FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Human sensing and indoor location: From coarse to fine detection algorithms based on consumer electronics RF mapping

Duarte Fleming Oliveira de Sousa

FOR JURY EVALUATION

FEUP FACULDADE DE ENGENHARIA UNIVERSIDADE DO PORTO

Mestrado Integrado em Engenharia Electrotécnica e de Computadores

Supervisor: João Paulo Trigeiros da Silva Cunha

Co-supervisor: João Vasco Tavares da Mota Ranito (Movvo)

March 8, 2017

© Duarte Fleming Oliveira de Sousa, 2016

Resumo

Nos dias de hoje, existem varios systemas de human location sensing e contagem de pessoas em espaços públicos. Os mais utilizados têm como base o video e desenvolvidos por empresas como a Footfall. A Footfall conta com milhares contadores de pessoas em portas implementados nos mais diversos espaços. Este tipo de sistemas são cruciais para o retalho. Infelizmente, as soluções baseadas em video sofrem de grandes erros, especialmente quando contando com enormes multidões, por exemplo, o food-court de um shopping em hora de ponta, ou espectadores a sair de um estádio de futebol. Além disso, geralmente só está coberta uma área de contagem muito reduzida ($< 6m^2$).

Neste âmbito, aproveitando-se da technologia Wi-Fi, a Movvo define zonas através de Geofencing nas quais as pessoas podem estar. Na presente tese, o objectivo principal será dedicado a complementar o sistema da Movvo com funcionalidades de tracking de movimento humano em grandes espaços públicos e com um baixo custo computacional. Várias técnicas de localização foram estudadas para encontrar a melhor implementação possível e abordar os problemas de localização em grandes espaços públicos.

Três dos algoritmos mais utilizados no âmbito da localização indoor foram implementados, um de cada tipo: multilateration, weighted centroid e K-Nearest neighbors (KNN). Uma experiência usando a plataforma Movvo foi concebida e implementada de forma a medir a performance das diferentes soluções. Num espaço com 1800 m^2 com uma densidade de sensores de 0.0022 sensores/m^2, os resultados apresentaram um erro médio de localização de 4.195 m, 6.548 m e 12.400 m para KNN, weighted centroid e multilateration respectivamente. Além disso, num espaço distinto de menor área e densidade de sensores 0.04 sensores/m^2, os erros médios de localização desceram para 1.929 m, 2.507 m e 4.495 m, respectivamente. KNN provou ser o melhor em termos de erro de localização. Contudo, o sistema que pode ser implementado mais rapidamente minimizando os custos de instalação é o método weighted centroid. Estas conclusões mostraram-se muito relevantes para as decisões futuras da Movvo de forma a incluir este tipo de funcionalidades de human tracking.

Abstract

There are already several ways of human location sensing and people counting in public spaces. Video is the most widespread one, using products developed by companies such as Footfall. They are today the reference, with literally thousands of sites counting people through doors on a daily basis. Retail could not live without it now. Unfortunately, video-based solutions suffer from large errors, especially when big crowds are involved (think of a shopping center food court in busy hours, or spectators leaving a football stadium) and cover only a very narrow area (< 6 m^2).

However, similarly to the rest of the industry, Movvo does not have a positioning system, instead Movvo defines zones through Wi-Fi Geo-fencing in which humans can be. In the present thesis, the main objective will be devoted to complement Movvo's system with fast, low computational load, motion tracking features algorithms for a RF human indoor position sensing system in large public places.

Several localization techniques were studied to find the best possible implementation to approach the localization problems in large public area scenarios.

Three of the most often used algorithms for indoor localization were implemented, one for each type: multilateration, weighted centroid and K-Nearest neighbors (KNN). A testbed within the Movvo platform was designed and implemented to measure the different solutions' performance. In a 1800 m^2 office space with a sensor density of 0.0022 sensors/m^2, results presented a mean localization error of 4.195 m, 6.548 m and 12.400 m for KNN, weighted centroid and multilateration respectively. Furthermore, when sensor density was increased to 0.04 $sensors/m^2$ mean errors lowered to 1.929 m, 2.507 m and 4.495 m, respectively. KNN proved to be the best in terms of localization error. However, the most rapidly deployable system minimizing installation costs is the weighted centroid method. These conclusions are relevant for Movvo future decisions on evolving their system to include this type of motion tracking human sensing features.

Acknowledgments

This work would not be possible without the help of my colleagues at Movvo. Go Movvers!

To Professor João Paulo Cunha and João Ranito, for all the patience, guidance and inspiration.

I could not pass the opportunity to thank Costa, Bernie and Xico. To my beloved Rita, for her support, encouragement and quiet patience.

Duarte Fleming

"If the facts don't fit the theory, change the facts."

Albert Einstein

Contents

List of Figures

List of Tables

Abbreviations

ACK	Acknowledgment
AN	Anchor Node
AOA	Angle Of Arrival
AP	Access Point
BS	Base Station
CDF	Cumulative Distribution Function
dBm	Decibel-milliwatts
ID	Identification
IPS	Indoor Positioning System
KNN	K-Nearest Neighbors
LAN	Local Area Network
LBS	Location Based System
LOS	Line Of Sight
GPS	Global Positioning System
GSM	Global System for Mobile Communications
NIC	Network Interface Card
NLOS	Nonline Of Sight
QOS	Quality Of Service
RF	Radio Frequency
RSSI	Received Signal Strength Indicator
RTS	Request To Send
SDR	Software Defined Radio
SSID	Service Set Identifier
TOF	Time Of Flight
USRP	Universal Software Radio Peripheral
WCC	Weighted Circumcenter

Chapter 1

Introduction

Human sensing answers the question of how is it possible to detect the presence of people. Nowadays, sensors are absolutely everywhere and being one of the most widespread devices, the smartphones allow every single person to become a moving sensor as such devices are equipped with a variety of these. This means such capabilities could be taken advantage of in order to locate persons for the most diverse purposes, for instance, smart city planning (law enforcement, garbage collection), smart traffic control, emergency, surveillance, health purposes and retail. Although GPS-based systems have been around for a while now and are capable of handling the outdoor positioning task quite successfully, the scenario is not the same for urban areas with high building and population density as well as indoor environments.

Numerous challenges arise when addressing the task of human localization, specially indoors. Active systems which require that the subjects being tracked have participation in the experience are therefore not suitable nor scalable for indoor tracking real world large groups in unpredictable situations. For the purpose of human indoor sensing and real world practical applications, such active systems will only be briefly addressed in the next chapter and will not be considered any further in this manuscript. In this work, passive human indoor localization is achieved by taking advantage of the ubiquitous mobile devices. Moreover, to accomplish this, ranging sensors, access points (APs) in this case, are used. However, changes in the environment such as ventilation systems, the air temperature contribute to the fluctuating propagation of RF signals.

Scalability, low complexity, cost, and minimal infrastructure are the key requirements for a localization system to be widely deployed, and to achieve this, usually systems fall short on accuracy.

1.1 Movvo

This thesis was developed in Movvo.

Movvo is a location analytics company headquartered in London with offices in Porto, which leverages Wi-Fi data in order to track humans in retail spaces.

Movvo's product delivers a software as a service (SaaS).

At the heart of the Movvo product is a cloud-based, behavior analytics engine, which consumes data streams from multiple sensor types and blends with any other data sources to build valuable and robust insight into customer behaviors in physical spaces.

The platform processes data streams in real-time to interpret the behaviors of people in defined locations (geometries). This approach means a constant stream provides a rich dataset of locations that can be queried for business insight.

Movvo attempts to answer questions such as:

- "How many people were here?"
- "What percentage of them went there?"
- "Where else did they go?"
- "How long did they spend there?"
- "Is that different to last time they were here?"
- "Is it different to what happened last week or year?"

1.2 Objectives

The ubiquitous Wi-Fi infrastructure could be used to achieve the task of human indoor localization with a relatively low cost. However, sensor disposition and ever-changing environments filled with thousands of humans everywhere pose a challenge to this task. Most often any attempt to localize will result in a dramatically high error. Movvo has developed a fencing system in order to constrain people inside a certain zone defined by sensor positions. This work attempts to complement Movvo's system by implementing indoor human localization. Hence, the main objective of this work is to develop a localization engine capable of performing in indoor environments using the existing Wi-Fi infrastructure with an acceptable localization error.

1.3 Structure

Following this introduction, this work has five additional chapters. In chapter 2, some background on human sensing and localization is explained as well as a brief survey of the current systems. In chapter 3, a theoretical description of three localization algorithms is presented. In chapter 4, the architecture description, technology overview and methodology of the experiments conducted in this work are made, test bed description and result discussion is done in chapter 5. Chapter 6 provides the conclusions and future work prospects for further contributions to the indoor localization problem.

1.4 Thesis Contributions

This thesis will enable Movvo to add positioning capabilities to their product. The effort made in this thesis will allow the weighted centroid algorithm implementation to be deployed into production in a future release of Movvo's solution. Furthermore, this manuscript contributed to provide knowledge on how sensor density deployment affects localization accuracy and may be adjusted in order to produce various service levels based on the desired localization performance.

Chapter 2

Human sensing, indoor localization and current State of the art

As the title indicates, in this chapter the aim is to introduce theoretical concepts behind human sensing, radio wave propagation and localization. Furthermore, current state of the art systems are briefly described.

2.1 Human Sensing

Human sensing encompasses direct or indirect measuring of human presence through acquisition of information regarding how humans affect the surrounding environment, these effects are often referred as traits. [1]

Traits can be classified as intrinsic, which refer to the individual characteristics of the person itself and these **intrinsic traits** can be subdivided into **static traits**, such as the weight, shape, scent and internal motion (for instance, the heartbeat), and **dynamic traits**, only measured when a person is moving, which include external motion, gait (movement of the hips), and vibrations. Furthermore, there is another type of traits referred to as **extrinsic**, which make use of carried objects such as mobile devices and it can also be subdivided into two categories depending on the flow of the information [1]:

- **Extrinsic environmental traits:** used in an active approach, the information flows from the environment into the device held by the person.
- **Extrinsic borrowed traits:** used in a passive approach, the information flows in the opposite direction, from the mobile device outwards. The characteristics of the device held by the person are used for sensing purposes, for instance, accelerometers, gyroscope, antennas, etc..

Extrinsic borrowed traits (passive) will be the focus of this work in order to extract information through the spatio-temporal properties, explained below and illustrated in figure 2.1.

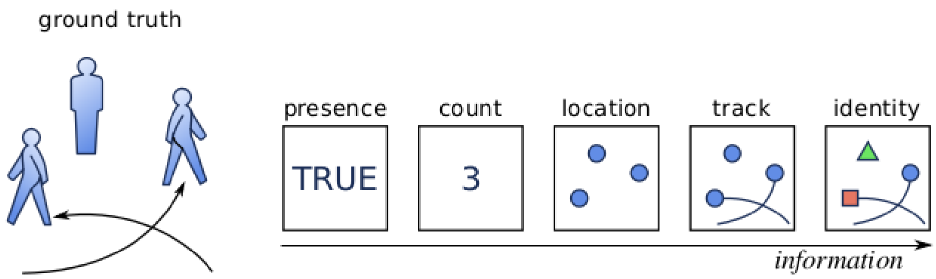

Figure 2.1: Spatio temporal properties measured. From [1]

- **Presence**: the simplest spatio-temporal property to be measured is presence. Presence is either true, meaning there is at least one person in the sensed environment, or false, meaning there is no one in the sensed environment.
- **Count**: refers to the number of people who are present in a particular environment.
- **Location**: this is the process of positioning a person in space. Usually represented in spatial coordinates, this information is static.
- **Track**: tracking is dynamic localization of a target (i.e. gathering information on previous locations of a target in order to build a location history). Tracking provides knowledge for instance, on the paths of the targets. With such knowledge, the most common paths could be determined and predictions about the next locations could also be made.
- **Identity**: for some applications tracking is not sufficient and more information is required, for instance, if the environment was sensed using the WI-Fi infrastructure, the MAC address of a device carried by a person could be stored and used as the identifier for further profiling over time.

2.2 Localization System

A localization system has many components using different technologies all combined together in order to achieve a position.

During the course of this work, the terms location and position as well as localization and positioning will be used interchangeably.

There are several important aspects to consider when evaluating a localization system, usually trade-offs have to be made by system designers, for instance, due to budget or requirement restrictions [2]:

- **Accuracy**: is often a representation of the mean error of the system. In positioning the error is measured as the euclidean distance between the true and estimated position, which is one of the most important requirements. However, accuracy by itself, may not be sufficient to assess if how good or bad the error is. Thus, a distinction between absolute and relative error may be defined, in which absolute error is the mean error of the system, while on the other hand, relative accuracy is the error with a relationship to sensor density, area covered and distance between sensors.

- **Precision**: sometimes confused with accuracy, precision describes how the distance error is distributed and is usually measured through cumulative probability functions (CDF), for instance, a system can have a precision of 50% for 2m (the CDF of 2 is 0.5) and 90% for 5m.

- **Coverage**: is the area covered by the system for accurate localization, different technologies may require different numbers of sensors covering the same area. Sensor density is also important to compare different accuracy and precision tests given that most often a system with higher density of sensors is more precise.

- **Update Interval**: is the time interval in which the location information changes. This requirement is often forgotten, for instance, if an ideal system could locate a person without error, for the purpose of tracking the path of a person walking, a time interval of 5 minutes would not seem very reasonable as there is a long period in which there is no information on the person's behavior.

- **Scalability**: outlines the ability of a system to perform normally when the amount of work increases. Localization systems may have to be able to support larger areas of coverage, for instance by adding more sensors, and to support a larger amount of units to be located.

- **Complexity**: complexity in most cases considered as the computational cost or time in order to perform a task, which in positioning systems directly affects the localization time.

- **Adaptiveness**: ability to encompass changes in the environment, for instance, additional interference cause by the increased number of devices, not to be confused with scalability, new walls and doors built that would block line-of-sight (LOS) with the sensors.

- **Cost**: hardware price, number of sensors, deployment and maintenance time, energy, these all affect the cost.

- **Privacy**: privacy has gained much attention in recent years with the growth of social media scandals and confidential data being exposed for everyone to see, hence network users may not appreciate their localization to be known without their knowledge.

2.2.1 Active vs. Passive

When pondering implementations for a given application an important factor to take into consideration is the interaction of the parties involved. For a specific solution a system could be designed and improved in order to meet the requirements, for instance if a system has a beacon approach, it may increase interactions with devices sensed. However, such system may lose invisibility and may not be applicable for security purposes as it may attract unwanted attention.

2.3 Radio Wave Propagation

Radio waves travel at the speed of light (c), approximately, 3.00×10^8 m/s in free space (or vacuum). Outdoors, the GPS is highly capable of handling the task of positioning. This is due to the fact that satellite signals have LOS which is the propagation in which there are no obstacles between the transmitter and the receiver. [3] Contrarily, indoor environments are full of obstacles between the transmitter and the receiver, thus LOS propagation is sometimes not possible. Such obstructions (e.g. doors, walls, desks and even humans), give rise to many phenomena that affect the propagation of RF signals [4]:

2.3.1 Reflection

When a wave encounters an object or a surface of dimensions much larger than the wavelength of the propagating wave, it is reflected. The incident wave encounters the object with a certain angle of incision, and is reflected with the same angle . Even though reflections are an important phenomenon in wireless communications in order to extend coverage, some part of the signal is absorbed by the reflecting object, which can produce unexpected fluctuations on the signal power on the receiving end.

2.3.2 Diffraction

Objects with sharp edges obstructing the path between the transmitter and the receiver cause diffraction. Diffraction effect is explained by Huygens' principle, which states that each point on a wavefront, for instance, a well-defined obstruction to an electromagnetic wave, can act as a secondary source, thus creating a new wavefront. This new wavefront propagates into the geometric shadow area of the obstacle. This is perhaps the most important aspect of this phenomenon as it allows propagation in shadowed regions, for instance, indoors, diffraction on wall edges and doors provides additional coverage to the site, as illustrated in figure 2.2. The simplest example is when a person is standing inside a room and is able to hear sounds from an adjacent room.

2.3.3 Scattering

Scattering occurs when a propagating wave encounters a high density of objects with dimensions much smaller than the wavelength of the propagating wave causing it to scatter, i.e. radiate in multiple directions, similar to a light beam propagating through fog, as illustrated in figure 2.3.

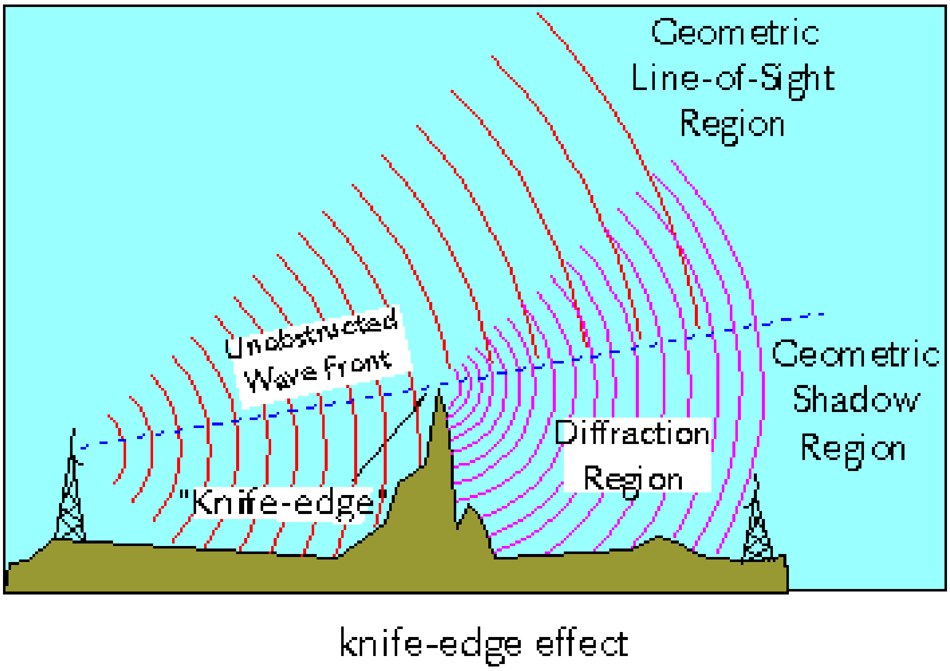

Figure 2.2: The radio wave encounters a sharp edge and that point acts as a secondary source. Taken from [5]

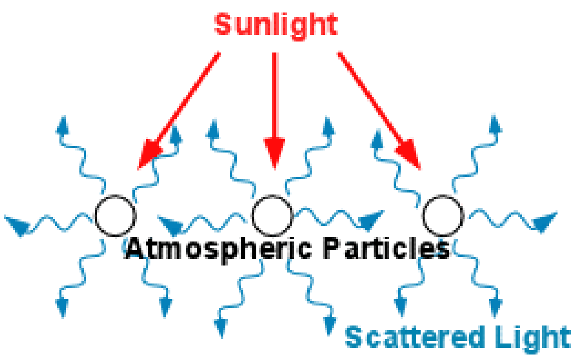

Figure 2.3: Light waves encounter small particles in the atmosphere and scatter in multiple directions. Taken from [6]

2.3.4 Multipath Propagation

As a result of the different phenomena the radio wave is able to reach the receiving end via multiple paths, these paths combine together resulting in the received signal. This is what is known as multipath propagation.

