , is based on Fermat's principle which is used to predict the existence of any diffracted rays. This theory is of particular importance in many cases and scenarios where diffraction might be the dominant propagation mechanism. It overcomes the GO inability to calculate the diffracted fields in the shadowed region. According to Keller, a ray obliquely incident upon the edge of an obstruction at an angle β to the edge produces a cone (Keller cone) of diffracted rays having a semi-angle β. This is illustrated in Figure 2-2. When β=90o the cone becomes a disc.

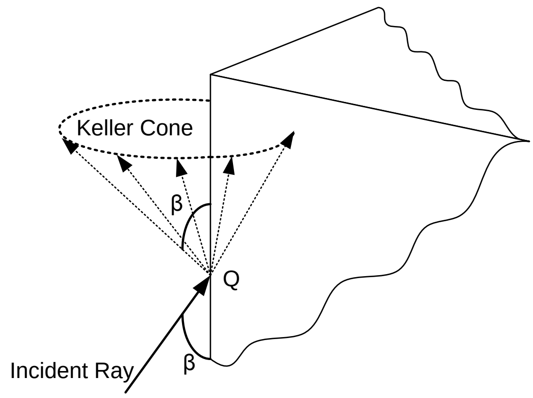

Figure 2-2: Generation of edge-diffracted rays

Now consider the situation in Figure 2-3. In Region 1 the field is the sum of direct and reflected rays, plus diffracted rays of negligible amplitude. In Region 2 there is no reflection, whereas in Region 3, which is the shadowed region, there is only a diffracted field. The diffraction coefficients calculated by GTD are discontinuous around the transition boundaries leading to incorrect field predictions close to those boundaries. In order to solve the problem of these discontinuities and predict the field correctly close to the transition boundaries, the original formulation of GTD was extended to the Uniform Theory of Diffraction (UTD). The extended theory yields continuous coefficients and is valid for all points in space.

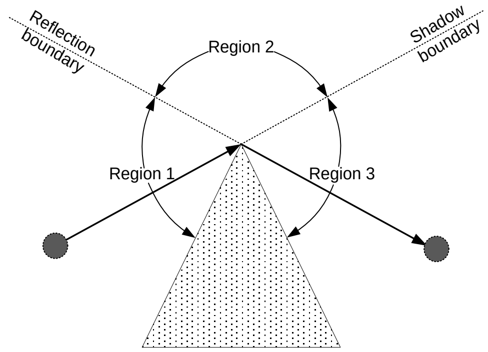

Figure 2-3: Regions around a wedge

When diffraction coefficients are calculated they can be included in the calculation of the total electric field as shown in (2.5),

$$E = \sum_i E_o A_i \left[\prod_{j=1}^{N_{Ri}} R_{i,j} \prod_{m=1}^{N_{Ti}} T_{i,m} \prod_{n=1}^{N_{Di}} D_{i,n} \right] \mathrm{e}^{-\mathrm{jkr_i}} \tag{2.5}$$

where, N_{Di} diffractions of each ray path i respectively and $D_{i,n}$ are the corresponding diffraction coefficients. A_i is the spreading factor that accounts for the wavefront curvature as well as the curvature of the reflection and transmission boundaries. This formulation applies for paths that only one diffraction is encountered. For multiple-diffraction, the spreading factor of the individual diffracted components will change and requires special treatment [125] .

2.3.3 Environment Description

The first step in a Ray Tracing Technique is to geometrically and morphologically represent the particular environment. Every deterministic propagation model requires geometric and morphological description of the environment. The more details that are included in the environment description the more accurate the model's predictions are.

2.3.3.1 Geometric Description

The geometric description of the environment is a description of geometry of the scenario under investigation in terms of the location and size of the obstructions (walls, windows, doors etc). It should be noted here that the more complex the geometric description is, the more computational overhead and more time will be required. Therefore, it is usually the case that depth of detail is traded for computation and time which means that only the most important features of the environment are described such as building and terrain data, where as small and mobile objects tend to be ignored. In the developed Ray Tracing model, objects which are large compared to the wavelength (like doors, windows etc) are taken into account. The most common form of representing the objects in the environment is by using plane facets (polygonal plane facets).

2.3.3.2 Morphological Description

The morphological description aims to describe the materials used in the particular scenario. For each geometrically described facet, the building material properties are defined since they significantly affect the reflection and transmission coefficients. These properties can be obtained by measurements or by simply providing the constitutive parameters of each material; these are:

- Relative permittivity ε_r
- Relative permeability μ_r
- Conductivity σ

The above parameters are used to characterise smooth surfaces. In cases where the surface is characterised as rough, according to the Rayleigh criterion, the surface roughness parameter Δh should be specified as well [112] .

2.3.3.3 Faceted model

Both the geometric and morphological descriptions will form the database for the model which can be stored in a separate file and loaded upon execution. This data might be either in raster or vector form. In the raster form the environment is subdivided into cells and each cell includes the corresponding information. In vector form the environment information is associated with geometric entities (lines or polygons). In case of deterministic modelling this information must be in a suitable vector form and if not, it should be transformed into one. All the data should be stored into a database structure using a facet model [112] . This means that every wall is represented by a polygon-shape (usually four-sided) facet which includes its geometric description (Cartesian coordinates of its vertices), its morphological description (constitutive parameters) and any other parameters that might be useful during the execution of the algorithm (e.g. if the facet contains other 'children' facets such as doors or windows which are defined as patches).

2.3.4 Ray Tracing Algorithms

The ray-tracing algorithms that have been proposed for high frequency propagation prediction mainly fall into two categories [112] . These are:

- Direct algorithms known as Ray Launching (or Shooting and Bouncing Rays Method SBR) and
- Inverse algorithms known as Image methods

2.3.4.1 Ray Launching Algorithm

Ray launching, which can also be referred as Shooting and Bouncing Rays Method (SBR) is considered to be a direct (or forward) algorithm since it is considered to follow the ray's actual path from the transmitter to the receiver location. Actually, for a given transmitter location a large number of rays is transmitted in all directions which only exist if they satisfy a number of criteria.

These criteria are:

- The ray exists only if its field strength has not fallen below the receiver's sensitivity
- The ray exists only if it has encountered a number of interactions (reflections, refractions, diffractions) that is less than a user predefined threshold.
- A ray exists only if it can be received by a certain receiver location. In other words if the ray escapes the scene then it is discarded.

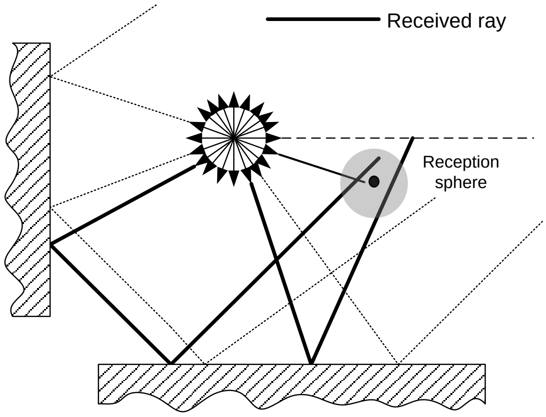

Figure 2-4: Ray Launching Concept

Every ray is a ray cone which occupies the same solid angle and as the tube advances its cross section increases. In this way the ray cones overlap and cover the whole spherical wavefront at the receiving location [108] .

If we consider the receiver as a single point then the probability of rays leaving the transmitter to reach that point would be considerably small. For this reason the receiver is considered as a sphere (reception sphere), as shown in Figure 2-5, so as to increase the probability for capturing more rays. When a ray intersects the sphere, it is considered to be received and it contributes to the overall field strength of that point. The radius of the sphere is given by [112] [126] .

The ability to vary the radius of the reception sphere according to the receiver distance from the transmitter (d), accounts for the divergence of the rays from the transmitter and ensures the uniqueness of the captured rays. From simple geometry, the radius of the reception sphere is set to be one-half of that distance [126] .

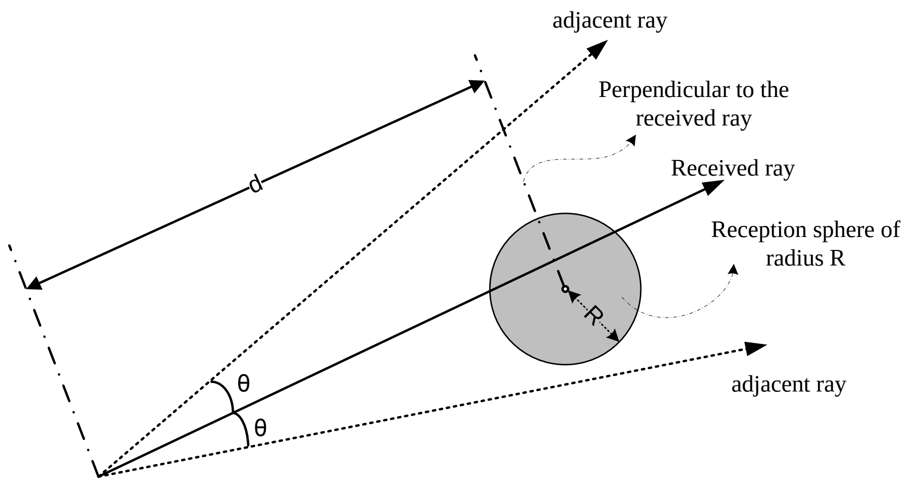

Figure 2-5: Reception Sphere

As the rays propagate they encounter a number of obstructions. When an object is hit, reflection, refraction, diffraction or scattering will occur depending on the geometry and morphology of the obstacle and the ray will follow different directions with different amplitude, phase and polarisation. This process continues for every ray as long as the aforementioned criteria are satisfied.

In indoor environments the number of ray traces increases significantly taking up CPU power and time. A convenient way is to arrange and store the whole propagation process in a *"ray-tracing tree"* [112] . In this tree, the branches correspond to emitted (launched) rays and the tree knots represent interactions with the environment obstacles (facets). An example is shown in Figure 2-6.

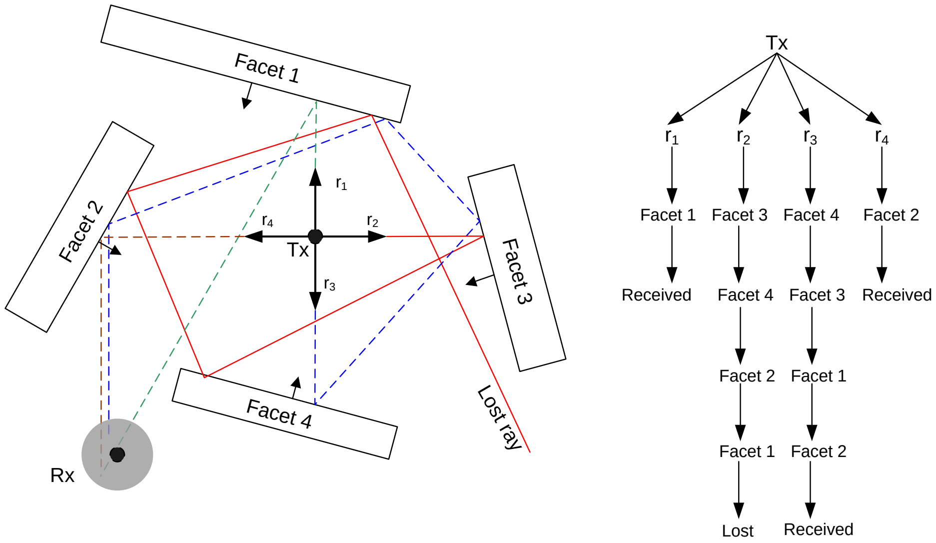

Figure 2-6: Ray-tracing example

The example above illustrates how the ray-tracing tree is constructed by considering reflections only. However in a practical situation, at every node of each ray branch the ray is decomposed into two children rays; the reflected and transmitted one; in order to consider refraction as well. Finally the total field strength at every receiver location can be obtained by summing up all the individual contributions.

2.3.4.2 Image Method

Compared to Ray-Launching, which is a direct method, the Image Method is referred as an inverse method. Instead of following the ray propagation path between the transmitter and the field points, this method tries to solve an inverse propagation problem. It is based on the image theory, where, for a given source point (*Tx*) and a facet, the reflected rays in the facet can be considered as being directly radiated from a virtual source called the image source (*Im*) which is symmetrical to the source with respect to the *facet*. This image theory is illustrated in Figure 2-7. In this figure, for a given receiver location Rx, the point of interaction with the facet Q can be easily calculated as the intersection of the line Im-Rx and the facet. The facet can be either described in 2D as a line or in 3D as a polygon.

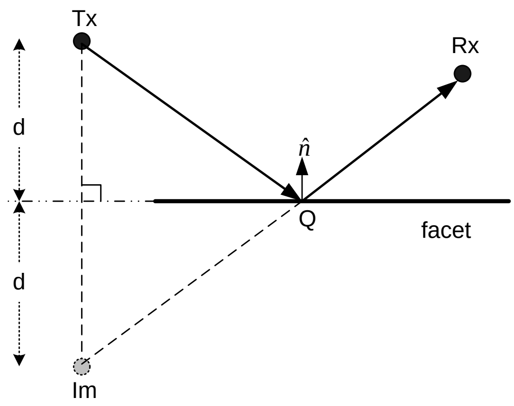

Figure 2-7: Image method for ray reflections

If we consider a scenario where only first order reflections are considered in an environment of *N* facets then the maximum number of rays that can reach the receiver location is equal to *N*. However this is almost never the case in practical scenarios because of the following reasons [112] :

- Only observers that are located inside the reflection region of a given facet can receive reflections from it, as shown in Figure 2-8. In other words, when the point of intersection between the image source and the receiver location lies inside the facet.
- The reflected ray or the incident ray may be hidden by another facet.

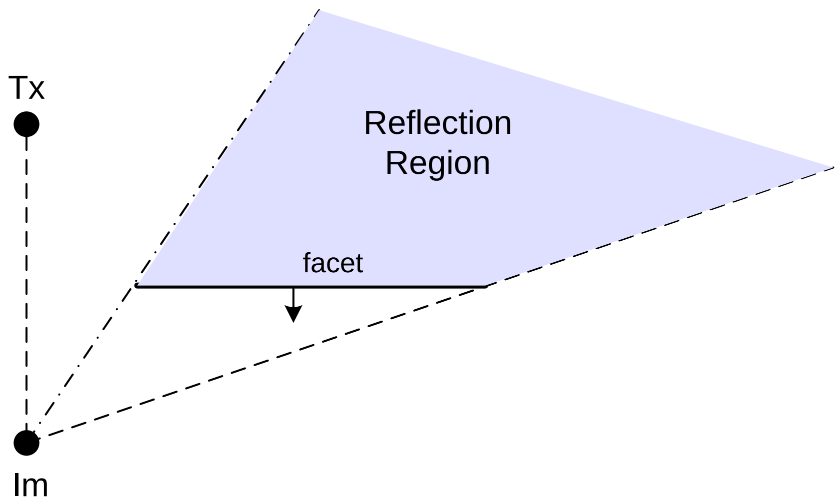

Figure 2-8: Reflection Region of a facet

Considering the same example as above, the *N* first order images are considered as the transmitting sources for double-reflected rays. The images of the first order images are called second order images. The number of these images is *N(N-1)* since the facets from which the parent first order images were derived are not considered. The case of double reflection is illustrated in Figure 2-9.

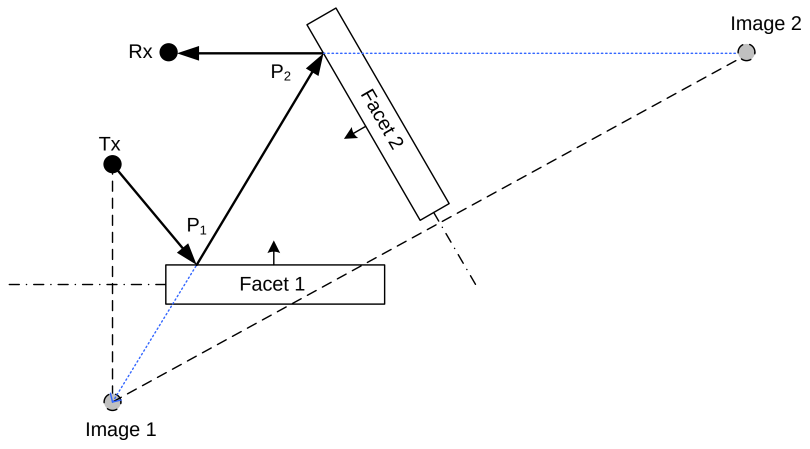

Figure 2-9: Image method for double reflections

For the above example the image of *Tx* due to *Facet 1* is first determined (*Image 1*). Then the image of *Image 1* due to *Facet 2* is determined (*Image 2*). By connecting the *Rx* and *Image 2* we can find the reflection point P_2. Now by connecting P_2 and *Tx*, P_1 is determined. This process demonstrates why this method is referred as "backward" method since in order to find the reflection points one starts from the receiver and by using the image sources goes back to the transmitter. For double reflections to exist the following three conditions should be satisfied [112] :

1. The observation points should lie inside the reflection region of the second facet.
2. The second reflection point P2 should be inside the reflection region of the first facet.
3. None of the three paths (Tx-P1,P1-P2, P2-Rx) should be hidden by any other facets.

The same procedure followed here for double reflections, is followed for multiple reflections. For *K* reflections then the number of K^{th}-order images will be $N(N-1)^{K-1}$.

These images are arranged in a tree graph called the *images tree*, in a similar way as the ray-tracing tree in the ray-launching method. The first branching contains the *N* first order images and for each branch *N-1* second order images exist. The *(N-1)*-branching continues to account for multiple reflections.

However, not all of these images exist in practice. Therefore in order to reduce computation and save time, these rays should be discarded. Images are discarded if they satisfy the following criteria:

1. When a facet (Facet 2) is completely hidden by another facet (Face 1), as shown in Figure 2-10a, then its image can be discarded and therefore is not considered for further reflections (all its 'children' images are discarded as well).
2. If a facet (Facet 2) is completely outside the reflection region of another facet (Facet 1), as shown in Figure 2-10b, then its image can be discarded as well.

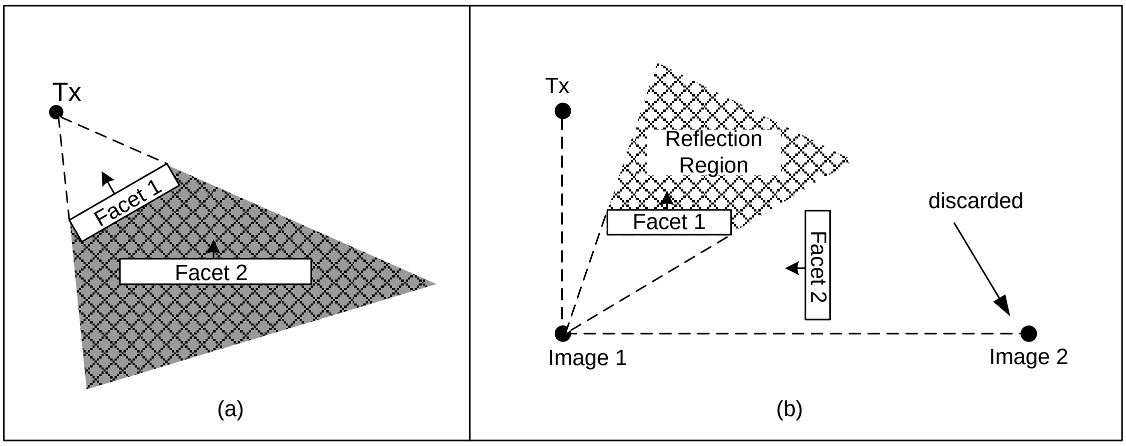

Figure 2-10: (a) Image discarded by hiding (b) Facet 2 out of reflection space of Facet 1

Using the above criteria the image tree can therefore be simplified by removing the images that do not exist in practice. The following figure illustrates an example of how the image tree is generated:

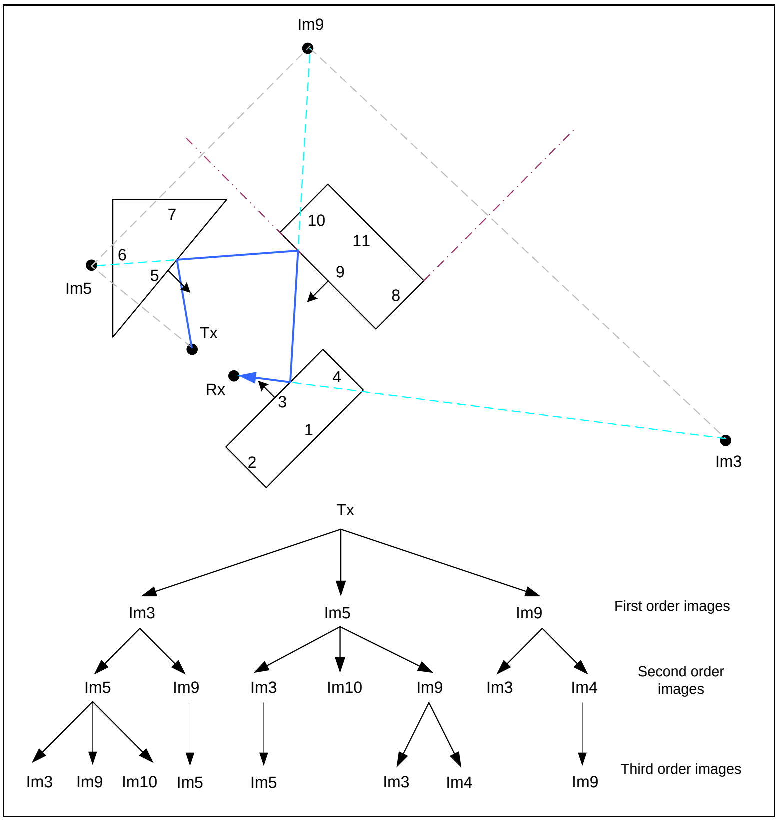

Figure 2-11: Image tree generation example

Considering the example in Figure 2-11, for a given receiver position the tree is searched in a reverse manner. Referring to the receiver position shown in the example:

- The algorithm starts by considering one bottom level image (Im3) and determines the reflection point on the respective facet (facet 3). If the reflection point lies outside the facet limits, no valid path with the last interaction been reflection from this facet exists; thus the path is rejected and the next 3rd order image is examined.
- If the reflection point lies inside the facet limits, a shadowing test is performed. If the path segment is shadowed by any other facet, the path is rejected and the next 3rd order image is examined.
- If the path segment is not shadowed, the algorithm follows the branch to the previous level image. That is the case for the example, so the 2nd order image Im9 is now considered.

For the new image the same tests are performed. If any of these fail, the algorithm moves again to the next bottom level image. Otherwise the algorithm moves another level up and so on, until it reaches the transmitter. In that case the corresponding ray path is valid.

The image method is accurate for indoor propagation prediction but it becomes computationally inefficient if the number of facets included in the environment description is high, and the number of reflections considered is high as well [128] . This increases the amount of computation required and consequently the time to produce results. For these reason special acceleration techniques are most commonly used to increase the efficiency of this method.

2.3.4.3 Acceleration Techniques

Ray-Tracing acceleration algorithms are used to improve the efficiency of simulations with respect to computational power and time required to produce results, when the environmental descriptions of the scenarios under test become very complex. There are several ways to achieve acceleration which are classified into four categories.

1. Reducing the cost of intersecting a ray with the primitives used in the model. For this reason the faceted model discussed earlier is used, since the polygonal shaped polygon is a very simple primitive and hence the intersection test cost is reduced.

2. Reducing the total number of ray-facet intersection tests. Since shadowing tests must be carried out several times in the propagation model the total number of the required intersection tests increases dramatically. For this reason the number of shadowing tests can be reduced by discarding facets (or images if the image method is used as discussed in section 2.3.4.2) and therefore the number of ray-facet intersection tests is reduced.

3. Reduce the number of rays which are intersected with the environment. This technique which is more suitable for the Ray-Launching method aims to reduce the number of rays which are intersected with the environment by setting up a

threshold related to the contribution of the ray to the overall result. If the contribution is less than the threshold then the ray is discarded.

4. Replacing individual rays with more general entities. The basic idea of such a technique is to trace many rays simultaneously. The problem of this technique is that it is not compatible with Geometrical Theory of Diffraction (GTD).

Some of the most common acceleration techniques are:

- The Binary Space Partitioning (BSP) Algorithm
- The Space Volumetric Partitioning (SVP) Algorithm
- The Angular Z-Buffer (AZB) Algorithm
- The Illumination Zones algorithm

Detailed information regarding these algorithms can be found in [112] [108] and [129] .

2.4 Indoor Localization Techniques/Methods

Researchers exploited the nature of the wireless channel in an attempt to estimate meaningful parameters that could be used for localization purposes. The most commonly used and accepted methods for performing localization are the geometrical ones, especially those based on the estimation of the Angle of Arrival (AOA), the Time of Arrival (TOA), the Time Difference of Arrival (TDOA), the estimation of the Received Signal Strength (RSS) or a combination of the above [1-14].

