Institutionen för systemteknik
Department of Electrical Engineering

Examensarbete

Evaluation of Different Radio-Based Indoor Positioning Methods

Examensarbete utfört i Kommunikationssystem
vid Tekniska högskolan vid Linköpings universitet
av

Sven Ahlberg

LiTH-ISY-EX--14/4760--SE

Linköping 2014

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Utvärdering av olika radio-baserade positioneringsmetoder inomhus

Evaluation of Different Radio-Based Indoor Positioning Methods

Författare
Author

Sven Ahlberg

Sammanfattning
Abstract

Today, positioning with GPS and the advantages this entails are almost infinitive, which means that the technology can be utilized in a variety of applications. Unfortunately, there exists a lot of limitations in conjunction with the signals from the GPS can't reach inside e.g. buildings or underground. This means that an alternative solution that works indoors needs to be developed.

The report presents the four most common radio-based technologies, Bluetooth, Wi-Fi, UWB and RFID, which can be used to determine a position. These all have different advantages in cost, accuracy and latency, which means that there exist a number of different applications.

The radio-based methods use the measurement techniques, RSSI, TOA, TDOA, Cell-ID, PD or AOA to gather data. The choice of measurement technique is mainly dependent of which radio-based method being used, since their accuracy depends on the quality of the measurements and the size of the detection area, which means that all measurement techniques have different advantages and disadvantages.

The measurement data is processed with one of the positioning methods, LS, NLS, ML, Cell-ID, WC or FP, to estimate a position. The choice of positioning method also depends on the quality of the measurements in combination with the size of the detection area.

To evaluate the different radio-based methods together with measurement techniques and positioning methods, accuracy, latency and cost are being compared. This is used as the basis for the choice of positioning method, since a general solution can get summarized by finding the least expensive approach which can estimate an unknown position with sufficiently high accuracy.

Nyckelord
Keywords

Indoor positioning,TOA, TDOA, RSSI, cell-ID, AOA, fingerprinting, probability detection, UWB, Bluetooth, Wi-Fi, RFID

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Sammanfattning

Idag är positionering med GPS och de fördelar som detta medför näst intill oändliga, vilket innebär att tekniken kan utnyttjas i en rad av applikationer. Tyvärr existerar en hel del begränsningar i samband med att GPS-signalens radiovågor inte når fram i t.ex. byggnader eller under mark. Detta betyder att en alternativ lösning som fungerar inomhus behöver tas fram för att kunna använda sig av alla fördelar som ett bra positioneringssystem kan bidra med.

I rapporten presenteras de fyra vanligaste radiobaserade metoderna, Blåtand, Wi-Fi, UWB och RFID, som kan användas till att bestämma en position. Dessa har alla olika fördelar med kostnad, noggrannhet och snabbhet på mätningarna vilket innebär att det existerar olika tillämpningsområden. De radio-baserade metoderna använder sig av mätteknikerna, RSSI, TOA, TDOA, Cell-ID, PD, och AOA för att kunna bestämma en position. Valet av mätteknik beror till stor del av vilken radio-baserad metod som används eftersom deras respektive noggranhet är beroende av kvaliteten på mätningar och storleken på detektionsområdet, vilket innebär att alla mättekniker har olika för- och nackdelar.

Mätdatan behandlas med en av positioneringsmetoderna, LS, NLS, ML, Cell-ID, WC eller FP, för att kunna estimera en position. Valet av positioneringsmetod beror även det av kvaliteten på mätningarna i kombination med storleken på detektionsområdet.

För att utvärdera de olika radio-baserade metoderna tillsammans med mättekniker och positioneringsmetoder jämförs, noggranhet, snabbhet och kostnad. Detta ligger som grund till valet av positioneringsmetod eftersom en generell lösning kan sammanfattas med att hitta det billigaste tillvägagångssättet som kan estimera en okänd position med tillräckligt hög noggranhet.

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Sven Ahlberg
Linköping, May 2014

Contents

Notation

NOTATION

Notation	Meaning
AOA	Angle Of Arrival
AP	Access Points
$Cell-ID$	Cell Identification
$CRLB$	Cramér–Rao Lower Bound
FP	Fingerprinting
LOS	Line Of Sight
LS	Least Squares
ML	Maximum Likelihood
MSE	Mean Square Error
$NLOS$	None Line Of Sight
NLS	Nonlinear Least Squares
PD	Probability Detection
PSD	Power Spectral Density
$RFID$	Radio-Frequency Identification
$RSSI$	Received Signal Strength Indication
SNR	Signal-to-noise ratio
$TDOA$	Time Difference Of Arrival
TOA	Time Of Arrival
TOF	Time Of Flight
UWB	Ultra Wide Band
WC	Weighted Centroid
WLS	Weighted Least Squares
$WNLS$	Weighted Nonlinear Least Squares

1 Introduction

This document is the report for a Master thesis in Electrical Engineering.The thesis is done on behalf of Combitech AB in Linköping and the division of Communication Systems, Department of Electrical Engineering at Linköping University. The purpose of this report is to describe the work and result of the thesis. This chapter will give an introduction to the work of the thesis together with a background and the aims and objectives of the project.

1.1 Background

Tunnels, basements, subway tunnels, factories, warehouses and coal mines are a few examples in which one may want to know a position. This is complicated since the signals from the satellites have difficulties reaching down to these areas because of buildings or rocks that prevents the radio waves to go through. GPS-positioning will therefore become impossible to use in its original form, but there are alternative ways to determine a position underground and indoors.

Today, there are several different radio-based methods with the ability to determine a position, all with different strengths and weaknesses. This means, in order to choose a suitable method for a positioning area the different possibilities and limitations needs to be understood. The most suited radio-based methods for positioning are RFID, Wi-Fi, Bluetooth and UWB. They all use different approaches to solve the positioning problem, so their advantages and disadvantages are different.
By understanding how these radio-based methods work, we can make a decision regarding how to customize a positioning system to a low cost with sufficient accuracy.

1.2 Aims and Objectives

The main objectives of this thesis are to analyze a number of indoor positioning methods to compare their cost, accuracy, latency and future development opportunities. These obejects can be summerized as:

Investigation of the different measurement techniques for positioning
By measuring signal strength, time, angle, ID number or the probability of detection, a first step for estimating a position is done. The measurement techniques will be evaluated by their complexity and accuracy together with the properties needed from radio waves to reduce errors.

Investigation of the different methods for positioning
By the use of measurement techniques together with a method for positioning, position estimation is possible. The different solutions will be evaluated from their complexity, latency, and cost together with the properties needed from measurement techniques to make each method effective.

Investigation of the different radio-based methods
Four different radio-based technologies will be evaluated, Bluetooth, Radio-Frequency Identification (RFID), Wi-Fi, and Ultra Wide Band (UWB). The properties for each method are different in terms of advantages and disadvantages which mean that a comparison between the methods strengths and weaknesses will be investigated.

By analyzing the differences between positioning techniques, measurement techniques and radio-based methods, we would be able to select and adapt accurate positioning systems to real problems.

1.3 Thesis Outline

The first chapter of this report presents the background together with a short introduction to the thesis. The following chapters can be divided into two parts, where the first part covers measurement techniques, positioning methods and radio-based methods. The second part describes the differences between the various methods together with conclusions.

Chapter 1: Gives a short introduction of the thesis and describes its aims and objectives.

Chapter 2: Describes the existing radio-based measurement techniques for accurate positioning.

Chapter 3: Describes the most common methods for estimating positions from measurements.

Chapter 4: Describes the most common radio-based methods for indoor positioning.

Chapter 5: Presents comparisons between earlier mentioned methods.

Chapter 6: Presents the conclusions and suggests improvements and future work.

2

Measurement Techniques for Positioning

This chapter describes the existing radio-based measurement techniques that can be used for accurate positioning. The approaches that will be investigated are Received Signal Strength Indication (RSSI), Time Of Arrival (TOA), Time Difference Of Arrival (TDOA), Angle Of Arrival (AOA), Cell-ID and Probability Detection (PB). Since many of these methods have advantages and disadvantages a comparison between the different solutions will be presented. All of the methods in this chapter are explained for a 2D-case, but they will work just as fine for a 3D-case with one extra observer. For a description of how to combine radio-based techniques with positioning methods and measurement techniques, see table 5.1.

2.1 RSSI

The RSSI ranging technique is based on how the distance between an observer and a target affect the received signal strength. In other words, the further away one target is from one observer the weaker the signal. RSSI is a cheap solution since it isn't dependent on well synchronized clocks or directional antennas in contrast to many other methods. Instead RSSI use theoretical or empirical path-loss models to translate RSSI to distance measurements.