For small distances, usually a few wavelengths, multipath propagation will not affect path loss very much. However, as distance varies, the different paths contribute with different magnitudes and angles, causing the signal to fade [7].

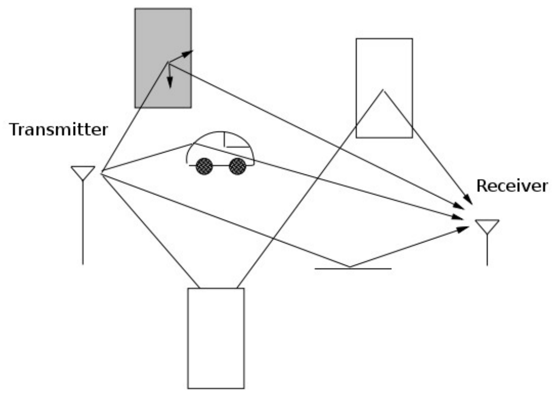

Figure 2.4: Multipath results of the combination of reflected, diffracted, scattered and direct components of radio waves propagation from the transmitter to the receiver. Taken from [7]

2.4 Indoor Propagation Models

Indoor propagation does not follow the same models as outdoor environments. The reason for this is that there are too many variations through time that add randomness to the environment, for instance, there are always doors opening and closing, and different amounts of people moving. The same phenomena of outdoor radio propagation, reflection, diffraction and scattering are present indoors. However, due to the randomness of these indoor scenarios, these effects become rather unpredictable.

The path loss is the difference in transmitted and received power resultant from the propagation through space, as illustrated in figure 2.5.

Free Space Path loss, which is the path loss in vacuum, in dB is given by:

$$PL(dB) = 10 \log P_t / P_r \tag{2.1}$$

where P_t is the transmitted power in expressed in Watts, and P_r is the Power received by the receiver, also expressed in Watts.

Rappaport [8] introduced the Log-Normal Shadow Model for indoor environments, in which the path loss is given by:

$$PL(dB) = PL(d_0) + 10n \log \frac{d}{d_0} - X_\sigma \tag{2.2}$$

where $PL(d_0)$ is the PL at a reference distance, usually $1m$, n is a parameter used to estimate indoor propagation models called path loss exponent (PLE), which differs from one environment to the other based on room temperature, air pressure and many other factors that would impact radio wave propagation, and X_σ is a random Gaussian variable expressed in dB that reflects the shadowing effects, with standard deviation σ in dB. d is the distance between the transmitter and the receiver , expressed in m, and it is given by:

$$\frac{d}{d_0} = 10^{\frac{PL(dB)-PL(d_0)+X\sigma}{10\times n}} \tag{2.3}$$

Although this is a widely accepted model and is the most used [9], it faces many challenges and is yet to accurately model indoor propagation. Several efforts have been made concerning this model and the path loss exponent [10] [11] but even the slightest changes in the environment will result in erroneous values propagating such error into poor distance and location estimations.

Log-Normal Shadow Model, is most often the model from which RSSI based indoor localization methods estimate distance to targets. Therefore, this method will be used in this work despite the challenges in indoor localization, given its simplicity, in order to quantify how would this method perform in a real system.

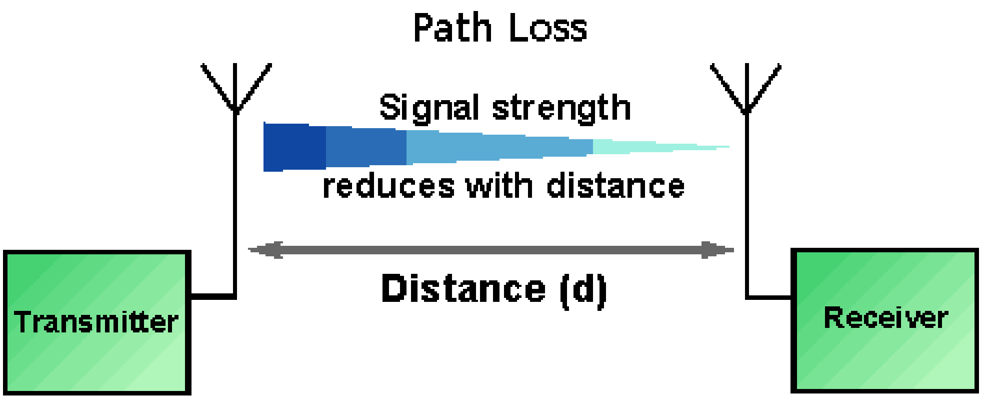

Figure 2.5: Free space path loss is the difference between power received by the receiver and the transmitted power by the transmitter. Taken from [12]

2.5 Existing Techniques

2.5.1 Angle of Arrival (AOA)

From angle based techniques, often referred to as direction finding techniques, AOA is the angle between the direction of the signal's propagation and a reference direction, see figure 2.6.

The main advantage of this technique is that only two angles are required for positioning when in LOS. On the Other hand, this technique requires LOS and therefore is not suitable for the majority of technologies in indoor environments. Furthermore, as distance increases this method tends to be more error prone [13].

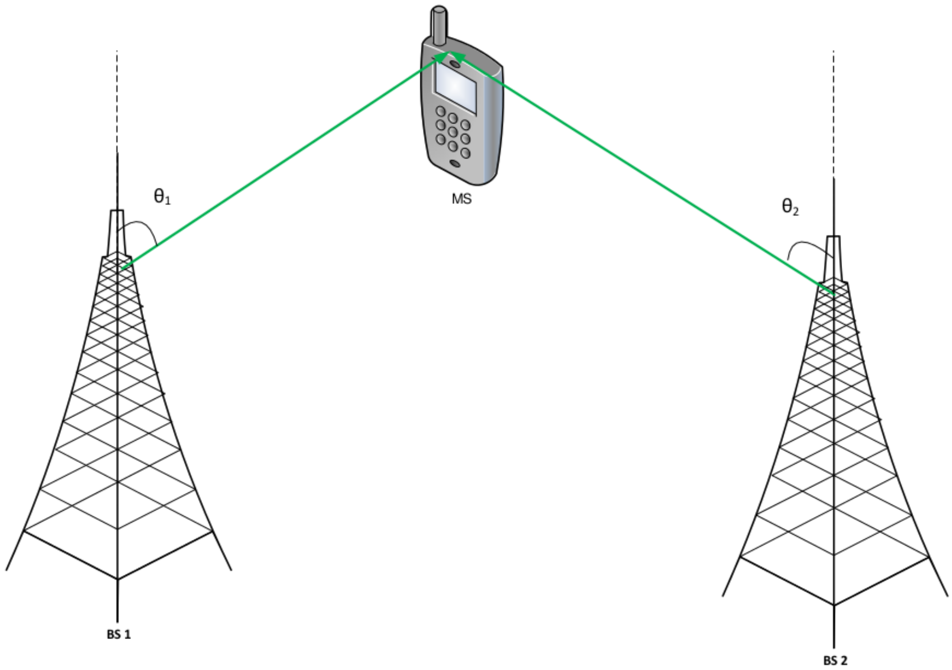

Figure 2.6: Angle of arrival technique.Taken from [14]

2.5.2 Time of Arrival (TOA)

The basic principle behind time of arrival is measuring the time that a signal takes from the transmitter to the receiver, known as time of flight (TOF), and multiplying that time by the speed of light, c. After computing the distance, a circle centered at the anchor node and with radius equal to the estimated distance of the traveling wave is drawn, see figure 2.7. Three measurements from three distinct anchor nodes are used in the trilateration algorithm see figure 2.8 [15].

TOA is the most accurate method because electromagnetic waves travel with a known constant velocity. This method brings many disadvantages, the first being it requires highly synchronized precise clocks because a difference of a few nanoseconds could result in a few meters of distance error. The second downside of this method is the need for LOS. Any path other than the direct path, will take longer to reach the receiver and will consequently result in a greater TOF, which after computing the distance, translates into an overestimated distance. Moreover, the cost of these implementations tends to be higher when compared to other alternatives.

2.5.3 Received Signal Strength Indicator (RSSI)

Power-based approaches can be grouped into three categories: site survey based, usually referred to as fingerprinting, propagation model based, and proximity detection based.

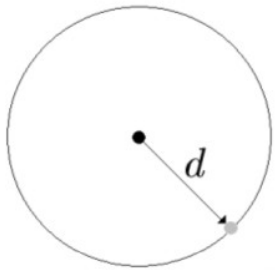

Figure 2.7: Circle centered at the anchor node and d is the distance estimation based on RSSI from equation 2.3. Taken from [16].

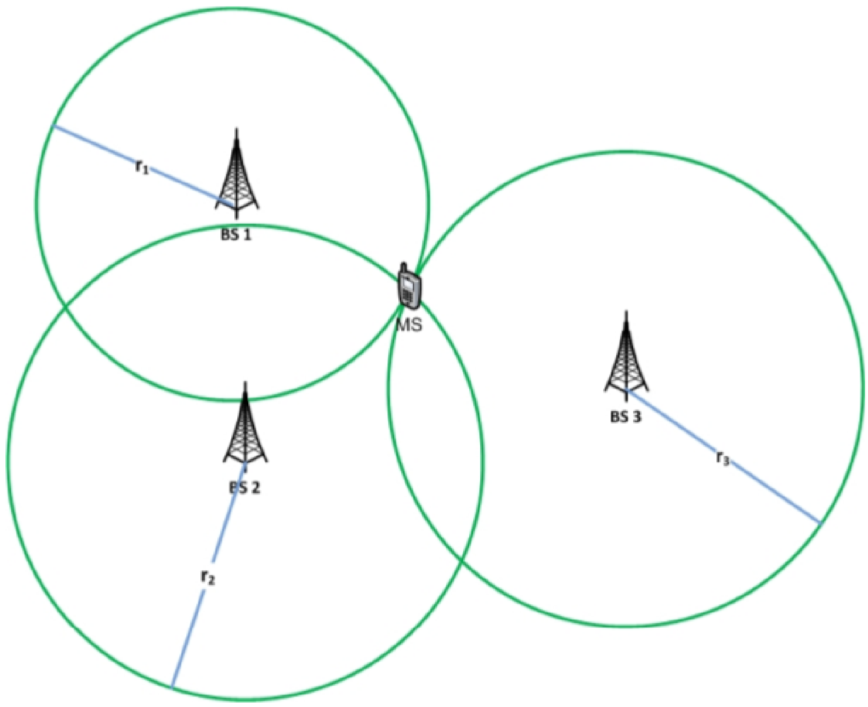

Figure 2.8: Trilateration positioning using TOA or RSSI ranging based techniques. Taken from [14]

2.5.3.1 Propagation Model Based

A generic localization system consists of sensors (anchor nodes), which are usually access points spread out to cover the area of interest, and mobile devices held by humans in order to be localized. Pajovik *et.al.*[17] used RSSI measurements, which provides information on the power of a received signal and may be used to compute the power loss of signal propagation and the distance. In order to acquire distance information through RSSI measurements, a path loss model was used and the problem with these models is the path loss exponent is site specific and therefore the authors made efforts in order to estimate this exponent using a statistical approach. Although the reported average localization error was below 4.5m, the targets were not moving. Ideally in a two-dimensional scenario, when an anchor node receives a signal and estimates the distance from the RSSI, a circle centered at the anchor node is created indicating that the signal could have been received from an unknown direction, see figure 2.7, three of these circles are then used for trilateration of the target. This approach may be extended to more than three anchor nodes, usually referred to as multilateration. However, in a real scenario the shape centered at the anchor node is not a well defined circle because of the interference. Moreover, omni-directional antennas have some degree of directivity.

The most desired feature about RSSI based approaches is that the most important global scale technologies all share RSS measurements and therefore an algorithm will be applicable to multiple technologies. Another advantage that is naturally a bias towards choosing to use RSSI is due to the ability to take advantage of the widespread WiFi networks, dramatically reducing the deployment costs.

2.5.3.2 Proximity Detection

This is perhaps the most basic of positioning techniques and the most widely used in sensor networks. A target is positioned by determining if it is near a known location. This type of approach does not require additional information on the target being tracked and usually employs geometric algorithms such as centroid method. The author in [18] proposes a comparison between linear weighted centroid method, combined differential RSSI and weighted circumcenter (WCC) geometric methods and showed that the WCC algorithm performs better than the others for locations outside the convex hull formed by the sensors nodes.

The granularity of this low complexity method is proportional to the number of sensors, i.e. as the number of sensors per area increases, the region around each sensor decreases. Cellular network employs this technique for coverage and for handling mobility through other cells, for instance, the mobile device is located in the area surrounding a cell which detects the mobile device with the strongest signal. Furthermore, this technique is not capable to pin point a target, but rather to estimate, with great confidence, that the target is within that cells range of coverage. Hence, to achieve a finer granularity more cells are needed for each of the sub-areas to become smaller.

Proximity detection can take advantage of signal strength measurements in order to associate the mobile device to the strongest receiving anchor node in a situation where areas overlap, but as the signal strength is not directly used to perform localization, thus the distinction from RSSI based approaches.

2.5.3.3 Site Survey (Fingerprinting)

This technique is divided into an offline, or a training phase, and an online phase [19]. In the offline phase, radio measurements are taken on site in order to create a radio mapping of RSSI values to (x,y) for instance.

This method benefits from acquiring the largest amount of measurements per area so a dense radio map can be generated. Afterwards, the online phase will take place and the actual localization is performed by comparing the received RSSI values to the radio mappings in the pre generated database.

The robustness of this localization technique relies on the performance of the matching algorithm, for instance the K-nearest neighbors. RADAR [20] makes use of K-nearest neighbors (KNN) algorithm to find the closest match between the RSSI and previously measured database (fingerprint). This is done by computing the minimum Euclidean distance between the fingerprint and the target. Klepal $et.al.$ [21] was able to achieve $1.6m$ of accuracy, by exploiting a probabilistic method of choosing sensor nodes through Gibbs distribution. Although this system has an acceptable performance indoors, it took 8 years to be developed, and since a sufficiently large number of measurements over time, combined with a good matching algorithm can help mitigate most of indoor propagation effects, a tedious and time consuming training phase needs to be done for proper database construction. Thus, many concerns arise, one being the increased deployment time due to the extensive training phase, that precludes this technique from some applications, for example, emergency response. Another concern is the constant need to update radio maps because of changes in the environment.

2.5.4 Software Defined Radio Based Techniques

Software defined radio (SDR) provides a simple method to implement even the most complex wireless communication systems. This is possible considering the signal processing is implemented in software instead of hardware and therefore can be performed by a personal computer. Having a personal GSM system is relatively easy to accomplish with universal software radio peripheral (USRP), and may be used for localization purposes as shown in [18]. Although RSSI techniques are used in the literature for GSM (Global System for Mobile Communications) indoor localization, due to constraints imposed by the company in which this work was developed, only Wi-Fi will be considered further in this thesis.

2.5.5 Movvo Indoor Localization Approach

Movvo's approach to the indoor localization is a very conservative proximity detection. This technique is most often referred to as geo-fencing [22].

In order to obtain maximal confidence in the data provided Movvo developed a zonal architecture, in which each sensor has a zone ID associated and therefore a device in the proximity of that sensor will be considered to be in that zone.

This is done by measuring the RSSI received at each sensor and choosing the one which has the highest RSSI.

Such approach raises a couple of challenges. On one hand, the localization error of Movvo's system is proportional to zone size, this makes it impossible to quantify and in order to increase localization accuracy, smaller zones need to be defined. Whilst on the other hand, additional attention is required when planning sensor deployment in order not to create blind spots, i.e. locations in which a mobile device is not detected. Additionally, in the unlikely case of a mobile device being detected by two sensors in different zones, i.e. different zone IDs, however, with the same RSSI, the second highest RSSI value is used to decide in which zone the mobile device is positioned.

Movvo's system was not included in the state of art techniques as Geo-fencing is not a positioning system.

Hence, this section was meant to give context to this thesis.

2.6 Summary

Wireless indoor localization systems and techniques have been extensively studied and surveyed and after careful review of the literature present in [23] [24] [25] [26], and despite being a coarse measurement, RSSI, enables different approaches to take advantage of the existing Wi-Fi infrastructure, which is available practically everywhere. Moreover, this allows a global scaled low cost solution when compared with other techniques. Hence, RSSI will be used throughout this work.

The next chapter describes three algorithms, which will later be used in a real world indoor environment, based on the most used RSSI techniques described in this section and in the literature, multilateration, proximity detection (weighted centroid) and fingerprinting (using KNN).

Chapter 3

Localization Algorithms

This chapter presents a description of three algorithms that attempt to address the localization problem and consequent challenges using three RSSI techniques discussed in section 2.5.3.

Additionally, a section is dedicated to propagation model calibration, which will be latter used.