The system architecture for a general indoor localization system is illustrated in Figure 2-12 [21]. Figure 2-12 shows a simplified illustration of an indoor localization system architecture. Choosing the appropriate localization system for any given environment requires the evaluation of existing device/sensor data. Based on the data collected, an appropriate indoor localization algorithm, such as RSSI, Time-based, Angle of Arrival, etc is then applied.

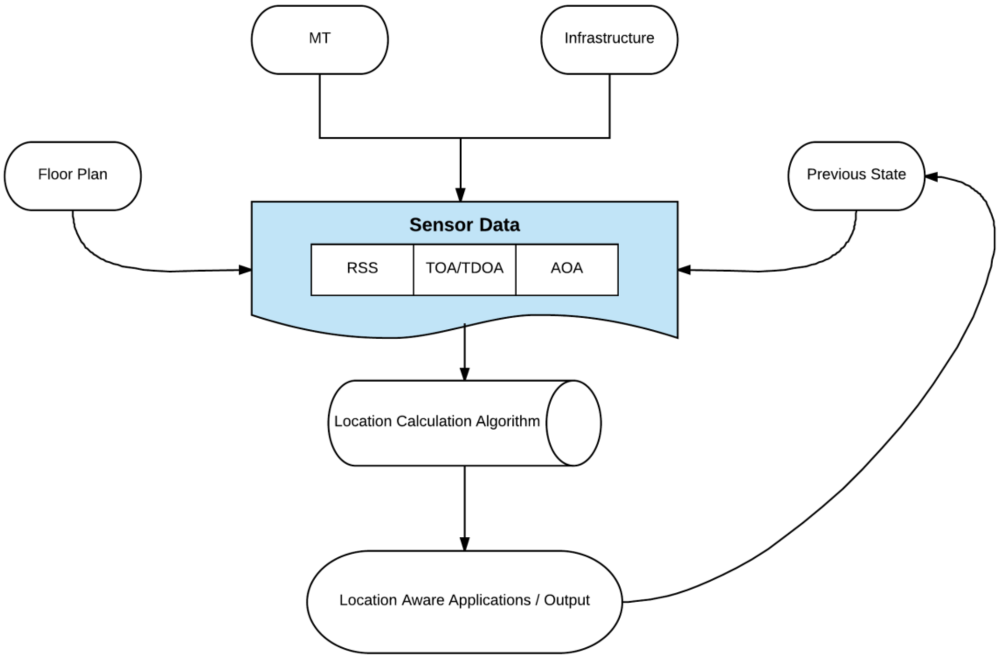

Figure 2-12: General system architecture for an indoor localization system

2.4.1 Time-based Methods

Time-based Localization methods falls into two main categories:

- Time of Arrival (TOA)/Time of Flight (TOF)
- Time Difference of Arrival (TDOA)

Most of the time-based methods rely on time synchronization. TOA/TOF methods are based on the arrival of a signal from a transmitter to one or more receivers. A packet containing timestamp information travels from the transmitter to the receiver(s). By using the timestamp information, the receiver calculates the transmission time delay, multiplies that by the signal speed and estimates the distance between the two nodes. Since radio waves travel at the speed of light, the transmission time delays for TOA/TOF systems operating in indoor environments is in the order of nanoseconds (ns) necessitating accurate time synchronization between all nodes. Thus, TOA/TOF systems require a time server which all nodes can use to synchronize their clocks.

2.4.1.1 TOA

The TOA method is considered to be one of the most accurate indoor localization techniques [28]. However, its implementation is made more challenging as well as costly by its heavy reliance on precise time synchronization [29, 55], which can be provided by a

Network Time Protocol (NTP) Server [54, 55] or some other time synchronization method [55]. The lack of Line of Sight (LOS), especially in populated and urban areas, also poses problems for TOA methods for localization as it affects the ability to accurately calculate the propagation delay of the transmitted signal.

TOA estimation can often happen at physical or higher layers. Various researchers have investigated localization aspects at the physical layer [29-31]. Estimating TOA at the physical layer typically requires specific and complex hardware modules leading to higher localization cost making the method less appealing to real world scenarios.

2.4.1.2 TDOA

TDOA techniques, also known as multilateration techniques, need multiple receivers [76, 93] of known location. Unlike TOA, TDOA techniques do not use absolute time and do not need synchronization between the transmitter and receivers via a common clock. Given the right infrastructure, separately keeping the receivers or transmitters synchronized can be sufficient [87, 93]. Some TDOA methods need synchronized receivers for localization [76, 87, 93] but since the receivers' position are known and they are part of the infrastructure, it can be easier to keep them synchronized. The location of the transmitter can be estimated by measuring the difference of arrival times of signals between receivers. A constant range difference between two nodes, derived from each time difference measurements, produces a hyperboloid. The intersection points of two or more hyperboloids give possible locations of the transmitter.

TDOA systems can be generally categorized into two basic types:

- Many synchronized transmitters and one receiver (MT1R)
- Many synchronized receivers and one transmitter (MR1T)

GPS is an example of the first type and an indoor localization system based on Mobile Terminal (MT) broadcasting signals for Access Points (APs) is an example of the second type.

2.4.2 RSS Methods

Received Signal Strength (RSS) can help to characterize and map the radio indoor environments as distinct areas to each point. Like many other localization techniques, RSS based methods utilize multiple radio nodes for triangulating a target.

A typical RSS localization method consists of two phases: an offline phase and an online phase. During the offline phase, a RSS fingerprint database (FDB) of the environment is created, where each entry of the database refers to an average RSS measurement estimated from multiple samples, received at a single static point at a known position. During the online phase, the database entries are compared with real time RSS measurements and localization algorithms can be applied to predict the position of the user. Typical localization algorithms include algorithms based on the k-nearest neighbor (kNN) [32, 33], neural network [34, 35], support vector machines [36, 37], probabilistic [38-41], and pattern recognition [42, 43]. RSS methods can be implemented as active or passive [32, 44, 45]. In active methods there is a need for active communication between the Mobile Terminal (MT) and the infrastructure. Passive methods refer to the case where the two sides do not need to communicate. An active method example can be a user positioning himself and finding his way throughout an environment. Passive methods can be used for localization scenarios of equipment or other resources in hospitals, factories, companies or similar environments.

Most of the indoor localization techniques based on RSS are considered off-the-shelf solutions since they utilize the existing infrastructures and require no modifications [32, 38, 89, 90].

2.4.3 Angle-based Methods

Angle of Arrival (AOA) techniques determine the direction of propagation of a signal and its angle of arrival. To use AOA for localization purposes a minimum of two base nodes equipped with antenna arrays are required. The use of the antenna arrays allows the direction of the receiving signal to be estimated, which helps to form a geometric relationship to estimate the intersection of two lines of bearing (LoBs) from the known base nodes. The use of accurate antenna arrays for base nodes makes AOA methods costly, complex and power- hungry. Similar to other localization methods, various AOA estimation techniques have been proposed [46-51]. Some examples include spatial spectral estimation method, called Delay and Sum, (DAS) [48] and eigenstructure methods, such as Multiple Signal Classification (MUSIC) [49], root MUSIC [50], and Estimation of Signal Parameters via Rotational Invariance technique (ESPRIT) [51].

2.5 Conclusion

This chapter has provided an overview of wireless positioning systems and localization algorithms that are currently in use for various applications. These positioning systems are usually based on one of the three basic methods: time (TOA, TDOA), signal property (RSS) and angle-based (AOA) methods. An overview of wireless positioning systems and their classifications based on environment, cooperation and technology has been provided. Moreover, a general system architecture for an indoor localization system was discussed together with a brief description of basic localization techniques while different categories of localization methods/techniques were discussed. These methods are compared in terms of complexity and performance. Background knowledge of TOA/TDOA, RSS and AOA was also briefly reviewed in this chapter.

In addition radio propagation modelling and deterministic modelling using Ray tracing was discussed in this chapter. If used properly ray tracing can accurately estimate the receive signal strength and other parameters of wireless communication system, as long the user can provide an accurate description of the environment both in terms of geometry and in terms of constitutive parameters of materials. Thus ray tracing can be used to create accurate fingerprinting database rather than carrying out labour intensive radio propagation campaigns [137] [138] . Furthermore ray tracing can estimate the exact power delay profile of a multipath environment and reveal the exact path length the signal travels between two transceivers. This ability is also very useful in localization timing based methods since knowledge of the exact travel path can lead to the exact propagation delay experienced between points which can assist algorithmic development for a timing based location system.

Chapter 3

3 Time-based Localization Methods

This chapter presents an overview of time-based localization methods and algorithms. In particular, it focuses on lateration approaches that use Time of Arrival (TOA) and Time Difference of Arrival (TDOA) to estimate the location including a presentation of a basic approach to each, as well as to some of the other well-known techniques, and their implementation. Since most of the time-based methods require some type of statistical post-processing to achieve better accuracy, some of these algorithms have also been discussed. Finally, a new time-based localization method is presented and its performance compared with existing methods.

3.1 Introduction

One of the main advantages of time-based methods over RSS or AOA-based localization methods is that the former do not require the creation of fingerprint databases or specialized antenna arrays. Most of time-based methods which benefit from measuring Round Time Trip (RTT), especially those with software implementations, have a similar diagram as shown in Figure 3-1[52]:

As Figure 3-1 illustrates, time-based localization process of this sort can be divided into two main parts:

- Pre-processing/Measurement data collection
- Post-processing/Statistical analysis

For most of time-based methods, lack of availability of accurate clocks on COTS hardware imposes an inevitable statistical post-processing effort to achieve acceptable localization accuracy. This is the very reason for collecting many packets before applying the statistical methods. Chapter 4 presents a comprehensive review on packet collection for time-based localization techniques and a new method for accelerating TOA/TDOA packet based localization methods.

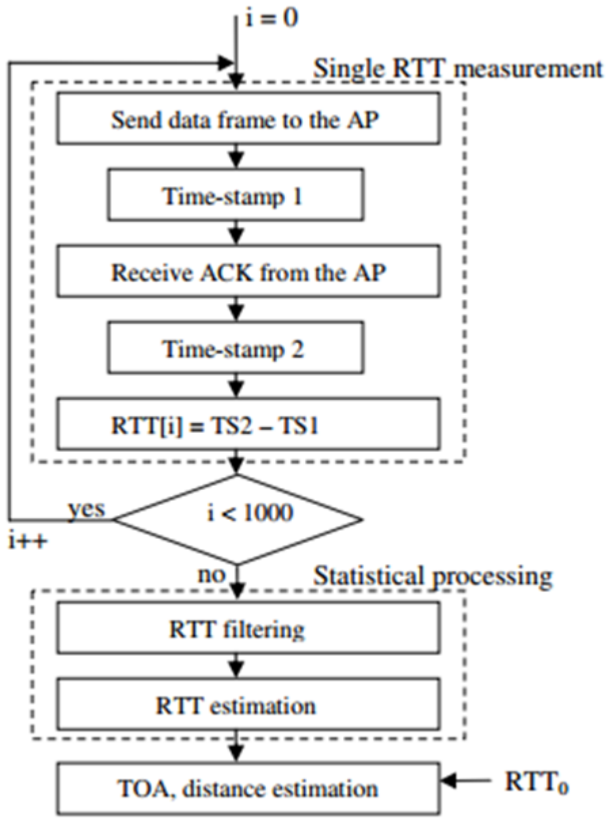

Figure 3-1: Time-based ranging process

Statistical post-processing for time-based methods is generally used to overcome the low resolution clock problem of WLAN cards. However, there are several other aspects that make distance estimation using time-based methods more challenging, with multipath and lack of direct line of sight being the most important.

3.1.1 Multipath

When it comes to time-based methods, multipath often considered one of the most important causes of measurement error in indoor environments [30, 53]. Unfortunately, there is no exact model for multipath as it is random and quite unpredictable [54]. Its effect varies depending on environment geometry and its surroundings. Many researchers have evaluated multipath fading where LOS does not exist [54, 55]. Decreasing multipath error contribution can improve localization accuracy. This can be achieved by advanced post processing ray tracing tools that can estimate the exact signal path length traveled.

The performance characteristics of time-based methods are very sensitive to availability of Line-of-Sight [56, 57]. In NLOS situations the calculated TOA or TDOA are subject to considerable error. Due to the complexity of indoor environments, it is almost impossible to have LOS situation at all times; thus, many NLOS identification and localization techniques have been developed [58-61].

3.2 TOA Positioning

TOA-based localization methods estimate the signal propagation delay from a transmitter to a receiver; hence, localization based on TOA requires accurate clock synchronization between the nodes. Implementation of accurate clock synchronization can be very costly and complicated. Moreover, calculating the transmission time delay based on the corresponding speed of the signal is a challenging task since wireless signals can be highly affected by multipath channels and their associated delay profiles [55]. A simple structure of a TOA positioning system is shown in Figure 3-2 [28].

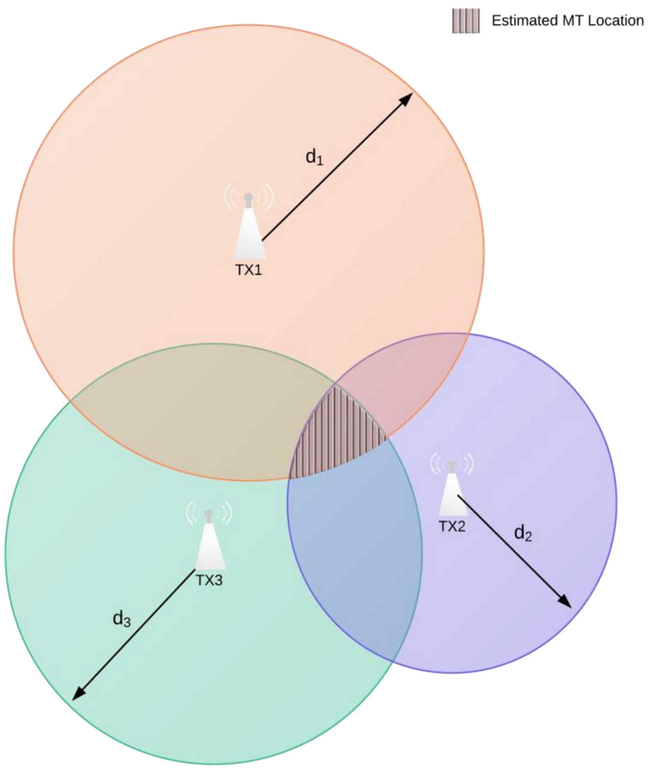

Figure 3-2: TOA-Based positioning System

As demonstrated in Figure 3-2, in order to localize the Mobile Terminal (MT), three or more access points (APs) are required. Each AP measures the TOA of the transmitted signal from the MT and calculates the distance. The circles around APs represent calculated distance based on TOA and the intersection represents possible area in which the MT resides.

The TOA measurement model can be formulated as follows [93]: let's assume $X = [xy]^T$ is the unknown source position and $X_l = [x_l y_l]^T$ are the known coordinates of the lth sensor, l = 1, 2, … , L , where L ≥ 3 is the number of receivers. The distance between the source and the lth sensor, denoted by d_l, is simply

$$d_l = \|X - X_l\|_2 = \sqrt{(x - x_l)^2 + (y - y_l)^2}, \qquad l = 1,2, \dots, L. \tag{3.1}$$

With no loss of generality, it is assumed that the source emits a signal at time 0 and the lth sensor receives it at time $\{t_l\}$; that is, $\{t_l\}$ are the TOAs and there is a simple relationship between t_l and d_l:

$$t_l = \frac{d_l}{c}, \qquad l = 1,2, \dots, L. \tag{3.2}$$

In practice, TOAs are subject to measurement errors. As a result, the range measurement based on multiplying t_l by c, denoted by $r_{TOA,l}$, is modelled as:

$$r_{TOA,l} = d_l + n_{TOA,l} = \sqrt{(x - x_l)^2 + (y - y_l)^2} + n_{TOA,l}, \qquad l = 1,2, \dots, L. \tag{3.3}$$

Where $n_{TOA,l}$ is the range error in $r_{TOA,l}$, which results from the TOA disturbance.

The channel state information (CSI) can be also used to develop Time of Flight TOF / TOA methods. Such methods utilize physical layer information processing to estimate the TOF. Although these methods can produce relative accurate results, accuracy can be constrained by the underlying available bandwidth of the technology (e.g. 802.11 hardware). CSI based methods, require specialized compatible hardware to estimate the time of flight information from physical layer [21, 22, 23] and thus it's out of the scope of the work performed in this thesis.

3.3 TDOA Positioning

Time difference of arrival (TDOA) methods, calculate the time difference in arrival of an emitted signal from a mobile terminal to two or more base stations. In this method there is need for clock synchronization between all base stations/receivers. Moreover, the exact locations of all base stations are known to the localization infrastructure. Each calculated TDOA forms a hyperbola in the localization space and the intersection of all hyperbolas represents the possible location of the mobile terminal.

The TDOA measurement model can be formulated as follows [93]: it has been assumed that the source emits a signal at the unknown time t_0 and the l^{th} sensor receives it at time $t_l, l = 1,2,\dots,L$ with L ≥ 3. That means there are $\frac{L(L-1)}{2}$ distinct TDOAs from all possible sensor pairs, which is denoted by $t_{k,l} = (t_k - t_0) - (t_l - t_0) = t_k - t_{l,k}, l = 1,2,\dots,L$ with $k > l$. However, there are only $(L - 1)$ nonredundant TDOAs. For example if $L = 3$, the distinct TDOAs are $t_{2,1}, t_{3,1}$ and $t_{3,2}$, that means $t_{3,2} = t_{3,1} - t_{2,1}$, which is redundant. To be able to reduce complexity without losing estimation performance, all $\frac{L(L-1)}{2}$ TDOAs should be measured and converted to $(L - 1)$ nonredundant TDOAs for source localization [46]. With no loss of generality, the first sensor is considered as the reference and the nonredundant TDOAs are $t_{l,1}, l = 2,3,\dots,L$.

Similar to Equations 3.2 and 3.3, the range difference measurements deduced from the TDOAs are modeled as:

$$r_{TOA,l} = d_{l,1} + n_{TOA,l}, \qquad l = 1,2,\dots,L. \tag{3.4}$$

Where

$$d_{l,1} = d_l - d_1 \tag{3.5}$$

and $n_{TOA,l}$ is the range difference error in $r_{TOA,l}$, which is proportional to the disturbance in $t_{l,1}$.

3.4 A New Time-Based Localization Method

One of the main advantages when comparing time over signal strength localization methods, is that the former do not necessarily require the creation of a fingerprint database. On the other hand, the majority of time-based methods require some sort of clock synchronization due to the drifting of the local clocks. The new time-based localization method presented in this section is based on information provided by 802.11 Beacon packet data. The advantage of this method over other time-based methods is that the Mobile Terminal (MT) does not require establishing a connection to an Access Point (AP) or sending and receiving packets. Also, the proposed method does not require any clock synchronization: it works by analyzing Beacon timestamp and MAC timestamp. By using Beacon Interval, Beacon timestamp and Service Set Identifier (SSID) of a packet, it was possible to optimally process the collected MAC timestamps to provide a hybrid TDOA-TOA localization method with an average error of less than 2.5 meters.

3.4.1 Introduction

There are many applications that benefit from GPS (Global Positioning System); however, GPS may not work well in outdoor environments that are heavily obstructed by high buildings or in indoor environments.

The provision of the location information of objects and people in an indoor environment is crucial to the delivery of novel indoor localization services [62-64]. For example, in a hospital timely access to all the necessary equipment and personnel in an emergency situation may determine the patient’s survival and can be enhanced by the ability to locate those resources with accuracy and speed. In another example, in airports and other transportation facilities where typical outdoor positioning system does not function, indoor positioning systems based on 802.11 or similar technologies can be used for tracking of valuable items.

Many of the time-based localization methods make use of the Round Time Trip (RTT) of a transmitted signal [24, 25, 65]. It has been also found that time based methods can be affected by the clock’s drift and noise [25, 27] or even multipath which introduces a degree of measurement error [66, 67].

According to literature, better localization accuracy can be achieved by changing the 802.11 driver or by modifying the hardware [68-72]. The method proposed here requires only Beacon data and makes use of two different timestamps: one for synchronization and localization process optimization (Beacon timestamp), and one for statistical analysis for distance estimation purposes (MAC timestamp). The IEEE 802.11 standard does not include high resolution timestamps, so in order to achieve an acceptable level of accuracy, statistical methods must be used. As stated in [25], the authors presented a method using RTT and low resolution clocks to measure the distance between two wireless nodes. They achieved fairly good resolution with a standard deviation of 8 meters by means of statistical methods and minor tweaks in their hardware. Moreover, their method necessitated the active cooperation of another MT or AP and a third node as a monitoring node. In [70] the authors obtained a timing resolution of 22 ns requiring specialized hardware for mobile terminals. The method presented in this section is a more practical approach as it does not demand the active cooperation of other nodes or high-end 802.11 hardware.

3.4.2 Distance Estimation

The localization method presented here is a mixture of TOA and TDOA estimations. The distance between a mobile terminal and an access point will be determined by calculating the time difference of a position, after calibrating out a known distance, that is, distance 0.

$$\mathrm{D} = \mathrm{c} \times \mathrm{TDOA} \tag{3.6}$$

$$\mathrm{TDOA} = TOA_n - TOA_0 \tag{3.7}$$

$$\mathrm{D} = \mathrm{c} \times [TOA_n - TOA_0] \tag{3.8}$$

Where D represents the distance (m), c is the speed of light (m/s), TOA_n is the calculated TOA (s) for distance *n* and TOA_0 is the calculated TOA for distance 0.

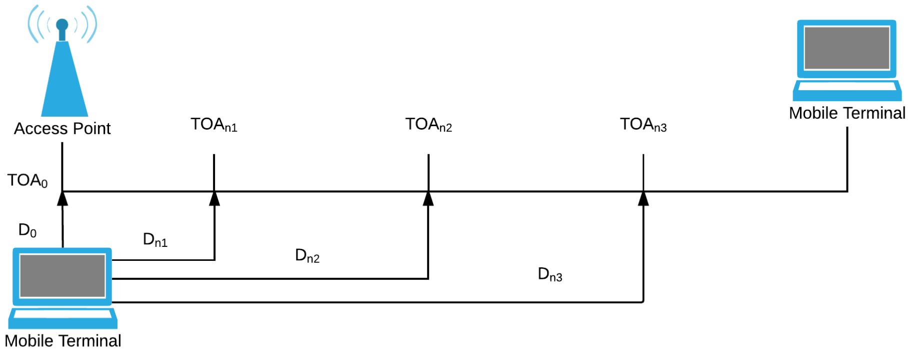

Figure 3-3: Calibration and Distance Calculation Phases

As shown in Figure 3-3: Calibration and Distance Calculation Phases, TOA_0, the typical average processing delay, is calculated by placing the MT next to the AP. Packets are collected and filtered appropriately by using statistical analysis in order to estimate TOA_0. This analysis is presented in sections 3.4.3 and 3.4.4. Similarly, TDOA is obtained by placing the MT at a distance n in order to calculate TOA_n, before subtracting it from TOA_0. The challenge was to evaluate TOA_0 precisely. Since the presented approach works without any cooperation from an AP, IEEE 802.11 Beacon frames are adopted for both synchronization and calculation purposes.

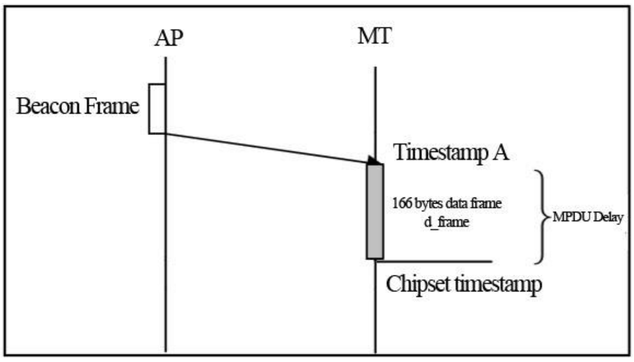

Figure 3-4: MAC Timestamp Position

In general, a chipset driver, after receiving the MAC Protocol Data Unit (MPDU), will place a timestamp at the end of a frame. This means that an extra 1.26648e6 ns or 1266.48 µs minimum processing time is required, which can affect the accuracy estimations. A simple driver modification [68, 69, 73] made it possible to position and thus record the MAC timestamp for each packet at the beginning of MPDU (timestamp A), which improved the process of timestamp measurement. The process is illustrated in Figure 3-4.