One of the simplest models is the free space radio propagation loss equation which is proportional to $\frac{1}{d^2}$, where d is the distance. This model works great in the ideal Line Of Sight (LOS) case between a target and an observer, unfortunately the reality is often more complex and demands a more suitable model for propagation loss. A model that is commonly used for characterizing RSSI

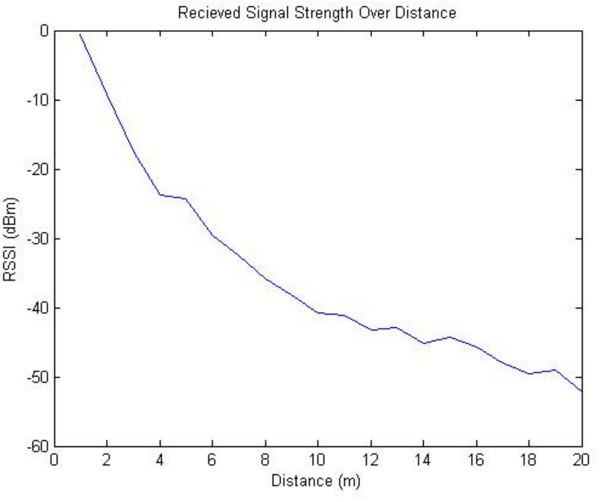

Figure 2.1: *The graph shows a possible relation between RSSI and distance.*

received by en observer is given by [Gustafsson, 2012]

$$P_r(d) = P^0(d_0) - 10\gamma log_{10}(\frac{d}{d_0}) + S \tag{2.1}$$

where $P_r(d)$ (dBm) is the received signal power, $P^0(d_0)$ is the received power (dBm) at a reference distance, this depends on the signal wavelength and the radio characteristic, d (meters) is the distance between observer and target. S (dB) is the noise that is usually modelled as Gaussian random variable with zero mean and standard deviation σ_s. The parameter γ is the path loss constant with typical values between 2 and 6 [Dardari.D, 2009]. A graph with possible measurement data from RSSI is shown in figure 2.1, where $\sigma_s = 1$ and $\gamma = 4$.

According to [Guoqiang Mao, 2007], a maximum likelihood estimation of the distance d_{ij} can be written as

$$\hat{d_{ij}} = d_0(\frac{P_{ij}}{P^0(d_0)})^{-1/\gamma} \tag{2.2}$$

In order to relate the true value d with the estimated value $\hat{d_{ij}}$ the equations (2.1) and (2.2) are used together with some logarithmic calculations which gives the following expression

$$\hat{d_{ij}} = d_{ij}10^{-\frac{S}{10\gamma}} = d_{ij}e^{-\frac{S}{\eta\gamma}} \tag{2.3}$$

where $\eta = \frac{10}{ln(10)}$. The expected value of the estimated distance $\hat{d_{ij}}$ is given by

$$E\{\hat{d_{ij}}\} = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} d_{ij} e^{-\frac{S}{\eta\gamma}} e^{\frac{-S}{2\sigma^2}} dS = d_{ij} e^{\frac{\sigma^2}{2\eta^2\gamma^2}} \tag{2.4}$$

In order to get an unbiased estimation of the distance d_{ij} the equation below should be met

$$E\{\hat{\theta}\} - \theta = 0 \tag{2.5}$$

Since the true value d_{ij} from equation (2.4) differs from the estimation's expected value $E\{\hat{d_{ij}}\}$ with a factor $e^{\frac{\sigma^2}{2\eta^2\gamma^2}}$, a compensation needs to be done. By adding the extra factor to equation (2.2) an unbiased estimation for the true distance can be expressed as

$$\hat{d_{ij}} = d_0 (\frac{P_{ij}}{P_0(d_0)})^{-1/\gamma} e^{\frac{-\sigma^2}{2\eta^2\gamma^2}} \tag{2.6}$$

2.2 One-Way TOA Ranging

The range between an observer and its target can easily be calculated using the Time Of Flight (TOF) which is the time it takes for a signal to go from a target to an observer in one way direction. This method is also called one-way TOA ranging and is given by [Dardari.D, 2009]

$$d = v\tau_f \tag{2.7}$$

where d (m) is the estimated distance between the observer and the target, v is the speed of electromagnetic waves (m/s) and τ_f (s) is the signal propagation delay. In order to make one-way TOA a viable method it is very important for the node clocks to be almost perfectly synchronized since a small error in the time measurement will result in a huge error in the distance measurement due to the large value of v (e.g., equal to speed of light). The propagation delay τ_f is given by [Dardari.D, 2009]

$$\tau_f = t_2 - t_1 \tag{2.8}$$

where t_2 (s) is the measured time from the observer and t_1 is the measured time from the target. An acceptable error at the propagation delay, for radio waves, is in the order of nano seconds who gives the distance measurement an error at less than a meter. The figure 2.2 below describes how TOA measurements is done. The final position can then be calculated using the intersection point of the circles with radius equal to estimated distances.

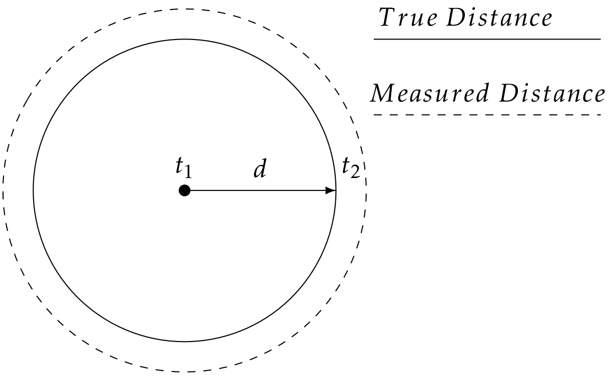

Figure 2.2: *Determination of a distance $d(m)$ with TOA measurements $t_1(s)$ and $t_2(s)$.*

2.3 Two-Way TOA Ranging

The two-way TOA calculates the distance between an observer and its target without a common time reference. Instead an observer sends out a signal to a target which replies by transmitting acknowledgement signal back with a response delay τ_d (s). The two-way TOA can then be determined by

$$\tau_{RT} = 2\tau_f - \tau_d \tag{2.9}$$

From which the distance can be calculated if the response delay is known. Unlike one-way TOA the two-way TOA doesn't need synchronized clocks between a target and an observer to get accurate measurements. However, other factors like relative clock drift and the response delay still affects the result.

2.4 TDOA

The TDOA technique is based on the measured time differences between several observers. This means that the observers should have as synchronized clocks as possible in order to give accurate target localization. The difference between TDOA and TOA is thus that the target's clock doesn't need to be synchronized with the observers to get an accurate range measurement. A TDOA measurement with three observers and one sender can be written as the equation system

$$\tau_{12} = (d_1 - d_2)/v \tag{2.10}$$

$$\tau_{13} = (d_1 - d_3)/v \tag{2.11}$$

where d_1 (m), d_2 (m) and d_3 (m) are unknown range distances between each observer and the sender, v (m/s) is the speed of light and t_{ij} (s) is the measured time difference between two observers. The range distances can be written as

$$d_i = \sqrt{(s_{ix} - p_x)^2 + (s_{iy} - p_y)^2} \tag{2.12}$$

where $S_i = (s_{ix}\, s_{iy})$ is the known X and Y positions for the observers and $P = (p_x\, p_y)$ is the unknown X and Y coordinate for the target. Equation (2.12) into equation (2.10) and (2.11) can then be rewritten as two different hyperbolic functions where p_x depends on p_y, one for each τ. These two hyperbolic functions will have an unambiguous solution which is the same as the intersection point and the target's position.

2.5 AOA

Observers that can measure the angle of an incoming signal are needed in order to make AOA possible, see figure 3.7. This method uses triangulation and can be expressed as

$$l = \frac{d}{tan(\alpha)} + \frac{d}{tan(\beta)} \tag{2.13}$$

where d (m) is the height of the target, l (m) is the distance between the observers S_1 and S_2, α is the angle for the incoming signal to S_1 and β is the angle for the incoming signal to S_2.

By applying some trigonometry, $tan(x) = \frac{sin(x)}{cos(x)}$, the equation (2.13) can be rewritten into

$$l = d\left(\frac{cos(\alpha)}{sin(\alpha)} + \frac{cos(\beta)}{sin(\beta)}\right) = d\left(\frac{cos(\alpha)sin(\beta) + cos(\beta)sin(\alpha)}{sin(\alpha)sin(\beta)}\right) \tag{2.14}$$

using the angle transformation formula, $sin(\alpha + \beta) = cos(\alpha)sin(\beta) + cos(\beta)sin(\alpha)$, equation (2.14) can be expressed as

$$d = \frac{l sin(\alpha)sin(\beta)}{sin(\alpha + \beta)} \tag{2.15}$$

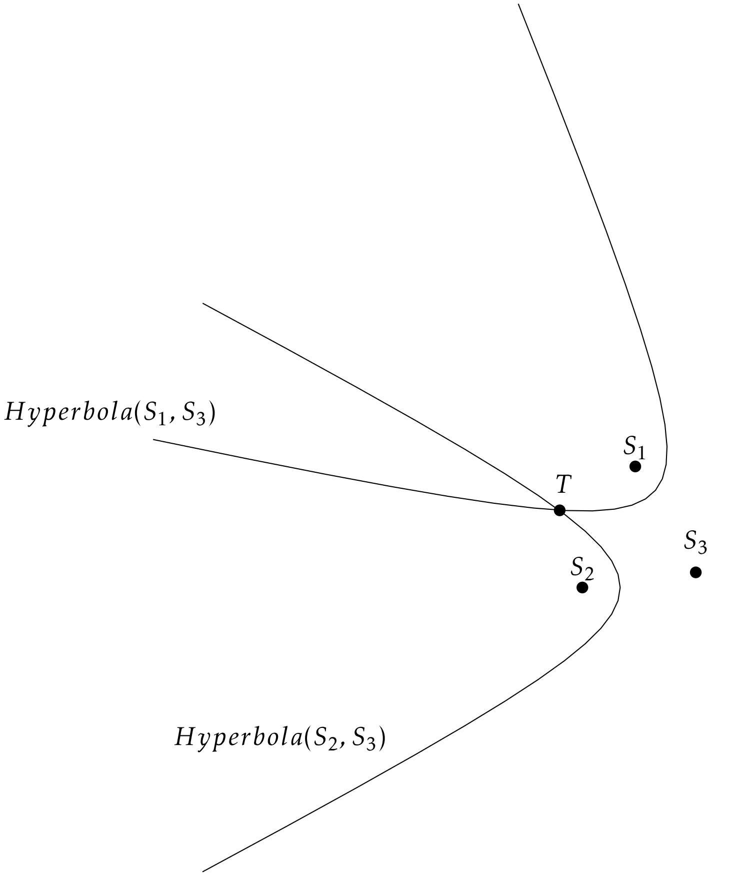

Figure 2.3: *TDOA measurements with three sensors S_1, S_2, S_3 and one transmitter T*