As this work was intended to address localization in a practical manner, a pragmatical need to quantify how would studied methodologies perform in an uncontrolled, real world environment. Therefore, this work focuses on the most widespread algorithms in the literature regarding RSSI indoor localization (i.e. propagation model based, proximity detection and fingerprinting methodologies). Moreover, a theoretical analysis on the behavior of such methodologies when faced with a hypothetical real system is presented.

Later, an analysis on the parameters described in section 2.2 will be made and all three algorithms compared.

3.1 Calibration

As previously referred in chapter 2, in order to use Log Normal Shadow Model described in equation 2.2 for an indoor environment, the path loss exponent, n, needs to be measured on site.

One way of doing this is to perform an analysis using sensor infrastructure, as all sensor positions are known, Log Normal Shadow model can be used to calculate the path loss exponent n, given by:

$$n = \frac{PL - PL_0 - X_\sigma}{10 \times \log \frac{d}{d_0}} \tag{3.1}$$

where PL is the RSSI received, PL_0 is the RSSI received at a reference point, X_σ represents unknown multipath and other effects, with mean 0 and variance σ^2, d is distance, in m, between the transmitter and receiver, and d_0 is the reference distance, at which PL_0 was measured.

Since sensor positions are known, equation 3.1 can be used to calculate n.

In order to help mitigate multipath and other effects which cause RSSI measurements to fluctuate, sometimes severely jumping from -50 dB to -75 dB and returning to -50 dB for no apparent reason in consecutive measurements, when in LOS, RSSI is aggregated during a time period dependent of the desired application. Moreover, in an attempt to add more information to the path loss exponent calculation, RSSI measurements from every sensor can be used to obtain more information about the propagation.

As such, figure 3.1 illustrates a setup in which AP1 receives RSSI measurements from every sensor and calculates an n for each corresponding measurement. Afterwards, all n values are averaged, resulting in the estimated n given by:

$$\hat{n} = \frac{1}{N} \times \sum n_i \tag{3.2}$$

where N represents the number of sensors RSSI used in the calculations, and n_i is the n value calculated for each RSSI measurement.

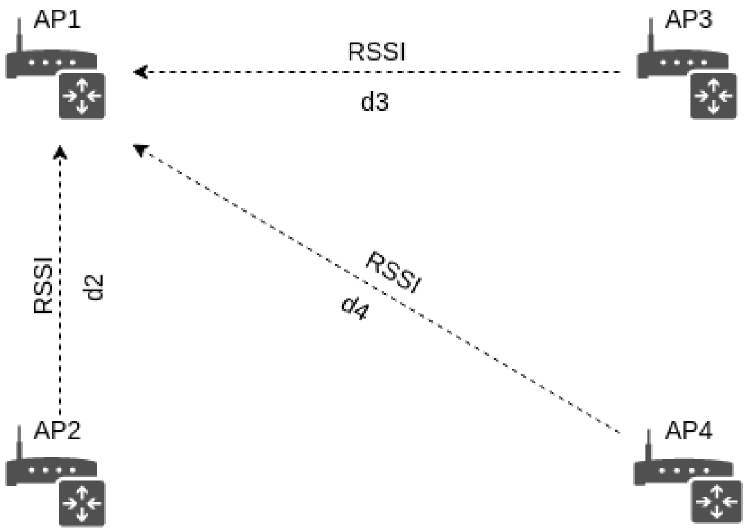

Figure 3.1: Calibration illustration. For a defined time window, AP1 measures RSSI incoming from every sensor. Since the distance to each sensor is known and the RSSI at a reference distance is also known, equation 3.1 may be used to calculate the path loss exponent as the average of the obtained values.

This work intends to develop a system capable of target localization, and as the vast majority of such targets will be in movement a 3 second time window was chosen.

The average human walks at a speed of 1 to 1.5 m/s [28], thus, in a 3 second period, the human could be at a maximum distance of 4.5 to 5 m apart from the original position, which, for the purpose of this work is perfectly acceptable.

Applying the same indoor propagation model to every scenario without careful consideration of all parameters and situations can be naive.

Additionally, using the same model to estimate the distance between every sensor and the mobile device would mean every sensor behaves exactly the same way, statement which this work will later prove to be false.

Hence, equation 3.2 will be used for each sensor in order to estimate one path loss exponent per sensor, instead of one for the whole space.

3.2 Algorithm 1: Multilateration

Being the most widespread propagation model when addressing RSSI based localization, Log Normal Path Loss suggests a natural approach to relate received signal strength and distance.

Equation 2.2 indicates a non-linear relationship between RSSI and distance traveled from the transmitter to the receiver in which as signal strength decreases, distance increases at a much higher rate.

In ideal free space conditions, non obstructed signals follow this propagation model as none of the phenomena described in section 2.3 occur, and as such, the path loss exponent, n, is 2. However, assuming the same value of n for a highly dynamic and uncontrolled indoor environment filled with obstacles, would be naive, and as such, the path loss exponent may need to be computed empirically through measurements.

As this method relies on estimating some distance based on signal attenuation, variations in the environment, i.e. obstructions, will severely alter the reality, for instance, consider the setup in which two APs, AP1 and AP2, are distanced by 10 meters and the received signal strength by AP2 is -65 dBm. Consider now the situation in which AP1 and AP2 are also distance by 10 meters, however there is a wall separating the two APs, the signal attenuation will be much higher and therefore, the same propagation model would compute the attenuated signal, -80 dBm, for instance, into a far higher distance, thus erroneously predicting the position.

Leveraging a classic approach for positioning, trilateration seemed almost a natural choice to perform localization since distances could be derived from RSSI. The trilateration term refers to the fact that three sensors are used, however, more sensors may be used. Hence, this algorithm may often be referred to as multilateration, in this work consider the terms interchangeable.

This method relies on the intersecting circles centered in the APs (figure 3.2) and with radius equal to the computed distance, i.e. perceived distance to the mobile device. Note that emphasis should be put in perceive, as this algorithm is naively blind when considering RSSI measurements, thus, increasing the error whenever there is a disturbance in signal propagation.

Possibly the greater challenge of this algorithm is when circles do not intersect. This is due to fluctuations in RSSI, and a higher instantaneous signal strength may cause the perceived distance to the APs to be lower, which would mean a smaller circle radius and, therefore, the algorithm would fail to localize the mobile device.

Faced with fluctuating RSSI and non intersecting circles, a simple extension for the trilateration algorithm was to define margins for computed distance, creating a ring, instead of a circle. This ensures that at least the two outer circles of the ring intersect. See figure 3.3.

Margins for these ring representations are calculated for each sensor by using the estimated n from equation 3.2 in distance calculation. Furthermore, the difference resultant from this estimated and real distance is averaged for each sensor and is given by:

$$e = \frac{1}{N} \times \sum d_i \tag{3.3}$$

in which e, expressed in m represents an average of the sum of individual errors in sensor to sensor distance and will be used for margin, N is the number of RSSI measurements used to calculate the error and d_i is the distance from one sensor to the ith sensor.

Whenever a new mobile device is detected, e will be used to define the inner and outer radius of the ring for each sensor. The inner circle radius is given, in m by:

$$r_{=} d(RSSI) - e \tag{3.4}$$

where d(rssi) is distance computed from the RSSI and e is the margin. Note that, there is a constraint here, as the radius can not be a negative number. Hence, this operation is only valid for every $d(RSSI) > e$

And the outer circle radius is given, in m by:

$$r_{=} d(rssi) + e \tag{3.5}$$

where d(rssi) is distance computed from the RSSI and e is the margin.

After the intersection is guaranteed, the estimated position is the centroid of the area defined by the intersection points which form the smallest area.

3.3 Algorithm 2: Weighted Centroid

This algorithm is much more conservative as accuracy is proportional to the density of sensors. Increasing the number of sensors per unit of area will decrease the localization error, however, this measure will also increase deployment and installation costs. Hence, there is a trade-off between increasing accuracy and maintaining the costs as low as possible.

The mobile device's estimated position is given by:

$$C = \frac{\sum w_i \times P_i}{\sum w_i} \tag{3.6}$$

where C is the estimated position of the mobile device, i.e. the weighted centroid, w_i is the weight correspondent to the RSSI received for sensor i, and P_i is the position of sensor i.

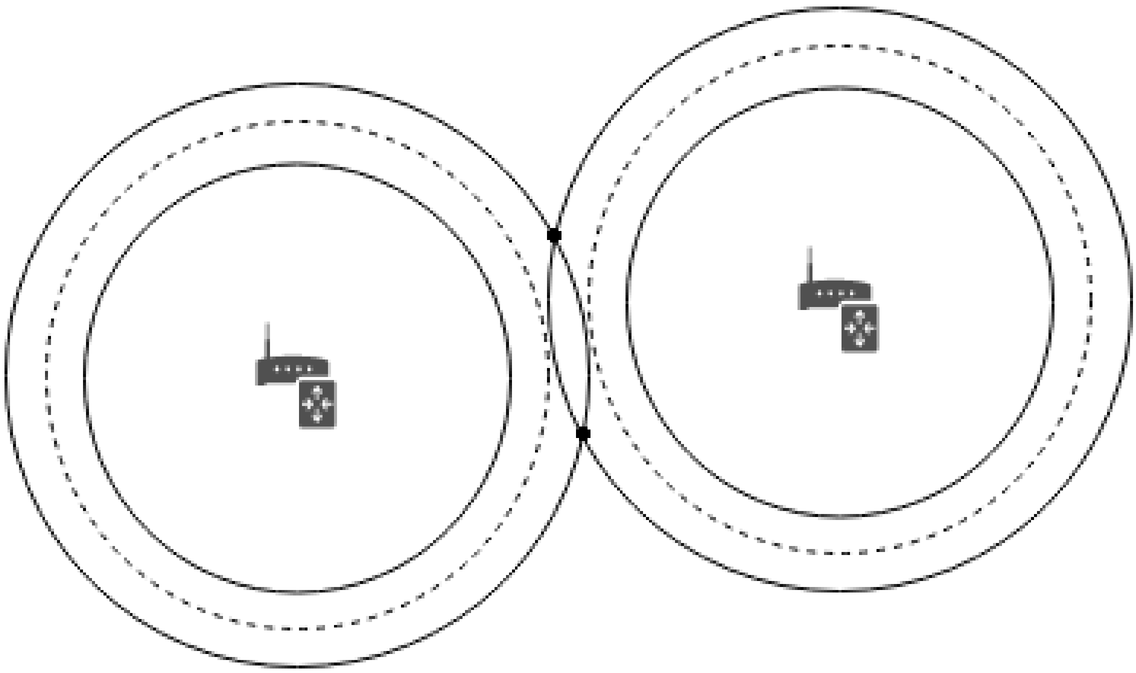

Figure 3.2: Extended circle representation. As illustrated, dashed circles, which represent computed distance from RSSI, would not intersect, thus, a margin is added to the interior and exterior of the circle. This increases the chances of an intersection.

Figure 3.4 shows how three APs contribute to pull the centroid towards them based on their weights [29].

Proposed weight is calculated as:

$$w = \frac{1}{d(rssi)} \tag{3.7}$$

in which the weight is w, and d(rssi) is the distance computed from RSSI using equation 2.3.

When using converted RSSI into distance for weight calculation, sudden RSSI drops will result in correspondent weight drops, which will essentially means that if an AP somehow measures a suddenly much lower RSSI while the others maintain the expected values, this suddenly fluctuation in RSSI will translate into a much greater distance, using equation 2.3, which will ultimately translate into a weight of nearly zero compared to the others, meaning this AP with a bad RSSI will be removed from the centroid calculation.

This method assumes targets to be localized are within the geometric polygon define by APs, as in figure 3.4.

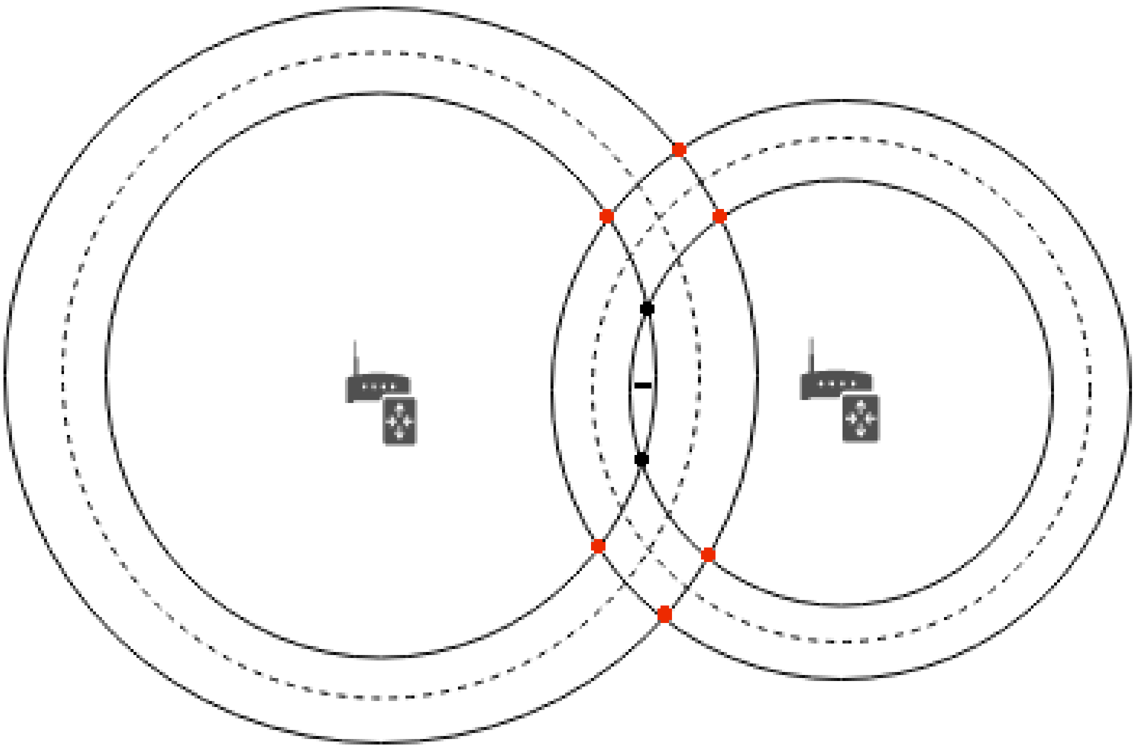

Figure 3.3: Inner circle intersection. The red points represent outer intersections, while the black dash represents the centroid of the two inner intersections, and therefore, the mobile device estimated position.

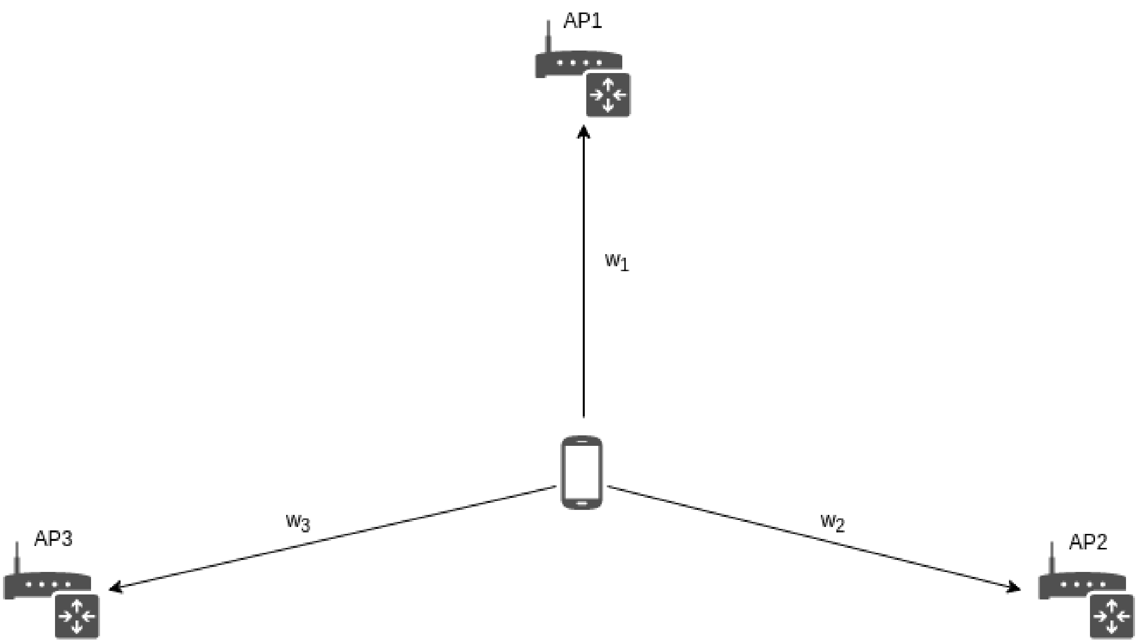

Figure 3.4: The sensor polygon centroid is shifted towards each sensor based on a weight.

3.4 Algorithm 3: Supervised Learning with KNN implementation

3.4.1 Training Phase

As mentioned in section 3.2, the need for a method that would better model the space in order to correctly correlate signal strength and a specific position was obvious.

Motivated by this challenge, fingerprinting techniques, leverage site specific properties otherwise unseen by a radio wave propagation model. The most basic example is the case of obstructions.

Figure 3.5 illustrates one such example, in which APs receive a specific set of RSSI measurements from the mobile device. Note that AP3 receives an RSSI of -80 dBm due to the obstructed path to the mobile device. Using the log normal path loss, the sensor would compute a higher distance than the other sensors even though the mobile device is equally distanced from all of them.