Table 3-1: Localization Algorithm using beacon and MAC timestamps

- TOA_0 Calculation (Initialization phase)
  - For each visible AP
    - * Collect beacon packets for n seconds
    - * Validate collected packets using beacon timestamp and the time delta calculated from the previous captured packet
    - * Calculate time delta from previous captured packet based on MAC timestamp
    - * Average the calculated time deltas
    - * Record calculated TOA_0 for the AP
- Distance Calculation
  - Calculate TOA for distance n
  - Calculate TDOA for distance n as (3.7)
    $TDOA = TOA_n - TOA_0$
  - Calculate MT distance to AP as (3.6)
    $D = c \times TDOA_n$

3.4.3 Methodology

A Beacon frame carries a wealth of information such as Beacon Interval, timestamp, Service Set Identifier (SSID), Support Rates, Parameter Sets, Capability Information and Traffic Indication MAP (TIM). In this approach, the most important statistics are drawn from the first three, that is, Beacon Interval, timestamp and Service Set Identifier (SSID). These parameters are shown in Figure 3-5.

For the analysis, two different timestamps have been collected and utilized: Beacon timestamp and, MAC timestamp. The first one is used mainly for synchronization purposes as well as assisting the identification of the valid and non-valid packets. Assuming a typical Beacon Interval (BI) of 100 ms (BI = 100); and a Beacon frame length of 140 bytes (2.4 GHz) and 166 bytes (5GHz), every 0.102400 seconds or 102400 microseconds, a node in range should receive a Beacon packet.

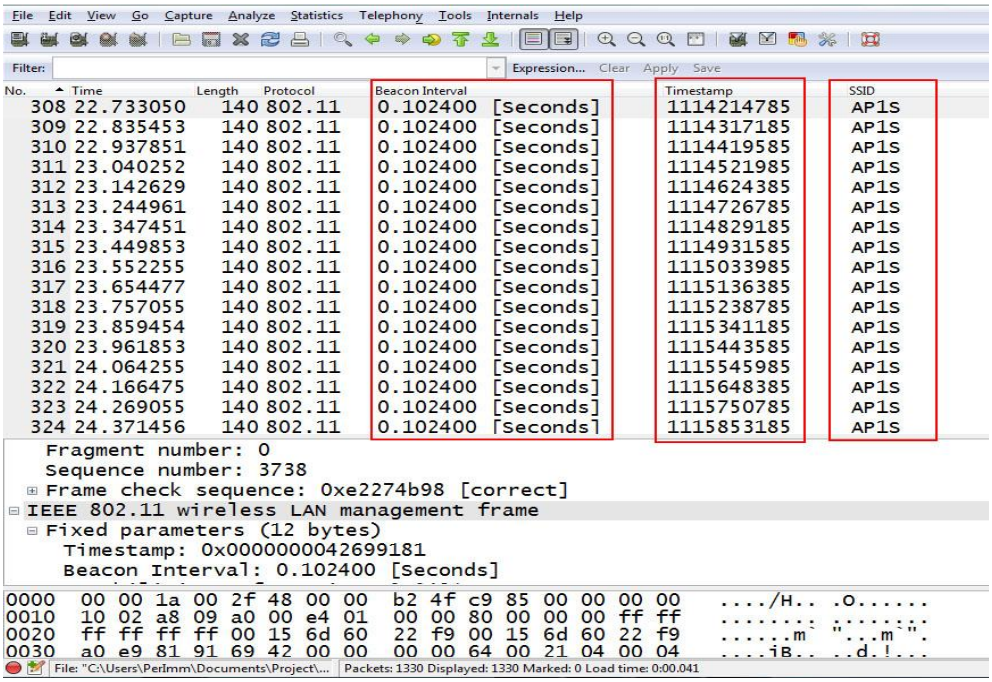

Figure 3-5: Beacon Packet Information

Figure 3-6 shows the calculated Time Delta from a previous displayed frame by Wireshark for a standard beacon interval of 100 ms. The calculated time delta clearly shows the 102400 microseconds time difference from previous beacon packet captured.

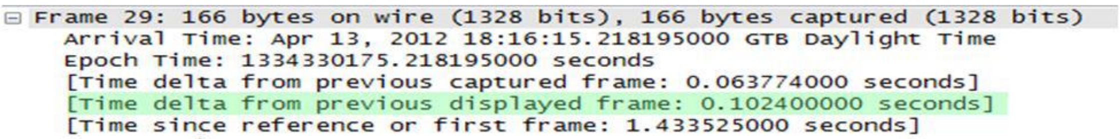

Figure 3-6: Time Delta

Figure 3-7 highlights both timestamps and how the data is selected or rejected. If a Beacon packet cannot be generated every 102400 µs or the Beacon packet timestamp fluctuates due to some hardware or software errors/delays, then those packets will be rejected. Assuming packets can travel a distance of 300 m in 1 µs and since typical 802.11 cards allow recording of timestamps at a resolution of 1 µs, a sufficient number of packets should be collected in order to assess the overall average and utilize the determined average time. The proposed method’s algorithm is outlined in Table 3-1.

MAC timestamp	Difference	Beacon Timestamp	Difference
1712507507		410726458	
1712609909	102402	410828858	102400
1712712309	102400	410931257	102399
1712814711	102402	411033658	102401
1712917110	102399	411136058	102400
1713019513	102403	411238458	102400
1713121912	102399	411340858	102400
1713224312	102400	411443258	102400
1713326714	102402	411545658	102400
1713429114	102400	411648058	102400
1713531516	102402	411750458	102400
1713633916	102400	411852858	102400
1713736318	102402	411955258	102400
1713838718	102400	412057658	102400
1713941120	102402	412160058	102400
1714043520	102400	412262458	102400
1714145922	102402	412364858	102400
1714248322	102400	412467258	102400
1714350724	102402	412569658	102400
1714453124	102400	412672058	102400
1714555524	102400	412774458	102400
1714657926	102402	412876858	102400
1714760326	102400	412979258	102400
1714862728	102402	413081658	102400
1714965128	102400	413184058	102400
1715067530	102402	413286458	102400

Figure 3-7: Valid and Non-valid Timestamps

3.4.4 Experimental Setup

The experiments took place at the premises of the School of Pure and Applied Sciences at the Open University of Cyprus. The floor is constructed from a mixture of concrete pillars and walls, including plasterboard walls. Figure 3-8 shows the floor plan of the building, access points and mobile terminal placements in line of sight condition. Beacon packets generated by the APs every 100 ms were captured by the MT. The measurements were conducted in Line of Sight (LOS) conditions at several distances.

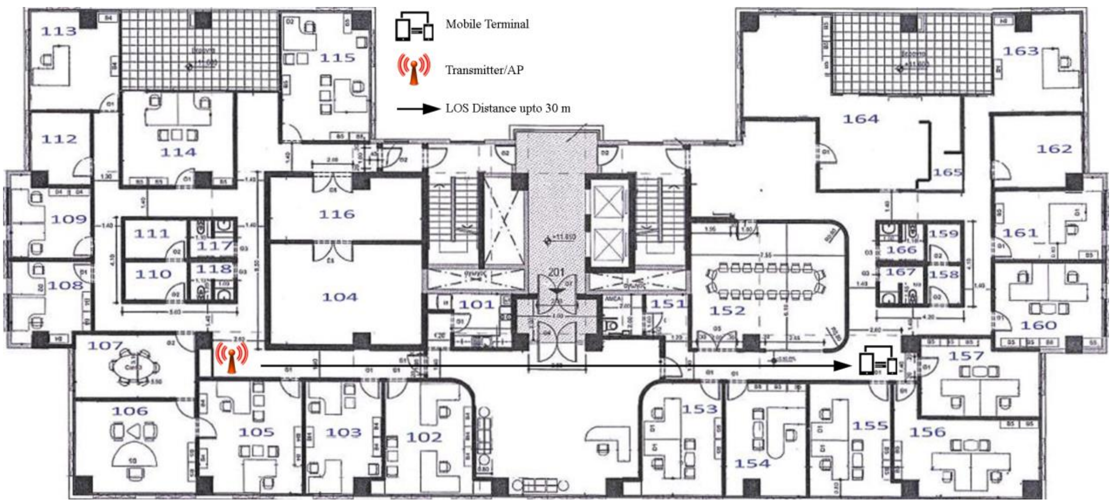

Figure 3-8: Floor Plan

Three different devices have been used in the testbed environment; a Cisco E4200, a Linksys WRT54GL and a Sony Vaio VPCYB2M1E. The APs were loaded with OpenWRT backfire firmware which provided a more flexible experimentation environment. The Mobile terminal was running Fedora 16 and tshark v1.6.3. Experiments were carried out at 2.4GHz and 5GHz bands, on channel 11(2462MHz), channel 13(2472MHz) and channel 36(5180MHz).

3.4.4.1 Single AP Measurement

Table 3-2 presents the actual and estimated distance results of the MT from a single AP. Measurements were conducted in the corridors of the building up to a maximum LOS distance of 25m. A TOA_0 value of 102400.833 µs was measured as the base average (Distance 0).

Table 3-2: Measurement Data

Distance (m)	$TDOA_n$ (ns)	Est. dist. (m)	σ (m)	# of Valid Packets
5	18	5.4	0. 4	2802
10	24	7.2	2.8	3004
15	44	13.2	1.8	3065
20	80	24	4	2938
25	91	27.3	2.3	2768

Figure 3-9 shows the projection of the actual distance vs. estimated distance based on Table 3-2.

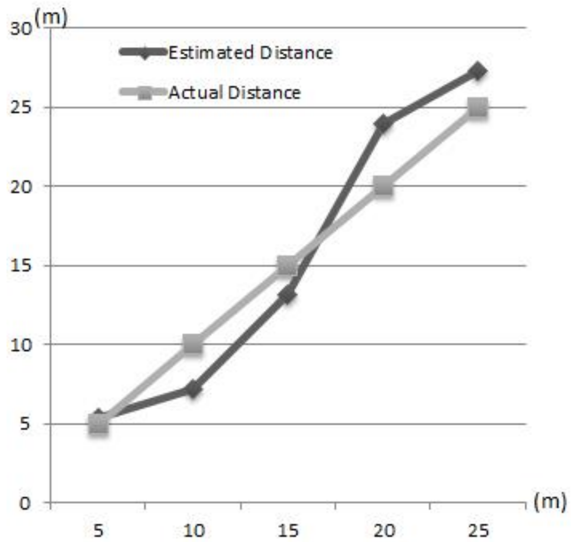

Figure 3-9: Actual Distance vs. Estimated Distance

3.4.4.2 Trilateration Test

In order to test the proposed method in a trilateration scenario, three APs were used. After calculating TOA_0, the averages were calculated separately for TOA_{n1}, TOA_{n2}

and TOA_{n3}. Table 3-3, Table 3-4, Table 3-5 and Figure 3-10 illustrate the outcome of all conducted measurements.

TOA_0 = 102400.822 μs (Calculated base average for the trilateration experiments).

In each experiment, three circles were intersected and the calculated distance was considered as radius, for example radius data for 1st trial.

r_1=11.7m, r_2=36m, r_3=35.1m.

Table 3-3: Position Estimation, 1st Trial

(SSID)	Average (μs)	Average Difference (ns)	Actual Distance (m)	Calculated Distance (m)	Valid Packets
AP1S	102400.861	39	10	11.7	3076
AP2S	102400.942	120	37	36	2995
AP3S	102400.939	117	37	35.1	3004

Table 3-4: Position Estimation, 2nd Trial

(SSID)	Average (μs)	Average Difference (ns)	Actual Distance (m)	Calculated Distance (m)	Valid Packets
AP1S	102400.888	66	20	19.8	2901
AP2S	102400.921	99	27	29.7	2743
AP3S	102400.923	101	27	30.3	2815

Table 3-5: Position Estimation, 3rd Trial

(SSID)	Average (μs)	Average Difference (ns)	Actual Distance (m)	Calculated Distance (m)	Valid Packets
AP1S	102400.919	97	25	29.1	2774
AP2S	102400.894	72	22	21.6	2807
AP3S	102400.900	78	22	23.4	2950

Table 3-3, Table 3-4 and Table 3-5 present the data used for the trilateration calculations.

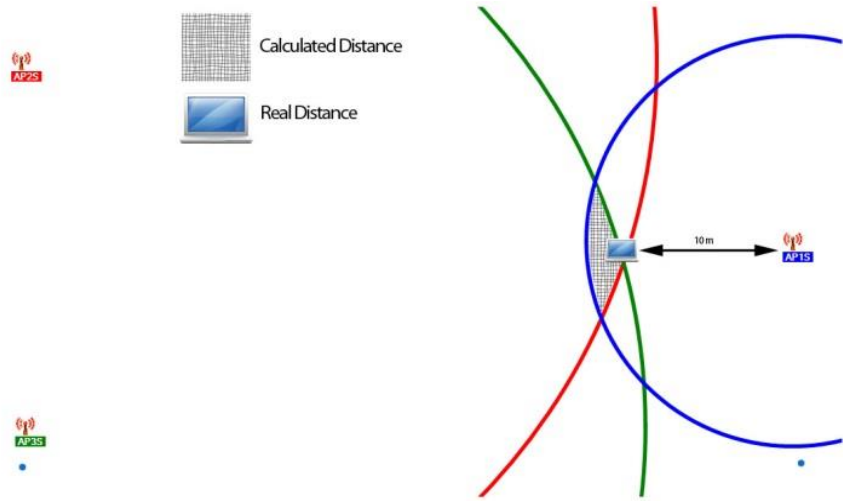

Figure 3-10: Position estimation, 1st trial

Figure 3-10 presents the actual distance of the mobile terminal and the calculated distances from each access point for the first trial, and finally how the position of the target estimated using trilateration.

3.5 Conclusion

This chapter briefly presented an overview of time-based localization methods and algorithms. Some of the well-known time-based localization techniques have been discussed in this chapter and the impact of multipath and NLOS have been explained.

Moreover, a connection-less time-based method has been proposed. The advantage of the proposed method over other time based localization methods is that it does not require connection to an access point; the method uses Beacon frame information which eliminates the need for bidirectional communication between the transmitter and receiver. By using the Beacon timestamp information in conjunction with MAC timestamp, system delay can be calibrated out. It was demonstrated that the proposed localization method can achieve an average error of less than 2.5 meters. The proposed method does not require an RTS-CTS mechanism and it could also be performed by utilizing a customized packet which broadcasts only the desired localization information.

The next activity in the framework of indoor localization using time-based methods will be the performance improvement and acceleration of data collection and evaluation time. In order to take advantage of time-based methods for real-time localization and tracking, any pre and post processing actions need to be as optimum as possible to eliminate any unnecessary delay on data collection and distance estimation processes.

Chapter 4

4 Accelerating TOA/TDOA Packet based Localization Methods

Time-based localization methods can be especially useful in dynamic environments where the usefulness of Received Signal Strength (RSS) fingerprint based methods can be limited. Typical ‘off the shelf’ 802.11 network packet time-based methods tend to collect a large number of packets and apply statistical analysis in order to localize a user. This packet collection process typically lies in the range of minutes, thus turning this type of localization into a non-real time process. This chapter presents a method to accelerate network packet time based techniques. By accelerating packet capturing in conjunction with packet validation, it has been shown that the localization process time can be shortened without reducing positioning accuracy.

4.1 Introduction

In complex dynamic environments such as airports, shopping malls, hospitals and schools, there is a constant change in the environment. Time-based methods do not require the construction of fingerprinting databases like RSS-based methods. On the other hand, practical implementation of Real Time Location Systems (RTLS) based on network packet time-based methods by using only off-the-shelf equipment is a challenging task. One of the main challenges is the packet collection and user position evaluation process which can take significantly more time than RSS-based methods [62]. Researchers have tried to optimize the process by using different techniques. In [23], the Time Difference of Arrival (TDOA) was measured by considering the clock offset and its local linear behavior around the offset. In [24], a four-way Time of Arrival (TOA) algorithm that measures the Round Trip Time (RTT) of IEEE 802.11 MAC was introduced. In another method the RTT between two wireless nodes was calculated by using data and acknowledgment packets [25]. In [66], the distance between nodes was calculated by using a two-way TOA measurement technique by utilizing 1-ppm clocks. In [20], another time-based RTLS was implemented by using high accuracy clocks. These latter processes [20, 66] impose an increased cost on RTLS deployment since special or more costly hardware is required.

Other researchers have tried to implement and use time-based methods by creating customized packets and hardware solutions. In [26] and [74], a measuring system integrated on a Printed Circuit Board (PCB) was used as additional hardware to the wireless adapter, aiming to increase localization accuracy. In [75], a Time of Flight (ToF) method was presented by using the G2 Microsystems tag, while in [76], a TDOA geolocation system was tested utilizing five sensors for localization. BeepBeep [77] is a time-based method that calculates the travel time of sounds between two mobiles; each mobile emits a set of sounds which helps distinguish the in-between distance of the two devices. Presented results in [77] suggest an achieved accuracy of 30 centimeters; however sound-based methods may not work well in crowded areas where the environment is very noisy.

Most of the time-based methods need collection times from a couple of minutes up to 20–30 minutes [23-25]. Such time durations may restrict practical usage of dynamic RTLS. In PinPoint [23], it takes about four minutes to collect and evaluate the packets, while [25] requires fifteen minutes of ping data collection in order to achieve the suggested accuracy. As mentioned in [24], collection and evaluation of data requires a large number of packets, suggesting a collection process of several minutes. In [14], 2000 to 2500 valid Beacon packets are required to meet the accuracy requirements. Since most of the commercial Access Points (APs) come with default Beacon Interval (BI) of 100 milliseconds, even this method takes several minutes to collect the required number of packets.

Typically, time-based localization methods can be divided into two main categories:

- Hardware-based localization
- Software-based localization

The first category refers to time-based methods that are using customized or modified hardware for localization purposes [20-22]. The second category is based on localization methods which are purely software based without using any specialized hardware or hardware modifications [14, 23-27]. Software-based methods are utilizing different types of packets such as RTS-CTS, Ping, Beacon and custom made packets. A correct packet type and an optimum packet generation technique can lead to faster and more accurate distance estimation in software-based localization. This chapter presents the findings on how a packet time based localization method can be accelerated with an 'off the shelf' technique, and how such acceleration technique may affect the throughput of a network. Results presented are based on the Beacon frame method [14]. To evaluate the effect of different Beacon intervals on localization accuracy and speed, the Beacon method [14] was further investigated by generating BIs down to 10ms. Several measurements conducted at different BIs (200, 100, 50, 20 and 10ms) and at various distances up to 30 meters. Moreover, the effect of different BIs on number of valid packets and channel throughput has been studied.

4.2 Description of the method

In the presented method, broadcasted beacon packets are captured and analyzed. After capturing the network beacon packets, TOA is calculated. The TOA calculation is carried out for all the Access Points (APs) seen by the Mobile Terminal (MT). As explained in [78], [79], the TOA can be calculated as follows:

$$\mathrm{r}_i = d_i + n_i \qquad \mathrm{i} \in \mathrm{B} \tag{4.1}$$

Where $r_i = c \times t_i$ in (m); c being the speed of light in free space ($c = 3 \times 10^8\ {}^{m}/_{s}$) and t_i is the signal propagation time between AP and MT in (ns); d_i is the actual distance between the two nodes in (m) and n_i represents the error introduced by the processing delays of the hardware, which can be calculated through a calibration process by placing the MT at a known distance. *B* represents a set of available APs seen by a MT and *i* represents a node/AP in the set. In this analysis, (4.1) is reformed to allow estimation of distance in terms of r_i and n_i. The formula (4.1) then becomes:

$$\mathrm{ed}_i = r_i + n_i \qquad \mathrm{i} \in \mathrm{B} \tag{4.2}$$

Where ed_i is the estimated distance of the i^{th} position in (m); n_i is the processing delay in (m).

4.2.1 Methodology

Since in this method beacon packets, Beacon Interval (BI) and Beacon Timestamp are used, the first step is to demonstrate what happens if we reduce packet generation time or BI. By generating beacons faster, more packets can be captured within the same timeframe. In order to evaluate the effect of beacon generation speed on the localization accuracy, different BIs including BI = 200, 100, 50, 20 and 10 milliseconds were generated and position estimation results were analyzed at distances of 5, 10, 15, 20, 25 and 30m.

Packets were captured by using Wireshark. Two different timestamps including beacon timestamp and MAC timestamp have been used for TOA calculations. For each test, 300 seconds (5 minutes) of data have been gathered and a measurement graph has been produced to illustrate the achieved localization accuracy. To obtain the valid packets, the beacon timestamp and MAC timestamp are compared. The beacon timestamp helps to confirm that each packet has been generated every *N* millisecond: *N* being a “Time Unit”, where according to the IEEE 802.11-1999 [80], a “Time Unit” is a measurement of time equal to 1024 μs.

4.3 Performance Evaluation and Comparison

The performance of the presented method has been evaluated taking into account two important factors for practical implementation of a RTLS. The first factor is acceleration of packet capturing and post-processing while the second factor is wireless channel throughput and quality of service.

Different APs and MTs have been used to confirm the consistency of the method. The APs used include Linksys WRT54GL, Ubiquity Bullet M2 and Cisco E4200 and mobile terminals consisted of a Sony Vaio VPCYB2M1E and a Dell Inspiron N5110. In order to test the method’s performance in different wireless bands, experiments were carried out at 2.4GHz and 5GHz bands, on channel 11(2462MHz), channel 13(2472MHz) and channel 36(5180MHz).

4.3.1 Measurements

Localization measurements were conducted in the corridors of the School of Pure and Applied Sciences at the Open University of Cyprus (OUC) at a maximum distance of 30 meters and with LOS (Line of Sight) conditions. The distance between MT and AP has been estimated by using equation 4.3[14].

$$\mathrm{D} = \mathrm{c} \times \mathrm{TDOA} \tag{4.3}$$

$$\mathrm{TDOA} = TOA_n - TOA_0 \tag{4.4}$$

Where D represents the distance in (m), c is the speed of light in (m/s), TOA_n is the calculated TOA for distance n in (μs) and TOA_0 is the calculated TOA for distance 0 in (μs). TOA_0 represents the typical average processing delay which is calculated by placing MT next to the AP. Packets are collected and filtered appropriately by using statistical analysis presented in [14] in order to estimate TOA_0. TDOA is obtained by placing the MT at a distance *n* in order to calculate TOA_n, before subtracting it from TOA_0.

Table 4-1 presents the calculated TOA_0 values for various capture durations where BI = 100ms.

Table 4-1: Calculated TOA_0 for AP1 with BI = 100ms

$TOA_0(\mu s)$	Capture Time(Sec)	Captured Packets	Relevant Packets	Valid Packets
102401.1877	300	5466	2916	2019
102401.1868	200	3772	1947	1344
102401.1789	100	1925	973	665
102401.1773	25	497	243	141
102401.1857	10	211	97	70
102401	1	42	10	6

Captured packets refer to the number of packets collected for the specific capture time from all visible APs at the point of interest. Relevant packets are the packets collected from the specific AP, for which the distance of the MT is calculated for, while dropping packets from all other APs in range. Valid packets are the selected packets based on the selection criteria discussed in chapter 3. Valid packets are the only ones used for calculating TOA_0 and TOA_n, required for estimating the distance between an AP and the MT. Figure 4-1 presents the calculated distances for 5m up to 30m for BI=100ms:

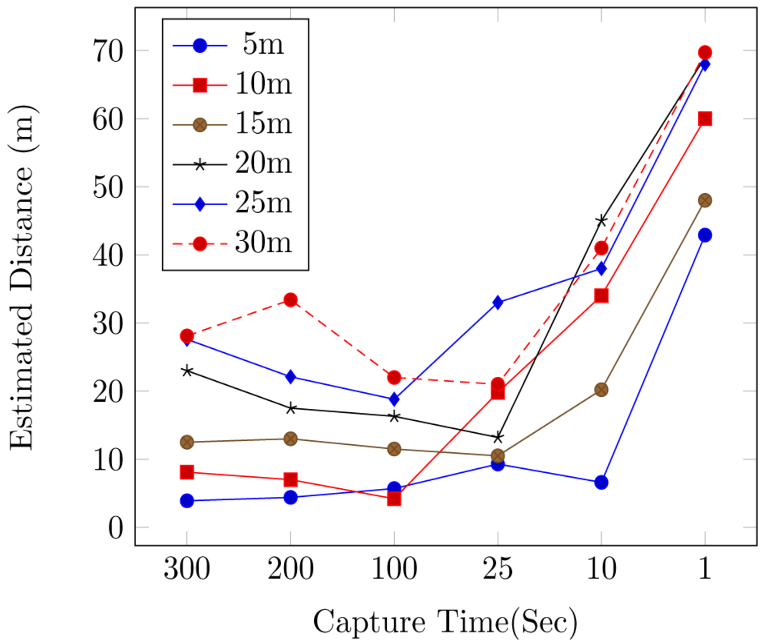

Figure 4-1: Calculated distance for AP1 with BI = 100ms

Figure 4-1 illustrates the decline in the accuracy of the estimated distances as capture time falls below 200 seconds. This happens because insufficient number of valid packets are collected during shorter times when BI=100ms in order for the statistical analysis to yield acceptable results. This is also evident from the results presented in Table 4-2.