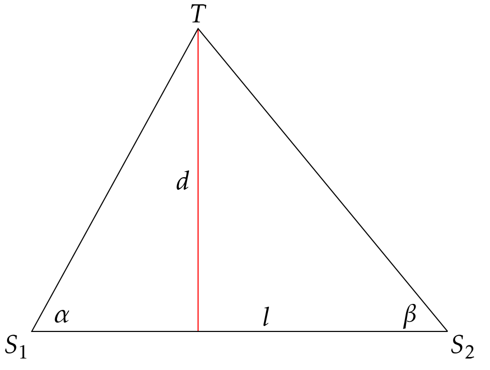

Figure 2.4: *Triangulation with a target T and two observers S_1 and S_2.*

One can then calculate the distance between the target and the observers with the equations

$$r_1 = \frac{d}{sin\alpha}$$
$$r_2 = \frac{d}{sin\beta} \tag{2.16}$$

The position is thus the intersection point between the two distances together with the angles for a clear solution. Note that this example has been shown for an ideal case, in practice more then two lines are needed.

2.6 Probability Detection

Probability detection is a technique that measures binary detections of observers in a surrounding positioning area. By calculating how many times a certain observer is detected and divide it by the number of scans that has been performed a probability for detection has been calculated. According to [A.F.C.Errington, 2008] these detections can be expressed as probabilities in the following way

$$p_i = \frac{1}{R}\sum_{k=1}^{R} V_{(i+kN-N)} \tag{2.17}$$

where R is the number of scans, N is the number of nodes, i stands for which node and V_i denotes whether the node is detected (visible) or not, $V_i = 1$ for detection and $V_i = 0$ for none detection. A position can e.g. get estimated by weighting the surrounding nodes after their respectively probability, see weighted centroid in chapter 3.

2.7 Cell-ID

The cell-ID approach is one of the simplest positioning techniques. The method use Access Points (AP) with a specific ID that is spread out all over the positioning area. The positioning area is then split up in smaller cells, with one AP for every cell, which can determine whether the target is in a cell or not. This means that the AP with the strongest measured signal strength generates the target position in the same cell. The method isn't very accurate since every AP has a relatively huge area to cover, se [Sammarco.C, 2008]. For a more accurate description of how cell-ID determines a position, see chapter 3.

2.8 Summary

This chapter desribed measurement techniques that is used for positioning estimations. The basic measurements can be summerized as

- **RSSI** $\hat{d_{ij}} = d_0(\frac{P_{ij}}{P_0(d_0)})^{-1/\gamma} e^{\frac{-\sigma^2}{2\eta^2\gamma^2}}$
- **One-Way TOA** $d = v\tau_f$, $\tau_f = t_2 - t_1$
- **Two-Way TOA** $\tau_{RT} = 2\tau_f - t_d$
- **TDOA** $\tau_{ij} = (d_i - d_j)/v$
- **AOA** $d = \frac{l sin(\alpha) sin(\beta)}{sin(\alpha+\beta)}$
- **PD** $p_i = \frac{1}{R}\sum_{k=1}^{R} V_{(i+kN-N)}$
- **Cell-ID** Measure detection

These six measurement techniques can be combined with a positioning method, which is explained in the next chapter, to receive a position estimation.

3

Different Positioning Methods

This chapter gives a short description of the most common methods for estimating a position with the earlier presented measurement techniques. The different approaches that will be investigated are Least Squares (LS), Weighted Least Squares (WLS), Nonlinear Least Squares (NLS), Weighted Nonlinear Least Squares (WNLS), Maximum Likelihood (ML), Cell-ID, Weighted Centroid (WC) and Fingerprinting (FP).There will also be some examples of possible solutions with different positioning methods. Since many methods have different advantages and disadvantages a comparison part will be presented in chapter 5. For a description of how to combine positioning methods with radio-based techniques and measurement techniques, see table 5.1.

3.1 Least Squares Estimation

Least Squares Estimation (LSE) together with trilateration is one of the most common algorithms for estimating a position with distance measurements. A possible scenario with three observers and one unknown position with range measurements are shown in figure 3.1 below.

The three different distances can be expressed as following

$$d_1^2 = x^2 + y^2 \tag{3.1}$$

$$d_2^2 = (x_2 - x)^2 + (y_2 - y)^2 \tag{3.2}$$

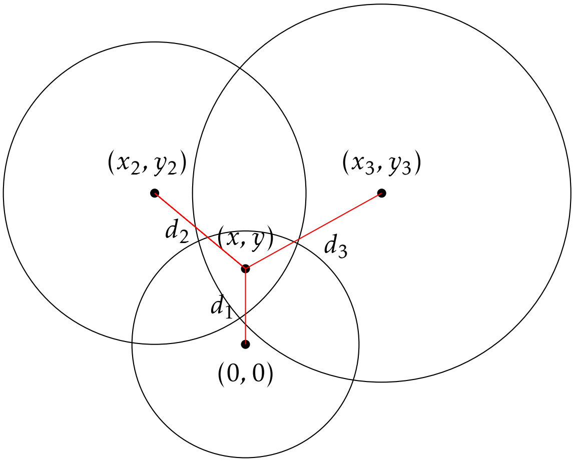

Figure 3.1: *Trilateration estimation with three distances, d_1,d_2 and d_3 to an unknown position (x, y).*

$$d_3^2 = (x_3 - x)^2 + (y_3 - y)^2 \tag{3.3}$$

where the constraint $d_1 < d_2 < d_3$ must be fulfilled.
A few subtractions between (3.1), (3.2) and (3.3) give the following equations

$$d_2^2 - d_1^2 = x_2^2 + y_2^2 - 2x_2x - 2y_2y \tag{3.4}$$

$$d_3^2 - d_1^2 = x_3^2 + y_3^2 - 2x_3x - 2y_3y \tag{3.5}$$

By rewriting the equations (3.4) and (3.5) into matrixes gives the expression

$$\begin{bmatrix} x_2 & y_2 \\ x_3 & y_3 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \frac{1}{2} \begin{bmatrix} x_2^2 + y_2^2 - d_2^2 + d_1^2 \\ x_3^2 + y_3^2 - d_3^2 + d_1^2 \end{bmatrix} \tag{3.6}$$

According to [Sayed A.H., 2005] a solvable linearized LS-problem can be written as

$$HX = Y \tag{3.7}$$

where $H = \begin{bmatrix} x_2 & y_2 \\ x_3 & y_3 \end{bmatrix}$, $X = \begin{bmatrix} x \\ y \end{bmatrix}$ and $Y = \frac{1}{2} \begin{bmatrix} x_2^2 + y_2^2 - d_2^2 + d_1^2 \\ x_3^2 + y_3^2 - d_3^2 + d_1^2 \end{bmatrix}$

The idea with LSE is to minimize the loss function $V^{LS}(X)$ which is the least value of the squares in the equation below

$$\hat{X}^{LS} = argmin_X V^{LS}(X) = argmin_X (Y - HX)^T (Y - HX) \tag{3.8}$$

By differentiation and setting the result to zero the unknown position can finally be estimated as

$$\hat{X}^{LS} = (H^T H)^{-1} H^T Y \tag{3.9}$$

where $\hat{X}^{LS}$ is the LSE for the position $X = \begin{bmatrix} x \\ y \end{bmatrix}$.

In case there are more then three observers their distance equations will be added in the same way as in equation (3.1) $\sim$ equation (3.5). This will affect the estimation since there will be more added rows in the matrixes H and Y.

3.2 Weighted Least Squares Estimation

In order to improve the LSE even further a weighting of the loss function $V^{LS}(x)$ can be done. By expressing the standard deviation e_k for each distance measurement as

$$Cov(e_k) = R_k \tag{3.10}$$

where k is the number of distances and

$$R = diag(R_1, ..., R_k) \tag{3.11}$$

the new loss function is given by

$$V^{WLS}(x) = (y - Hx)^T R^{-1} (y - Hx) \tag{3.12}$$

with the solution

$$\hat{x}^{WLS} = (H^T R^{-1} H)^{-1} H^T R^{-1} y \tag{3.13}$$

where $\hat{x}^{WLS}$ is the Weighted Least Squares (WLS) estimation for the position $X = \begin{bmatrix} x \\ y \end{bmatrix}$.