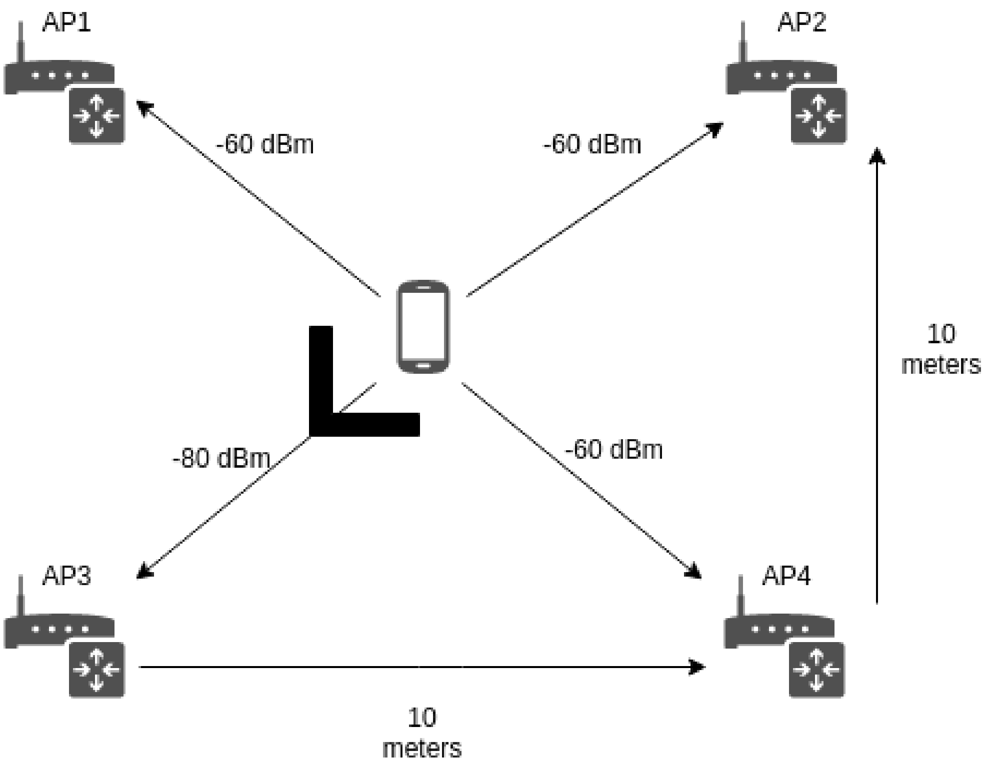

Figure 3.5: Scenario in which a wall obstructs LOS with AP3, severely attenuating received signal strength.

Possibly the most important feature of such approach is that for each location, a set of specific measurements from all sensors will be stored in a database of radio measurements creating a radio map, which means that for situations such as the one illustrated in figure 3.5, the database stored measurements for that location will contain information in which for that specific location a lower set of RSSI measurements is expected. Thus, reducing the localization error.

As this method is to be used on new unseen RSSI measurements, a database of previous examples of sets of RSSI values and the expected output positions is required, this relies on collecting samples directly on site and link every sample to a specific location, which means a tremendous amount of work has to be put into measuring enough samples in order to build a robust database, i.e. training dataset.

In order to build the training dataset, each of the collected samples was attributed a class. In supervised learning, or in this case, classification, classes are attributes which represent the output of the sample [30]. In the context of indoor localization a class is point which is represented by a set of Cartesian coordinates.

All classes should be equally distributed in order to achieve a balanced dataset.

3.4.1.1 Feature Selection

As mentioned earlier, in order to build the training dataset, a set of RSSI measurements from every sensor would be attributed a class for every location. This set of RSSI measurements used for training and afterwards testing are called features, which represent information about the observation.

In the context of indoor localization, there are N features, where N is number of APs.

In large spaces where there are locations in which all APs do not detect the mobile device, a different approach needs to be used in order to assure the same number of features, i.e. RSSI measurements, is used by the pattern matching algorithm.

One way to approach this is to have sensor IDs as features.

3.4.2 Classification Phase

After the sample collection and the training phase, new sets of RSSI measurements are grouped and sent to the classifier in order to achieve a position estimate.

The chosen classifier is a well known and used many times in the literature, K-Nearest Neighbor classifier (KNN) [31].

KNN is a non-parametric classifier which computes and stores the distance from other samples and finds the K nearest. This algorithm finds the distance between samples in a two dimensional space using euclidean distance equation expressed by:

$$d(P_1, P_2) = \sqrt{(P1_x - P2_x)^2 + (P1_y - P2_y)^2} \tag{3.8}$$

The purpose of this algorithm is to match the set of measured RSSI during the classification phase with one or more fingerprints previously store in the database.

As illustrated in figure 3.6, the algorithm calculates the distance between every training sample and observation, afterwards, the class which has the highest number of occurrences between the neighbors is selected as the class of the observation.

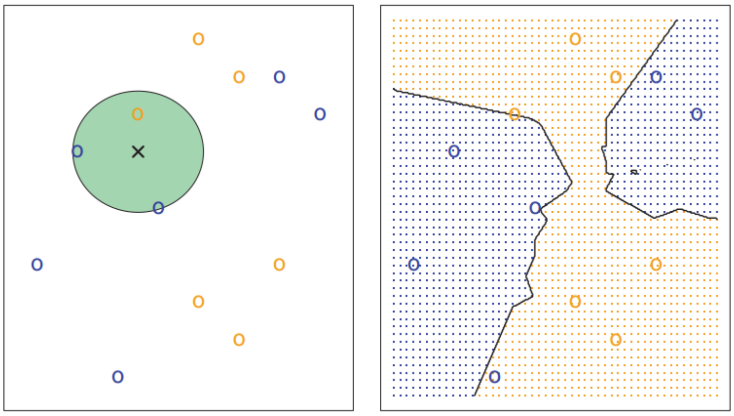

Figure 3.6: K-Nearest neighbors illustration. On the left, the black cross (unseen observation) will be classified as the most commonly occurring of the three nearest neighbors. On the right side, the Voronoi diagram representing classification decision boundaries, is illustrated. Taken from [32].

These fingerprints can contain many types of features dependent of the implementation. In this case, in order to address and account with temporal instability, sample collection time of 1 minute was enough to capture some irregular behaviors of RSSI measurements, thus storing for each location, both expected and unexpected behaviors. Another approach is to store as a fingerprint the average of RSSI obtained for each sensor at every location. Such method is used in RADAR [20], and served as motivation for this work.

The most captivating advantage of this method is the simplicity.

3.4.2.1 Data splitting

In order to assess the performance of predictions of the classifier a validation procedure needs to ensure that the same dataset used for training of the KNN is not being used for testing purposes, as this would result in an astonishingly biased prediction in which every observation would have an exact match in the training dataset [33]. Hence, a proper dataset splitting is necessary to split the dataset into two distinct datasets, one for training and one held out specifically for testing purposes.

The splitting method which will be used in the experimental procedure is to randomly split the data set into 80% for training and 20% for testing, these percentages are based on similar principles studied in the literature [34] [35].

Above-mentioned literature describes more methods and K-fold cross validation, in which the original dataset is split into k smaller ones and only k-1 are used for training and the remaining one for testing, is the most often used one as well as the one described above.

3.5 Comparison

All three algorithms have advantages and disadvantages, table 3.1 offers a comparison regarding calibration effort, deployment cost, adaptiveness, described in chapter 2.

Calibration effort relates to the time consumed between installing the sensors and the system to be ready to perform.

	Calibration Effort	Cost	Adaptiveness
KNN	Bad	Bad	Very Good*
Multilateration	Very Good	Very Good	Good
Weighted Centroid	Very Good	Very Good	Good

Table 3.1: Comparison of key aspects of all algorithms. *Note that the robustness of a KNN approach is dependent of the fingerprint database.

Although KNN can in theory provide with good localization results, the extensive amount of time consumed in order to build a solid training dataset can pose as a blockage when deciding which technique to deploy, due to the fact that human resources need to be deployed as currently there is no automation framework for the radio mapping collection process, thus, raising the costs.

Calibration effort in both multilateration and weighted centroid are residual when compared to the KNN.

Both weighted centroid and multilateration have good adaptiveness due to the fact that both algorithms can perform in every possible location of a space, independently of the density of obstacles. On the other hand, KNN, can be very adaptive if the database of RSSI measurements contains a sufficiently high number of samples to account for every possible situation.

3.6 Summary

This chapter introduced three algorithms which will be used later in this thesis. Three different approaches were used in order to diversify and better understand the possibilities and challenges of each.

The next chapter describes the technology leveraged in this thesis to approach indoor localization.

Chapter 4

Passive Wi-Fi Localization

This chapter will provide an overview on the technical aspects of the work, starting with a brief description of the system architecture, later, an explanation on Wi-Fi properties involved in communications which can be exploited, and lastly, technology used for sensor and mobile devices used will be presented. Additionally, a section describing the situation in which a human is sensed with some testing and discussion about the future of solution will be included.

4.1 System Architecture

4.1.1 Distributed Processing

Given the great amount of sensors required to cover a large area, a distributed approach allows the flexibility to add or remove sensors without overloading a central server as spectrum analysis and processing is performed by each sensor.

The distributed messaging architecture, illustrated in figure 4.1 is used by Movvo and as such, its usage was imposed. Moreover, in Movvo's case information flow from the sensors to each specific application is based upon a client server topic subscribe messaging transport protocol, MQTT [36], in which workers, in this case the sensors, generate messages containing the processed information that is afterwards published with a topic to the broker, for instance "wifi". The broker is responsible for handling message publishing, subscription and topics.

Moreover, whenever a client, i.e. an application, wishes receive messages, a connection to the broker has to be established and the desired topic needs to be subscribed in order to start communication.

4.1.2 Security And Privacy

The proposed system complies, throughout all stages, with information safety and privacy. Prior to being stored, the MAC address, which is the only information captured and necessary for distinguishing multiple mobile devices, and ultimately multiple individuals, is ciphered using a cryptographic hash function SHA-256 [37]. This ensures the data captured is treated according to the

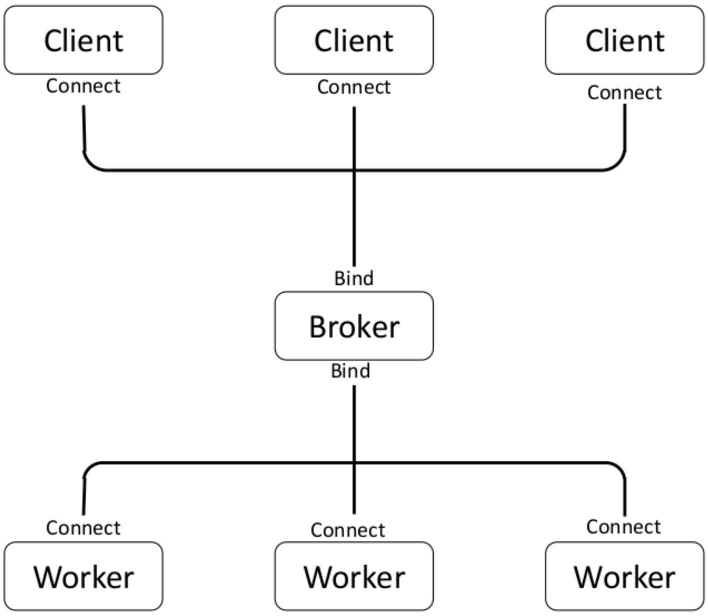

Figure 4.1: Achitecture of distributed messaging protocol. Taken from [14]

highest standards in information protection and management.

4.2 Localization Sequence

A mobile device initiates interaction with the system, illustrated in 4.2 by emitting an 802.11 frame, most often a probe request, which is captured by the sensor.

Afterwards, some processing is done, a message containing information regarding the sensor, timestamps, MAC address of the device captured and the RSSI, is published to the topic.
The broker is responsible for managing topics and therefore, publishing incoming messages to the localization API. In this stage, the API prepares every available information in order to be latter fed into the localization engine. The output in this stage is the set of RSSI measurements for each mobile device.
The localization engine then, according to the used algorithm, computes an estimate of the device's position. The output for this is the final position estimation.

Figure 4.3, shows how RSSI data flows from mobile devices into the customer viewing the dashboard. Furthermore, the localization algorithms described in this work will be processed by the Key Performance Indicators (KPI) & Localization Engine shown in the figure.

Furthermore, in appendix A, a state diagram representing system states and transactions is included.

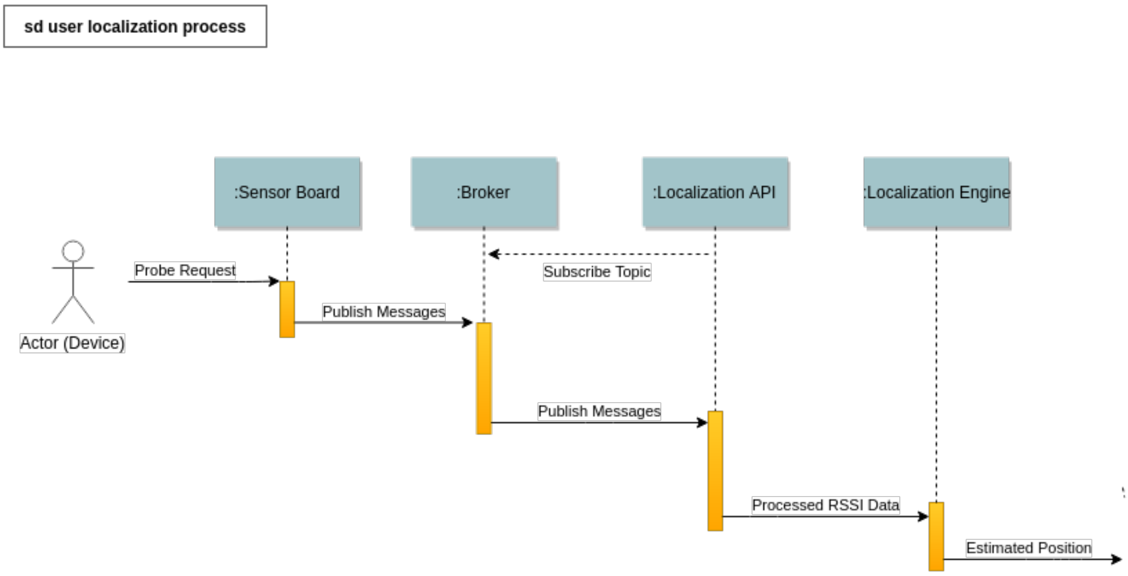

Figure 4.2: Localization Sequence Diagram.

4.3 Wi-Fi (802.11)

In order for a system to be non-intrusive and invisible, the mobile device data acquisition process needs to leverage some communication property.

APs are responsible for connecting mobile devices to the network. In order to start communication with the network (through the AP), a specific control process, denoted here as 802.11 association request, has to be followed, as illustrated in figure 4.4.

The mobile device requiring association with an AP, initiates as **not authenticated**. This scenario occurs, for instance, when the mobile device has just entered the vicinity of the AP[39].

802.11 frames may have information regarding the transmitter or destination address, as such, frames broadcasted by the mobile device can be captured using a sniffing software. The sniffing software used by the company, captures the following 802.11 frames [39]:

- **Probe Request:** this is possibly the most alluring packet to be captured considering it is an advertisement of the mobile device's presence. Mobile devices send probe requests in order to discover other devices who share similar 802.11 capabilities such as data rates and encryption types. These management frames were initially designed for WEP based encrypted authentications and therefore are widely considered vulnerable.

- **Association request:** sent by the mobile device, this management frame carries the network SSID to which the mobile device intends to connect establish a connection.

- **RTS:** request-to-send are optional frames designed to reduce collisions in multiple access communications.

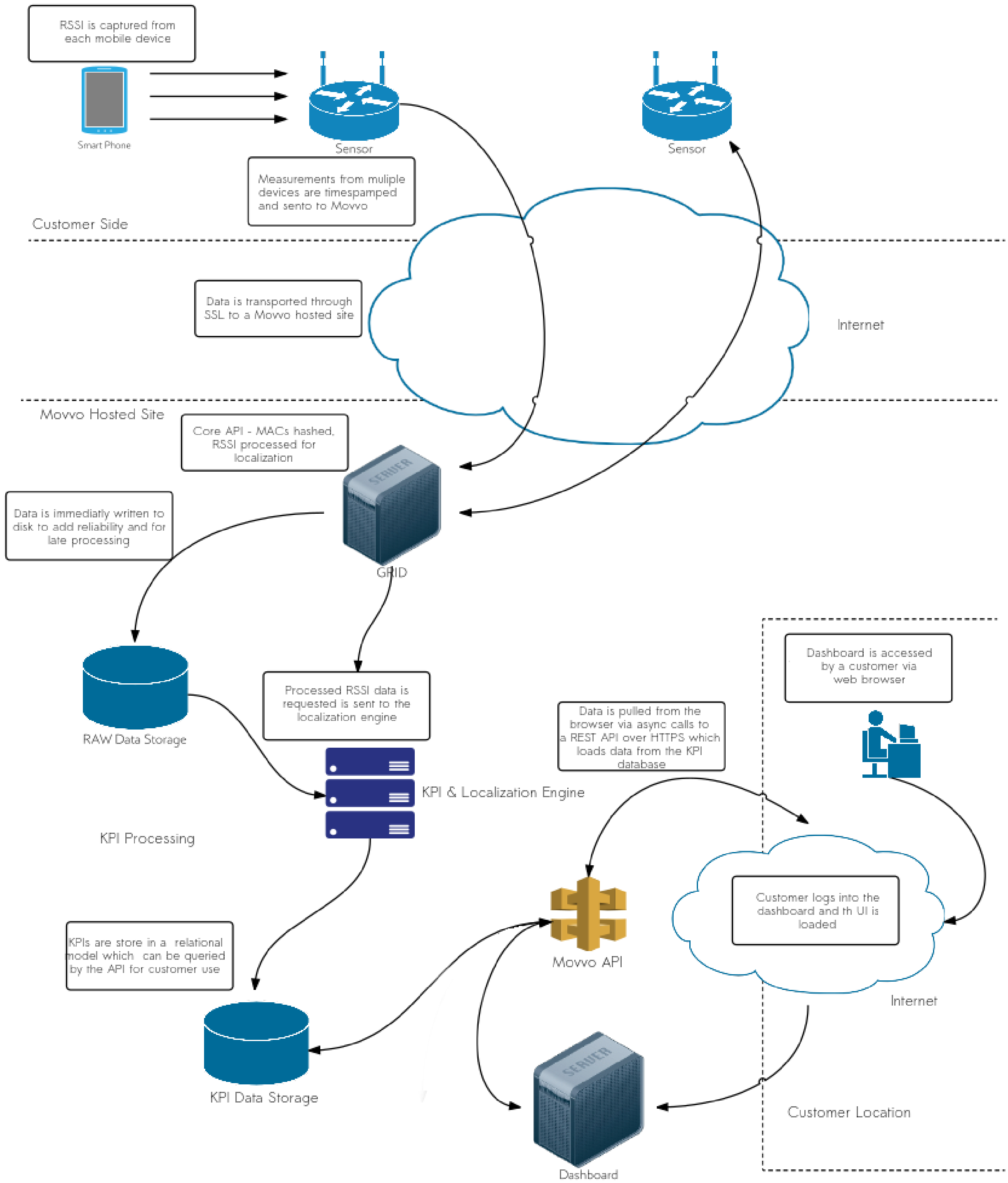

Figure 4.3: Movvo infrastructure. Developed localization algorithms are incorporated in the KPI & Localization Engine.