Table 4-2: Collected data, analysis and estimated distance for 10m with BI = 100ms

Capture Time(Sec)	Relevant Packets	Valid Packets	Est dis(m)	σ(m)
300	2918	2008	8.1	1.9
200	1945	1501	7.0	3.0
100	973	582	4.2	5.8
25	241	146	19.8	9.8
10	96	49	34.0	24.0
1	10	5	60.0	50.0

As shown in Table 4-2, as the number of valid packets starts to fall below 1000, the estimated distance, and its standard deviation, becomes unreliable implying that at least 1000 valid packets are required for acceptable distance estimation. Figure 4-2 and Table 4-3 show the results for the same tests for a BI = 20ms.

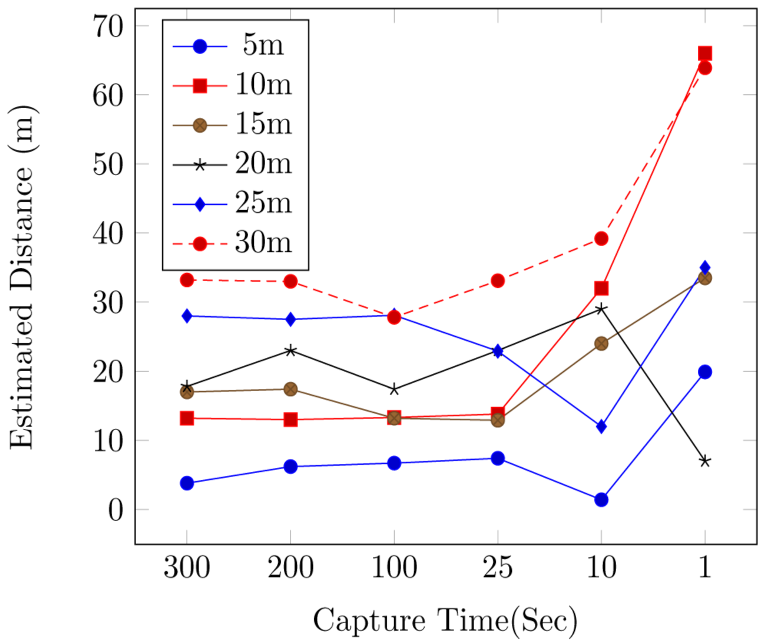

Figure 4-2: Calculated distance for AP1 with BI = 20ms

Table 4-3 shows the data, analysis and estimated distance for 10 meters and BI = 20ms.

By reducing the BI time to 20ms, the minimum required valid packets (1000 packets) are collected in 25sec. Figure 4-3 presents the number of valid packets for different collection times for all the tested BIs. Presented numbers are the average of valid packets collected at different distances (30m down to 5m) for each BI.

In this figure the 1000 packets threshold which had previously been established as the minimum number of packets required to achieve reliable distance estimation, is represented with a darker background color. It was found that the minimum BI that can provide reliable distance estimation in this occasion is 20ms. Selecting smaller BIs, such as BI=10ms was found to significantly affect the number of valid packets leading to inaccurate localization estimations.

Table 4-3: Collected data, analysis and estimated distance for 10m with BI = 20ms

Capture Time(Sec)	Relevant Packets	Valid Packets	Est dis(m)	σ(m)
300	14469	8528	13.2	3.2
200	9652	6227	13.0	3.0
100	4830	3521	13.3	3.3
25	1209	1015	13.8	3.8
10	484	374	32.0	22.0
1	47	41	66.0	56.0

Presented results in Figure 4-3 suggests that more than 1000 packets have been collected in 25 seconds using a BI=20ms. The outcome is almost 8 times faster than using a BI=100ms, which is typically the default BI for commercial APs.

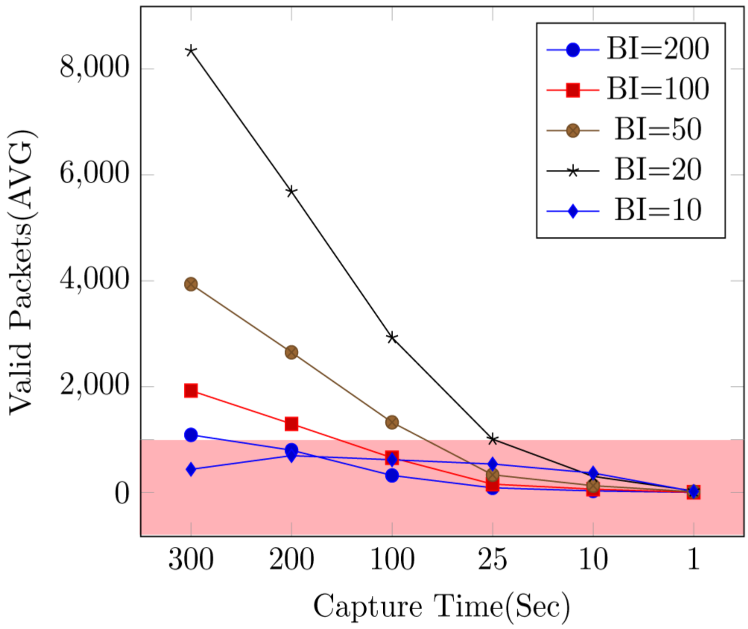

Figure 4-3: Number of valid packets for different BIs in time

4.3.2 BI Selection and performance measurement

The BI's value plays a significant role in various aspects of localization and the overall performance of the localization platform. It is very important that a localization platform based on 802.11 does not impose a negative impact on network communications. This section analyses BI selection methods and the importance of having a correct interval for this type of localization technique.

Two of the most important functionalities of beacon packets are:

- Synchronization of Wireless Local Area Network (WLAN)
- Advertising the Service Set Identifier (SSID) of the network

Generating a faster BI introduces overhead to the network. As a consequence it can influence the channel throughput and the Quality of Service (QOS).

Evaluating different beacon intervals and selecting the appropriate one based on environment of interest helps to reduce collisions, allowing delivery of more valid packets over a shorter period of time.

Presented results in Figure 4-4 show that as BI changes, it affects throughput which can influence the number of valid packets.

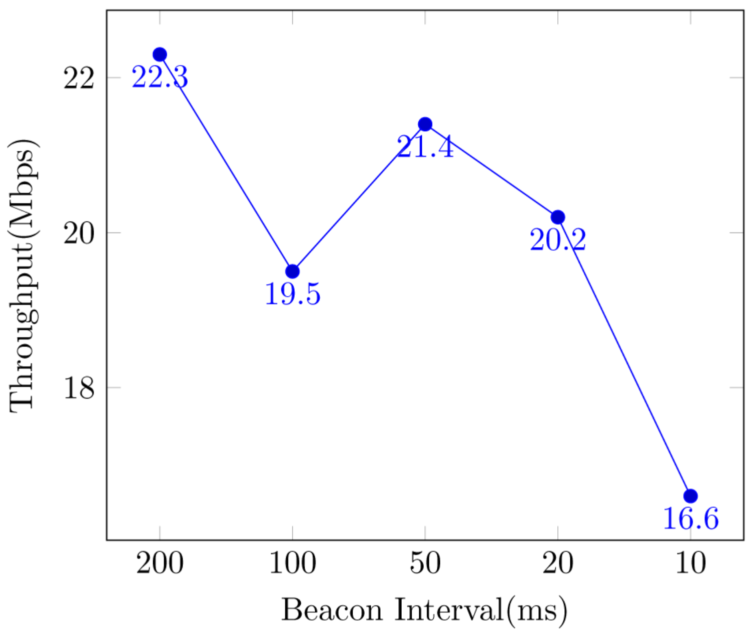

Figure 4-4: Channel 11 throughput@54MBps, 20m distance

4.4 Conclusion

By reducing the beacon interval value, packet time-based localization methods can be significantly accelerated. It was also found that the localization process acceleration advantage does not necessarily scale linearly with the BI generation process. By using the beacon packets and adjusting the beacon interval, more valid packets can be generated and captured in much less time. Additionally, it has been shown that the localization system can localize almost 8 times faster when compared to existing methods.

Chapter 5

5 Indoor Target Tracking Based on Time Difference of Arrival and Particle Filtering

Tracking wireless devices in an indoor environment using off-the-shelf equipment is a challenging task. Typical time-based off-the-shelf indoor localization methods tend to collect a large number of packet timestamps and subsequently apply statistical analysis in order to localize the target. However, the kinematic characteristics of the target and past measurements offering target trajectory information which have the potential to improve localization are not taken into account. This chapter presents a particle filtering method to address the problem of tracking a moving target in an indoor environment using off the shelf time-based methods. The particle filter based method sequentially estimates the posterior of the target state and is able to fuse past and present measurements from multiple sensors with the target kinematic information in order to improve localization. The localization performance has been assessed using different number of particles and different number of access points (APs). Simulations to assess the effectiveness of the method are also presented in this chapter. Simulation results are based on statistics of real data collected from a real environment.

5.1 Introduction

Localization activities can be divided into two main categories: 1) indoor and 2) outdoor. Location-aware applications can rely on GPS, GLONASS and GALILEO [19] for outdoor localization, but this is not the case when a terminal moves into an indoor environment. It has been more than a decade from the introduction of the first indoor localization algorithm [32]. Since then, localization based on Received Signal Strength (RSS) was investigated in depth [81, 82]. Compared to localization methods based on RSS, time-based methods have the benefit of not typically requiring a Fingerprinting Database to operate. Moreover, changes in the localization environment do not easily influence time-based methods. Time-based localization can be divided into two main categories: 1) Time of Arrival (ToA)/Time of Flight (ToF); and 2) Time Difference of Arrival (TDoA).

ToA/ToF methods are based on the arrival of a signal from a transmitter to one or more receivers. A timestamped packet travels between nodes and the receiver calculates the transmission time delay and estimates the distance between the two nodes based on the timestamp information. Moreover, in ToA/ToF systems, a time server is typically required so nodes can synchronize their clocks. As discussed in previous chapter, it was proved that by using only off-the-shelf equipment, indoor localization based on time methods is possible within the accuracy of few meters. In [15], the information provided by 802.11 Beacon packet data was utilized to measure the distance of the Mobile Terminal (MT) to the Access Point (AP). It was demonstrated that by using the Beacon timestamp information in conjunction with MAC timestamp, system delays can be calibrated out. To further improve the presented algorithms and minimize delays and achieve a real-time localization, a particle filter method is applied to the problem of tracking a moving target in an indoor environment using time difference of arrival measurements. A particle filter method can use realistic models to characterize the state and measurement space and accurately handle the non-linear relationship between target state and measurements described by (5.2) and (5.3). Moreover, as a sequential Monte Carlo method, the particle filter uses a prediction-update process to track changes in the target state. Therefore, the particle filter utilizes information from past measurements and past target states in order to improve localization accuracy for moving targets, when compared to triangulation methods. The particle filter is able to estimate the posterior distribution of the target state and therefore describe the uncertainty in localizing the target. A simulation based study is conducted to assess the effectiveness of the method. In order to generate multiple Monte Carlo runs of a realistic tracking scenario, measurement data were generated based on statistics of real data collected from the same physical location where the simulation scenario is placed.

5.2 Related Work

Practical implementation of Real Time Location Systems (RTLS) based on time-based methods and off-the-shelf equipment is a challenging task. One of the main challenges is the packet collection and user position evaluation process which can take significantly more time than RSS-based methods [62]. Researchers have tried to optimize the process by using different techniques. In [23] the Time Difference of Arrival (TDOA) was measured by considering the clock offset and its local linear behavior around the offset. In [24] a four-way Time of Arrival (TOA) algorithm that measures the Round Trip Time (RTT) of

IEEE 802.11 MAC was introduced. In another method the RTT between two wireless nodes was calculated by using data and acknowledgment packets [25]. In [66] the distance between nodes was calculated using a two-way TOA measurement technique by utilizing 1-ppm clocks. In [20] another time-based RTLS was implemented by using high accuracy clocks. Other researchers have tried to implement and use time-based methods by creating customized packets and hardware solutions. In [26] and [74], a measuring system was used as additional hardware to the wireless adapter, aiming to increase localization accuracy. In [83] a Time of Flight (ToF) method was presented by using a tag, while in [76] a TDOA geolocation system was tested utilizing five sensors for localization. Moreover, in [15] a method to accelerate network packet time-based localization methods was presented. The focus of this chapter is to investigate the effect on localization performance when using different number of particles and APs in the particle filtering algorithm.

5.3 Problem Formulation

This section presents the target motion model and measurement model used for the simulations. It also provides information regarding the environment where simulations were performed. Moreover, it discusses the relevant time delay and the model used to generate it.

5.3.1 Motion Model

The target moves within the corridor of the building shown in Figure 5-1. The target motion is modeled by a nearly constant velocity motion model in Cartesian coordinates. The state vector for the target at time step $k = 1, \dots, K$ is given by $x_{k=[x_k\,\dot{x}_k\,y_k\,\dot{y}_k]^T}$, where x_k, y_k are the positions in the x and y coordinates, and $\dot{x}_k$, $\dot{y}_k$ are the corresponding velocities. The motion is formulated as:

$$x_k = Fx_{k-1} + Qv_{k-1}, \tag{5.1}$$

where

$$F = \begin{bmatrix} 1 & \delta t & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \delta t \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

and δt is the time difference between state transitions. The matrix Q is a diagonal process noise covariance matrix, and v_k denotes a zero-mean, unit variance Gaussian process that models errors in velocity. The model in (5.1) is associated with the kinematic prior distribution $p(x_k|x_{k-1})$.

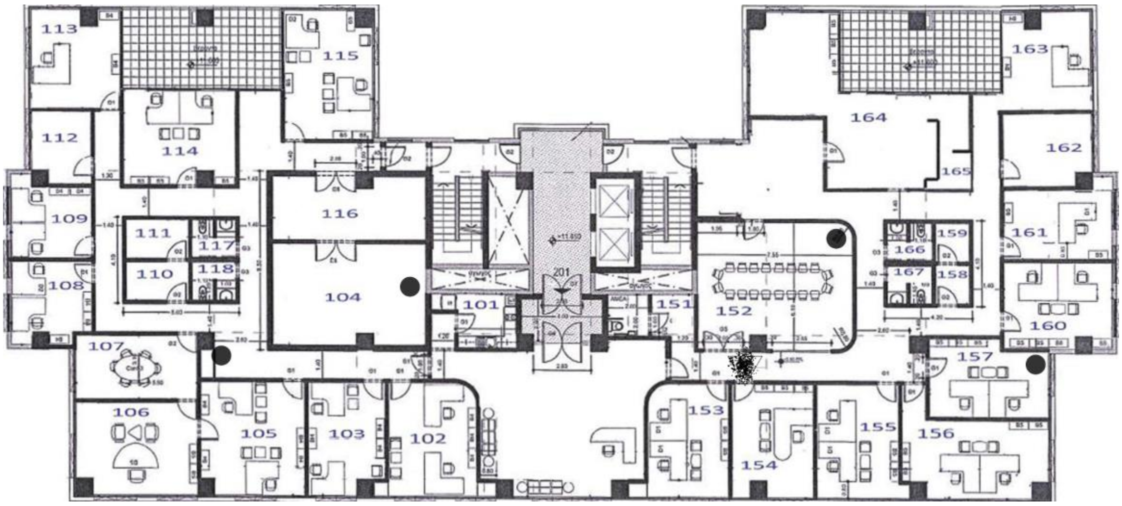

Figure 5-1: Instance of tracking. The true target state is indicated with a '+', the target estimate is indicated with a '∇', the particle locations with a '.', and the APs with a '•'.

5.3.2 Measurement Model

The signal bears information on the range of a target relative to each AP $u = 1, \dots, \mathrm{U}$ given by

$$r_{u,k} = \sqrt{(\chi_u - x_k)^2 + (\psi_u - y_k)^2} \tag{5.2}$$

where χ_u and ψ_u denote the location of the uth AP in the Cartesian coordinates in the form of a time delay

$$\tau_{u,k} = r_{u,k}/\mathrm{c} \tag{5.3}$$

Where c is the velocity of propagation of the signal. The time delay is measured as the time difference of arrival between the MT and the AP. In this work, the time delay is generated based on statistics derived from real data. The model used for generating the time delay is

$$\tilde{\tau}_{u,k} = \tau_{u,k} + \eta_{u,k} \tag{5.4}$$

where $\tau_{u,k}$ is calculated based on the true target state that is unknown to the tracker, using (5.2) and (5.3) and $\eta_{u,k}$ is a zero mean Gaussian noise realization with variance σ^2. The variance σ^2 of the measurement noise has been experimentally obtained using real measurements in the location where the simulations are also based in order to create a realistic simulation model.

5.4 Tracking Algorithm

Next the sampling importance resampling (SIR) particle filter (PF) [84] is described that has the goal of estimating target location using time delay measurements.

5.4.1 SIR Particle Filtering Algorithm

A particle representing a hypothesis on the state x_k of a target is denoted as x_k^n where $n = 1, \dots, N$ is the particle index and *N* is the total number of particles used. Then state x_{k-1}^n proposed by particle $n = 1, \dots, N$ at time $k - 1$ is propagated to time step *k* as

$$x_k^n = Fx_{k-1}^n + Qv_k \tag{5.5}$$

which is equivalent to sampling from a Gaussian distribution with mean Fx_{k-1}^n and covariance matrix Q as in (5.1) [84]. Then the state in Cartesian coordinates x_k^n is transformed to range with respect to each access point *u* as

$$r_{u,k}^n = \sqrt{(\chi_u - x_k^n)^2 + (\psi_u - y_k^n)^2} \tag{5.6}$$

which in turn corresponds to delay

$$\tau_{u,k}^n = r_{u,k}^n / c\,. \tag{5.7}$$

Since the error in time delay is modelled as a zero mean Gaussian with variance σ^2 then the likelihood probability for particle *n* and each sensor *u* is given by

$$p^n\left(\tilde{\tau}_{u,k} \middle| \boldsymbol{x}_k^n\right) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{\left(\tilde{\tau}_{u,k} - \tau_{u,k}^n\right)^2}{2\sigma^2}} \tag{5.8}$$

Following the proposal, each particle is weighted as

$$\omega_k^n \propto \prod_{u-1}^{U} p^n\left(\tilde{\tau}_{u,k} \middle| \boldsymbol{x}_k^n\right) \tag{5.9}$$

where the particle weights are provided in terms of the likelihood in (5.8) as the prior was used for particle proposal in (5.5). Then weights are normalized and the estimate of the posterior distribution and the estimate of the target state given respectively by

$$\hat{p}\left(\boldsymbol{x}_k \middle| \left\{\tilde{\tau}_{u,k}\right\}_{u=1}^{U}\right) = \sum_{n=1}^{N} \omega_k^n \, \delta(\boldsymbol{x}_k - \boldsymbol{x}_k^n) \tag{5.10}$$

and

$$\hat{\boldsymbol{x}}_k = \sum_{n=1}^{N} \omega_k^n \, \boldsymbol{x}_k^n \tag{5.11}$$

which is followed by particle resampling [84]. The algorithm is outlined in Table 5-1. In summary, accurate localization of a target improves due to the information utilized from past measurements during the tracking scenario by the prediction update process of the tracking method.

Table 5-1: Particle filter tracking algorithm using TDOA measurements

- For each particle $n = 1, \ldots, N$
  - Propose a new target state as (5.5)
    $\mathbf{x}_k^n = \mathbf{F}\mathbf{x}_{k-1}^n + \mathbf{Q}\mathbf{v}_k$
  - For each sensor $u = 1, \ldots, U$
    * Calculate proposed range as (5.6)
      $r_{u,k}^n = \sqrt{(\chi_u - x_k^n)^2 + (\psi_u - y_k^n)^2}$
    * Calculate proposed time delay as (5.7)
      $\tau_{u,k}^n = r_{u,k}^n / c$
  - Calculate likelihood as (5.8)
    $p_u^n(\tilde{\tau}_{u,k}|\mathbf{x}_k^n) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(\tilde{\tau}_{u,k} - \tau_{u,k}^n)^2}{2\sigma^2}}$
  - Calculate weights (5.9)
    $w_k^n \propto \prod_{u=1}^{U} p_u^n(\tilde{\tau}_{u,k}|\mathbf{x}_k^n)$ and normalize
  - Calculate estimate of posterior (5.10)
    $\hat{p}(\mathbf{x}_k|\{\tilde{\tau}_{u,k}\}_{u=1}^{U}) = \sum_{n=1}^{N} w_k^n \delta(\mathbf{x}_k - \mathbf{x}_k^n)$
  - Calculate estimate of posterior (5.11)
    $\hat{\mathbf{x}}_k = \sum_{n=1}^{N} w_k^n \mathbf{x}_k^n$
  - Particle resampling

5.5 Simulation Results

In the simulations, a single target moves in a two dimensional plane in the Cartesian coordinates and the motion is completed in 500 time steps. Four APs are located at coordinates a) χ_1 = 0 m, ψ_1 = 1 m, b) χ_2 = 11.4 m, ψ_2 = 4.2 m, c) χ_3 = 41 m, ψ_3 = 3 m, and d) χ_4 = 31 m, ψ_4 = 8 m. An instance of the tracking scenario showing the true target location, the estimate, the particle locations, and the location of the sensors is shown in Figure 5-1. For the simulations a varying number of particles N = 1000, 5000, 10000 particles were used and the results were averaged over 1000 Monte Carlo runs. Moreover, the simulations were repeated with a varying number of active APs U = 1, 2, 3, or 4. In Figure 5-2 and Figure 5-3 the percentage of lost tracks and the root mean squared error (RMSE) tracking performance in meters is shown for different values of the number of particles *N* and for different numbers of APs activated. A lost track is counted if at 20 consecutive time steps the RMSE exceeds 5m, otherwise the RMSE is recorded for valid tracks. We observe that as the number of particles increases the performance improves as the posterior and estimate in (5.10) and (5.11) improve. Moreover, the information on target state improves as the number of APs activated increases. Therefore, the tracking performance improves with an increase in APs used.

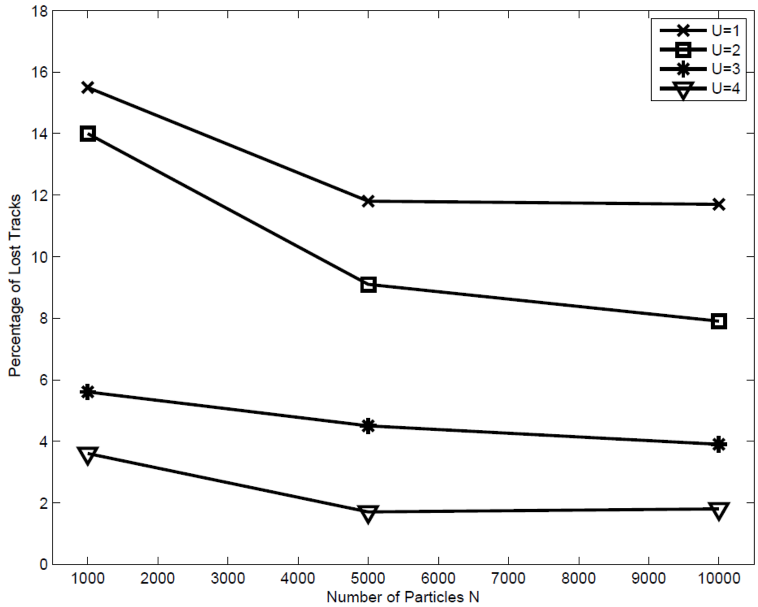

Figure 5-2: Percentage of lost tracks for different number of particles N and different number of APs U activated

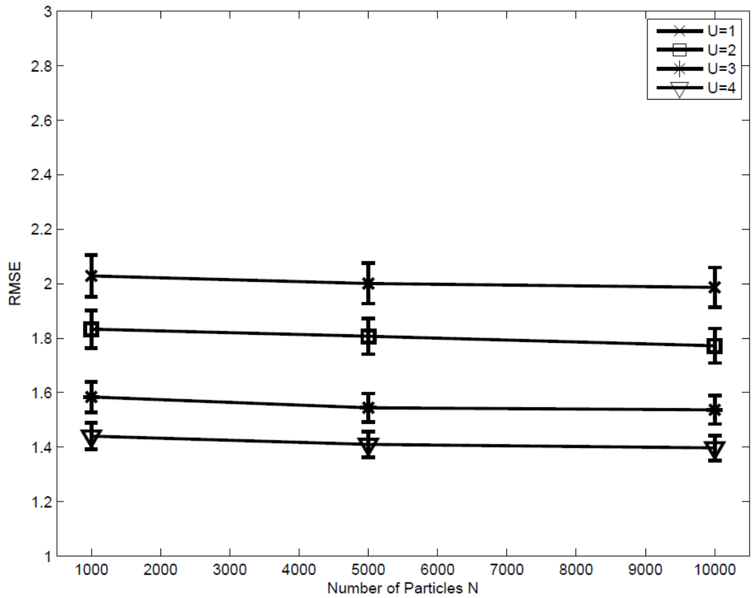

Figure 5-3: RMSE tracking performance for different number of particles N and different number of APs U activated

5.6 Conclusion

This chapter demonstrated that the particle filter is able to achieve reliable tracking performance due to its ability to fuse measurements from multiple APs and through a prediction update process. The prediction-update process used by the particle filter enables the algorithm to combine information from the kinematic model of the target, which contains information on the target trajectory based on past measurements with current measurements. Therefore, the particle filter method has the potential to perform better than typical localization methods as shown by the estimation accuracy improvement which is due to the ability of the particle filter to utilize more accurate measurement models that are created based on real data. Moreover, the particle filter has the ability to improve further in the presence of more collected data.