3.3 Least Squares Estimation with Probability Detections

Another common scenario for position estimations with LS are when the target's measurements are binary detections rather than distances. This means that a node can be either detected or not detected. By using equation (2.17) the different probabilities for each observer can become estimated and a possible positioning area can be seen below in figure 3.2.

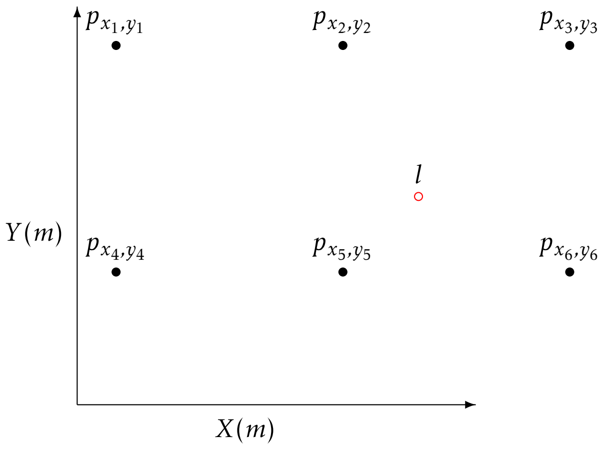

Figure 3.2: *Graph shows six nodes ($p_{x_1,y_1}, ..., p_{x_6,y_6}$), where p stands for the probability of detection and $l(x, y)$ is the coordinates for an unknown target position.*

In order to estimate the node reader's position $\theta(x\,y)$, the loss function from (3.22) can be expressed as

$$V(\theta) = \sum_{i=1}^{M} (m_i(\theta) - p_i)^2 \tag{3.14}$$

where $m_i(\theta)$ is the probability model for a node to be detected. This probability model is determined by gathering real measurement data with known positions for θ and then minimizing the loss function to get the LS estimate. One non linear model that has been used in [A.F.C.Errington, 2008] can be written as

$$
\begin{aligned}
m_i(\theta_k) = bexp[&-a(t_x - x_k)^2 - p(t_x - x_k)(t_y - y_k) \\
&- c(t_y - y_k)^2] - dexp([-e(t_x - x_k + g)^2 \\
&- p_2(t_x - x_k + g)(t_y - y_k + h) \\
&- f(t_y - y_k + h)^2]
\end{aligned}
\tag{3.15}
$$

where the model parameters $\Psi_i = (a, b, c, d, e, f, g, h, p, p2)$ and $(t_x\ t_y)$ are the ith node's position and $(x_k\ y_k)$ are the coordinates for the node reader θ_k. Note that this model is very complex which means that a simpler exponential model can probably give sufficiently accurate results.
The LS estimation for the model parameters is then given by minimizing the loss function

$$
V_i(\Psi_i) = \sum_{k=1}^{K} [m_i(\theta_k; \Psi_i) - p_i(\theta_k)]^2 \tag{3.16}
$$

When the model parameters are determined, equation (3.14) can be used together with the model in order to calculate a target's unknown position $\hat{\theta}^{LS} = (\hat{x}\ \hat{y})$.

3.4 Nonlinear Least Squares Estimation

Nonlinear Least Squares (NLS) problems are similar to the LS problem since both types of problems try to minimize a loss function $V(x)$. What is different for the NLS case is thus the appearance of the loss function which for the nonlinear case can be described by the equation below

$$
V^{NLS}(x) = (y - h(x)^T)(y - h(x)) \tag{3.17}
$$

where y is measurement data and $h(x)$ denotes a general nonlinear model, e.g. TOA, TDOA, RSSI or AOA. According to [Gustafsson, 2012] a loss function with multivariable residuals can be expressed as

$$
V^{NLS}(x) = \frac{1}{2} \sum_{k=1}^{N} \varepsilon_k^T(x) \varepsilon_k(x) = \frac{1}{2} \varepsilon^T(x) \varepsilon(x) \tag{3.18}
$$

where $\varepsilon_k(x) = y_k - h_k(x)$ is a residual and the total residual is received by stacking individual residuals as $\varepsilon(x) = \left(\varepsilon(x)_1^T\ \varepsilon(x)_2^T\ \cdots\ \varepsilon(x)_N^T \right)^T$.

By collecting the first order of derivatives from the residuals the Jacobian $J(x) \in \mathbb{R}^{n_x \times N n_y}$ can be written as

$$J(x) = \frac{\partial \varepsilon^T(x)}{\partial x} = \begin{pmatrix} \frac{\partial \varepsilon_{11}}{\partial x_1} & \frac{\partial \varepsilon_{12}}{\partial x_1} & \cdots & \frac{\partial \varepsilon_{N n_y}}{\partial x_1} \\ \frac{\partial \varepsilon_{11}}{\partial x_2} & \frac{\partial \varepsilon_{12}}{\partial x_2} & \cdots & \frac{\partial \varepsilon_{N n_y}}{\partial x_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial \varepsilon_{11}}{\partial x_{n_x}} & \frac{\partial \varepsilon_{12}}{\partial x_{n_x}} & \cdots & \frac{\partial \varepsilon_{N n_y}}{\partial x_{n_x}} \end{pmatrix} \tag{3.19}$$

where the different residuals can be indexed in the following way

$$\varepsilon_k(x) = \begin{pmatrix} \varepsilon_{k1}(x) \\ \varepsilon_{k2}(x) \\ \vdots \\ \varepsilon_{k n_y}(x) \end{pmatrix} \tag{3.20}$$

Using the results from above the first and the second derivative of the loss function can be expressed as

$$\frac{dV(x)}{dx} = \sum_{k=1}^{N} \sum_{i=1}^{n_y} \varepsilon_{ki}(x) \frac{d\varepsilon_{ki}(x)}{dx} = J(x)\varepsilon(x) \tag{3.21a}$$

$$\begin{aligned} \frac{d^2V(x)}{dx^2} &= \sum_{k=1}^{N} \sum_{i=1}^{n_y} \frac{d\varepsilon_{ki}(x)}{dx} \left(\frac{d\varepsilon_{ki}(x)}{dx} \right)^T + \sum_{k=1}^{N} \sum_{i=1}^{n_y} \varepsilon_{ki}(x) \frac{d^2\varepsilon_{ki}(x)}{dx^2} \\ &= J(x)J^T(x) + \sum_{k=1}^{N} \sum_{i=1}^{n_y} \varepsilon_{ki}(x) \frac{d^2\varepsilon_{ki}(x)}{dx^2} \end{aligned} \tag{3.21b}$$

This results can be used to solve the optimization problem for NLS estimations which can be expressed as

$$\hat{x}^{NLS} = argmin_x V^{NLS}(x) = argmin_x (y - h(x))^T (y - h(x)) \tag{3.22}$$

where the iterative solution will be presented later in this chapter.

3.5 Maximum Likelihood

The Maximum Likelihood (ML) estimate is defined by the equation that maximizes the conditional probability density function which according to [Gustafsson, 2012] can be written as

$$\hat{x}^{ML} = argmax_x p(y_{1:N}|x) \tag{3.23}$$

where $\hat{x}^{ML}$ is the best estimator for the parameter x and $y_{1:N}$ is the measured data. One common property of the ML estimation is that its asymptotically Gaussian distributed which mean that $\hat{x}^{ML}$ is approximately distributed as $\mathcal{N}(x^0, P/N)$ where P is the variance of $\hat{x}^{ML}$ and N is large, P and N are also independent.

For the case when the noise is Gaussian and the model is linear Gaussian, the likelihood can be expressed as the Gaussian Probability Density Function (PDF)

$$p(y_{1:N}|x) = \frac{1}{(2\pi)^{Nn_y/2}\prod_{k=1}^{N}\sqrt{det(R_k)}} e^{-\frac{1}{2}\sum_{k=1}^{N}(y_k - H_k x)^T R_k^{-1}(y_k - H_k x)} \tag{3.24}$$

where the loss function can be expressed as

$$V^{WLS}(x) = (y_k - H_k x)^T R_k^{-1}(y_k - H_k x) \tag{3.25}$$

In order to solve the optimization problem for the loss function, equation (3.24) can be rewritten into the negative log likelihood where a minimization gives the same solution as maximizing the likelihood. The negative log likelihood is minimized in the following way

$$-2log(p(y_{1:N}|x)) = Nn_y log(2\pi) + \sum_{k=1}^{N} log(det(R_k)) + V^{WLS}(x) \tag{3.26}$$

Which means that the ML estimation generates the same estimation as an ordinary WLS approach when the noise is Gaussian and x^0 is the true value of the parameter x.

$$\hat{x}^{ML} = \hat{x}^{WLS} \in \mathcal{N}(x^0, P) \tag{3.27}$$

For a second case when the noise still is Gaussian with covariance R_k but the model is nonlinear, the maximum likelihood can be expressed as

$$p(y_{1:N}|x) = \frac{1}{(2\pi)^{Nn_y/2}\prod_{k=1}^{N}\sqrt{det(R_k)}} e^{-\frac{1}{2}\sum_{k=1}^{N}(y_k - h_k(x))^T R_k^{-1}(y_k - h_k(x))} \tag{3.28}$$

with the loss function

$$V^{WNLS}(x) = (y_k - h_k(x))^T R_k^{-1}(y_k - h_k(x)) \tag{3.29}$$

The Gaussian ML estimation can thus be written as

$$\hat{x}^{ML} = argmin_x V^{NWLS} = \hat{x}^{NWLS} \tag{3.30}$$

However if the error has a given probability distribution $p_E(e)$ the loss function can according to [Gustafsson F., 2005] be described efficiently by the equation

$$V^{ML}(x) = log(p_E(y_t - h(x)) \tag{3.31}$$

3.6 Iterative Optimization Methods

Since both NLS and ML estimations generally are nonlinear optimization problems an iterative algorithm is necessary to achieve an acceptable result. A common optimization problem can be expressed as

$$\hat{x}^{(i+1)} = \hat{x}^{(i)} + \alpha^{(i)} f^{(i)} \tag{3.32}$$

where $f^{(i)}$ is the search direction and $\alpha^{(i)}$ stands for which step length. A first procedure to solve the iterative problem is to make an initial "guess" for the starting value $\hat{x}^{(0)}$. This can be done by applying a rough algorithm such as centroid or cell-ID.