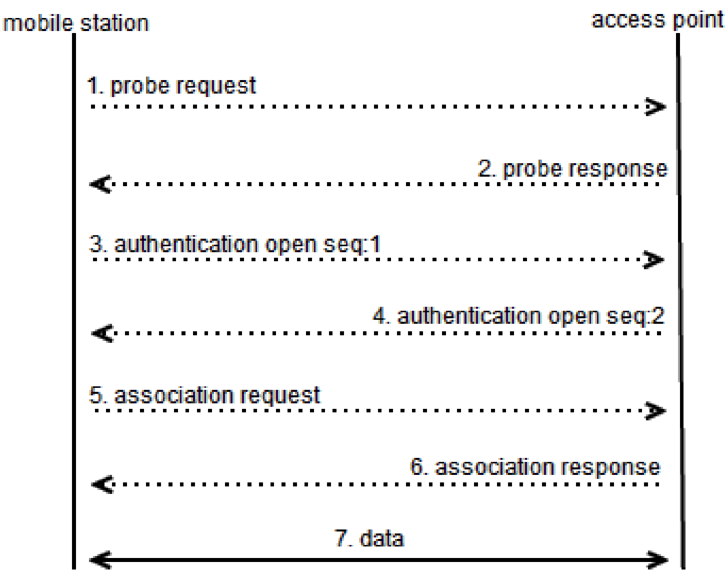

Figure 4.4: 802.11 Association request setup. Figure based on [38]

- **Disassociation:** frames alert the AP to disassociate the mobile device, for instance, when the NIC is shutting down.
- **PS-Poll:** is a legacy poll based management frame which frames are buffered while the device is in power saving mode. Afterwards, buffered frames are sent to the device when a PS-Poll is receive by the AP.
- **Deauthentication:** is sent to the AP in order to end communications.
- **Block-ACK:** groups several ACK into one frame, thus, improving the efficiency of 802.11 communications.
- **Data:** frames contain protocols or data from higher layers, for instance web browser packets or files.
- **Data Null:** these frames carry no data and serve the purpose of providing the AP with information regarding the power saving mode of the mobile device. Moreover, the power management bit in the Null data frame is set to 0 if the mobile device is not in sleep mode or power saving mode and is set to 1 if the mobile device is entering sleep mode or in a power saving mode.
- **QoS Data:** frames carry QoS control information to regulate communication on parameters such as priority and ACK policy.
- **QoS Null:** similarly to Data Null frames, QoS Null carries no data and the main purpose is to inform the AP of power management status.

Table 4.1 shows statistics of processed Wi-Fi traffic, more specifically the 802.11 frames previously described in which the sniffing software is able to acquire the MAC address of the mobile device.

Although the highest number of occurrences is because of request-to-send collision avoidance frames, they are produced by a surprisingly low number of unique MAC addresses.

Probe requests take 59.9% of the unique MAC addresses, which was expected, since every mobile device with the Wi-Fi interface turned on, even in sleep mode, will broadcast probe requests.

Association requests unique MAC addresses and low number of occurrences suggest that a relatively low percentage of people connect to the public Wi-Fi offered in this shopping mall.

Table 4.2 shows all traffic captured by Movvo's sensors and indicates in column Processed which frames provide mobile device MAC addresses.

4.4 Technology Setup

4.4.1 Development Software

The development of all three algorithms was possible using programming language Python [40].

Frame Subtypes	Unique MACs	Total Occurrences	% Uniques	% Occurrences
Association Request	123	231	3.2	0.1
Probe Request	2268	40932	59.9	19.6
Disassociation Request	48	1200	1.3	0.6
Deauthentication	39	546	1.0	0.3
Block ACK	276	33111	7.3	15.8
PS-Poll	45	3876	1.2	1.9
RTS	234	65685	6.2	31.4
Data	12	135	0.3	0.1
Data Null	351	35538	9.3	17.0
QoS Data	348	26349	9.2	12.6
QoS Null	42	1488	1.1	0.7
Total	3786	209109	100.0	100.0

Table 4.1: Frame statistics of 802.11 frames captured by Movvo's sensors for one hour, during the afternoon peak hour of a shopping mall.

Frame Subtype	Hex	# Received	% Of Total	Processed	# Processed	% Processed	% Of Total Processed
Association Request	0x00	71	0.0	yes	71	0.0	0.00
Association Response	0x01	111	0.0	no	0	0.0	0.00
Reassociation Request	0x02	47	0.0	no	0	0.0	0.00
Reassociation Response	0x03	70	0.0	no	0	0.0	0.00
Probe Request	0x04	20024	0.7	yes	20024	0.7	1.29
Probe Response	0x05	119485	4.0	no	0	0.0	0.00
Beacon	0x08	347434	11.7	no	0	0.0	0.00
Disassociation	0x0a	8	0.0	yes	8	0.0	0.00
Authentication	0x0b	552	0.0	no	0	0.0	0.00
De authentication	0x0c	149	0.0	yes	149	0.0	0.01
Action	0x0d	11995	0.4	no	0	0.0	0.00
Block-ACK Request	0x18	10271	0.3	no	0	0.0	0.00
Block-ACK	0x19	502559	16.9	yes	502559	16.9	32.32
Ps-Poll	0x1a	1107	0.0	yes	1107	0.0	0.07
RTS	0x1b	524894	17.7	yes	524894	17.7	33.76
CTS	0x1c	483090	16.3	no	0	0.0	0.00
ACK	0x1d	438084	14.8	no	0	0.0	0.00
CF-End	0x1e	2865	0.1	no	0	0.0	0.00
Data	0x20	86464	2.9	yes	86464	2.9	5.56
Data Null	0x24	104754	3.5	yes	104754	3.5	6.74
QoS Data	0x28	298004	10.0	yes	298004	10.0	19.17
QoS Null	0x2c	16870	0.6	yes	16870	0.6	1.08
Total		2968908	100.0		1538034	52.4	

Table 4.2: Frame statistics for one hour at Movvo's Office.

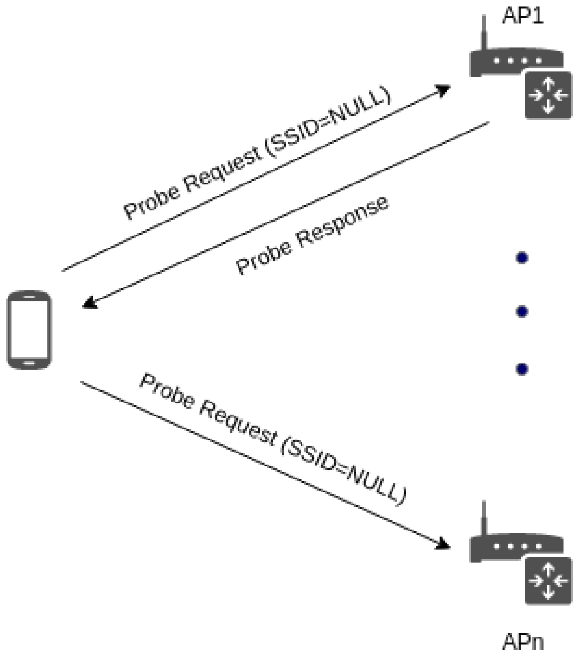

Figure 4.5: 802.11 Mobile device broadcasts probe request packets to every AP in range.

Python is a multipurpose programming language with possibly one of the largest communities nowadays.

The main reason why Python programming language was chosen is due to Python library Scikit-Learn [41], which is a machine learning simple tool containing implementations of the most wide variety of machine learning algorithms and tools, from which the KNN and data split algorithms will be used in this work. Since, both multilateration and weighted centroid do not require complex implementations Python was used to develop the localization API and engine, described below:

- **localization API** consists in a single module responsible for processing RSSI contained in messages coming from the sensors, in order to prepare data for the localization engine. This module runs on Movvo main server (GRID) and is illustrated in figure 4.3.

- **Localization engine** contains three submodules which hold all three algorithms.

  Class diagram of algorithm implementations and a system state diagram are included in appendix A.

4.4.2 Capturing Software

The capturing software which will be used throughout this work is intellectual property of Movvo and as such will not be discussed in this work. However, in some tests, Wireshark [42], was used due to it's extended features and simplicity.

4.4.3 Sensor Setup

At the time of this work, Movvo installations, and therefore all experiments in this thesis, used TP-Link MR3420, fig 4.6, as . Hardware characteristics are described below:

- **Interface:** 1 USB 2.0 Port for LTE/HSPA+/HSUPA/HSDPA/UMTS/EVDO USB Modem 1 10/100Mbps WAN Port, 4 10/100Mbps LAN Ports, support the auto-Negotiation and auto-MDI/MDIX.
- **Dimensions (W x D x H):** $8 \times 5.4 \times 1.7$ in. $(204 \times 138 \times 44$ mm)
- **External Power Supply:** 12VDC/1A.
- **Antenna Type:** Omni directional, Detachable, Reverse SMA
- **Antenna Gain:** $2 \times 5dBi$
- **Wireless Standards:** IEEE 802.11b, IEEE 802.11g, IEEE 802.11n.
- **Frequency:** 2.4-2.4835 GHz
- **Transmit Power:** <20 dBm

4.4.4 Propagation Symmetry

At first, the idea of two sensors distanced by 10 m in LOS measuring the same RSSI of one another, see figure 4.7, and that propagation between the two is symmetric, did not seem far-fetched, however, figure 4.8, shows there is no symmetry in the propagation of radio waves in a 60 seconds measurement.

This is mainly due because 802.11 frames are not sent exactly in the same instant of time, devices may increase or decrease transmitting power due to power saving profiles, the 802.11 channel in which the AP is listening also interferes.

Although it is clear two sensors from the same manufacturer and from the same batch behave differently, no conclusion can be drawn as to the real cause of these effects.

Given that sensor reciprocity is not guaranteed, it would be wise to develop a model which would account for this, and would penalize sensors that would behave differently from expected.

4.4.5 Mobile Device Setup

In order to test if device specific characteristics affected RSSI measurements, six devices, in LOS with the sensor, were used in order to test if device .

All six devices were positioned at a distance of 5 m in LOS with the sensor, as illustrated in figure 4.9. A total of 200 samples were collected, for each device, over the course of 5 minutes.

The list of devices used is:

Figure 4.6: TP-Link MR3420. Taken from [43]

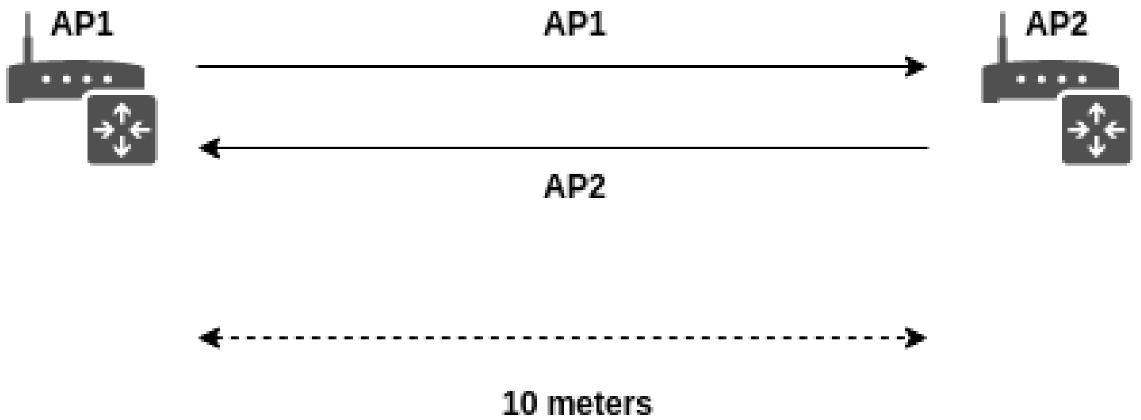

Figure 4.7: RSSI captured from AP1 and RSSI captured from AP2. AP1 represents the RSSI measured from 802.11 frames emitted by AP1 and captured by AP2. AP2 represents the opposite

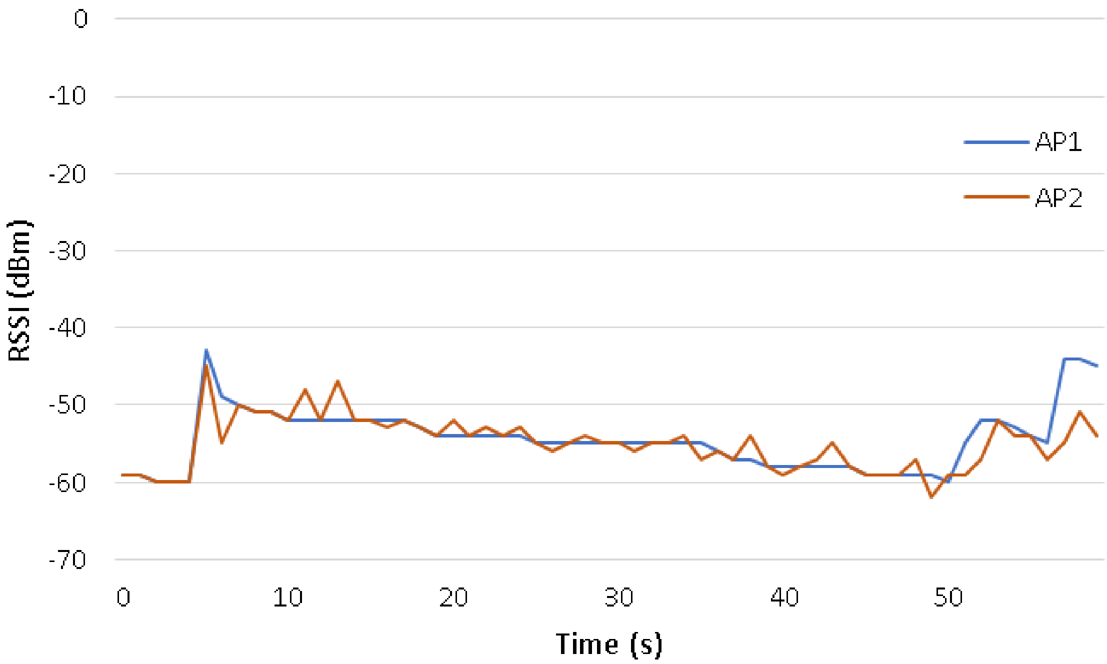

Figure 4.8: RSSI measurements for two sensors, 10 meters apart, AP1 represents the RSSI measured from 802.11 frames emitted by AP1 and captured by AP2. AP2 represents the opposite.

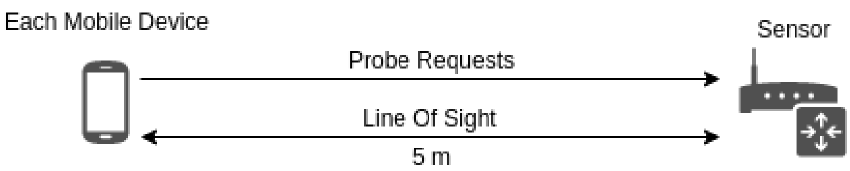

Figure 4.9: Device measurement setup, at a distance of 5 m during 5 minutes. This setup was replicated for each device.

- Apple Iphone 6
- HTC One M8
- Huawei Y8
- Samsung Galaxy S2
- Samsung Galaxy S7
- Wiko Ridge 4G

Every device showed a different behavior, as illustrated in figure 4.10. However, differences in median between mobile devices were less than 3dB in a 5 meter range. Both the Iphone 6 and Samsung Galaxy s2 suggest a normal distribution. Additionally, results show no indication of manufacturer specific behavior, since both Samsung devices have different values.

Although no conclusion can be drawn regarding whether such deviation in RSSI measurements was due to multipath effects or manufacturer specific characteristics, a real system needs to be robust enough to abstract of such impact and therefore, address all mobile devices independently of the localization technique used.

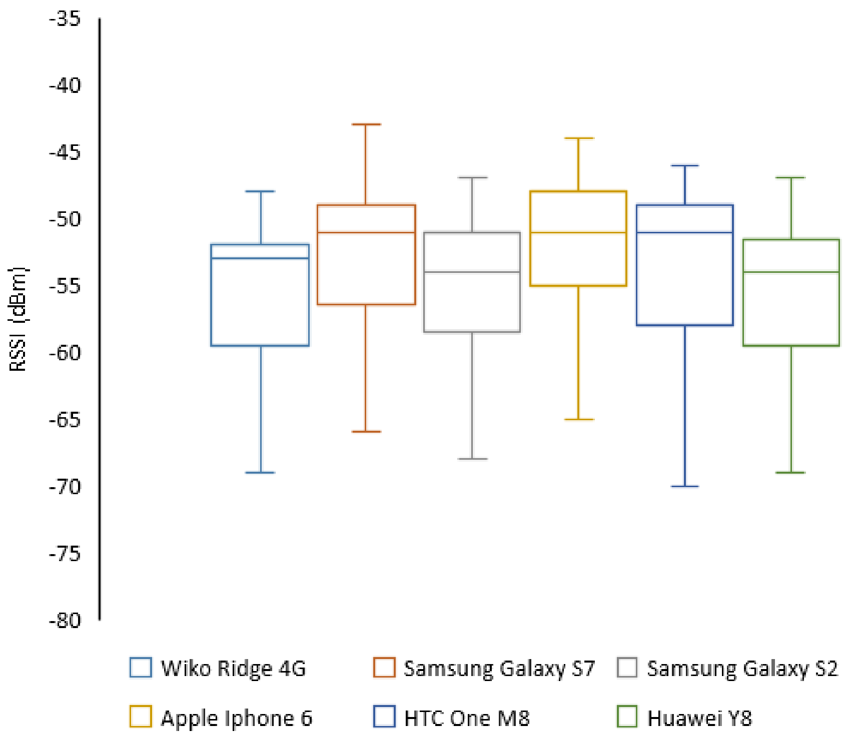

Figure 4.10: Box Plot of RSSI measurements for six different mobile devices, taken at a distance of 5 *m* from the sensor. For each device, 200 samples were measured over the course of 5 minutes.