Finally, Table 5-2 presents the comparison of the proposed Time-based methods with other well-known methods, and the ones which have been replicated during the course of this PhD and discussed throughout chapter 3 to 5. Also, it worth mentioning that by “Algorithm Execution time”, we mean the time required for collection of data, storing of data, processing of data and result presentation.

Table 5-2: Time Based Methods Comparison

Method/Ref	Accuracy	Algorithm Execution time / Required localization time	Solution Type
Proposed method [14, 15]	< 2.5 m	20 sec	COTS
Proposed method (PF) [16]	1.5 m to 2.1 m	20 sec	COTS
PinPoint [23]	~ 3 m	~ 4 min	COTS
[24]	~ 4 m	Several minutes	COTS
[25]	< 8 m	~ 15-20 min	COTS
[27]	< 2 m	Several minutes	Specialized Hardware
CEASAR [70]	< 2 m	~ 26 – 30 min	Specialized Hardware
[74]	~ 3.2 m	~ 15 min	Specialized Hardware
[75]	< 2.1 m	2 sec	Specialized Hardware

Chapter 6

6 Signal Property based Localization Methods

Accurate indoor localization algorithms are a vital part of systems providing localization services. Localization can be typically achieved through the use of Received Signal Strength (RSS), timing methods (TOA, TDOA), Angle of Arrival (AOA) or hybrid methods. RSS methods based on off-the-shelf 802.11 equipment can be implemented with almost no modification to the existing infrastructure. They also typically have the lowest capital expenditure since 802.11 infrastructures can be used to support such activities. This chapter presents a new RSS localization method based on path analysis. While current fingerprint RSS methods estimate the average RSS values at a static single point, the proposed localization method utilizes the captured RSS values over a short path in an effort to capture a more detailed signal behavior, when compared to the single point case. Presented results are based on an indoor radio campaign and suggest a significant improvement of the average achieved accuracy and its standard deviation when compared to typical RSS methods. Moreover, the method has been tested with device diversity and various user walking speeds. This chapter also presents the usage of deterministic ray tracing simulations for creating accurate fingerprinting databases instead of performing resource intensive radio measurements.

6.1 Introduction

GPS, GLONASS and Galileo are commonly used to provide device localization in outdoor environments; however they cannot typically do the same for devices operating in indoor environments. To achieve the latter, various techniques have been used in the past. These techniques utilize algorithms based on Time of Arrival (ToA) [20, 21, 81, 82, 85-87], Time Difference of Arrival (TDoA) [23, 25], Angle of Arrival (AoA) [48, 88], Received Signal Strength (RSS) [12, 32, 38, 89, 90] and hybrid methods [14, 91, 92]. Currently, indoor localization techniques based on the Received Signal Strength of 802.11 systems are considered off-the-shelf solutions, since they are based on infrastructure installed in the environment of interest and require no modification to this infrastructure or its related devices [32, 38, 89, 90].

A typical RSS method consists of two phases: an offline phase and an online phase. During the offline phase, a RSS fingerprint database (FDB) of the environment is created, where each entry of the database refers to an average RSS measurement estimated from multiple samples received at a single static point at a known position. This radio–map can be constructed either by measurements or radio simulations [105], [106]. During the online phase, the database entries are compared with real time RSS measurements, and localization algorithms can be applied to predict the position of the user. Typical localization algorithms include algorithms based on the k-nearest neighbor (kNN) [32, 33], neural network [34, 35], support vector machines [36, 37], probabilistic [38-41], and pattern recognition [42, 43]. RSS methods can be implemented as active or passive [32, 44, 45]. In active methods there is a need for active communication between the Mobile Terminal (MT) and the infrastructure. Passive methods refer to the case where the two sides do not need to communicate. An active method example can be a user positioning himself and finding his way throughout an environment. Passive methods can be used for localization scenarios of equipment or other resources in hospitals, factories, companies or similar environments. The purpose of this work was to investigate if the accuracy achieved by RSS-based localization systems can be improved through the provision of a more informative fingerprint database. To this purpose, this chapter presents a new localization method based on signal strength analysis recorded over indoor radio 802.11 paths, resulting from the user's non-line-of-sight (NLOS) and line-of-sight (LOS) movement in the environment of interest. It is expected that the captured faded signals from multiple access points which constitute a fingerprint path, will provide a more informative description of the area, compared to methods that are based on static point observations, aiming to lead to a more precise localization process. For comparison purposes, it was decided to choose one of the most often used RSS localization methods and apply it in this work. Thus, this chapter investigates possible localization accuracy improvements, when a kNN-based method is used to analyze RSS values captured over paths rather than single points. Results obtained from the previous process are compared with existing kNN methods of RSS measured over static single points.

Novel research contributions in regards to this chapter can be summarized as follows:

1. Introduction of a novel kNN-based localization algorithm based on RSS captured over paths.

2. Analysis of k selection impact on kNN algorithms and the proposed method.
3. Investigate the impact on the performance of the proposed method in the case of device diversity, as well as the effect of a variable captured RSS sample number for various user walking speeds.

6.2 Method

RSS-based localization systems create fingerprint databases by collecting signal strengths from multiple Access Points (APs). Each location of an indoor environment is characterized based on the collected signal strength values. To create the fingerprint database, a MT is placed at known locations. The collected data from the radio visible APs is then recorded by the MT and stored in the fingerprint database. The proposed method named "PathLoc", characterizes the known locations of the indoor environment based on the signal fading statistics of RSS recorded over a short path rather than typically used single static point. In this approach, each entry in the fingerprint database represents a specific short path in the area of interest. To investigate possible performance improvements between the different approaches, a kNN algorithm is implemented [42, 43].

6.2.1 Offline Phase / Survey Phase

The offline or survey phase focuses on the creation of the fingerprint database that describes the localization environment of interest. For each survey point, the MT travels a short path, 1.8 meters in this occasion, representing the distance traveled over three 60cm floor tiles. While traveling over this short path, the MT captures the RSS values, including any fast faded signals. The existence of the fast faded signals became evident based on the observation that the recorded signal strength for measurements over a single short path varied up to 40 dB. Equation (6.1) highlights the required fingerprint database data that has to be recorded at each survey point:

$$P_{x,y} = (a_1, a_2, \dots, a_k) \tag{6.1}$$

Where x, y represent the point coordinates on the map and a_k represents survey points for access point k. Equation (6.2), whose components are V, the average of the squared differences from the sample mean (Variance) and s, the sample standard deviation, allows to calculate a for each visible AP.

$$a_k = \frac{V^2}{2(s^2)} \tag{6.2}$$

To address device diversity, all a_k need to be normalized [39, 93]. Equation (6.3) calculates N which is the normalized vector for $A = (a_1, a_2, \ldots, a_k)$:

$$N = (a_{n=1}^{k} - \mathrm{Max(A)}) \tag{6.3}$$

Calculation of the Vector N concludes the offline phase.

6.2.2 Online Phase

During the online phase the following data is collected by the MT:

$$T = (a_1, a_2, \ldots, a_k) \tag{6.4}$$

TN represents the normalized vector for T:

$$TN = (a_{n=1}^{k} - \mathrm{Max(T)}) \tag{6.5}$$

Next, the Euclidean distance between the target node and each $P_{x,y}$ in the database is calculated by using Equation (6.6):

$$D_{RL} = \sqrt{\sum_{i=1}^{K} (TN_i - N_i)^2} \tag{6.6}$$

Where D represents the Euclidean distance between the target and an entry in the fingerprinting database, RL is the index of the reference position, TN is the normalized linear values of the MT signal strength vector, N represents the linear vector of the signal strength values as stored in FDB, i represents the index of the AP and K is the number of available APs. The reference position of the fingerprint database that returns the smallest D is considered as the most probable target position. In other words, the smallest D is the closest neighboring location to the target's position. After finding the smallest Ds (Nearest Neighbors to the target) based on Equation (6.6), the final coordinates (x, y) are calculated by using a *k*NN algorithm and a weighted term given by Equations (6.7) and (6.8). Equation (6.7) shows the location estimation based on multiple nearest neighbors by using the weighted factor:

$$x = \frac{\sum_{m=1}^{M} \frac{1}{D_m} \cdot x_m}{C} \qquad y = \frac{\sum_{m=1}^{M} \frac{1}{D_m} \cdot y_m}{C} \tag{6.7}$$

Where *x*, *y* are the location coordinates, *M* is the number of nearest neighbors and *C* is the sum of calculated coefficients for all the selected neighbors. Equation (6.8) presents the calculation of *C*:

$$C = \sum_{m=0}^{M} \frac{1}{D_m} \tag{6.8}$$

Based on our observations, applying the weighted factor is especially useful in scenarios where *D* values for the *M* nearest neighbors are not very close to each other. In these cases a simple average of coordinates may not produce accurate results. The proposed method's algorithm is outlined in Table 6-1.

Table 6-1: A New WKNN Approach Algorithm using Path Analysis

- Offline/Training Phase
  - For each path/point in RM (P_x, y)
    - ∗ Collect all RSS values for visible APs as (6.1)
      $P_{x,y} = (a_1, a_2, ..., a_k)$
    - ∗ Normalize all a values as (6.3)
      $N = (a^k_{n=1} - Max(A))$
    - ∗ Record it in FDB
- Online/Localization Phase
  - Collect all RSS values for visible APs $(a_1, a_2, ..., a_k)$
  - Extract the normalize vector for MT as (6.3)
    $N = (a^k_{n=1} - Max(A))$
  - Compare normalized vector for MT to RM using WKNN
    - ∗ For each P in FDB
      - · Calculate Euclidean distance (6.6)
        $D_{RL} = \sqrt{\sum_{i=1}^{K} (TN_i - N_i)^2}$
      - · Select the K nearest neighbors
    - ∗ Apply the Weighted term & Draw the location of MT
      - · Calculate C the sum of calculated coefficients for K selected neighbors as (6.8)
        $C = \sum_{m=0}^{M} \frac{1}{D_m}$
      - · Calculate x, y coordinates using (6.7)
        $x = \frac{\sum_{m=1}^{M} \frac{1}{D_m} \cdot x_m}{C}, y = \frac{\sum_{m=1}^{M} \frac{1}{D_m} \cdot y_m}{C}$

6.2.2.1 Neighbors Selection

Traditional RSS methods select the closest neighbors based on the smallest values of *D*. The goal of the proposed method is to find the closest neighbors based on the path analysis. During the online phase, the localization algorithm tries to match the MT's signal to the closest possible signal in the FDB. In order to localize the MT by using the path's faded signals, an extra step has been added to the traditional closest neighbor algorithm. To eliminate false positives, distance *D* is first calculated for all of database entries. Next, the raw data gets sorted based on RSS values (strongest to weakest) and AP names. This helps to provide a list of AP names sorted by strongest to weakest average RSS values for each database entry. Finally, based on the lists, the *K* distances are selected from the entries which have the most similarities to the target's list of sorted APs. The final list of selected *K*s includes entries from the FDB with the most similarities to the MT's sorted AP list, followed by an ascending order of their distances (*D*s).

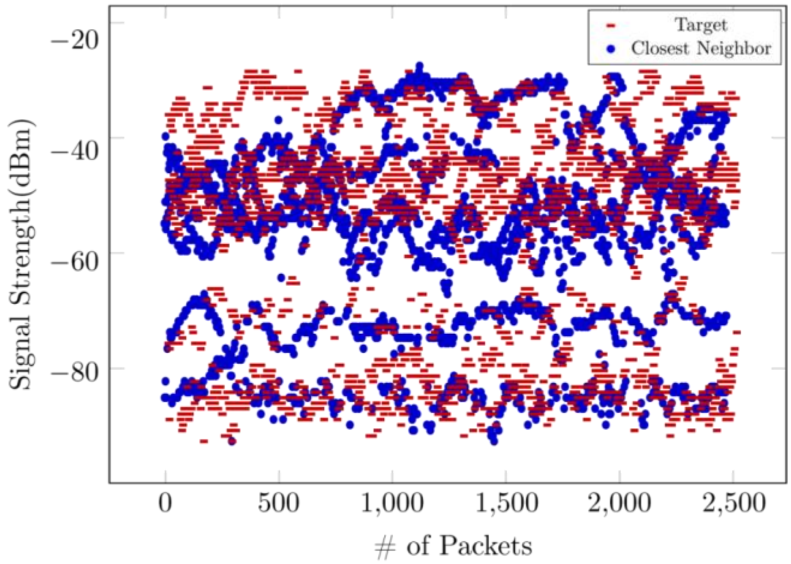

Figure 6-1: Online VS closest neighbor Raw data

Figure 6-1 presents the raw data of the MT to be localized, i.e. the target and that of the closest neighbor. In Figure 6-1 data have been presented as captured by the MT. The MT captures the relevant packets in the order of AP radio visibility. Figure 6-2 presents the comparison between the online signal (Target) and the closest neighbor found, by applying the proposed algorithm.

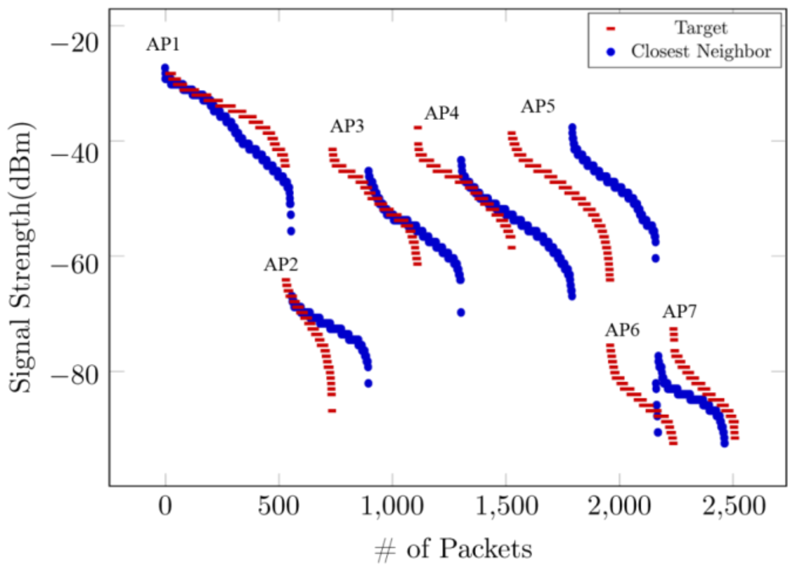

Figure 6-2: Online VS closest neighbor signals

A fingerprint database of a large environment contains many reference points. Finding *K* neighbors, only based on smallest *D*s may not always lead to the best localization result as demonstrated in Figure 6-3.

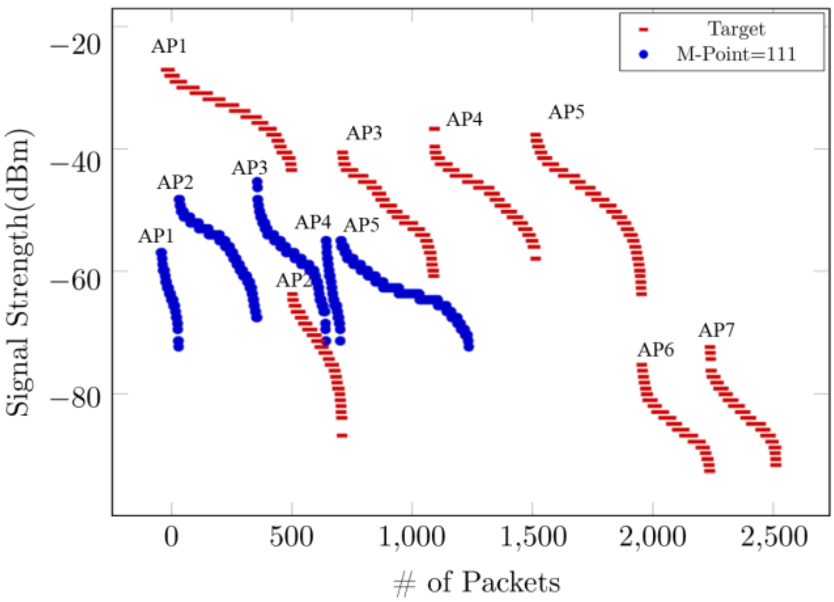

Figure 6-3: A false positive introduced as a nearest neighbor in traditional *k*NN algorithm

It has been found that fewer data samples can lower the *D* value and introduce a false-positive close neighbor as demonstrated in Figure 6-3. In this example, the traditional *k*NN algorithm chooses a nearest neighbor for the target by only calculating *D*. Figure 6-3 shows the sorted RSS for both the target and a closest neighbor as a visual representation of the above statement about the *D* value. In this case, the selected neighbor refers to a point on the map near room number 111 (Figure 6-4). Due to the environment characteristics of that room, which contains concrete walls, fewer packets have been captured within the given time during the offline phase, due to an increased signal loss.

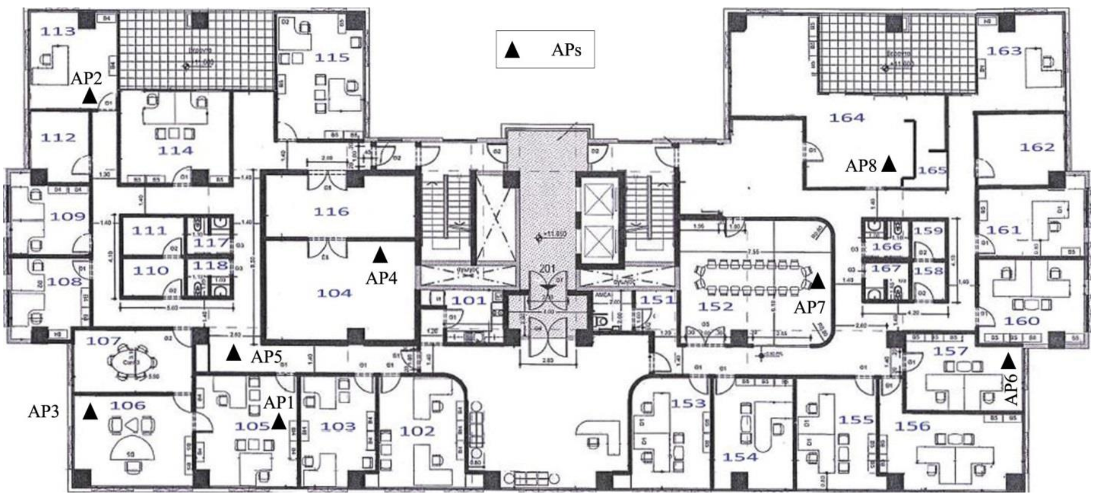

Figure 6-4: Floor plan and APs Distribution

Figure 6-5 shows the selection of a nearest neighbor for the same target signal by using the proposed ”PathLoc” method. The selected neighbor is near room number 103 (see Figure 6-4) which is the actual position of the online signal.

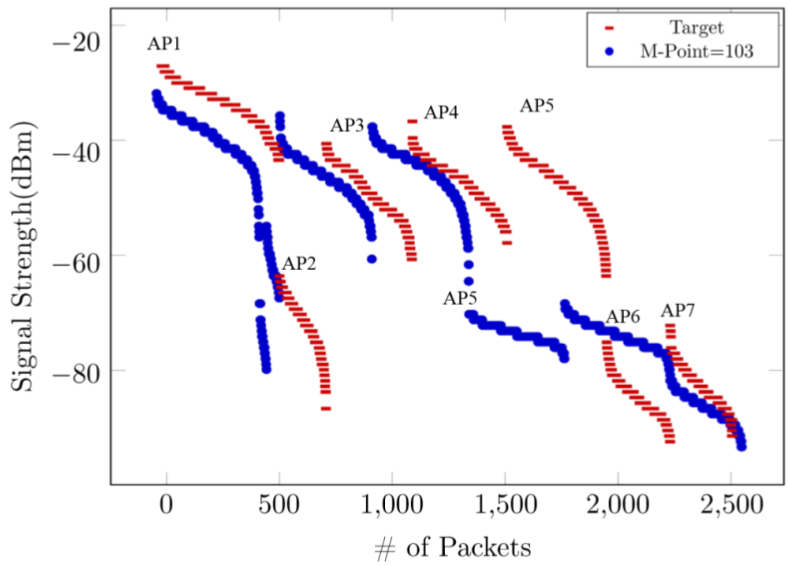

Figure 6-5: Sorted RSS signals of the target and a nearest neighbor found by the proposed method

Figure 6-3 and Figure 6-5 clearly demonstrate that by utilizing traditional algorithms, the closest neighbors are not necessarily the most optimum ones. The new algorithm ”PathLoc” helps to distinguish points from the FDB which have closer patterns to the target line. It also proves that by using ”PathLoc”, the nearest neighbors patterns are a better fit to target, than the patterns produced by the traditional algorithm.

6.3 Experimental Setup and Performance Analysis

The tests have been carried out at the premises of the School of Pure and Applied Sciences of OUC. Eight Linksys WRT54GL access points have been distributed throughout the floor. In order to collect more samples, the APs beacon interval was changed from 100 ms to 10 ms. Figure 6-4 shows the floor plan and the APs positions. Mobile terminals consisted of a Sony Vaio VPCYB2M1E and two USB wireless cards, including a TP-LINK TLWN821N and an AirPcap NX. Different mobile terminals and wireless cards were used to test the method in device diversity scenarios.

Table 6-2: Methods Description

Method Name	Description
PathLoc	The proposed method which uses a weighted K-nearest neighbor algorithm.
Path Average	Follows the same philosophy of typical RSS methods, but instead of averaging the signal at stationary points, the average of the recorded values along the path is used.
1D RSSI	In this method, the creation of the FDB has been performed by collecting signal strength values only in one orientation/direction at stationary points.
1D RSSI weighted	1D RSSI method using the same weighted factor applied in the proposed *PathLoc* algorithm.
4D RSSI	In this method, the creation of the FDB has been performed by collecting signal strength values in all four orientations/directions at stationary points.
4D RSSI weighted	4D RSSI method using the same weighted factor applied in the proposed *PathLoc* algorithm.

The performance of the proposed method has been compared to five other methods whose short descriptions can be found in

Table 6-2. Four separate databases have been created for the experiments, one for the presented method, and three for comparison methods (PathLoc, Path Average, 1D RSSI, 4D RSSI). The 4D RSSI method can be considered the most common/well-known RSS method to date [139] . Similar to the proposed method, collected reference points for the comparison method cover the same areas and the same number of reference points. The terminal collects four sets of data (one for each direction), combines all measurements and saves the results in a fingerprinting database. Figure 6-6 presents a typical RSS based localization technique.

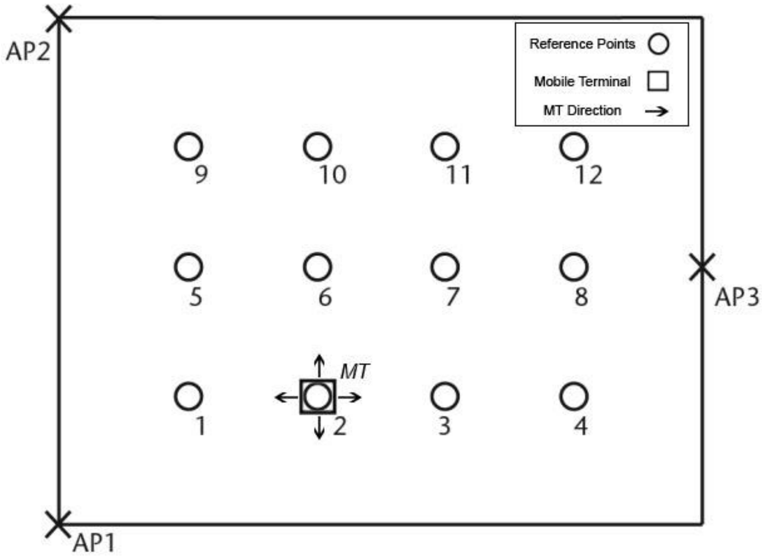

Figure 6-6: Typical RSS based localization setup.

6.3.1 Measurements

For the offline phase, over a hundred reference points have been collected for each method. For the PathLoc method, the offline phase was created by measuring reference paths of 1.8 meters. To gather data for a reference point, the MT moves along a straight line with a steady pace collecting signal strengths from all visible APs.

6.3.2 Experimental Results

Table 6-3 presents the performance of the different methods. As the results suggest, the proposed method achieved almost 40% better localization average accuracy and 26% smaller standard deviation compared to typical RSS methods. The average accuracy of the proposed method was found to be 1.9 meters.