3.6.1 Gauss Newton Algorithm

The Gauss-Newton algorithm is an iterative method that solves the general optimization problem from equation (3.32).

For a NLS optimization problem the step length can be described by the equations (3.21a), (3.21b) and the iterative Gauss-Newton algorithm can according to [Gustafsson, 2012] be written as

$$\hat{x}^{(i+1)} = \hat{x}^{(i)} + \alpha^{(i)} \left(J(x)J^T(x)\right)^{-1} J(x)\,(y - h(x)) \tag{3.33}$$

where the second term from (3.21b) has been neglected since a good guess at the initial position value $\hat{x}^{(0)}$ makes the first term to grow faster due to its quadratic form. The step length $\alpha^{(i)}$ is chosen arbitrarily, but preferably a small value, with the requirement that the loss function should decrease for every iteration. The estimated position is good enough when the change in cost, estimate or gradient is sufficiently small.

The equation (3.33) can be extended for cases when the noise covariance $R_k = Cov(e_k)$ is known. This scenario will generate a similar loss function as equation (3.12), but for the nonlinear descent which can be expressed as

$$\hat{x}^{NWLS} = argmin_x \frac{1}{2} \sum_{k=1}^{N} (y_k - h(x_k))^T R_k^{-1} (y_k - h(x_k)) \tag{3.34}$$

The optimization problem from equation (3.32) can be solved by replacing equation (3.33) with the Nonlinear Weighted Least Square (NWLS) which can be written as

$$\hat{x}^{(i+1)} = \hat{x}^{(i)} + \alpha^{(i)} \left(J(x) R^{-1} J^T(x) \right)^{-1} J(x) R^{-1} \left(y - h(x) \right) \tag{3.35}$$

3.6.2 Steepest Descent

The steepest descent algorithm is another way to solve NLS and ML problems by minimizing the loss function $V(x)$. Steepest descent is very similar to Gauss-Newton since it solves the optimization problem from equation (3.32). According to [Gustafsson F., 2005] the steepest decent can be expressed as

$$\hat{x}^{(i+1)} = \hat{x}^{(i)} + \alpha^{(i)} J^T(x) \left(y - h(x) \right) \tag{3.36}$$

where J(x) is the Jacobian from ekv (3.19), $\hat{x}^{(0)}$ is an initial guess for the position and $\alpha^{(i)}$ is the step length. The number of iterations for solving the optimization problem is determined in the same way as for the Gauss-Newton case.

For a scenario where the noise covariance R_k is known a weighted solution for equation (3.34) can be described as

$$\hat{x}^{(i+1)} = \hat{x}^{(i)} + \alpha^{(i)} J^T(x) R^{-1} \left(y - h(x) \right) \tag{3.37}$$

$$\hat{x} = argmin(y_k - h(x)) \tag{3.38}$$

3.7 Positioning with Cell-ID

The Cell-ID measurements can determine which node is closest to the target and thereby estimate its own position. As mentioned earlier in chapter 2 this approach doesn't give the best accuracy and a better positioning method is therefore needed. One way to deal with this problem is suggested in [Chawathe, 2009] where the solution relies on the visibility of an AP, thus if the target can get any reception or not. A possible positioning area with Cell-ID is shown in figure 3.3.

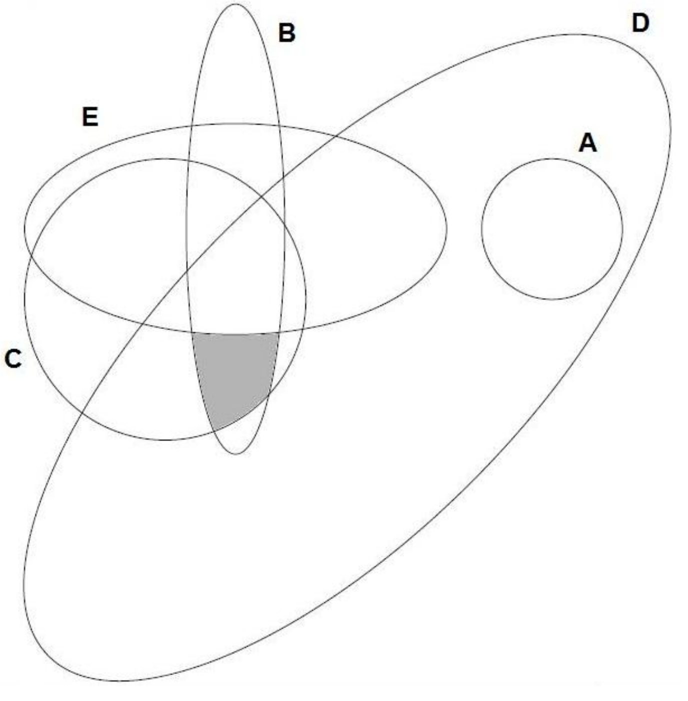

Figure 3.3: *A possible positioning system with Bluetooth nodes where A, B, C, D and E are nodes and the grey area is where the object is positioned.*

Since every AP gives two different measurements, reception and no reception, the number of cells will increase even though the number of transmitters stays the same. An easy example is shown in figure 3.3 where the grey area is described by the following expression

$$R(Z) = \cap_{g \in Z} g = R(\bar{A}\ B\ C\ D\ \bar{E}) \tag{3.39}$$

where R(Z) is the visibility pattern, A, B, C, D and E are the different visible areas for a transceiver. A conjugate means that the area isn't visible for a transceiver which means that the example should be interpreted as only B, C and D are visible for a receiver in the grey area.

Another important aspect with this kind of cell-ID solution is the order in which the target probes the different transmitters. For example, Bluetooth that is a very slow positioning method that can only probe one target at a time and the measuring can take up to 2.5 seconds according to [Chawathe, 2009]. This means that a good probing order greatly reduce the positioning method's latency.

For example, if it is known that the target is inside the grey area before searching after probes. Then is it also known that the target needs to be in one out of six possible places before the next probe search, see figure 3.4.

In order to solve this problem a binary tree is used together with some optimization which minimizes the number of search for probes. In figure 3.5 below there is a possible binary tree which solves the positioning, it is not necessarily the optimized tree with the lowest cost.

In [Chawathe, 2009] there is an explanation of how to produce an optimal binary tree.

3.8 Weighted Centroid

Weighted centroid is a robust method that works well for areas both with and without dynamic changes. The algorithm use a high density of reference nodes (tags) with known positions in order to estimate a target's location. Let M be the number of nodes and $x_i, (i = 1, 2, \ldots, M)$ be their respective position and l stands for the unknown position. According to [Athalye et al., 2013] the position l can be estimated with the following expression

$$\hat{l} = \sum_{i=0}^{M} \frac{x_i}{n} \tag{3.40}$$

where n is the total number of detected tags (the measurement is binary which means either the tag is detected or it is not detected). This method is called centroid and use averaging in order to estimate a position. In order to get a

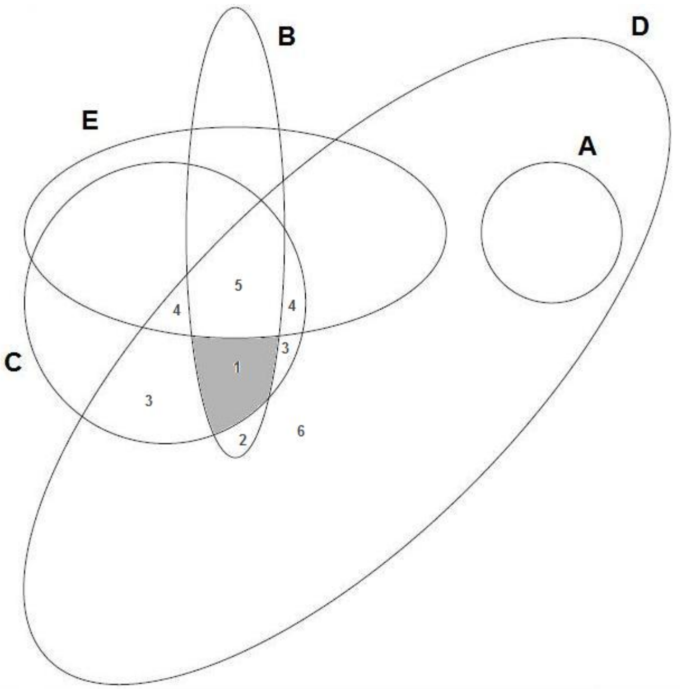

Figure 3.4: *A possible positioning system with Bluetooth nodes where the numbers 1,2,3,4,5 and 6 are possible positions for an object.*