4.4.6 Environmental Effects

Environmental changes such as air temperature, ventilation and electromagnetic interference affect radio wave propagation. Furthermore, in an attempt to quantify the impact of such effects on the propagation, RSSI measurements were collected throughout a 24 hour period of time and averaged by hour. These measurements were collected in the food-court testbed, which opened for public at 09:00 and closed at 00:00. This allowed to assess how the increase in number of devices would impact radio propagation.

Throughout the day over 5000 people passed through a 1800 m^2 area and during peak hours, from 12:00 until 13:00, and from 19:00 until 20:00, the number of mobile devices inside this area was 950 and 887, respectively.

Illustrated in figure 4.11 is the setup which was used to verify if changes in the environment impacted RSSI measurements, in which two APs were distanced by 40 meters and AP1 broadcasted an 802.11 frame every second for a 24 hour period. Afterwards, the RSSI measurements were averaged by hour.

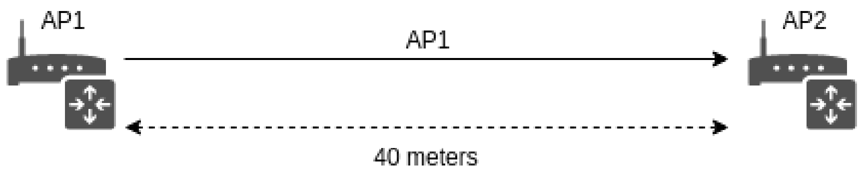

Figure 4.11: Environmental effect measurement setup, two APs distanced by 40 m during 24 hours. AP1 periodically sent an 802.11 frame every second and measurements were averaged every hour.

Figure 4.12 shows the variation of captured RSSI averaged by hour throughout a full day and during opening hours there is a noticeable decrease in signal strength with minimum values during peak hours, i.e. from 18:00 until 19:00, which could slightly degrade the localization performance.

In terms of instantaneous RSSI, a setup in which the mobile device was in LOS with the sensor at a distance of 5m, as in figure 4.9, allowed RSSI measurements to provide knowledge about the behavior for 1 minute captured during closing hours, the results are shown in figure 4.13. During 60 seconds, these RSSI measurements registered 7 spikes, dropping RSSI in more than 15 dBm. Although no conclusion can be drawn as to the causes of such effect, there seems to be a pattern in which after a spike, another one is followed a few seconds later.

A similar test was conducted at 13:00 (peak hour), and the same variation was observed except the average RSSI decreased 3 dB, which is expected since the hourly average RSSI also decreased.

4.4.7 Update Interval

In a typical day-to-day situation, mobile devices do not always have the screen on, in fact, often people carry their mobile devices, i.e. smartphones, in their pockets. Manufacturers have different power saving profiles and security and privacy policies, i.e. MAC randomization in probe requests, thus, it is expected that different phones have different behaviors in terms of how many probe requests mobiles devices broadcast and how often do they do [44].

Table 4.3 reflects the results of a test conducted to confirm update interval of the probe requests with the mobile device in sleep mode, performed with an Apple manufactured Iphone 6, a common high end smartphone at the time of this work.

As a side result, and although MAC randomization is not relevant for anonymous static localization given that captured 802.11 frames from an invalid MAC address still represent one device,

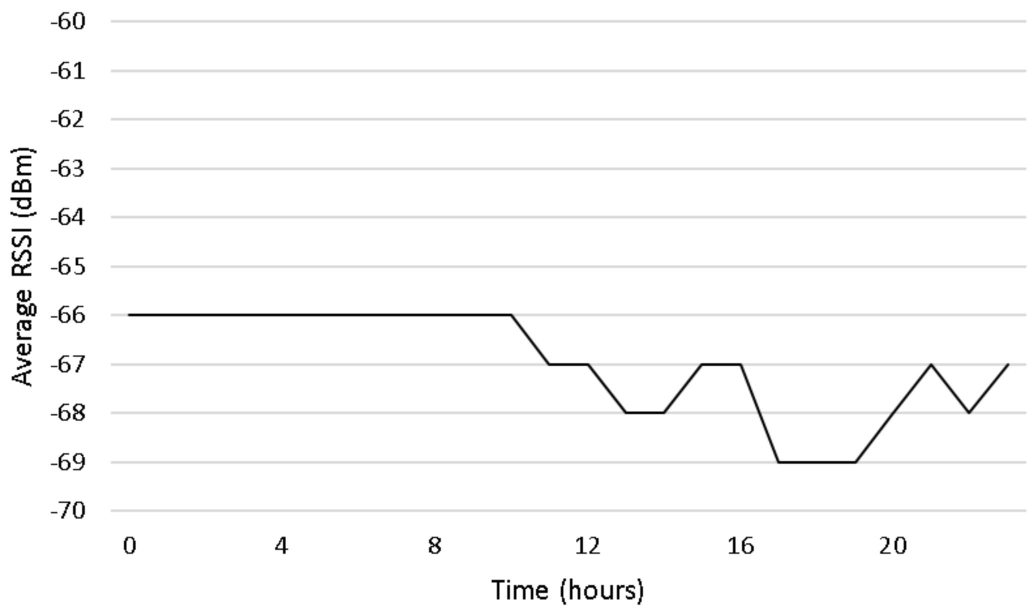

Figure 4.12: RSSI measurements averaged by hour captured by AP2 distanced by 40 *m* from AP1 during 24 hours. AP1 periodically sent an 802.11 frame every second and measurements were averaged every hour

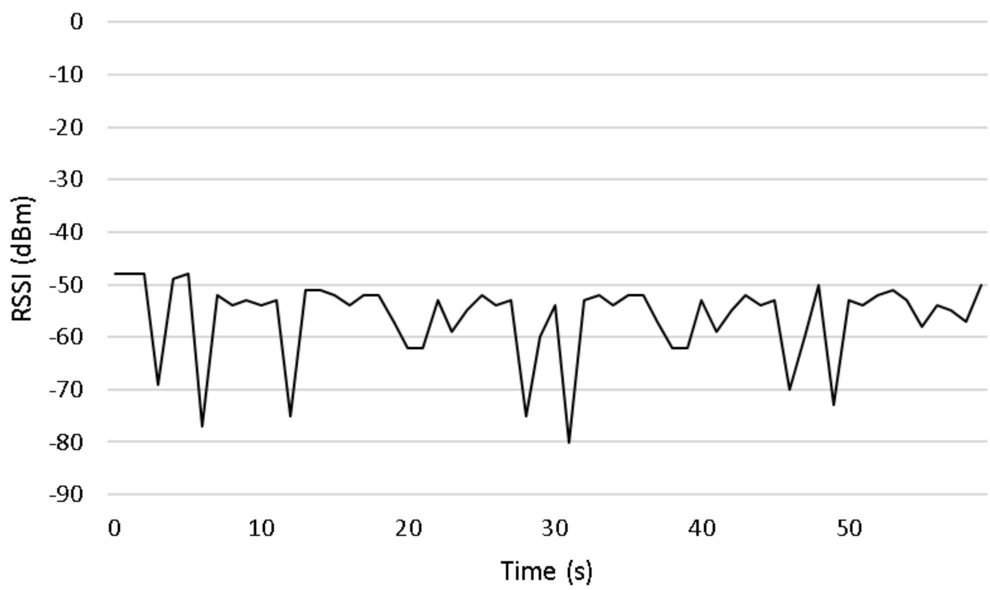

Figure 4.13: Instantaneous RSSI measurements from a mobile device at a distance of 5m in LOS with the sensor.

when faced with identity localization, for instance, applications which require tracking, MAC randomization becomes a big challenge.

Figure 4.14, shows MAC address structure in which the three most significant bytes (24 bits), represent the Organizationally Unique Identifier (OUI) and represents the manufacturer of the network card.

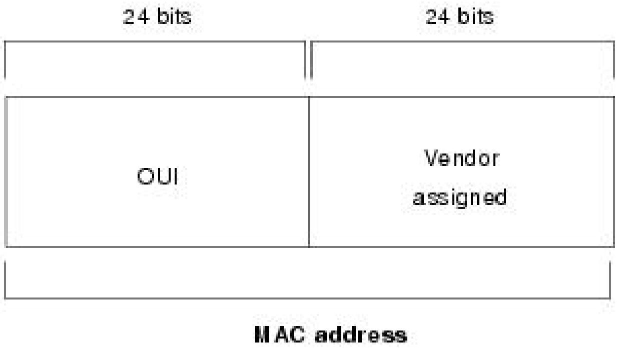

Figure 4.14: MAC address structure. Taken from [45].

Therefore, this paragraph is dedicated to discuss figure 4.15, in which a single device in sleep mode, i.e. screen turned off, for 30 minutes, produces 8 different MAC addresses whose OUI are not registered in the IEEE OUI list [46], even though for each of the 802.11 frames sent by these MAC addresses, probe requests clearly show vendor specific tags. Moreover, table 4.4 shows that 76.4% of unique MAC addresses captured during are randomized.

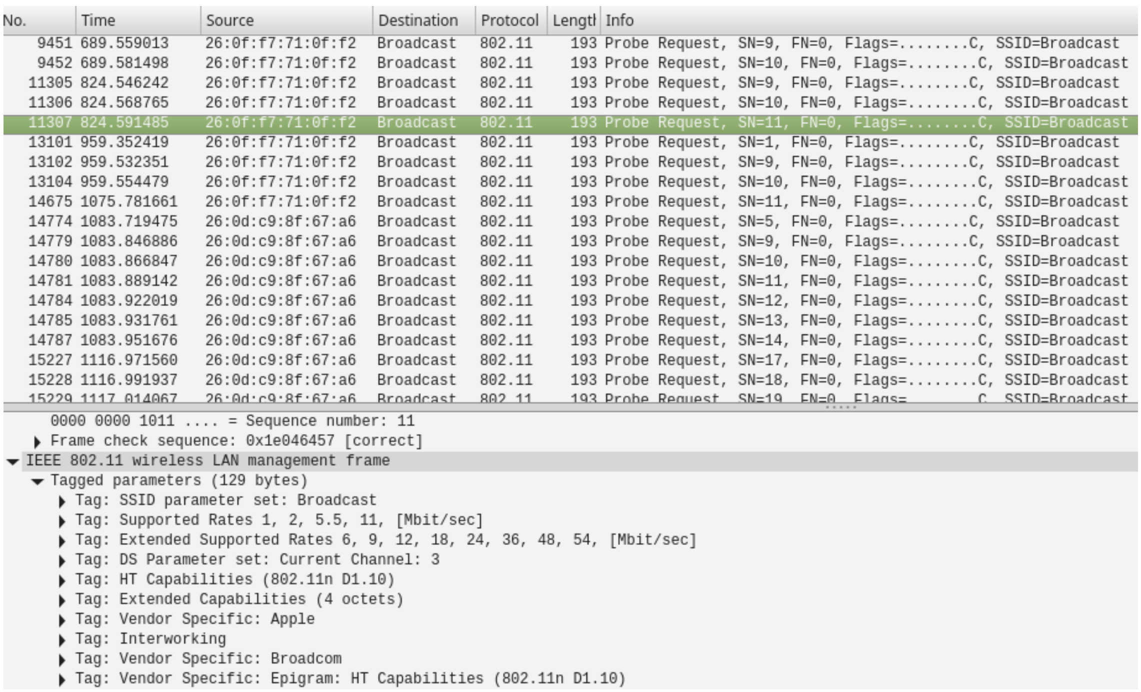

Figure 4.15: Wireshark capture of an Apple Iphone 6 with IOS 10 in sleep mode for 30 minutes.

Spoofed MAC Addresses	Total Occurrences	Time (s)
26:0D:C9:8F:67:A6	17	270
26:0F:F7:71:0F:F2	9	10
66:9A:66:D2:CA:2D	4	202
7A:9E:92:1B:DE:46	8	67
86:F1:3C:AC:3D:82	12	270
9E:FD:78:0D:0D:64	6	34
B2:4B:8D:C5:94:00	31	1
EA:2D:20:F7:CC:69	10	135

Table 4.3: Results for the test shown in figure 4.15. MAC addresses generated by an Iphone 6 with IOS 10 during a 30 minutes capture with screen locked.

4.5 Summary

This chapter described the technology involved in this thesis and explored some of the research questions imposed when considering the objectives of this work, such as "How do different manufacturers impact signal strength?", "How would this affect the system when detecting unknown devices?", "How does the system respond when the environment changes?" and "Could this system be used for tracking purposes?". Tests with devices from several manufacturers were performed to conclude that no two devices are identical regarding radio frequency communications, however, this difference is not significant to the problem at hands.

Results also showed RSSI differences throughout the day indicating environmental changes impact signal strength, however, proposed algorithms should be able to deal with this difference.

Furthermore a brief study on the impact of MAC address randomization in the data received for human sensing was presented, showing an increasing amount of security being added in order to prevent human sensing applications from discovering the identity of mobile devices, which poses a threat to device Wi-Fi tracking systems nowadays present.

MAC Addresses	% Occurences
Valid	23.6
Spoofed	76.4
Total	100.0

Table 4.4: Unique MAC addresses captured for a full day, the total number of unique MAC addresses for this day was 25040.

Chapter 5

Test Methodology and Results

In this chapter, the sample collection methodology and performance evaluation results of all algorithms described in section 4 will be presented. Moreover, an analysis of the various performance trade-offs in real world scenarios will be discussed.

5.1 Testbed

In this section an evaluation of all three algorithms on error distribution, calibration effort, cost, robustness to changes in the environment will be made.

Two testbeds were setup, figure 5.1 illustrates a food-court, filled with dinning tables, where 4 sensors are installed. Figure 5.2 illustrates Movvo's office.

For the purpose of performance and robustness evaluation six datasets, one for each mobile device described in section 4.4.5 were collected and merged into a training dataset. As discussed previously a real system should be able to abstract from device manufacturer differences in signal strength. Hence, a total of 300 sample points were collected and as this is a large food-court area with many objects such as wall columns, corridors between dining areas filled with tables and chairs, each point was spread 2 *m* apart from neighbor points. This 2 *m* separation was chosen due to the fact that RSSI measurements are integer values and are not a fine grained measurement unit, thus, the RSSI fingerprint two locations excessively close would result in similar measurements, making it impossible to distinguish from those locations. Additionally, this resulted in a less dense fingerprint database, which took far less time to obtain than what would be expected if the sample points were distanced, for instance, by 0.5 or 1 *m*.

In each location, the mobile device remained on top of high stool, to emulate the height at which smartphones are carried, with the screen on, unlocked, with the Wi-Fi interface on, however, not connected to any network, forcing the mobile device to broadcast probe requests. Note that this is not the standard behavior of a mobile device, nor is it attempting to model day-to-day utilization of such equipments, this setup was conceived merely to capture as many samples as possible. In regular usage, a mobile device will not communicate as often as in this mode.

With this setup, an average of 1 sample every 2 seconds was collected, which represents around 30 sets of measurements from all the sensors for each location.

The total duration of the capturing phase involved 4 nights of work during closing hours of this space.

In order to prepare the data for the supervised classification algorithm and avoid over fitting of a class, every location had the same number of measurements, which means homogeneously distributed classes.

Although device orientation was proven to achieve different results in RSSI measurements [47], orientation was kept random as a real system is required to be robust to such uncertainty and creating a database that encompassed every combination of location and device orientation would be extremely time consuming.

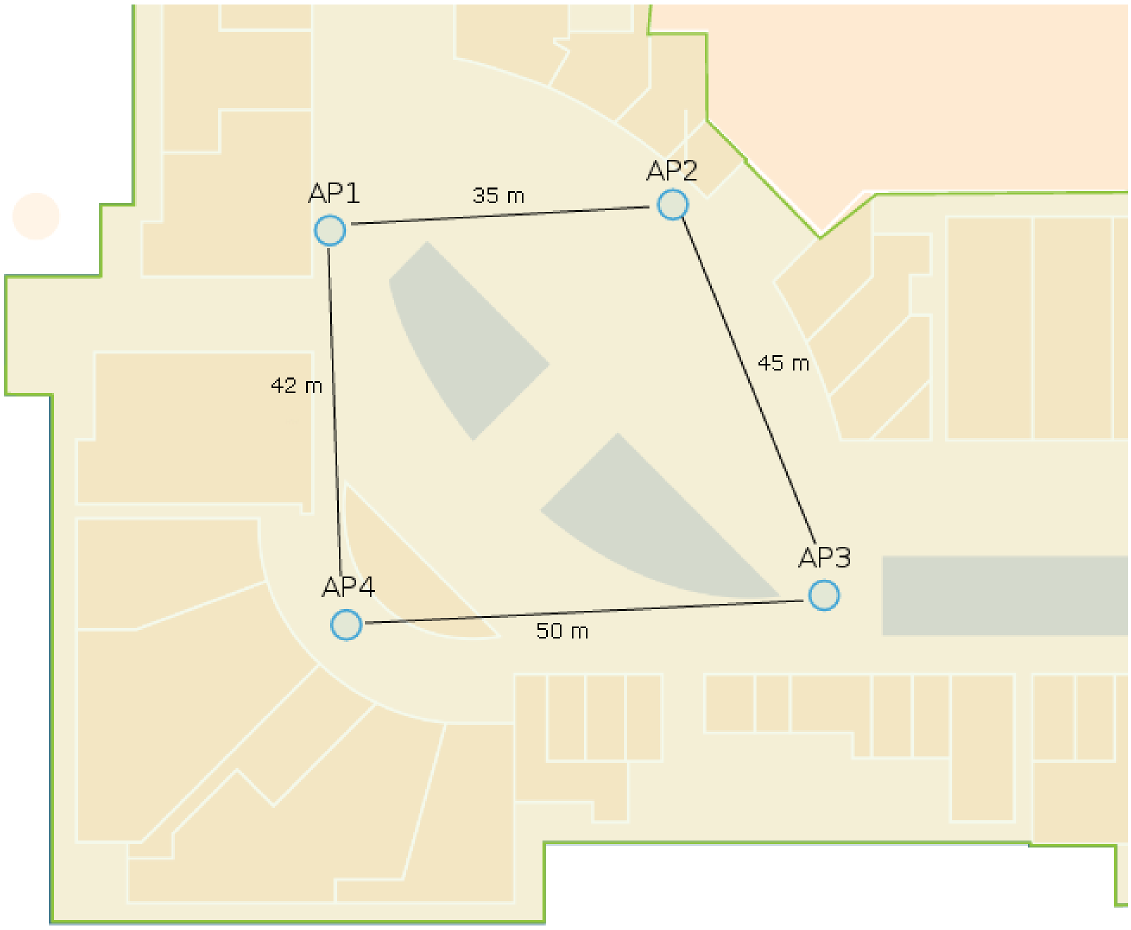

Figure 5.1: Test bed set in the food-court area, blue dots represent sensors, and due to this experiment being conducted in a mezzanine level, grey shapes represent balconies to the lower level. The area defined by the sensors is 1800 m^2 and the distance between AP3 and AP4, which is the longest, is 50 m.