Table 6-3: Method comparison for: (M1) PathLoc, (M2) Path Average, (M3) 4D RSSI, (M4) 4D RSSI weighted, (M5) 1DRSSI, (M6) 1D RSSI weighted

	M1	M2	M3	M4	M5	M6
Max[m]	4.8	5.4	8	8	16.8	14.4
Min [m]	0	0	0.6	0.6	0.6	0.6
Average [m]	1.9	2.4	3.0	2.9	6.0	4.0
σ [m]	1.4	1.9	1.9	1.9	5.1	3.6
Var [m]	2.1	3.5	3.6	3.5	26.0	12.6
$<=0.6$ m	39%	22%	13%	13%	9%	4%
<2 m	57%	39%	35%	35%	17%	17%
$<=3$ m	83%	70%	65%	65%	35%	39%
<5 m	100%	83%	74%	78%	61%	83%

Also as Figure 6-7 suggests, the average accuracy of the proposed method outperforms the other methods.

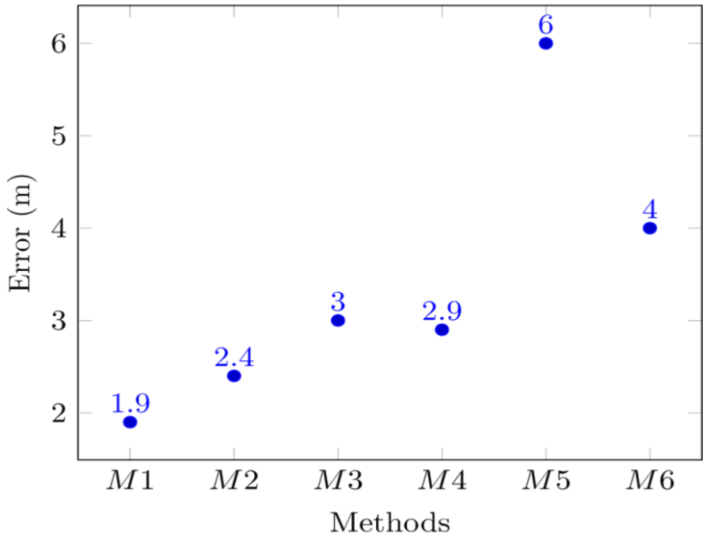

Figure 6-7: Average error for methods: (M1) PathLoc, (M2) Path Average, (M3) 4D RSSI, (M4) 4D RSSI weighted, (M5) 1D RSSI, (M6) 1D RSSI weighted

6.3.3 Device Diversity and *K* Selection

In order to test the method in device diversity scenarios, all tests have been repeated by using three different devices: a Vaio VPCYB2M1E, a TP-LINK TL-WN821N and an AirPcap NX. Figure 6-8 presents the average localization error for each of the devices along with their standard deviation (σ) obtained from the related dataset.

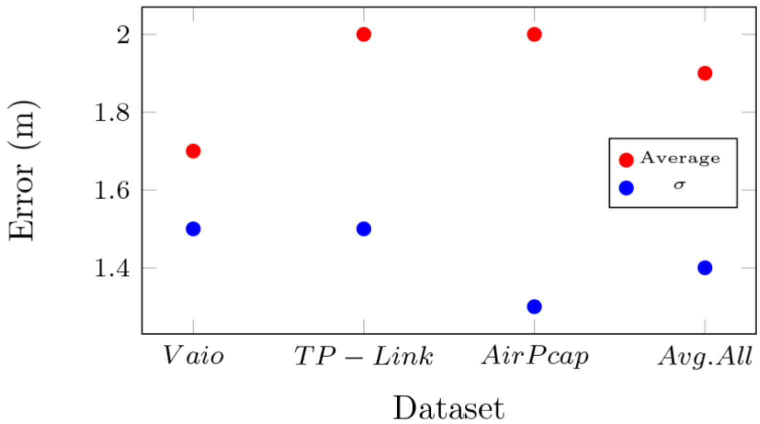

Figure 6-8: Device diversity and localization error

In this figure "*Avg.All*" indicates the average localization error and average standard deviation of all three devices. Based on the various samples recorded in different environments, including office rooms, corridors and laboratories, and by evaluating the proposed localization method with different *K*s, it was decided to set *K*= *5*. As Table 6-4 suggests, the proposed method performance can vary by selecting different values for *K*. The average errors for all the cases are very close to each other, supporting the stability of the proposed method.

Table 6-4: Method performance with different Ks

	K=1	K=2	K=3	K=4	K=5	K=6
AV Error [m]	2.2	2.3	2.1	2.1	1.9	2.1
σ [m]	2.2	2.1	1.7	1.7	1.4	1.7

Similar tests have been conducted to measure the effect of different *K*s on other methods. Figure 6-9 presents the comparison of all methods.

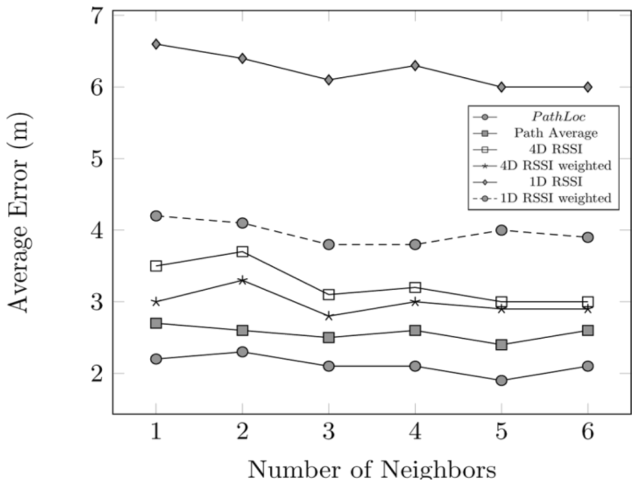

Figure 6-9: Effects of different *K* selections on localization accuracy

6.3.4 Speed impact

In order to further examine and evaluate the validity of the proposed method, the method was tested with various MT speed sampling intervals. The aim of this test is to examine whether the estimated localization accuracy degrades with a decreasing number of samples, due to a user moving faster over the 1.8 meters path.

Typically a larger number of samples can be obtained either from a longer path, or if the MT/User moves slower or if an AP transmits with a shorter (i.e. faster) beacon interval. The original fingerprinting data was collected at a slow user pace and a beacon interval of 10 ms. The 1.8 meter path was traveled in a six seconds interval in order to maximize the collection of samples.

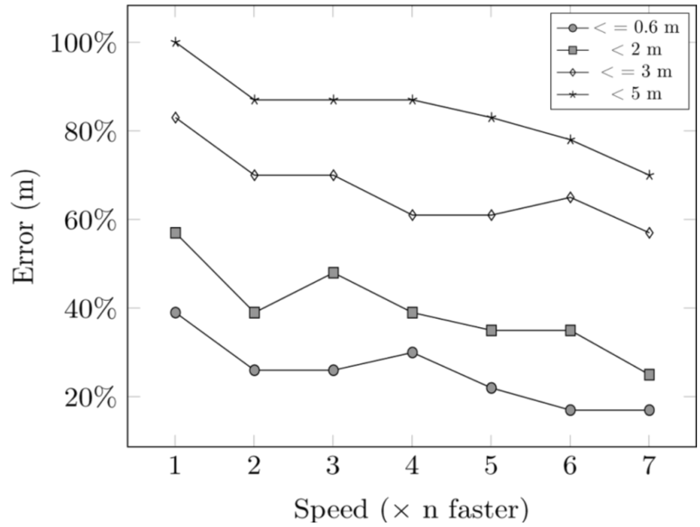

Figure 6-10: Detection rate VS Speed interval

According to [94], the average walking speed of a person is between 1.25 to 1.5 meters per second. In indoor environment this speed can drop down to 0.7 m/s [95]. Since in many cases people might walk with different paces, the online phase samples that were gathered at the same six seconds per 1.8 meters pace were resampled at $\times n$ speed, for $n = \{2, 3, 4, 5, 6, 7\}$. This allowed the creation of online data samples that would represent faster paces, leading also to fewer collected samples over the same path length. Resampled data represents traveling speeds of {3, 2, 1.5, 1.2, 0.9} seconds for the same path. Faster paces would mean fewer online data samples, allowing to test the performance of the suggested algorithm in non-optimum conditions when fewer online RSS values are available. Figure 6-10 presents the detection rate changes in relation to the speed interval increases. Figure 6-11 presents the average errors, together with the standard deviation at each speed.

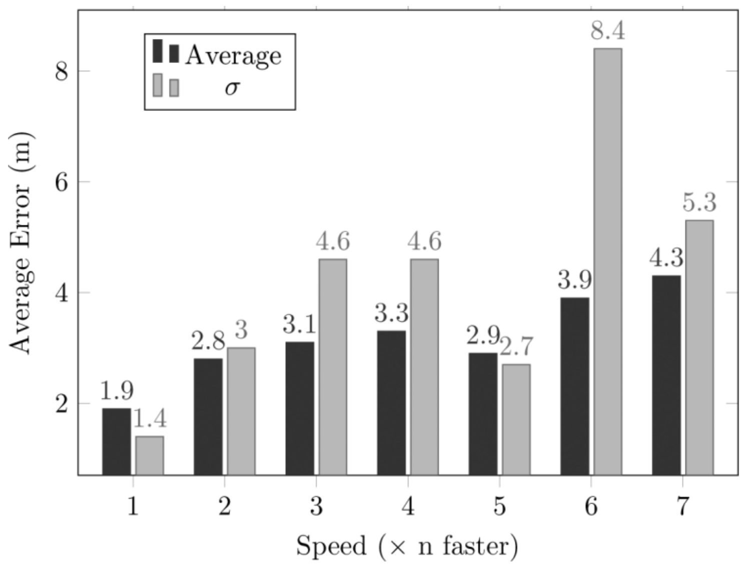

Figure 6-11: Localization error VS Speed interval

6.3.5 Path length selection

Another necessary step to further evaluate the proposed method is to examine the effect of path length on localization accuracy. The purpose of this test is to find the most optimum path length for the proposed method and how shorter/longer paths affect the average accuracy and standard deviation. An optimum path length can help to better characterize the localization environment. The proposed method has been tested with various path lengths. The initial tests have been performed over a 1.8 meters path, which in our environment this was the distance over 3 x 60cm floor tiles.

After proving the concept as presented earlier in section 6.3, smaller and larger path lengths have been tested to evaluate the effect on localization accuracy. The tested path lengths were 0.6m, 1.2m, 1.8m, 2.4m representing 1, 2, 3 and 4 floor tiles respectively. Figure 6-12 presents the performance of "*PathLoc*" using different path lengths and number of k-nearest neighbors. This figure suggests that the optimum path length for "*PathLoc*" algorithm is between 1.8m to 2.4m.

In our tests it was found that path length of 1.8 m and k = 5 resulted to a localization accuracy of 1.9 m as presented in Table 6-3. Similar results were obtained for a path length = 2.4m. From the results collected it appears that path lengths between 1.8 m and 2.4 m were producing the most optimum results.

It was found that using smaller paths (shorter than 1.8m) in our indoor environment did not provide enough data to achieve a localization accuracy better than 1.9m. This does not necessarily mean that smaller paths cannot provide better accuracies since the fingerprint database created did not exhaustively cover the whole floor.

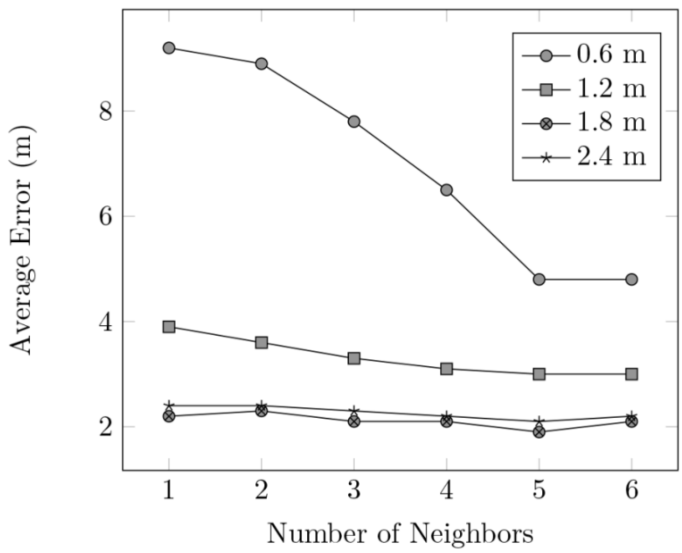

Figure 6-12: Effects of different K selections and path lengths on

Figure 6-13 presents the proposed method average accuracy and standard deviation (σ) using different path lengths for "*PathLoc*" algorithm. Presented average error and (σ) are based on K = 5 (the most optimum number of nearest neighbors for "*PathLoc*"). Three different wireless cards were used to test each path length for device diversity purposes.

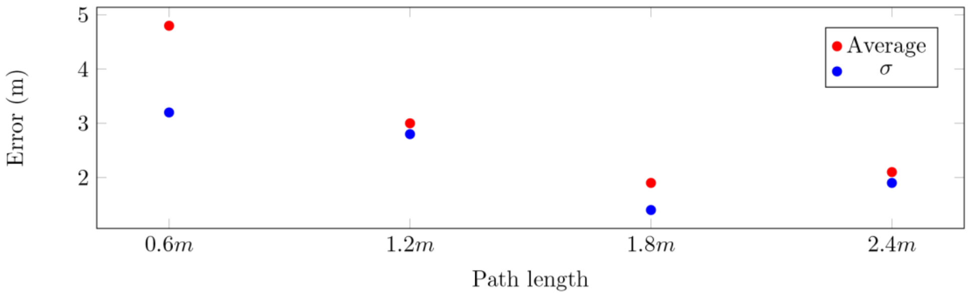

Figure 6-13: Path-length and localization error.

6.4 Usage of Simulated Data

We also use simulations to evaluate and verify the performance and accuracy of the proposed method and to compare the real world measurements with the simulation results.

Similar to the real world measurements, simulation can be used for both offline and online phases. In this chapter we use simulation for comparison purposes. Moreover, The ability of the proposed methods to handle complex tracking scenarios, to utilize signal strength data and fast fading information from environment is successfully demonstrated using simulations.

6.4.1 Simulation Setup - Offline phase

To generate a simulated offline phase fingerprint radio map of the environment, a 3D ray tracing simulator (TruNET Wireless) was used. The 3D plan of the environment was considered, including a description of the constitutive parameters of the building materials obtained from literature [13]. In order to be able to capture fast fading, the distance between subsequent cells was set at $\leq\lambda/2$. An isotropic receiver was assumed and was placed at a height of 1.5 m. The wireless network implemented based on the real world scenario (Figure 6-4 and Figure 6-14) which consist of 8 APs spread around the environment of interest and placed at a height of 2.2 m. The estimated RSS values from the simulator were used to populate to a database (fingerprint radio map). Subsequently and for comparison purposes another fingerprint radio map database was generated based on real measurements.

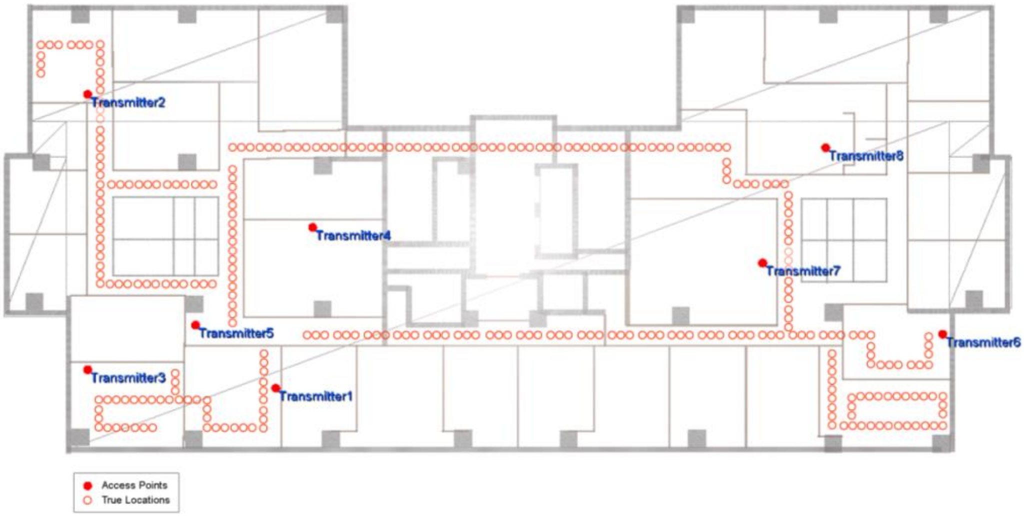

Figure 6-14: Test Environment and Test Routes/Paths

6.4.2 Simulation Setup - Online phase

To evaluate the performance of the proposed method using simulations and compare it to the real measurements, various simulations have been carried out to estimate the location of a mobile terminal moving along the test paths as shown in Figure 6-14. The test paths were simulated at the height of 1.5 m and consisted of 70 paths. Estimated RSS values have been passed through a normally distributed RSS fluctuation filter with a σ = ±3dB in an effort to better simulate the dynamic effect of the real environment. This sort of RSS fluctuation can be observed in real world scenarios due to human movements, device diversity, operating conditions and many other factors [107]. The position estimation was performed using the proposed method (*PathLoc)* which is a weighted K-nearest neighbour algorithm.

Table 6-5 presents the comparison between real measurements vs simulations. The results shown here are obtained from 30 simulation repetitions.

Table 6-5: Real Measurements vs Simulation Performance Comparison

	Real Measurements	Simulation
Max[m]	4.8	6.2
Min [m]	0	0.6
Average [m]	1.9	2.2
σ [m]	1.4	1.7
Var [m]	2.1	3.3

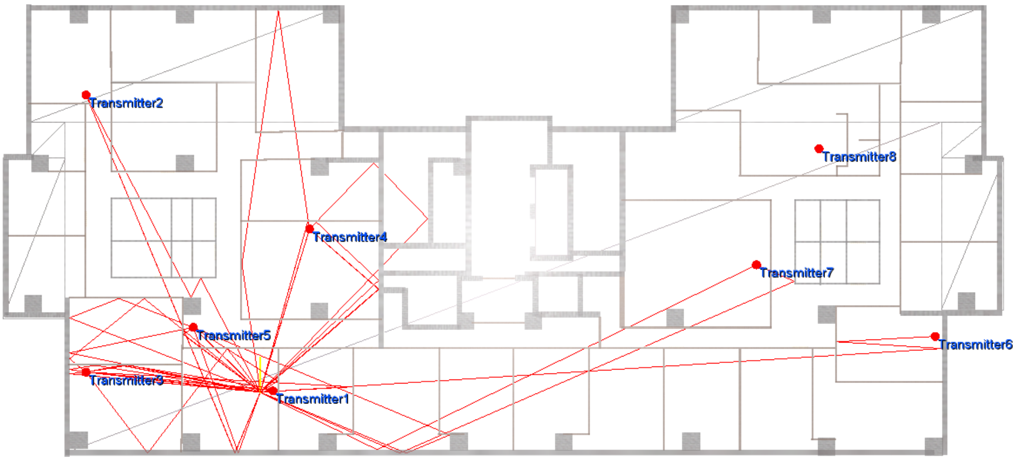

Figure 6-15: 2D description of the environment and the various propagation mechanisms exist in the environment

Above figure presents a 2D description of the environment and the various propagation mechanisms that exist in the environment. In the above figure it becomes obvious that the resultant RSS is the combination of multiple contributions (multipath) arriving at the receiver. The different paths arriving at the receiver travel different distances and thus have slight different arrival times.

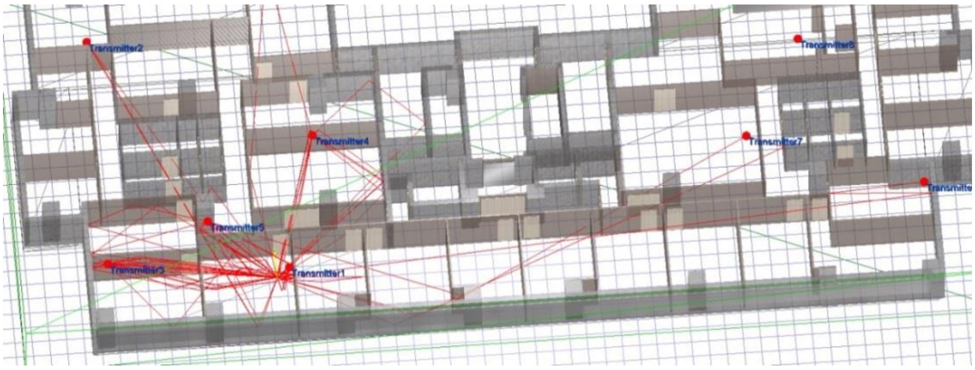

Figure 6-16: 3D description of the environment and the various propagation mechanisms exist in the environment

Above figure presents the same scenario as above but in a 3D view, clearly identifying that these propagation mechanisms take place in 3D, a fact that has to be taken into consideration when considering the propagation mechanisms. TruNET wireless automatically considers the correct value of the 3D interaction.

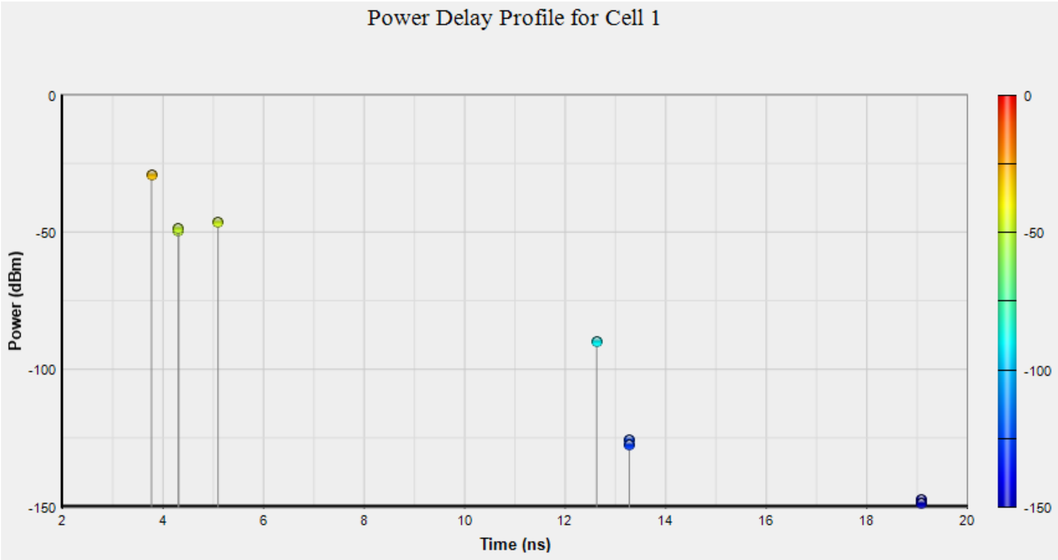

Figure 6-17: Power Delay Profile (PDP) For Cell 1 from Transmitter 1

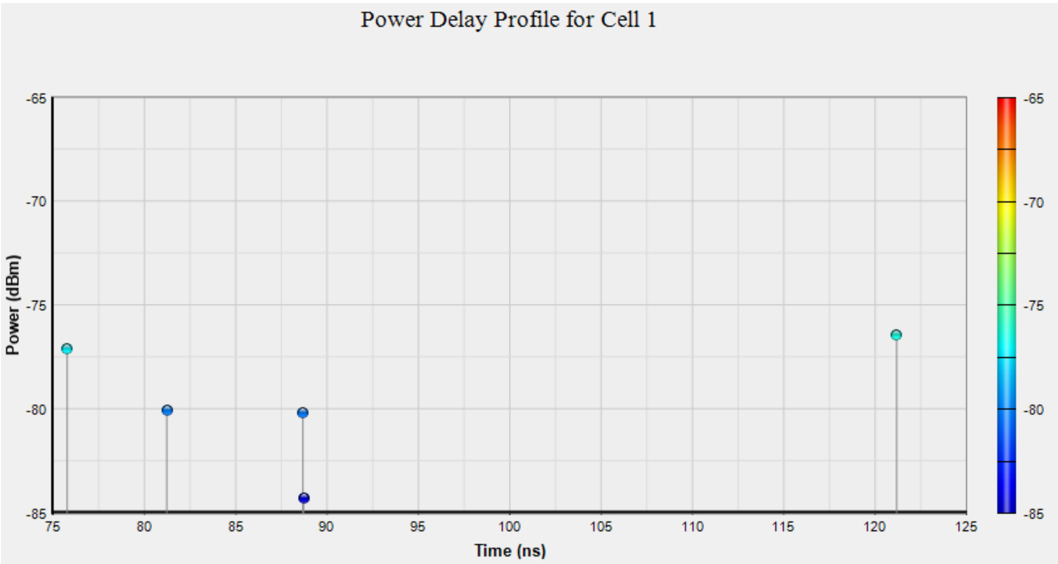

Figure 6-18: Power Delay Profile (PDP) For Cell 1 from Transmitter 2

The figures above presents a simulation result from TruNET Wireless and describe the Power Delay Profile (PDP) for the same cell (cell 1) presenting contributions from two different transmitters. It is evident that different contributions reach the receiver at different times, and thus phases, and with different amplitudes. The sum of these components is the final RSS value.