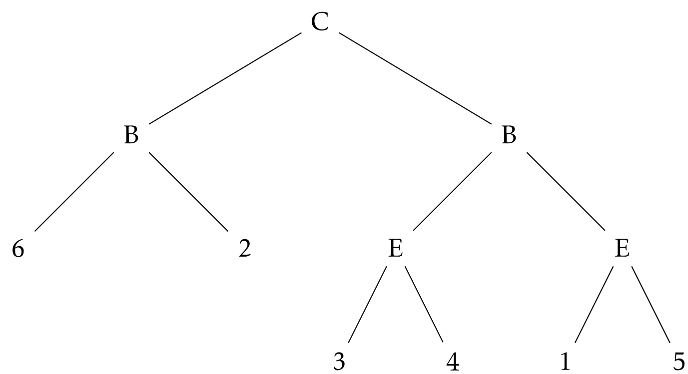

Figure 3.5: *A binary tree solution for probe order where the right child means inside a node's area and the left child means outside a node's area. This example starts by probing for node C, which means inside the node's detection area the possible solutions are 1, 3, 4, 5 and outside C's detection area the solutions are 2 or 6. The next step for a more unambiguous solution is thus to scan B and depending on the result also E.*

more accurate estimation some consideration regarding the node ranges need to be taken. One common approach is to use probabilities which means that a closer target is more likely to get detected by an observer, an alternative approach could be to use RSSI as weights. The probabilities are calculated by counting the number of detections for each tag and then dividing it with the number of scans. The estimated position can thus be written as

$$\hat{l} = \sum_{i=0}^{M} \hat{p}_i x_i = \sum_{i=0}^{M} \frac{n_d^i}{n_q} x_i \tag{3.41}$$

where n_q is the number of scans, and n_d^i is the number of times a tag gets detected. A possible scenario for a 2D-case with one target and six nodes can be seen in figure 3.7, where x_2, x_5 and x_6 will be detected with different probabilities. After the WC estimation $\hat{l}$ will be known as the target's position.

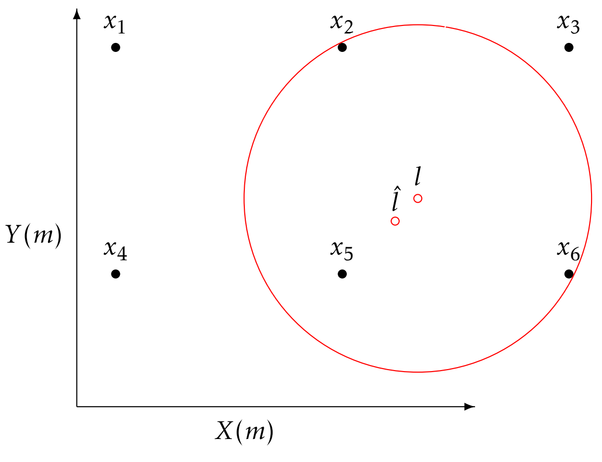

Figure 3.6: *Graph shows six nodes ($x_1, ..., x_6$) together with an unknown target position $l(x, y)$ where the red circle denotes the target's detection range and $\hat{l}$ is the estimated position.*

3.9 Mean Square Error with RSSI

Mean Square Error (MSE) is a method that minimizes the difference between true and estimated positions. A possible positioning area with M observers and one target can be expressed as following

$$MSE(n) = |P_1 - S_1(n)|^2 + |P_2 - S_2(n)|^2 + ... + |P_M - S_M(n)|^2 \tag{3.42}$$

where P_1 to P_M are the measured RSSI values, S_1 to S_M are the different RSSI models for each observer at a position n. There are N numbers of positions spread out over a grid with one square for each position. A possible signal model that has been used in [Shuai Shao, 2012] can be written as

$$S = A\frac{G(\theta)}{R^2} \tag{3.43}$$

where $G(\theta)$ is an angle-dependent function, A is a constant that depends on the target, R_i is the distance between the target and an observer. By using equation (3.42) and (3.43) a final expression for MSE is given by the equation

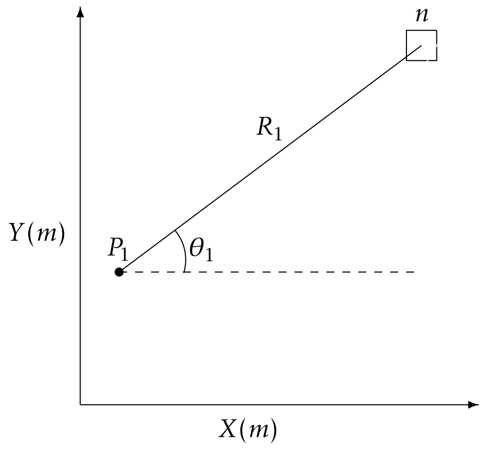

Figure 3.7: *Graph shows sensor P_1 with the distance R_1 from point n with an angle θ_1.*

$$MSE(n) = |P_1 - A\frac{G(\theta_1)}{R_1^2}|^2 + |P_2 - A\frac{G(\theta_2)}{R_2^2}|^2 + ... + |P_M - A\frac{G(\theta_M)}{R_M^2}|^2 \tag{3.44}$$

The unknown tag constant A can then get calculated by minimizing the MSE for a given test point n which is done by differentiating the equation with respect to A and set the expression equal to zero. This gives

$$A = \frac{B_1P_1 + B_2P_2 + ... + B_MP_M}{B_1^2 + B_2^2 + ... + B_M^2} \tag{3.45}$$

where $B_i = G(\theta_i)/R_i^2$. By substituting the constant A in (3.44) with the equation A from (3.45) for every possible position n, the point with the minimum value of

MSE is the target estimation.

3.10 Fingerprinting

In [Ching.W, 2010] there is a developed version of the cell-ID that is called fingerprinting. The fingerprinting method use that each location has a unique combination of detectable signal strengths from the APs. These signal strengths gets collected by an offline phase in order to create a database with "fingerprints" over the map. When the system then turns to the online phase a target measures the surrounding signal strengths from the different APs and compares them with the fingerprint database. As soon as there is a match the target's position becomes known. Two different methods for fingerprinting will be explained below.

3.10.1 K-Nearest Neighbour

The first phase divides the area into rectangular grid blocks where each block has a measured RSSI (typically 100 measurements for every block) and a position described by the integers (x, y). The second phase measures a target's RSSI and compares it with all the fingerprints in the area to find the closest neighbours. One commonly used method to find these matches is described in [Ni L.M., 2003] by the equation

$$E_j = \sqrt{\sum_{i=1}^{n} (\theta_i - S_i)^2} \tag{3.46}$$

where E_j is a vector with Euclidean distances between measured RSSI for the fingerprints θ_i and measured RSSI for the target S_i. This means that every element in E_j denotes a possible neighbor where small values at E_j indicates a higher similarity. In order to get the final position an averaging over the smallest values at E_j (the nearest neighbors) is done by the following expression

$$(x, y) = \sum_{i=1}^{k} w_i (x_i, y_i) \tag{3.47}$$

where x and y are coordinates for the target, k is the number of used neighbors, x_i and y_i are known positions of the i-th closest grid point and w_i is the weighting factor which can be described by the equation

$$w_j = \frac{\frac{1}{E_i^2}}{\sum_{i=1}^{k} \frac{1}{E_i^2}} \tag{3.48}$$

which means that greater values at E_i gives a lesser weighting factor at the position estimation, this approach is also used in [Subhan.F, 2011].

3.10.2 RSSI Probability Distribution with Maximum Likelihood Estimation

This algorithm divides the area into cells or blocks with a reference point in the centre. At each reference point there will be a set of training data as we can denote as a fingerprint R_i, where i stand for which fingerprint. The reference points can be expressed as

$$R_i = P(\bar{O}|l_i) = \prod_{j=1}^{k} \frac{C_{0_j}}{N_i} \tag{3.49}$$

where l_i is the reference point's location, $\bar{O}$ is the reference point's observation, C_{0_j} is the number of times a certain RSSI value appears for a reference point and N_i is the training dataset. The fingerprint database can then be denoted as

$$D = (R_1, R_2, ..., R_m) \tag{3.50}$$

Since the gathering of all fingerprints is very costly another approach is suggested in [Pei et al., 2010]. This approach approximates the RSSI values' distribution with a Weibull function. Since Weibull fairly properly modulates the radio propagation's RSSI the method needs fewer measurements to get robust fingerprints and can be written as

$$f(x;k,\lambda,\Theta) = \begin{cases} \frac{k}{\lambda}(\frac{x-\Theta}{\lambda})^{k-1} e^{-(\frac{x-\Theta}{\lambda})^k} & \text{if } \Theta < x, \\ 0 & \text{else.} \end{cases} \tag{3.51}$$

where $k > 0$ is the shape parameter, $\lambda > 0$ is the scale parameter and Θ is the distribution's location parameter which can be expressed as

$$k = \frac{\delta}{ln(2)}, 1.5 \leq k \leq 2.5 \tag{3.52}$$

$$\lambda = \begin{cases} 2(k+0.15) & \text{if } \delta < 2, \\ \delta(k+0.15) & \text{if } 2 \leq \delta \leq 3.5, \\ 3.5(k+0.15) & \text{if } \delta > 3.5 \end{cases} \tag{3.53}$$

$$\Theta = \bar{O} - \lambda\Gamma(1+\frac{1}{k}) \tag{3.54}$$

$$\bar{O} = \frac{1}{n}\sum_{i=0}^{n} O_i \tag{3.55}$$

$$\delta = \sqrt{\frac{1}{n}\sum_{i=0}^{n}(O_i - \bar{O})^2} \tag{3.56}$$

where $\bar{O}$ is the mean value for each RSSI observation set O_i,Γ is the gamma function and δ is the standard deviation.