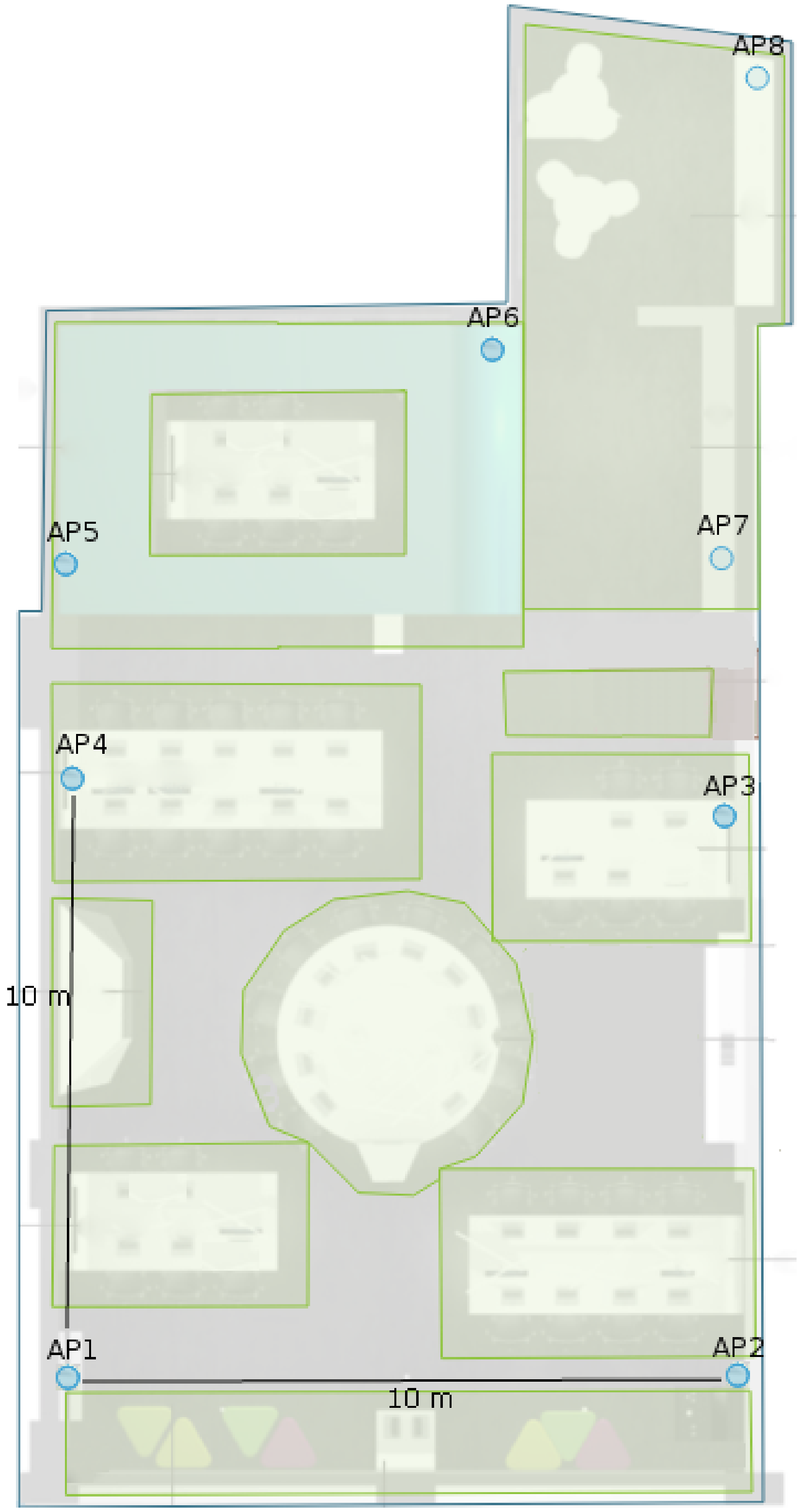

Figure 5.2: Testbed set in Movvo's office, blue dots represent sensors.

5.2 Results

In this section, the performance results of the system using all three algorithms are presented and compared for both testbeds considering several aspects mentioned in chapter 3, with special emphasis on mean localization error, standard deviation, error CDF and sensor density.

The performance evaluation was based on the mean localization error, expressed in m, given by equation:

$$e = \sum \hat{P} - P \tag{5.1}$$

where $\hat{P}$ is the estimated position, P is the actual position and e is error (i.e. Euclidean distance between the two). Two separate testbeds were setup, one in Movvo's office 5.2, which is 10×20 m^2, and one in a large food-court area, with 1800 m^2.

As during the collection phase for training the classification algorithm only a discrete number of samples was collected, it would make sense that the multilateration and weighted centroid algorithms were tested with such samples.

Table 5.1 shows a performance comparison between the three evaluated algorithms, in terms of mean localization error and standard deviation.

	Movvo			Foodcourt		
	Mean	σ	Sensor Density	Mean	σ	Sensor Density
KNN	1.929	1.869	0.04	4.195	7.253	0.0022
Multilateration	4.495	1.610	0.04	12.400	8.613	0.0022
Weighted Centroid	2.507	1.424	0.04	6.548	4.842	0.0022

Table 5.1: Mean localization error and standard deviation and sensor density comparison between all three algorithms described in this work. Movvo column refers to the results tested in Movvo's office (figure 5.2), while Food-court refers to the results of testing made in the Food-court testbed (figure 5.1).

A preliminary analysis of the obtained results indicates that KNN yields the best output in terms of average localization error. This is mainly due to the fingerprinting method's ability to cope with the environment. However, when considering standard deviation, KNN clearly has the error values a lot more spread than trilateration and weighted centroid. Furthermore, figure 5.3 and 5.4 shows a much more soft slope. KNN also shows an impressive 30% chance of correct class classification, which translates into 0 meters of error. On the other hand, it is also noticeable a not so smooth CDF curve for KNN.

The sparsity of KNN errors, and the cause of a standard deviation greater than the mean, is due to the fact that sensors which are not listening in the same, or overlapping 802.11 channels, as the mobile device is emitting, will fail to detect the mobile device.

This severely degrades aggregated sets of RSSI measurements, as in a 4 sensor setup system, there are cases in which the mobile device is only detected by one of the sensors.

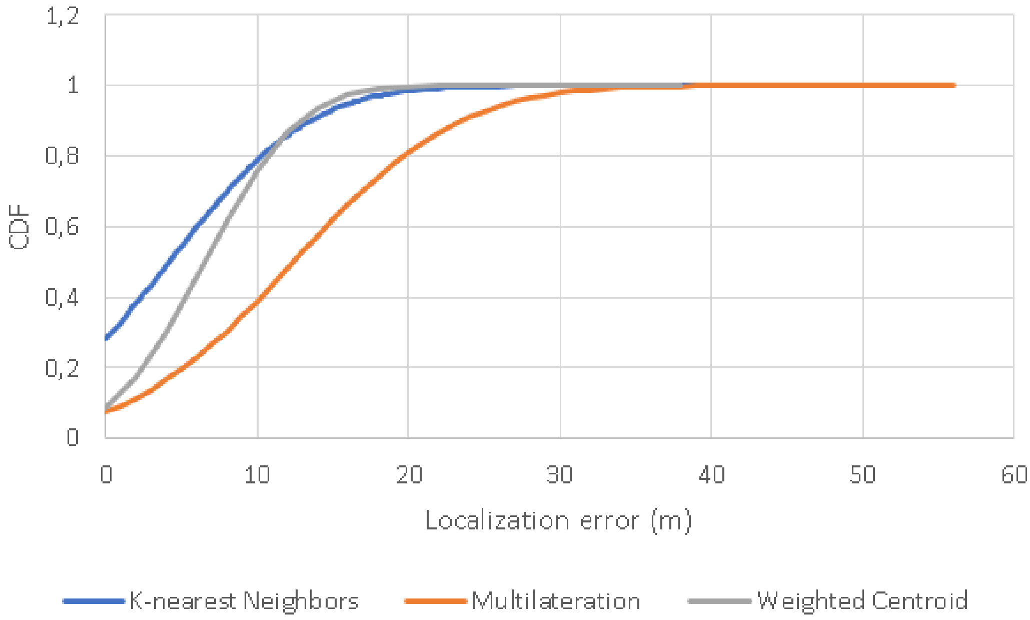

Figure 5.3: Localization error CDF of all three algorithms in the food-court area.

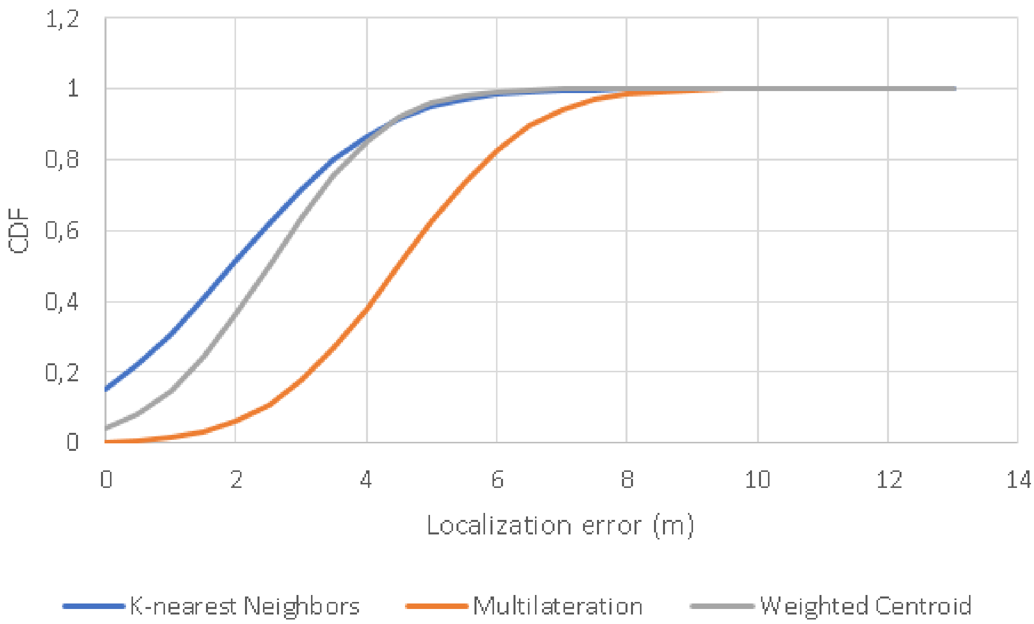

Figure 5.4: Localization error CDF of all three algorithms in Movvo's office.

Hence, a tremendous amount of error is introduce into the system, even with a 3 second time window of aggregation is used for RSSI measurements.

This is mainly due to the sparsity of data points collected imposed by the environment disposition, which means constraints to where the location can be estimated, as opposed to Movvo where this percentage is only 17%.

Both multilateration and weighted centroid are robust enough to deal with this type of issue as they will estimate the mobile device to be exactly where the only sensor detecting is, whereas in the case of fingerprinting, there will be an entry in the database, for every fingerprint, i.e. set of RSSI measurements from all the sensors, in which only one sensor has detected the mobile device and therefore only one RSSI measurement. This type of redundancy in the data overloads the algorithm with an indistinguishable set of RSSI measurements.

To help dealing with this and RSSI fluctuation, a 3 second time window is used to aggregate RSSI measurements as mentioned in chapter 3.

Figure 5.3 shows interesting results for the weighted centroid. Although the mean localization error of the weighted centroid is close to 6.5 m and CDF value for 18 meters of error is nearly 1, the chart still shows the maximum error being 38 meters. However, these localization error values are not common as shown in the chart. As part of the future work, an RSSI filtering with historic data would prevent such position estimation jumps.

5.2.1 Spatial Error Distribution

Multilateration showed promising results in Movvo, however, in the food-court, 12.4 *m* of mean localization error with an equally high standard deviation is not at all within the acceptable for this work. Being a radio wave propagation model based method, the main disadvantage of this algorithm is that for RSSI measurements in the range of -70 dBm, a sudden fluctuation of 8 or 9 dBm may translate into an exponentially high distance.

In Movvo, the best localization accuracy was achieved within the area of AP1, AP2, AP3, AP4 for multilateration and weighted centroid algorithm, whereas KNN yielded better results in the meeting room (AP5 and AP6) and kitchen (AP7 and AP8).

The difference in error distribution was expected, as RSSI measurements the meeting room were much different from the main area, the differentiation of samples will ease KNN decision when classifying a new sample.

The challenge KNN encountered was lack of classification accuracy in the area between AP2 and AP3, due to sample ambiguity, caused by the short distance separating the samples. This result was also seen in the food-court, in which KNN showed better results in the areas surrounding the center. In the food-court this is in part due to the high density of tables, columns and TV structures present in that area which pose a LOS challenge and a higher instability of instantaneous RSSI.

Additionally, table 5.1, provides information concerning the sensor density of both Movvo office setup and the food-court area. Sensor density refers to the number of sensors divided by the area of coverage, i.e. the area of the polygon defined by the sensors, which is considered to be the localization area.

In the food-court area on the other hand, results were not similar to the ones in Movvo.

Weighted centroid showed better localization results in areas closer to the sensors and away from the center, contradicting the behavior in Movvo's office. This is due to the weight penalization being more aggressive in the food-court than in Movvo, for instance, if the mobile device was positioned on top of AP1 in figure 5.2, other sensors would still detect it with an RSSI of -50 dBm, which would bring the estimated position closer to the center of Movvo. In the food-court area, the same situation would result in a weight of practically 0 for the distant sensor, which would not shift the estimated position to the center.

Multilateration, showed better results in the localization area center and the error increased moving outwards to the sensors. This result was expected, since RSSI spikes would produce very large circles from the sensors far distanced and in some situations the estimated position, resultant of circle intersection, could be outside the sensor area, which is not at all accurate, since measurements were only collected inside the polygon defined by sensor positions.

5.3 Summary

The best localization accuracy was obtained using KNN algorithm, which, was expected, since it is the algorithm which can capture the largest amount of information regarding the properties of a specific location. Although weighted centroid did not achieve the best accuracy, it is a good practical alternative to fingerprinting, simply due to the fast deployment, which reduces installation costs yielding acceptable results.

This experiment concluded that although device type, height at which it is carried and the orientation of the device impact RSSI measurements and subsequently localization error, such parameters can be ignored when deploying a similar system as the localization accuracy achieved is perfectly acceptable.

Chapter 6

Conclusions and Future Work

6.1 Conclusions

This thesis studied the implementation of three algorithms, a multilateration approach based on widely used indoor propagation model, a weighted centroid in which weight calculation was based on the distance from the propagation model, and a fingerprinting approach using nearest neighbors.

Although the fingerprinting approach stood out from the rest when considering mean localization error performance, time spent collecting samples for the radio map database presented a downside, as this time consumed turns this approach too costly.

In order to build the radio map database for training the fingerprinting approach, 16 hours over the course of 4 nights were involved. This time consuming process was made for an area of 1800 m^2. The area of the shopping mall in which the food-court described in section 5.1 is located, is 15000 m. This implies that nearly 128 hours would be needed to cover gather the same database for the whole shopping mall.

As such, this work evaluates weighted centroid as the most balanced and suitable to be deployed due to minimal calibration effort and lowest standard deviation of all three methods, indicating errors in estimations are closer to the expected mean.

As a challenge and motivation, the company imposed a 5 m mean localization error.

Although only KNN was able to reach this goal, the accuracy achieved with the proposed algorithm weighted centroid is considered to be acceptable for the purpose of this work, which was to develop a fully functional localization algorithm to run on Movvo's platform. Thus, weighted centroid interested Movvo and will soon be deployed as part of Movvo's product. As a side conclusion, due to MAC randomization, this thesis can not recommend using Wi-Fi probe requests for tracking.

As a contribution for further implementations and usage of one such system, in order to achieve an accuracy of 3 m, sensor density should be 0.05 $sensors/m^2$, displayed in a squared manner for optimal results.

6.1.1 Context

This thesis was developed in Movvo.

Movvo is a location analytics startup headquartered in London with offices in Porto, which leverages Wi-Fi data in order to provide insights about human behavior in retail spaces.

All the infrastructure related with Movvo's product was predefined by the company and therefore little to no control was given to the author during the course of this work.

As part of a startup life cycle, adaptations have to be made. The market is constantly evolving and therefore companies have to adjust their goals in order to thrive.

Movvo began as a location analytics startup which used GSM, Wi-Fi and Bluetooth to perform indoor localization in retail spaces. However, during the course of this thesis and in order to respond to the market, Movvo stopped using GSM and Bluetooth technology. This was due to the fact that software defined radios, used for capturing GSM traffic, severely increased the cost of the product. Hence, the company decided to only use Wi-Fi as the radio frequency data source.