6.4.3 Comparison of real and simulated raw data

The comparison between real measurement and simulation raw data is a necessary step to evaluate the accuracy and reliability of the proposed method. For each simulated path the real measurement data have been extracted and compared by averaging the RSS of each transmitter from real data VS simulation data. Figure 6-19 presents the comparison for a sample path. Presented data show that the real measurements and simulation data are very similar which suggests that simulations can be used safely to further calibrate the method and the diversity equations.

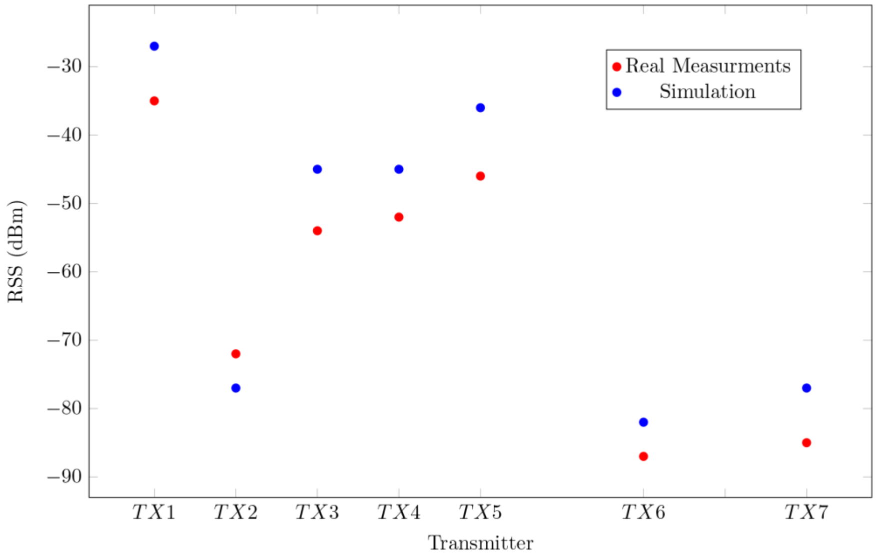

Figure 6-19: Real world VS Simulation RSS Comparison for multiple transmitters captured on a sample path

6.4.4 Comparison of raw data based on number of collected samples per path

The simulation has been configured to generate an average received signal strength value every 5 cm ($\sim \lambda/2$ $@2{,}4GHz$) that means for a 1.8 m path we will have 36 RSS values collected from each visible transmitter. When collecting data using a handheld/laptop in the real environment we have 550-600 packets collected for a visible transmitter for the same distance. In order to have a better comparison between real measurements vs simulations, first an average of every 15 signal strength collected from the real environment is calculated in order to have one value which represents 5 cm for the real measurements. The final results brings the simulation data closer (makes them more comparable) to the real measurements by ±2 to ±3 dBm. Figure 6-20 present the comparison of the raw data calculated based on 1/15 ratio.

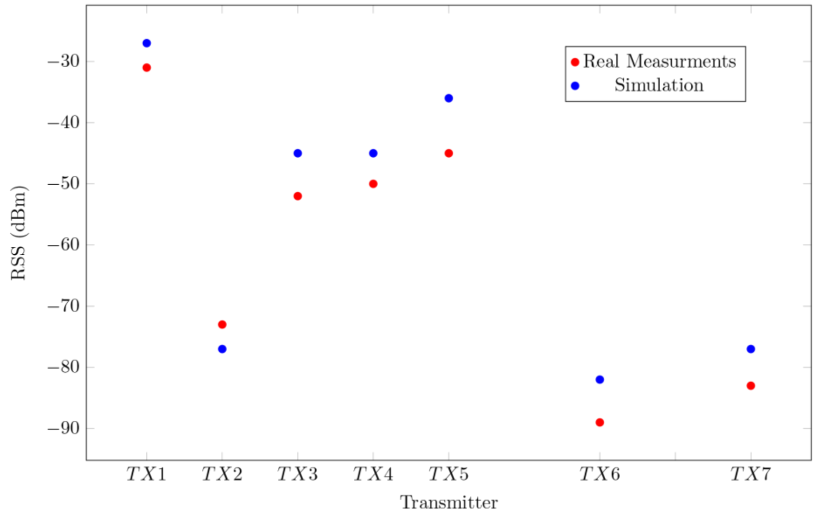

Figure 6-20: Comparison of raw data based on number of collected samples per path

6.4.5 Comparison of real and simulated raw data for one transmitter

Analysing the raw data for one transmitter allows to better evaluate the simulation results and their effectiveness on localization. Presented data shows that simulation results are very close and comparable to the real data. The results can differ ± some dB but the patterns are very similar. This behaviour is expected and can be seen in real world scenarios as well due to device diversity and other environmental factors such as human/machine movement.

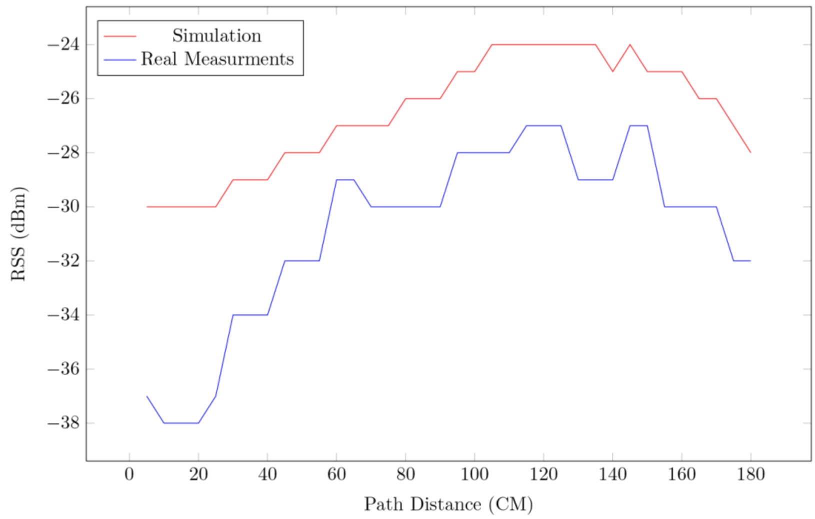

Figure 6-21: Comparison of raw data for one transmitter

6.5 Conclusion

This chapter presented a novel localization method based on analysis of RSS samples obtained over a path than over a stationary point. Compared to typical RSS methods where the average signal of a number of APs is recorded at a stationary point, the proposed method demonstrates that better localization results can be achieved by analyzing RSS signals recorded over a path. The proposed method has been compared to a number of well-known and widely used RSS techniques and has been shown to produce smaller average errors than the other methods. Moreover, the ability of the proposed methods to handle complex tracking scenarios, to utilize signal strength data and fast fading information from environment is successfully demonstrated using simulations.

Finally, Table 6-6 presents the comparison of the proposed RSS method with the other well-known methods and the ones which have been replicated in our test environment. Also, it worth mentioning that by “Algorithm Execution time”, we mean the time required for collection of data, storing of data, processing of data and result presentation.

Table 6-6: RSS Based Methods Comparison

Method/Ref	Accuracy	Algorithm Execution time / Required localization time
Proposed method [17, 18]	~ 1.9 m	Instantly
RADAR [32]	< 4 m	Instantly
[33]	~ 6 – 8 m	Instantly
[34]	~ 2.3 m	Unknown
[90]	< 5 m	Unknown
1D RSSI [139]	~ 6 m	Instantly
1D RSSI Weighted [139]	~ 4 m	Instantly
4D RSSI [139]	~ 3 m	Instantly
4D RSSI Weighted [139]	~ 2.9 m	Instantly

Chapter 7

7 Localization Platform

7.1 Introduction

Research on indoor localization and development of location based algorithms requires more than just wireless node hardware. Researchers and developers need smarter and more efficient tools that can provide them with proper data collection and analyzing capabilities. In order to facilitate the process of real data collection, which is time consuming, a localization platform is needed to collect the packets, processes them, and to plot the estimated location of the user. The platform also helps to replicate other methods for performance comparison purposes.

In this chapter we present an indoor localization platform that is able to provide a real-time estimation of a mobile terminal using time-based and signal strength based methods presented in previous chapters. The platform has been developed during the course of this PhD and makes it incredibly easy and quick to perform data gathering and location estimations in indoor environments. Moreover, the platform helps to better visualize the approximate distance and position of the mobile terminal.

The localization platform was developed using C# and Microsoft SQL Server. The platform helps to collect packets for each method, processes them, and plots the estimated location of the mobile terminal. The localization platform has been used both for time-based methods and signal property-based methods. This chapter will briefly explain and review the localization platform and its usage and functionality.

7.2 Time-based Methods

The work on the localization platform started while conducting literature survey and started experimenting with time based methods [14-16]. With the amount of collected data growing at an exponential rate, the need for having a proper tool, which can better accommodate data collection and evaluation while testing different methods and ideas, became more obvious. Work on creating a new localization platform started with an eye towards the vision of creating a useful and user friendly contextual tool that can accelerate data collection and processing while visualizing the output data in a meaningful way.

While testing and conducting experiments for our proposed time-based method [14], we confirmed that in order to meet the accuracy requirement, collection of thousands valid beacon packets were necessary. As proposed in [14], calibrating the system by calculating distance 0 is the first step. Both system calibration and distance calculation can be performed using functionalities of the platform.

Below, we present some screenshots of the platform along with more detailed explanations for each of the functions and how the distance between a mobile terminal and an access point is determined by calculating the time difference of a position, after calibrating out a known distance, i.e. distance 0.

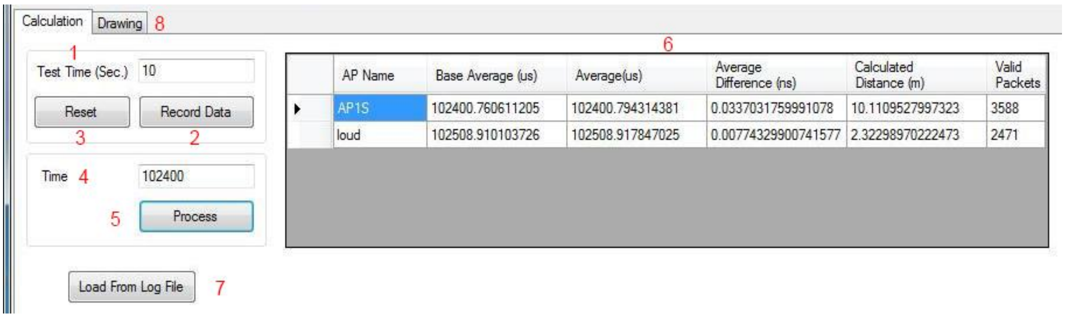

Figure 7-1: Packet Collection and Evaluation Screen

Figure 7-1 shows the main screen of localization platform developed and used for time-based methods followed by Table 7-1 which provides a brief description of the functionalities marked with a number in Figure 7-1. A more detailed description of each functionality will follow in this chapter.

As shown in Figure 7-1 the first step is to assign a testing time period (1). This is the duration of packet collection for the respective test. In order to have more reliable performance/results, the assigned value for test time needs to be the same for calibration phase and distance estimation phase. This will insure a fair comparison between data collected for distance 0 and each estimated distance after that.

Table 7-1: Brief explanation of platform functionalities for time-based methods

Reference #	Description
1. Test Time	The duration of packet collection for the experiment.
2. Record Data/Initialization	It triggers the start of a packet collection. It is used to initialize the system and collect data to calculate distance 0 TOA_0 [14] and TOA_n for mobile terminal respectively.
3. Reset	Resets the test time and change the state of Record Data button to Initialization in case TOA_0 needs to be recalculated.
4. Time	It refers to the Beacon Interval time used for the experiments. This value is especially important when conducting tests with different BIs as discussed in chapter 4 [15].
5. Process	It starts the statistical analysis and distance estimation based on time methods discussed in chapter 4 and presents the results in the results window next to it
6. Results Window	It displays estimated distance in meters to mobile terminal from each visible access point. Calculated distances then can be used to estimate location of the mobile terminal using trilateration.
7. Load From Log File	It accommodates the use of previously captured data by simply loading respective pcap files for processing.
8. Drawing	To load floor plans, place infrastructure access points/base stations and assign the measurement ratios of the environment. In general, it helps to better visualize the calculated distances and location of MT.

Record Data/Initialization button (2) triggers the start of a packet capture using *tcpdump* which will last for *n* seconds as specified in previous step. Next, collected data are saved in a pcap file format and can be used for calculation of TOA_0 and TOA_n respectively [14]. This button is designed for both calibration and distance calculation phases. Its functionality changes automatically depending on the respective phase. For example, during the initialization phase which distance 0 is calculated, the button label is set to “Initialization”. Once the calibration/initialization phase is completed and distance 0 is calculated, the label changes to “Record Data” automatically stating that new data will be collected for calculation of TOA_n and distance estimation.

The reset button (3), resets the duration of test time (1), deletes the temporary collected data in case there is any and changes the state of ” Record Data” button to “Initialization” in case TOA_0 needs to be recalculated. This feature also can be used to verify consistency of distance 0 calculation by recalculating it multiple times and comparing the results.

The statistical analysis presented in chapter 4 [14, 15] depends on the value of beacon interval and calculated time delta from previous captured beacon packet for the same access point. This value helps to identify valid and non-valid packets as explained in chapter 4. In the localization platform, the value can be set in microseconds using “Time” field (4) and it represents the predefined beacon interval value of APs. The “Time” field accelerates measurements and localization speed especially in experiments where different beacon interval is used [15].

The *Process* button (5) in the platform is disabled by default until successful setup of parameters and collection of some data. When enabled, this button starts the statistical analysis and distance estimation based on time methods discussed in chapter 4 and presents the results in the result panel next to it (6). The result panel (6) displays estimated distance in meters to mobile terminal from each visible access point. Calculated distances then can be used to estimate location of the mobile terminal using trilateration.

As mentioned before, all collected packets are saved in a pcap file format. This allows use of recorded data in an offline/non-real-time mode for further data analysis. The platform accommodates the use of previously captured data by simply loading respective pcap files for processing (7). This feature is specifically useful while conducting device diversity experiments as the required pcap files can be collected in a variety of platforms and using different devices. Moreover, it eliminates the need to have the localization platform installed on all mobile terminals in testbed since packets can be captured and saved into pcap files using just a terminal and tcpdump.

Figure 7-2: Drawing tab

The drawing tab (8) helps to better visualize the approximate distance and position of the mobile terminal calculated by the proposed methods. Using this tab, the environment map can be imported or even drawn from scratch. The drawing tab also provides the ability to set dimensions and ratios, placing transmitters and monitoring mobile terminal location in real-time. Figure 7-2 presents a screen shot of the drawing tab.

7.3 Signal Property-based Methods

During the literature survey and replication of existing methods many RSS-based localization techniques have been evaluated [12, 32, 38, 42, 62, 89, 90], which motivated some additional objectives and ultimately led to development of a new WKNN localization technique [17, 18]. The replication and evaluation of signal strength-based methods can be computationally intensive and requires creation of fingerprint database, hence a dedicated page for signal property-based methods has been added to the localization platform. Figure 7-3 presents a screenshot of signal property-based localization tab in the platform.

The RSS tab allows mapping the environment of interest and automates offline and online phases. Almost all signal property-based localizations start with creating a radio map of the environment. The “Create New FP DB” button (1), creates a brand new database for the area of interest which is populated during the offline phase. When the platform creates a new database to store radio map data, it also asks for a floor plan image to better visualize the approximate location of collected data or calculated distance for MT (4). Depending to the environment dimensions and localization algorithm the offline phase can take a long time to be completed and might be divided into multiple runs. Using “Load FP DB” button (2) the last fingerprinting database can be automatically loaded and used for both offline and online localization tasks. The load button shows areas which have been covered already in offline phase and it helps updating the fingerprinting database in case more path/points need to be added or new data need to be collected for an existing point.

One of the challenging tasks during creation of fingerprinting database is to record the exact trajectory of the survey points/paths and store the relevant coordinates for each of them. In order to achieve that, the environment of interest needs to be accurately divided into a grid.

Table 7-2Table 7-2 provides a brief description of the functionalities marked with a number in Figure 7-3 and a more detailed description of each functionality follows.

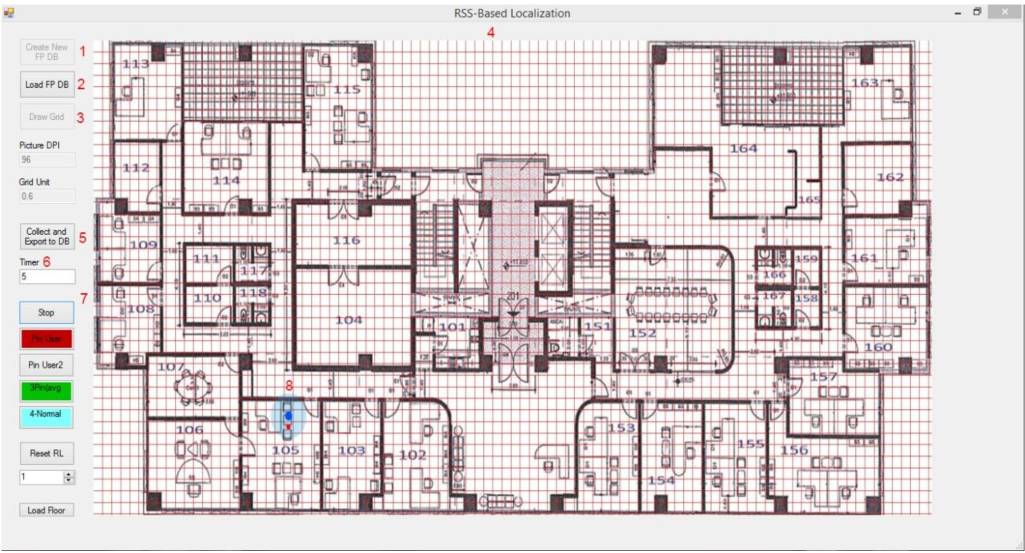

Figure 7-3: Signal property-based localization platform screen

The RSS tab allows mapping the environment of interest and automates offline and online phases. Almost all signal property-based localizations start with creating a radio map of the environment. The "Create New FP DB" button (1), creates a brand new database for the area of interest which is populated during the offline phase. When the platform creates a new database to store radio map data, it also asks for a floor plan image to better visualize the approximate location of collected data or calculated distance for MT (4). Depending to the environment dimensions and localization algorithm the offline phase can take a long time to be completed and might be divided into multiple runs. Using "Load FP DB" button (2) the last fingerprinting database can be automatically loaded and used for both offline and online localization tasks. The load button shows areas which have been covered already in offline phase and it helps updating the fingerprinting database in case more path/points need to be added or new data need to be collected for an existing point.

One of the challenging tasks during creation of fingerprinting database is to record the exact trajectory of the survey points/paths and store the relevant coordinates for each of them. In order to achieve that, the environment of interest needs to be accurately divided into a grid.

Table 7-2: Brief explanation of platform functionalities for RSS-based methods

Reference #	Description
1. Create New FP DB	Creates a new fingerprinting database for the area of interest.
2. Load FP DB	To load a previously created fingerprinting database in order to use it for offline/online localization phases.
3. Draw Grid	It adds a custom overlay reference grid to the floor plan. This helps to assign a unique reference number for each point/path while creating radio map of the environment. The grid overlay size and divisions are based on *Picture DPI* and *Grid Unit* numbers.
4. Output Frame	It provides an interactive floor plan which allows selection of points/paths for offline phase and visualizes calculated distance and location of mobile terminal during online phase.
5. Collect & Export to DB	It starts collection of data and exports them into fingerprinting database for each of the reference point.
6. Timer (sec)	In offline phase, it indicates the collection time for a reference point/path. In online phase it refers to localization update frequency.
7. Online phase/Localization section	It contains five buttons used to perform packet collection and distance estimation for RSS-based localization algorithms. The first two buttons perform calculations based on proposed algorithms in chapter 6 [17, 18], while rest of the buttons are replication of well-known RSS-based methods for comparison purposes [32, 86, 93].
8. Calculated Distance/Location Indicator	The indicator shows calculated distance and location of the localization target in online phase. For presented methods [17, 18] it shows a blue dot and a light blue circle, other algorithms are distinguished with the respective colors of their buttons.

The “Draw Grid” button (3) allows dividing the area of interest into multiple grids for better clarity and numbering of the fingerprinting database locations especially for offline phase. The grids will be drawn by using two elements: “Picture DPI” and “Grid Unit” in meters. For our environment it has been set to 0.6 meter / 60 cm which is the equivalent size of floor tiles in Open University of Cyprus building.

Moreover, the interactive floor plan in localization platform (4) allows marking/selecting area of interest prior to data collection for offline phase. First a survey point/path is selected and using “Collect and Export to DB” button (5), the localization platform starts capturing packets and stores them into database for that specific point/path while assigning a unique number/label to it. The packet collection duration can be defined in seconds using “Timer” option located just below the collect button (6). This value defines test times for both offline and online phase and it helps to better evaluate the effect of data collection duration on localization accuracy.

The platform contains five buttons for packet collection and signal property-based localization algorithms (7). The first two buttons perform calculations based on proposed algorithms in chapter 6 [17, 18], while rest of the buttons are based on some of well-known RSS-based methods [32, 86, 93]. This feature provides a quick way to compare and visualize localization accuracy for different methods.

Last but not least, during the online phase, location of the mobile terminal is presented by a blue dot and a light blue circle (8) for the proposed method [17, 18] and the respective button color for each of the other algorithms. The platform updates location of pointers every *n* seconds based on the defined collection time (6).

7.4 Discussion and Future Development

Further development is needed to make the localization platform available for more operating systems, mainly major mobile platforms such as iOS and Android. This allows for an easier and more efficient data collection and provides more flexibility to the end-user. Moreover, this helps to better investigate the hybrid methods, since a wide range of sensors available in today's powerful smartphones can be utilized for localization. Also, the platform's ability to easily collect data could be used for automated fingerprinting in the future for example with robots with known trajectories.

Chapter 8

8 Conclusion and Future Work

8.1 Conclusions

8.1.1 Introduction

The research presented in this thesis is involved with wireless user localization in indoor environments using Commodity off the Shelf (COTS) Hardware with special focus on time, signal property and particle filtering methods. It has been inspired by the difficulty to perform localization in indoor environments where the outdoor positioning systems such as GPS, GLONASS and GALILEO may not work well. A series of algorithms have been developed and presented which enable localization in indoor environment using off-the-shelf equipment, and which can be incorporated in real world application such as wayfinding systems, advertisement, monitoring and many more. These algorithms utilize novel concepts from time of arrival, time difference of arrival, receive signal strength, weighted k-nearest neighbors and particle filtering. This chapter presents a summary of the main contributions, conclusions and limitations of this thesis. Suggestions of further research directions are also presented.

8.1.2 Summary and Contributions

This thesis investigates the problem of indoor localization from multiple aspects and introduces innovative methods based on Time, Signal property and Hybrid techniques as means of performing localization and increasing the position detection accuracy. Extensive research and replication of the existing localization methods were followed by the identification of limitation of those methods including ways of optimizing them. New localization algorithms and techniques have been developed in both time and signal property domains including hybrid methods.

The localization methods applicable to indoor environment using commodity off the shelf hardware that have been developed include:

- An innovative time-based localization method that utilizes the information provided by 802.11 Beacon packet data. Utilizing Beacon packet for localization, eliminates the need for establishing a connection between base stations and MTs. Also, the proposed method does not require any clock synchronization.
- A method on how to accelerate network packet time-based localization techniques and its effect on localization performance metrics.
- A particle filtering method as a means of addressing the problem of tracking a moving target in an indoor environment using off-the shelf time-based methods.
- A new kNN-based localization algorithm based on RSS compared with fingerprint data captured over paths and not points.

This research work started with a literature survey, which covered the basic principles of localization in indoor environments using 802.11commodity off-the-shelf equipment, highlighting all its relevant techniques and algorithms. These techniques, namely time-of-arrival (TOA), time-difference-of-arrival (TDOA), received signal strength (RSS) and angle of arrival (AOA) are of great importance in order to implement an optimized indoor localization system that can be used to locate objects/mobile terminals in an indoor environment. As 802.11 becomes more popular and widely available, it provides more opportunities for a low-cost, off-the-shelf indoor localization system. For this reason, this work has looked into various issues related to distance estimation and localization accuracy in indoor environment using COTS hardware and highlighting the major limitations and factors that may give rise to errors.