In order to localize these fingerprints that are given by the Weibull function a Maximum Likelihood Estimation is used. This estimation check for the best match between a fingerprint and an observation vector $\vec{S} = (s_1, s_2, ..., s_k)$. The best match is described by the equation

$$argmax_l[P(l|\vec{S})] = argmax_l[\frac{P(l|\vec{S})P(l)}{P(\vec{S})}] \tag{3.57}$$

Using the Bayesian theorem together with the assumption of constant probability for both the reference point $P(l)$ and the observation vector $P(\vec{S})$ equation (3.57) can be rewritten as

$$argmax_l[P(l|\vec{S})] = argmax_l[P(\vec{S}|l)] = argmax_l[\prod_{i=1}^{k} P(s_i|l)] \tag{3.58}$$

The maximum conditional probability is then derived from the fingerprints' RSSI histograms which is the same as the best position estimation for l.

3.11 Summary

This chapter estimates positions from measured data. The most common methods can be described by the following expressions

- **LS** $\hat{x}^{LS} = argmin_x V^{LS}(x) \Rightarrow \hat{x}^{LS} = (H^T H)^{-1} H^T Y$
- **WLS** $\hat{x}^{WLS} = argmin_x V^{WLS}(x) = (H^T R^{-1} H)^{-1} H^T R^{-1} Y$
- **NLS** $\hat{x}^{NLS} = argmin_x V^{NLS}(x) = argmin_x (y - h(x)^T)(y - h(x))$
- **ML** $\hat{x}^{ML} = argmin_x - 2log(p(y|x)) = argmin_x V^{NWLS}$
- **Cell-ID** $R(Z) = \cap_{g \in Z} g$

- **WC** $\hat{l} = \sum_{i=0}^{M} \hat{p}_i x_i = \sum_{i=0}^{M} \frac{n_d^i}{n_q} x_i$
- **MSE** $MSE(n) = |P_1 - S_1(n)|^2 + |P_2 - S_2(n)|^2 + ... + |P_M - S_M(n)|^2$
- **Fingerprinting** $E_j = \sqrt{\sum_{i=1}^{n} (\theta_i - S_i)^2}$

Where the principle of linearization has been used for the LS case to solve nonlinear problems with a linear model and LS method. NLS and ML use an iterative solution like steepest descent or Gauss Newton which can be described by the general iterative forumla

$$\hat{x}^{(i+1)} = \hat{x}^{(i)} + \alpha^{(i)} f^{(i)}$$

For fingerprinting, the position estimation can be determined by e.g. k-nearest neighbour or probability distribution with ML estimation.

4

Different Radio-Based Techniques

This chapter gives a description of the most common radio-based methods that are suitable for indoor positioning. A comparison of the different advantages and disadvantages for each of the investigated methods will then conclude the chapter.

4.1 Bluetooth

The first group of radio-based methods to be evaluated is the Bluetooth technique. Bluetooth operates in the 2.4 GHz band with low power consumption for short-range wireless data communication. The most common Bluetooth device today is the Class 2 module, which is used in phones and has an effective range at about 20-30 meters [Ling Pei, 2012]. Other aspects with Bluetooth are that the technology has a slow response time and it doesn't give the best precision [Xu Yang, 2013].

Today most of the Bluetooth positioning systems use fixed nodes and cell-ID or RSSI in order to track a Bluetooth device, se [Xu Yang, 2013]. This is mainly because other tracking methods like TOA and TDOA demands very precise time measurements and that's something the Bluetooth devices lacks with its cheap design. There is also very uncommon that a Bluetooth device has directional antennas which mean that it's impossible to use the AOA method as well.

Unfortunately the Bluetooth technique using RSSI as a distance measurement isn't that accurate either. Accordingly to [Hossain, 2007] the reason for this is that the RSSI measurement is completely dependent on the Bluetooth device's Golden Received Power Range (GRPR). GRPR is a measurement that denotes whether the received power level (RX) is within, above or below the ideal power range. Exam-

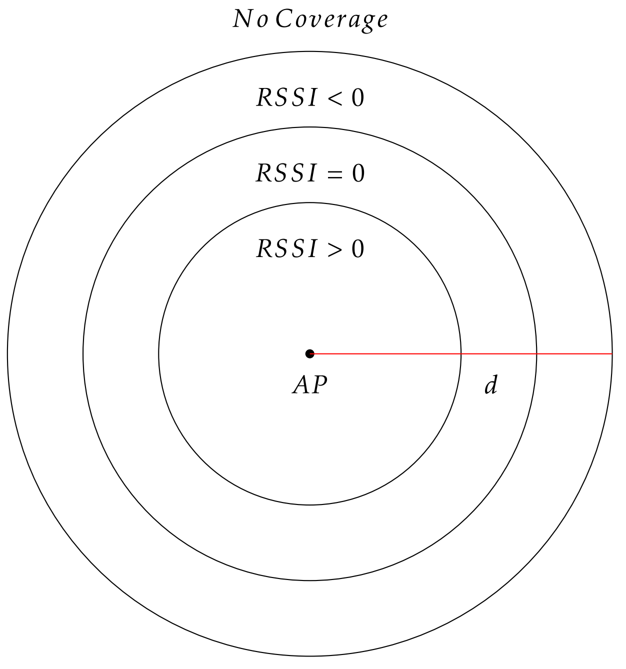

Figure 4.1: *Range graph of how GRPR depends on RSSI. When RSSI is equal to zero the received power level (RX) is within GRPR. AP is the Access Point and d is the distance.*

ples of a possible range graphs for RSSI measurements are shown in figure 4.1 and figure 4.2.

As can be seen in figure 4.1 and figure 4.2 there is an interval in where the RSSI measurement always will get the value zero which means that the device is inside the GRPR. Since there are different distances between the target and the observer inside the GRPR, even though the RSSI value is equal to zero, the measured distance accuracy will get affected.

With the intention to get a more accurate distance measurement for Bluetooth devices something that's called "Inquiry Results with RSSI" is used. This method monitors a nearby device's received RX power level of a current inquiry response. The RX power lever is then derived into a corresponding RSSI in order to make a better distance measurement. See figure 2.1 for an illustration of how a Bluetooth inquiry-based RX power level (dBm) can depend on a distance (m).

One setback with Bluetooth inquiry referring to [Hossian:2007] is the delay that occurs during the inquiry which makes the RSSI measurements slow.

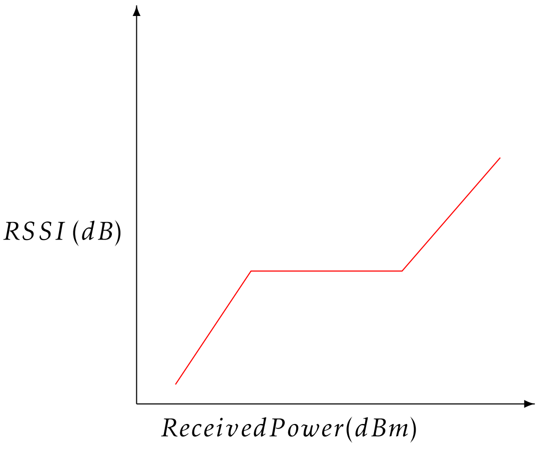

Figure 4.2: *Graph shows how RSSI depends on the received power.*

4.1.1 Bluetooth positioning with fingerprinting

When it comes to accuracy with Bluetooth positioning there are some interesting results. In [Pei et al., 2010] and [Subhan.F, 2011], the solution is to use RSSI together with the two phased fingerprinting technique, where the first phase gather fingerprints and the second estimate the position. These approaches can give position accuracy within 3-5 meters.

4.1.2 Bluetooth Positioning with RSSI and LS

One method that has been suggested in [Xu Yang, 2013] is RSSI based measurements together with trilateration to estimate the position. By applying this method a position can be determined within a couple of meters when there is LOS. However, this was achieved with six inquiry scan readings in order to improve the RSSI measurement which makes the position estimation slower.

4.1.3 Bluetooth with Cell-ID

A third commonly used method for determining a position with Bluetooth is Cell-ID. This method uses the Bluetooth's paging protocol instead of the Bluetooth inquiry which is accordingly to [Chawathe, 2009] the fastest way to determine the visibility of a single node's ID. Unfortunately the paging protocol (probing), can take up to 2.5 seconds for a single node scan, therefore [Chawathe, 2009] suggest some methods for speeding up the positioning estimation. However if the tracked object is moving slow enough and a reasonable amount of nodes is used, an accuracy within a few meters is possible. The properties of the Bluetooth frequency can get summarized by table 4.1.