Additionally, Movvo shifted into providing consultancy specifically focused on shopping centers. This lead to a trade-of between promoting the development of a positioning system (with focus on accuracy) and investing in a highly skilled team of consultants to better understand and master the retail market. Emphasis was put on integrating data from multiple sources in order to maximize the amount of information to the customer.

All these changes took place during the course of this work as part of a new strategic vision of the company lead by the new CEO, Cyrus Gilbert-Rolfe. This included a complete restructuring of the development team, in which, the former head of research, and the author's internal supervisor, was dismissed .

The work described throughout this manuscript was developed in the largest, most visited shopping center in Porto. This required special authorization, which delayed the time window available for the experiments made, and ultimately, this thesis.

6.2 Future Work

In this work a practical indoor localization system was developed and although acceptable accuracy was achieved, there is margin for improvement in order to better map RSSI to distance. Furthermore, a data preparation procedure prior to localization in which RSSI is filtered and processed could be created in order to compensate and attenuate fluctuations.

Such procedures should include:

- Recent detection history to prevent sensor and device instability, other environmental factors and consequently localization estimation differences (i.e. jumps) and help to extend tracking capabilities.

- Interpolate RSSI measurements, due to sparse mobile device detections.

- Further investigate how to address MAC randomization for tracking purposes.

- Develop and deploy a system which takes advantage of staff usually present in large public areas, for instance, cleaning staff in large areas most often use a vehicle to vacuum and wash the floor. With a mapping software, this vehicle could help automate the process of collecting and calibrating the radio database of a certain space.

This thesis will help understand better the indoor localization problem, its challenges and possibilities.

Appendix A

Diagrams

In this appendix class diagrams can be found for each algorithm, figure A.2 illustrates class diagram for multilateration, weighted centroid and KNN methods. Additionally, Localization API, used by all methods, is represented in the diagram.

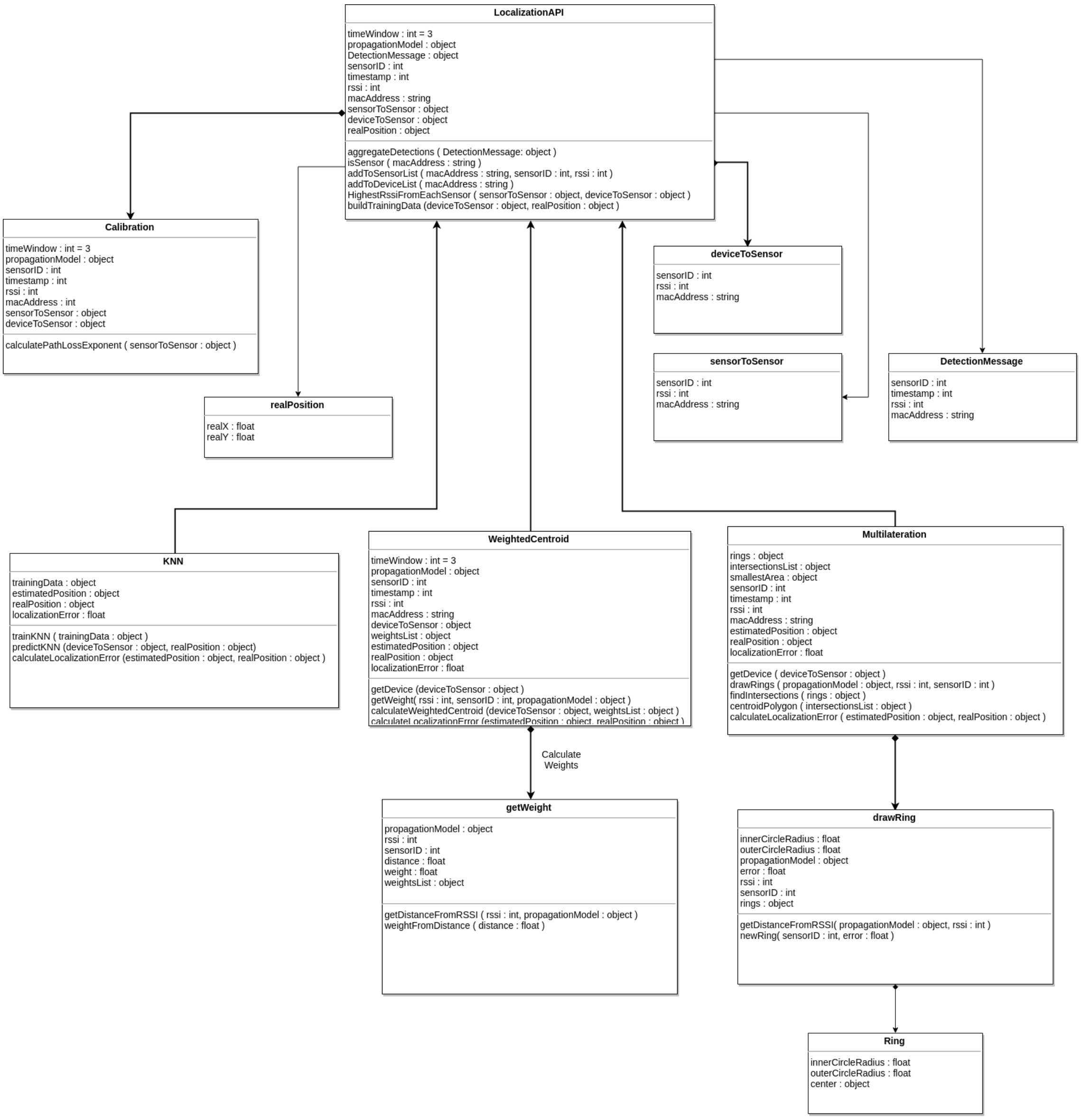

Figure A.1: UML class Diagrams for multilateration and weighted centroid. Both algorithms use calibration.

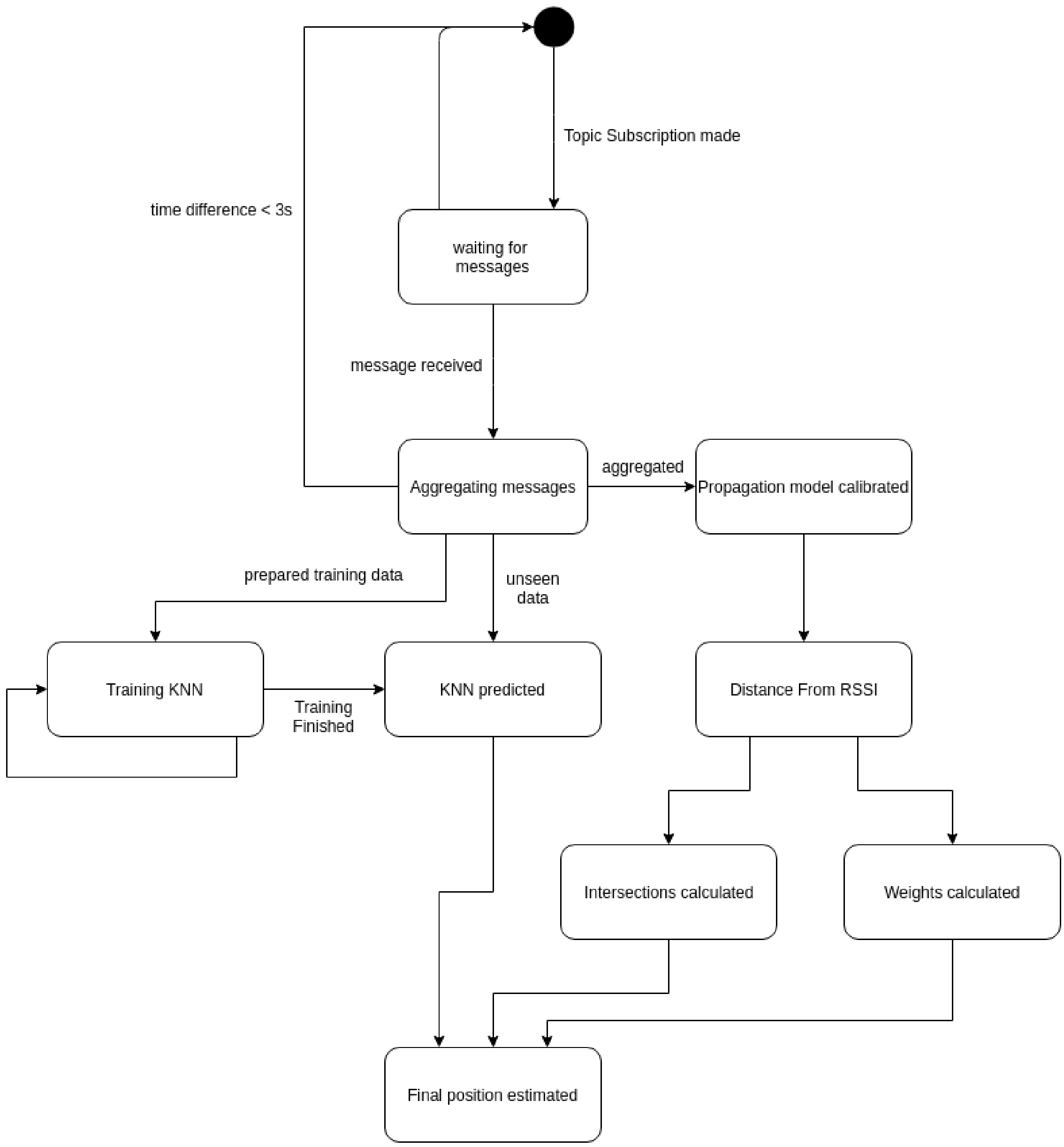

Figure A.2: System state diagram for a single system run until an estimation of the position is made. Note that as this system is constantly listening for incoming messages from the sensors, after a final position estimation is made, the system returns to the initial state of waiting for messages.

References

[1] THIAGO Teixeira, GERSHON Dublon, and ANDREAS Savvides. A survey of human-sensing: Methods for detecting presence, count, location, track, and identity. *ENALAB Technical Report*, 2011.

[2] S. Tekinay, E. Chao, and R. Richton. Performance benchmarking for wireless location systems. *IEEE Communications Magazine*, 36(4):72–76, Apr 1998.

[3] J. G. McNeff. The global positioning system. *IEEE Transactions on Microwave Theory and Techniques*, 50(3):645–652, Mar 2002.

[4] Simon Haykin. *Communication Systems*. Wiley Publishing, 5th edition, 2009.

[5] ATIS telecom glossary. http://www.atis.org.

[6] Weather World 2010 university of illinois. http://ww2010.atmos.uiuc.edu/(Gh)/guides/mtr/opt/mch/sct.rxml, 2010.

[7] Andrea Goldsmith. *Wireless Communications*. Cambridge University Press, New York, NY, USA, 2005.

[8] Theodore Rappaport. *Wireless Communications: Principles and Practice*. Prentice Hall PTR, Upper Saddle River, NJ, USA, 2nd edition, 2001.

[9] Christopher Haslett. *Essentials of Radio Wave Propagation*. Cambridge University Press, 2007. Cambridge Books Online.

[10] J. Miranda, R. Abrishambaf, T. Gomes, P. Gonçalves, J. Cabral, A. Tavares, and J. Monteiro. Path loss exponent analysis in wireless sensor networks: Experimental evaluation. In *2013 11th IEEE International Conference on Industrial Informatics (INDIN)*, pages 54–58, July 2013.

[11] R. Mardeni and Y. Solahuddin. Path loss model development for indoor signal loss prediction at 2.4 ghz 802.11n network. In *Microwave and Millimeter Wave Technology (ICMMT), 2012 International Conference on*, volume 2, pages 1–4, May 2012.

[12] Free Space Path Loss. http://www.radio-electronics.com/info/propagation/path-loss/free-space-formula-equation.php.

[13] M. Li and Y. Lu. Angle-of-arrival estimation for localization and communication in wireless networks. In *2008 16th European Signal Processing Conference*, pages 1–5, Aug 2008.

[14] Mohamed Laaraiedh. *Contributions on Hybrid Localization Techniques For Heterogeneous Wireless Networks*. Theses, Université Rennes 1, December 2010.

[15] K. W. Cheung, H. C. So, W. K. Ma, and Y. T. Chan. Least squares algorithms for time-of-arrival-based mobile location. *IEEE Transactions on Signal Processing*, 52(4):1121–1130, April 2004.

[16] Sinan Gezici. A survey on wireless position estimation. *Wireless Personal Communications*, 44(3):263–282, 2008.

[17] M. Pajovic, P. Orlik, T. Koike-Akino, K. J. Kim, H. Aikawa, and T. Hori. An unsupervised indoor localization method based on received signal strength (rss) measurements. In *2015 IEEE Global Communications Conference (GLOBECOM)*, pages 1–6, Dec 2015.

[18] Islam Alyafawi, Desislava C. Dimitrova, and Torsten Braun. Sdr-based passive indoor localization system for gsm. In *Proceedings of the 2014 ACM Workshop on Software Radio Implementation Forum*, SRIF '14, pages 7–14, New York, NY, USA, 2014. ACM.

[19] X. Tian, R. Shen, D. Liu, Y. Wen, and X. Wang. Performance analysis of rss fingerprinting based indoor localization. *IEEE Transactions on Mobile Computing*, PP(99):1–1, 2016.

[20] P. Bahl and V. N. Padmanabhan. Radar: an in-building rf-based user location and tracking system. In *INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, volume 2, pages 775–784 vol.2, 2000.

[21] C. Beder and M. Klepal. Fingerprinting based localisation revisited: A rigorous approach for comparing rssi measurements coping with missed access points and differing antenna attenuations. In *Indoor Positioning and Indoor Navigation (IPIN), 2012 International Conference on*, pages 1–7, Nov 2012.

[22] H. Rahimi, A. Nur Zincir-Heywood, and B. Gadher. Indoor geo-fencing and access control for wireless networks. In *2013 IEEE Symposium on Computational Intelligence in Cyber Security (CICS)*, pages 1–8, April 2013.

[23] H. Liu, H. Darabi, P. Banerjee, and J. Liu. Survey of wireless indoor positioning techniques and systems. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 37(6):1067–1080, Nov 2007.

[24] Y. Gu, A. Lo, and I. Niemegeers. A survey of indoor positioning systems for wireless personal networks. *IEEE Communications Surveys Tutorials*, 11(1):13–32, First 2009.

[25] Dimitrios Lymberopoulos, Jie Liu, Xue Yang, Romit Roy Choudhury, Vlado Handziski, and Souvik Sen. A realistic evaluation and comparison of indoor location technologies: Experiences and lessons learned. In *Proceedings of the 14th International Conference on Information Processing in Sensor Networks*, IPSN '15, pages 178–189, New York, NY, USA, 2015. ACM.

[26] Jie Yang, Yingying Chen, Richard P. Martin, Wade Trappe, and Marco Gruteser. *On the Performance of Wireless Indoor Localization Using Received Signal Strength*. John Wiley & Sons, Inc., 2011.

[27] D. C. Montgomery and G. C. Runger. *Applied Statistics and Probability for Engineers*. John Wiley and Sons, 2003.

[28] Jun-geun Park, Ami Patel, Dorothy Curtis, Seth Teller, and Jonathan Ledlie. Online pose classification and walking speed estimation using handheld devices. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*, pages 113–122. ACM, 2012.

[29] Stephan Schuhmann, Klaus Herrmann, Kurt Rothermel, Jan Blumenthal, and Dirk Timmermann. Improved weighted centroid localization in smart ubiquitous environments. In *International Conference on Ubiquitous Intelligence and Computing*, pages 20–34. Springer, 2008.

[30] J. Ross Quinlan. *C4.5: Programs for Machine Learning*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 1993.

[31] E.A. Patrick and F.P. Fischer. A generalized k-nearest neighbor rule. *Information and Control*, 16(2):128 – 152, 1970.

[32] Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani. *An Introduction to Statistical Learning: With Applications in R*. Springer Publishing Company, Incorporated, 2014.

[33] Max Kuhn and Kjell Johnson. *Applied predictive modeling*, volume 26. Springer, 2013.

[34] Annette M. Molinaro, Richard Simon, and Ruth M. Pfeiffer. Prediction error estimation: a comparison of resampling methods. *Bioinformatics*, 21(15):3301, 2005.

[35] M. Stone. Cross-Validatory Choice and Assessment of Statistical Predictions. *Journal of the Royal Statistical Society. Series B (Methodological)*, 36(2):111–147, 1974.

[36] Andrew Banks and Rahul Gupta. Mqtt version 3.1. 1. *OASIS standard*, 2014.

[37] Ling Bai and Shuguo Li. Vlsi implementation of high-speed sha-256. In *2009 IEEE 8th International Conference on ASIC*, pages 131–134, Oct 2009.

[38] 802.11 Association Process. cisco meraki. https://documentation.meraki.com/MR/WiFi_Basics_and_Best_Practices/802.11_Association_process_explained.

[39] IEEE 802.11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications. http://standards.ieee.org/about/get/802/802.11.html, 2012.

[40] Wireshark the wireshark foundation. https://www.wireshark.org/, 2016.

[41] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[42] Python Language Reference, version 3.5 python software foundation. http://www.python.org/, 2017.

[43] tp-link. http://www.tp-link.com.

[44] Julien Freudiger. How talkative is your mobile device?: An experimental study of wi-fi probe requests. In *Proceedings of the 8th ACM Conference on Security & Privacy in Wireless and Mobile Networks*, WiSec '15, pages 8:1–8:6, New York, NY, USA, 2015. ACM.

[45] Internetworking Basics Documentation cisco press. http://docwiki.cisco.com/wiki/Internetworking_Basics, 1999.

[46] IEEE Registration Authority. Ieee registration authority organizational unique identifier (oui) list. http://standards-oui.ieee.org/oui/oui.txt.

[47] Yogita Chapre, Prasant Mohapatra, Sanjay Jha, and Aruna Seneviratne. Received signal strength indicator and its analysis in a typical wlan system (short paper). In *Local Computer Networks (LCN), 2013 IEEE 38th Conference on*, pages 304–307. IEEE, 2013.