The main part of this research started with an investigation of wireless positioning systems and location algorithms. Location-aware applications can rely on GPS, GLONASS and GALILEO [19] for outdoor localization, whereas a terminal in an indoor environment requires implementation of other technologies to benefit from those applications. An indoor localization system is either a Self-Positioning System or a Remote/Cooperative Positioning System. Using self-positioning, a mobile terminal is able to locate itself with respect to static/known points in the indoor environment. Remote or cooperative positioning refers to techniques that allow mobile terminals or infrastructures to locate other terminals in their coverage area. Amongst the numerous existing localization techniques, the most commonly used and accepted methods are the geometrical ones, especially those based on the estimation of the Angle of Arrival (AOA), the Time of Arrival (TOA), the Time Difference of Arrival (TDOA), Received Signal Strength (RSS) or a combination of the above [1-14]. One of the main advantages when comparing time over signal strength localization methods, is that the former do not require the creation of fingerprint databases. On the other hand, the majority of time-based methods require some sort of clock synchronization due to the drifting of the local clocks. Moreover, synchronization requires infrastructure nodes and mobile terminals to establish bidirectional connections, causes more complexity and imposes higher processing intensity to the localization system. This has raised the idea of using connection less packets such as 802.11 beacon packet for localization purposes. By using Beacon Interval, Beacon timestamp and Service Set Identifier (SSID) of a packet, it was possible to optimally process the MAC timestamps recorded for each packet which lead to development of a hybrid TDOA-TOA localization method with an average error of less than 2.5 meters. Calculating TOA/TDOA precisely down to *ns* using 802.11 COTS hardware without statistical analysis would be difficult if not impossible. In addition, for the proposed method the challenge was to precisely calculate time difference between two consecutive beacon packets using MAC timestamp. In general, a chipset driver will place a timestamp (MAC timestamp) at the end of a data frame after successfully receiving the MPDU. This process found to impose an extra 1.26648e6 ns or 1266.48 µs of processing time on infrastructure node for a standard beacon frame which contains 166 bytes of data. It was found that such delays can directly affect the accuracy of distance estimation and therefore localization accuracy. A simple driver modification [6, 7, 15] made it possible to position and thus record the MAC timestamp for each packet at the beginning of MPDU, which improved the process of timestamp measurement (See section 3.4.2).

Another challenge which has been addressed in this work is packet collection duration for time-based methods, when using COTS hardware. Typical ‘off the shelf’ 802.11 network packet time-based localization methods tend to collect a large number of packets and apply statistical analysis in order to localize a user. This packet collection process typically lies in the range of minutes [65-67], thus turning this type of localization into a non-real time process. An investigation was carried out to study the effect of packet collection duration on time-based localization methods and how to accelerate TOA/TDOA packet based localization techniques (see chapter 4). For the proposed method [14], 2000 to 2500 valid beacon packets are required in order to achieve the claimed accuracy. It is also usually the case for commercial access point that default beacon interval is set to 100 milliseconds. Therefore, several minutes are required to collect the required number of packets. Although, the method could still be used for non-real time scenarios (e.g localizing equipment and asset tracking in a hospital, warehouse or a school), the investigation was concentrated on finding ways to accelerate the method so it can serve real-time scenarios as well.

An extensive investigation was carried out based on real measurements to study the effect of packet generation time for improving localization speed and achieved accuracy. Since a beacon packet collection process has been used for the proposed method, first step was to study the effect of beacon interval variation. Although reducing beacon interval helps generating packets faster and therefore providing more packets for statistical analysis, it can also directly influence the number of valid packets used for distance estimation [15]. To evaluate the effect of beacon generation speed on localization accuracy, different *BI*s including *BI* = 200, 100, 50, 20 and 10 milliseconds were generated and position estimation results were analyzed at distances of 5, 10, 15, 20, 25 and 30m. Two different approaches have been proposed in this thesis while evaluating the non-realtime limitations of TOA/TDOA packet based localization methods using COTS hardware. In the first approach, acceleration of packet generation was performed to collect the required packets for distance estimation in a shorter period of time. Subsequently, taking into account wireless channel throughput and quality of service while performing indoor localization has helped to generate more valid packets for each measurement which in turn causes to achieve a better accuracy using the same number of collected packets.

It was observed that as the number of valid packets starts to fall below 1000, the estimated distance/position, and its standard deviation increases drastically, implying that at least 1000 valid packets are required for an acceptable distance estimation. This finding was crucial to the success of accelerating packet based methods, since a limitation threshold was found with regards to the number of valid packets required to achieve a certain accuracy. Therefore, the investigation was concentrated on finding other ways to accelerate the proposed method, such as reducing number of dropped packets, in order to collect more valid packets in a shorter period of time.

It is very important that a localization platform based on 802.11 COTS hardware does not impose a negative impact on the performance of an existing wireless setup, especially if it is used for data communication. To study the effect of beacon interval variation on surrounding wireless networks, an investigation was carried out to demonstrate beacon interval effect on channel throughput and quality of service in 802.11 networks (see chapter 4, section 4.3.2). It was observed that selecting the correct beacon interval helps to reduce collisions, allowing delivery of more valid packets over a shorter period of time. Additionally, it was demonstrated that the proposed method is able to localize a mobile terminal almost eight times faster when compared to existing methods. It has been also shown that by reducing the beacon interval without considering the surrounding data networks and their settings, an overhead can be added, causing reduced channel throughput and thus a drop in quality of service.

In an effort to further improve the proposed method, an extensive investigation was carried out through both real-world measurements and simulations, to study the effect of statistical post-processing analysis and processing cost of such analysis on dynamic real-time localization systems. In many cases, calculation of all possibilities requires a great deal of processing power while imposing various delays to localization techniques. However, the kinematic characteristics of the target and past measurements offer target trajectory information which have the potential to improve localization and reduce some overheads. This has raised the idea of using particle filtering to address the problem of tracking a moving target in an indoor environment using time-based methods. The particle filter based method sequentially estimates the posterior of the target state and is able to fuse past and present measurements information from multiple sensors with the target kinematic information in order to improve localization. Furthermore, a particle filter method can use realistic models to characterize the state and measurement space and accurately handle the non-linear relationship between target state and measurements. Moreover, as a sequential Monte Carlo method, the particle filter uses a prediction-update process to track changes in the target state. Therefore, the particle filter utilizes information from past measurements and past target states in order to improve localization accuracy for moving targets. For the proposed method, the localization performance has been assessed using different number of particles and different number of access points. In addition, statistics of real data collected from a real environment, highlighted the effectiveness of the method.

Although the main focus of this work was on time-based localization methods, during this research, many RSS-based methods have been evaluated [12, 32, 38, 42, 62, 89, 90] for comparison purposes. This motivated some additional objectives and led to the development of a new WKNN localization technique – a novel RSS-based localization method using path analysis [17, 18]. While typical RSS methods utilize the average signal of surrounding APs recorded at stationary points, it has been found that better localization results can be achieved by analyzing RSS signals over a path [17, 18]. This approach, allows the collection of more information and detailed signal behavior, when compared to the single point case. To test the method and its performance, indoor radio campaigns and simulations have been carried out which showed a significant improvement of the average achieved accuracy and its standard deviation when compared to typical RSS methods. Novel research contributions in regards to signal property based localization can be summarized as follows:

- Introduction of a novel kNN based localization algorithm based on RSS information captured over paths.
- Analysis of *k* selection impact on kNN algorithms.
- Analysis of device diversity impact on the performance of the proposed method, as well as the effect of a variable captured RSS sample number for various user walking speeds.

Moreover, the ability of the proposed methods to handle tracking scenarios with measurements that are non-linearly related to the target state, to utilize signal strength data and fast fading information from environment, is successfully demonstrated using simulations (See section 6.4).

8.2 Future Research Direction

The work can be further extended in the following fields:

Optimum TOA/TDOA Deployment: Further investigate whether utilizing a customized packet which broadcasts only the desired localization information can achieve similar or even better results than the ones presented in this thesis. Since the proposed method does not require an RTS-CTS mechanism, it could also be performed by utilizing a customized packet generated with a packet manipulation program such as Scappy [136]. This allows to generate a much smaller packet which includes only the necessary information needed for localization. It should be investigated whether using a custom generated packet which includes selective data can achieve similar or even better results. The process can also help to replace the AP with router boards or credit-card size open-source hardware such as Raspberry Pi [96-98], Arduino [99-101] and similar microcontroller kits for a more portable and easy to distribute indoor localization infrastructure.

Advanced Hybrid Indoor Localization Method: Investigate the benefit from using particle filtering to naturally incorporate measurements from multiple sensing modalities combining time difference of arrival measurements, received signal strength measurements and mobile terminal originated measurements such as acceleration or gyro data. This should include the development/use of a hybrid method that incorporates best features of time-based, signal property based and particle filtering techniques. Such hybrid method can help to further improve the localization accuracy while decreasing the pre and post-processing time. It can also help to increase the flexibility and fault tolerance of the localization platform especially in NLOS scenarios.

Machine Learning, Measurements Automation and Platform Optimization: Investigate the use of machine learning for constantly improving measurement models (fingerprinting, path loss, ray tracing). Also, the platform’s ability to easily collect data could be used for automated fingerprinting.

Analysis of Power Delay Profiles for Localization Purposes: This research direction can aim to investigate the effect of power delay profiles on time based localization techniques, which are based on COTS technologies. It has become evident from the work performed in the scope of this thesis, that multipath contributions, described by the power delay profile, can influence the accuracy of COTS time based localization techniques. To avoid utilizing specialized hardware, thus not COTS hardware, an idea is to utilize rigorous deterministic modelling techniques like ray tracing, to pre examine the power delay profiles of an area of interest with the scope of utilizing this information to improve the localization process. With such an approach, the real path lengths, and thus expected TOA/TDOA characteristics between two communication links will become evident. Pre-processing in the sense that a pre-characterization of the area of interest can be carried out and thus one can even draw conclusions about high and low ‘time’ correlation areas, allowing the system designer to rearrange the COTS infrastructure or even create a ‘time based’ fingerprinting database.

Appendix

Appendix 1: Collection of Beacon Packets and Calculation of TOA_0, TOA_n and TDOA

```
//Collect beacon packets using tshark and store them in a file
private void initializationBtn(object sender, EventArgs e)
   {
      int t;
      if (!int.TryParse(testTimeTxtBox.Text, out t))
        {
            MessageBox.Show("Invalid Test Time", "Error", MessageBoxButtons.OK,
            MessageBoxIcon.Error);
              return;
         }
       string strCmdText;
       strCmdText = @"/C tshark.exe -i 1 -T fields -E separator=, -E quote=d -e
       wlan_mgt.fixed.timestamp -e radiotap.mactime -e wlan_mgt.ssid -a duration:" +
       testTimeTxtBox.Text + @" > output.txt";

       System.Diagnostics.Process.Start("CMD.exe", strCmdText);

       if (initializationBtn.Text == "Initialization")
            {
                isInitializing = true;
                initializationBtn.Text = "Record Data";
            }
     }

//Process collected beacon packets, Separate Valid and non-valid packets and
calculate TOAn

  private void processBtn (object sender, EventArgs e)
        {

            Int64 decValue;

            StreamReader sr = new StreamReader("output.txt");
            StreamWriter[] outFiles = new StreamWriter[10];
            String[] fileLabels = new string[outFiles.Length];
            Int64[] lastEntry = new Int64[outFiles.Length];
            Int64[] lastEntry2 = new Int64[outFiles.Length];
            Int64[] sums = new long[outFiles.Length];
            int[] count = new int[outFiles.Length];
            for (int i = 0; i < outFiles.Length; ++i)
            {
                outFiles[i] = new StreamWriter("output" + i.ToString() + ".txt");
                fileLabels[i] = "";
                lastEntry[i] = -1;
                lastEntry2[i] = -1;
                sums[i] = 0;
                count[i] = 0;
            }

            //Stream Writer
            int freeFileIndex = 0, indexToWrite = -1;

            // Read Line
            string line, hexString, decimalString, tmpHex, accessPointName;
```

```
        Int64 secondDecimal = 0;
        while ((line = sr.ReadLine()) != null)
        {
           if (line.Length > 15)
           {
            // Remove first "
            hexString = line.Substring(3);


            // Parse only the Hex Number
            hexString = hexString.Substring(0, hexString.IndexOf('\"'));

            // Get Decimal Value (2nd column)
            try
            {
      decimalString = line.Substring(hexString.Length + 6);
      decimalString = decimalString.Substring(0, decimalString.IndexOf('\"'));


      // Remove extra 0's
      tmpHex = hexString;
      while (tmpHex[0] == '0')
          tmpHex = tmpHex.Substring(1);
           }
            catch
            {
                continue;
            }

               // Convert to decimal
             if(Int64.TryParse(tmpHex,  System.Globalization.NumberStyles.HexNumber,
      null, out decValue))
                    if (Int64.TryParse(decimalString, out secondDecimal))
                    {
                        // If successfully parsed, then continue

                        // Get name of access point
                        accessPointName = line.Substring(line.Length - 5, 4);

    if (accessPointName == "AP1S")
 //To take only AP1S and drop all the other packets
     {
        indexToWrite = -1;

           for (int i = 0; fileLabels[i] != ""; ++i)
              if (fileLabels[i] == accessPointName)
              {
                 indexToWrite = i;

                 if (((decValue - lastEntry[indexToWrite]) == timeBetween))
                 {
                  sums[indexToWrite] += secondDecimal - lastEntry2[indexToWrite];

                         line = line.Replace("0x" + hexString, decValue.ToString());

                        if (isInitializing)
                        outFiles[indexToWrite].WriteLine(line);

                        ++count[indexToWrite];

                  }
                     lastEntry[indexToWrite] = decValue;
                     lastEntry2[indexToWrite] = secondDecimal;
```

```
                                break;
                            }

// If this entry is not indexed, allocate a file to it
  if (indexToWrite == -1)
  {
       fileLabels[freeFileIndex] = accessPointName;
       indexToWrite = freeFileIndex;
       lastEntry[indexToWrite] = decValue;
       lastEntry2[indexToWrite] = secondDecimal;
       count[indexToWrite] = 0;
       ++freeFileIndex;

       line = line.Replace("0x" + hexString, decValue.ToString());

       if (isInitializing)
          outFiles[indexToWrite].WriteLine(line);
    }

   //// Replace hex number with equivalent decimal
   line = line.Replace("0x"+hexString, decValue.ToString());

   //// Write to the new file
      sw.WriteLine(line);
                  }
                 }
               }
            }

            sr.Close();

            List<string> logEntries = new List<string>();
            logEntries.Add("--------------------");
            string tmpLog = "";
            for (int i = 0; i < outFiles.Length; ++i)
            {
                if (count[i] != 0)
                {
                    if (isInitializing)
                    {
                        // Add Average
                   outFiles[i].WriteLine("Average = " + (double)sums[i] / count[i]);

                        // Add Count
                   outFiles[i].WriteLine("Count = " + count[i]);
                    }


                    int indexToAdd;
                    if (isInitializing)
                        indexToAdd = resultTable.Rows.Add();
                    else
                    {
                        // Safeguard
                        indexToAdd = i;

         // Find the respective index for the selected entry for update
        for (int j = 0; j <= outFiles.Length; ++j)
          if (resultTable.Rows[j].Cells[0].Value.ToString() == fileLabels[i])
          {
               indexToAdd = j;
                break;
           }
          }
```

```
                    resultTable.Rows[indexToAdd].Cells[0].Value = fileLabels[i];
       if (isInitializing)
           resultTable.Rows[indexToAdd].Cells[1].Value = (double)sums[i] / count[i];
           resultTable.Rows[indexToAdd].Cells[2].Value = (double)sums[i] / count[i];
                    resultTable.Rows[indexToAdd].Cells[3].Value                     =
Math.Abs(double.Parse(resultTable.Rows[indexToAdd].Cells[2].Value.ToString())
                                                                                -
double.Parse(resultTable.Rows[indexToAdd].Cells[1].Value.ToString()));
                    resultTable.Rows[indexToAdd].Cells[4].Value                     =
double.Parse(resultTable.Rows[indexToAdd].Cells[3].Value.ToString()) * 300;
                    resultTable.Rows[indexToAdd].Cells[5].Value = count[i];

                    // Gather Log
                    tmpLog = "";
                    for (int c = 0; c < 6; ++c)
                        tmpLog   +=   resultTable.Columns[c].Name   +   "   =   "   +
resultTable.Rows[indexToAdd].Cells[c].Value + ",   ";
                    logEntries.Add(tmpLog);
                }
                outFiles[i].Close();

            }
            isInitializing = false;

            StreamWriter logWriter = new StreamWriter("Logfile.txt", true);
            logWriter.WriteLine();
            foreach (string logEntry in logEntries)
                logWriter.WriteLine(logEntry);
            logWriter.Close();

            sw.Close();
 }
```

Appendix 2: Tracking a Single Moving/Resting Target Using Timestamps From Access Points

```
% This code tracks a single moving/resting target using timestamps from
access points
% Evaluates the uncertainty of the target at during the motion/rest

MCruns=1;
K=500;
ploton=1;
saveon=0;

N=1000;
N=2000;
N=5000;

for U=4; %1:4
U
% AP locations
% ap(x or y,ap index)
ap(1,1) = 0;
ap(2,1) = 1;
ap(1,2) = 19*0.6;
ap(2,2) = 7*0.6;
ap(1,3) = 41;
ap(2,3) = 3;
ap(1,4) = 31;
ap(2,4) = 8;

%Plot AP locations
if ploton==1
figure(1)
for u=1:U
    plot(ap(1,u),ap(2,u),'g.','MarkerSize',60); hold on
end
axis([-5 45 -5 15])
end

% true target motion
% xtrue(x or y,timestep)

sigmapos=0.01;
sigmavelx=0.1;
sigmavely=0.05;

minx=1;
maxx=29;
minpartx=0;
maxpartx=50;
miny=0.3;
maxy=1.5;
minparty=0;
maxparty=50;
maxvelx=.7;
maxvely=.1;

for MCrun=1:MCruns
% MCrun/MCruns
kind=1;
xtrue(1,kind)=1+10*rand;
```

```
xtrue(2,kind)=1;
vtrue(1,kind)=0.05*randn;
vtrue(2,kind)=0.01*randn;

if vtrue(1,kind)>maxvelx
    vtrue(1,kind)=maxvelx;
end
if vtrue(2,kind)>maxvely
    vtrue(2,kind)=maxvely;
end

stopprobabilitythreshold=.95;
stopcnt=0;
for kind=2:K
    if rand>stopprobabilitythreshold
        stopcnt=1+10*randn;
    end
    if stopcnt>0
        xtrue(1,kind)=xtrue(1,kind-1);
        xtrue(2,kind)=xtrue(2,kind-1);
        vtrue(1,kind)=0;
        vtrue(2,kind)=0;
        stopcnt=stopcnt-1;
%         'stopped'
    else
        vtrue(1,kind)=vtrue(1,kind-1)+sigmavelx*randn;
        vtrue(2,kind)=vtrue(2,kind-1)+sigmavely*randn;
        xtrue(1,kind)=xtrue(1,kind-1)+vtrue(1,kind)+sigmapos*randn;
        xtrue(2,kind)=xtrue(2,kind-1)+vtrue(2,kind)+sigmapos*randn;
        if vtrue(1,kind)>maxvelx
            vtrue(1,kind)=maxvelx;
        end
        if vtrue(2,kind)>maxvely
            vtrue(2,kind)=maxvely;
        end

    if xtrue(1,kind)<minx
        vtrue(1,kind)=-vtrue(1,kind);
        xtrue(1,kind)=minx;
    end
    if xtrue(1,kind)>maxx
        vtrue(1,kind)=-vtrue(1,kind);
        xtrue(1,kind)=maxx;
    end
    if xtrue(2,kind)>maxy
        vtrue(2,kind)=-vtrue(2,kind);
        xtrue(2,kind)=maxy;
    end
    if xtrue(2,kind)<miny
        vtrue(2,kind)=-vtrue(2,kind);
        xtrue(2,kind)=miny;
    end

    end
end % K


% generation of measurements from true state
clight=2.997925*10^8; %speed of light
for u=1:U
r(1:K,u)=sqrt((xtrue(1,1:K)-ap(1,u)).^2+(xtrue(2,1:K)-ap(2,u)).^2);
%range
```

```
tau(1:K,u)=r(1:K,u)/clight; % time delay
end
% the time delay above is assumed to be calculated
% by subtracting timestamp of AP to timestamp of target

% add uncertainty to time delay
% this is what is the measured time delay for each point
sigmatime=10e-9;
tau(1:K,1:U)=tau(1:K,1:U)+sigmatime*randn(K,U);

% Tracking algorithm
sigmapartpos=.1;
sigmapartvelx=0.03;
sigmapartvely=0.01;
% initialize particles, weights, and estimate

xpart(1,1:N)=30*rand(1,N);
xpart(2,1:N)=1+0.00001*randn;
vpart=0.001*randn(2,N);
weights(1:N)=1/N;
xhat=xpart*weights';

vpart(1,find(vpart(1,1:N)>maxvelx))=maxvelx;
vpart(2,find(vpart(2,1:N)>maxvely))=maxvely;


xpart(1,find(xpart(1,1:N)<minx))=minx;
xpart(1,find(xpart(1,1:N)>maxx))=maxx;
xpart(2,find(xpart(2,1:N)<miny))=miny;
xpart(2,find(xpart(2,1:N)>maxy))=maxy;

for kind=2:K

if ploton==1
figure(1)
hold off
for u=1:U
    plot(ap(1,u),ap(2,u),'g.','MarkerSize',60); hold on
end
axis([-5 45 -5 15])
plot(xtrue(1,kind),xtrue(2,kind),'k+','MarkerSize',30); hold on
end

% propose particles
vpart(1,1:N)=vpart(1,1:N)+sigmapartvelx*randn(1,N);
vpart(2,1:N)=vpart(2,1:N)+sigmapartvely*randn(1,N);



vpart(1,find(vpart(1,1:N)>maxvelx))=maxvelx;
vpart(2,find(vpart(2,1:N)>maxvely))=maxvely;
xpart(1:2,1:N)=xpart(1:2,1:N)+vpart(1:2,1:N)+sigmapartpos*randn(2,N);
xpart(1,find(xpart(1,1:N)<minpartx))=15+2*randn(1,length(find(xpart(1,1:N
)<minpartx)))';
xpart(1,find(xpart(1,1:N)>maxpartx))=15+2*randn(1,length(find(xpart(1,1:N
)>maxpartx)))';

xpart(2,find(xpart(2,1:N)<minparty))=minparty;
xpart(2,find(xpart(2,1:N)>maxparty))=maxparty;


% calculate projected measurements
```

```
for u=1:U
  rpart(u,1:N)=sqrt((xpart(1,1:N)-ap(1,u)).^2+(xpart(2,1:N)-ap(2,u)).^2);
%range
  taupart(u,1:N)=rpart(u,1:N)/clight; % time delay
end

% compare projected measurements to true measurements to get weights
% weights=likelihood ratio
sigmagauss=0.00000000000000010;
weights(1:N)=prod(exp(-((taupart(1:U,1:N)-
tau(kind,1:U)'*ones(1,N)).^2)/sigmagauss),1);

weights(find(weights==0))=10^(-10);
weights=weights/sum(weights);

if ploton==1
plot(xpart(1,1:10:N),xpart(2,1:10:N),'b*','MarkerSize',2)
end

% calculate estimate
xhat(1:2,kind)=xpart*weights';

if ploton==1
plot(xtrue(1,kind),xtrue(2,kind),'k+','MarkerSize',30); hold on
plot(xhat(1,kind),xhat(2,kind),'bv','MarkerSize',30)
end

% resampling
[xpartinds]=resample_v2([1:N],weights,N);
xpart=xpart(1:2,xpartinds);

if ploton==1
plot(xpart(1,1:10:N),xpart(2,1:10:N),'r*','MarkerSize',1)
end

if ploton==1
plot(xhat(1,kind),xhat(2,kind),'bv','MarkerSize',30)

end

figure(1)
filename = strcat('TrackingShots_timeindex=', int2str(kind), '.jpg');
saveas(gcf,filename)

pause(0.01)
end %K

if saveon==1
filename   =   strcat('TrackingSingleTimestamp_U=',   int2str(U),   '_N=',
int2str(N), '_K=', int2str(K), '_mcrun_', int2str(MCrun), '.mat');
save(filename, 'ap', 'U', 'K', 'N', 'sigmapos', 'sigmavelx', 'sigmavely',
'xtrue',       'vtrue',       'stopprobabilitythreshold',       'sigmatime',
'sigmapartpos',   'sigmapartvelx',   'sigmapartvely',   'xpart',   'vpart',
'weights', 'xhat')
end

end %mcruns

end %U
```

```
% Resampling Algorithm

function [xnew,wnew,rej] = resample_1rej(xExt,w,M)

len = length(w);

% Cumulative Distributive Function
cumpr = cumsum(w(1,1:len))';
cumpr = cumpr/max(cumpr);

u(1,1) = (1/M)*rand(1,1);
i=1; rej=0; acc=0;
for j = 1:M
    u(j,1)= u(1,1) + (1/M)*(j-1);
    while (u(j,1) > cumpr(i,1))
        i = i+1;
        if i > M
           break
        end
    end

    if i <= M
      xnew(j) = xExt(i);
    end
    if (j<=M) & (i>M)
      xnew(j:M) = xExt(M)* ones(1,M-j+1);

    end
    wnew(:,j) = 1/M;
    ij(:,j) = i;
end

for r=2:M
    if xnew(1,r-1)==xnew(1,r)
        rej=rej+1;
    end
end
```

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