Table 4.1: *Characteristics for Bluetooth Frequency, note that fingerprinting has the possibility to achieve better results than RSSI+Trilateration, especially for NLOS problems.*

Frequency	Method	Accuracy	Latency	Cost
Bluetooth	RSSI+Trilateration	1-2 Meters	Very Slow	Low
Bluetooth	Fingerprint	3-5 Meters	Very Slow	Mid
Bluetooth	Cell-ID	3-10 Meters	Slow/Mid	Low

4.2 Wi-Fi

One of the most common groups of radio-based methods today is the Wi-Fi which is the same as any Wireless Local Area Network (WLAN) that is based on the IEEE 802.11 standards. A Wi-Fi signal generally operates in the ultra high frequency band and can usually receive ranges at 20-30 meters indoor. One advantage with Wi-Fi is its wide usage in different public environments, like malls and hospitals, together with most of the Wi-Fi devices can work both as a receiver and as a transmitter.

Some of the most common positioning methods for Wi-Fi use different distance measurements like TOA or RSSI for their positioning estimations. There is also usual with solutions based on fingerprinting that use RSSI.

4.2.1 Wi-Fi with Fingerprinting and K-Nearest Neighbor

One fingerprinting approach that has been suggested in [Ching.W, 2010] uses RSSI to match online data with predetermined fingerprints. This is followed by a K-Nearest Neighbor (KNN) solution to calculate the coordinates. By applying this method a positioning accuracy within 5-10 meters is possible.

4.2.2 Wi-Fi with RSSI and Trilateration

Another Wi-Fi solution that has been proposed for indoor positioning is distance estimation with RSSI followed by a trilateration. In [Atia M.M., 2012], several APs have been placed evenly over a tracking area. These APs' measure a target's RSSI and transmits the information to a control centre which creates a propagation model over the RSSI and its distance. By using an AP's observed RSSI values together with its propagation model a distance between the target and the AP can get estimated. The estimated distances combined with trilateration and WLS can finally determine the targets position with accuracy around 1-5 meters.

4.2.3 Wi-Fi with TOA

Wi-Fi with TOA One method that has been suggested in [Stuart A. Golden, 2007] is TOA measurements to estimate a distance. By applying some multipath decomposition to the measurement data the Root Mean-Square Error (RMSE) for the distance estimation can reach accuracy within a few meters. This also means that a positioning accuracy within a few meters is possible if a positioning estimation like trilateration is used. The properties of the Wi-Fi frequency are summarized by table 4.2.

Table 4.2: *Characteristics for Wi-FI Frequency, note that fingerprinting has the posibility to get improved*

Frequency	Method	Accuracy	Latency	Cost
Wi-Fi	RSSI + FP	5-10 Meters	Mid	Mid/High
Wi-Fi	RSSI + LS	1-5 Meters	Mid	Mid
Wi-Fi	TOA	1-5 Meters	Mid	Mid

4.3 RFID

The second group of radio-based methods to be evaluated is the Radio Frequency Identification, RFID. RFID usually operates in the ultra high frequency band with low power consumption and a short range wireless data communication. Today most of the RFID based indoor positioning techniques use a semi-passive system with one active reader and a set of passive RFID tags that relies on the emitted power from the reader. This approach can accord to [Athalye et al., 2013] give reading ranges up to a couple of meters, depending on the reader and the environment.

One other possibility with the RFID technique is to use active tags as well as an active reader. By adding a power source, such as a battery, to the tags a much longer detection range is possible. Unfortunately this type of technique is much more expensive and therefore hasn't been evaluated.

Other aspects with RFID are its cheap design which limits the number of possible ranging methods with suitable accuracy. The most common solution for indoor positioning with RFID is thus based on binary measurements which mean if a tag gets detected or not.

4.3.1 RFID Positioning with PD and WC

One solution that has been proposed by [Athalye et al., 2013] is to measure the detect ability from backscattering between a semi-passive UHF RFID tag (target) and a grid with passive RFID tags. In order to determine a position these binary detections is weighted by the number of times they get detected together with an averaging between which passive tags that have been detected. This approach has been fully explained in chapter 3 and can give accuracy within a meter when estimating a target's position.

4.3.2 RFID Positioning with Cell-ID

This approach has been studied a lot in the literature and is one of the most common methods for indoor positioning with the RFID technique. As mentioned earlier cell-ID uses grids with nodes that transmits a signal with ID and location for a target to receive. By receiving this information a positioning estimation is possible. In [Li-Chieh Cheng, 2011] and [Ching-Sheng Wang, 2009] cell-ID has been used for a positioning accuracy within a few meters.

4.3.3 RFID Positioning with PD and LS Estimation

Another method that has been used in [A.F.C.Errington, 2008] is a grid with nodes. These nodes are transmitters called a tag which sends out a signal that an observer (target) can receive. These received signals can then determine a probability to detect a signal, from a tag, at every single scan. By using this probability together with a probability model for the detection of a node a minimizing loss function can be created. Solving this loss function gives the coordinates for a target as a LS estimation and this approach gives position accuracy within one or two meters.

4.3.4 RFID Positioning with RSSI and MSE

One approach that has been proposed by [Shuai Shao, 2012] is to use RSSI measurements together with the localization algorithm MSE in order to estimate a target's position. In this specific case an interrogation zone has been used together with four surrounding observers that measure a passive tag's RSSI. By comparing the measured data with modeled RSSI values for the observers a target's position is possible to estimate with MSE. This solution can give position accuracy within 0.5 meters for an area with LOS. However, this result is expected to impair a lot for more common NLOS scenarios since RSSI's accuracy is very sensitive to non ideal conditions.

4.3.5 RFID Positioning with RSSI and FP

LANDMARC is a well known method for estimating a position with RFID and fingerprints. In [Ni L.M., 2003] several active RFID tags together with a number of RFID readers have been used. A first procedure is to place the main part of the active tags at advantageous positions with known coordinates and use these as reference tags.

The meaning of having reference tags as constant transmitters and not just gathering fingerprints in advance makes the system less sensitive to environmental changes like people's movement, furniture and other disorders.

A second procedure is to place the RFID readers at clever locations for a favorable coverage of the different reference tags. By having this grid of tags and readers a tracking of a new active tag with unknown position is possible.

By measuring the RSSI from both the reference tags and the unknown target a K-nearest neighbor can be used in order to estimate the target's position. After averaging the nearest neighbors, position estimation within 1-2 meters of accuracy is possible. The properties of the RFID frequency can get summarized by table 4.4.

Table 4.3: *Characteristics for RFID Frequency, note that RSSI + LS was achieved during much easier circumstances since this approach is expected to give the worst accuracy.*

Frequency	Method	Accuracy	Latency	Cost
RFID	PD + WC	1-2 Meters	Fast	Low
RFID	Cell-ID	1-2 Meters	Fast	Low
RFID	PD + LS	1-3 Meters	Mid/Fast	Low/Mid
RFID	RSSI + LS	0.5-1 Meters	Mid	Low/Mid
RFID	RSSI+FP	1-2 Meters	Mid	Mid

4.4 UWB

UWB stands for Ultra Wide Band and is the best radio-based technique for accurate positioning estimations. This is due its wide bandwidth (atleast 500 MHz) which can provide very high temporal resolution and also reduce the positioning error related to multipath. The reason for this is according to [Krzysztof W., 2006] that UWB sends out very short pulses (around 30 cm each) where every pulse is at a different wavelength. So when one of these short-duration waves reflects on a wall or the ceiling the next pulse contains a new wavelength which means that the risk of cancellation is reduced. Further is that UWB includes a lot of different wavelengths which means that UWB has greater abilities to penetrate obstacles then other radio-based methods.

The most common solutions for indoor positioning with UWB are time measurement approaches like TOA or TDOA. The reason for this can be shown with Cramér–Rao's Lower Bound (CRLB) which achieves the best distance estimation $\hat{d}$ derived from TOA. The CRLB inequality can be expressed as [Dardari.D, 2009], [Gezici S., 2005]

$$\sqrt{Var(\hat{d})} \geq \frac{c}{2\sqrt{2}\pi\sqrt{SNR}\beta} \tag{4.1}$$

where c is the speed of light, SNR is the signal to noise ratio and is defined as

$$SNR \equiv \frac{E_p}{N_0} \tag{4.2}$$

where E_p is the average received energy, N_0 is the power spectral density of the noise and β is the effective signal bandwidth which can be described as

$$\beta = \sqrt{\frac{\int_{-\infty}^{\infty} f^2 |S(f)|^2 df}{\int_{-\infty}^{\infty} |S(f)|^2 df}} \tag{4.3}$$

where $S(f)$ is the Fourier transform of the transmitted signal. As can be seen in equation (4.1) the distance estimation depends on both SNR and β, which means that an increase of these two factors will improve the distance accuracy. The UWB can thus use its wide bandwidth to increase factor β and achieve a better performance. Another possibility to increase the accuracy with UWB is to increase the signal power which attains a bigger value for the SNR.

According to [Anwarul.A, 2011] the dissimilarities between the different radio-based methods in the width of the frequency bands together with their Power Spectral Density (PSD) can be seen in figure 4.3.

4.4.1 UWB with TOA

One method that has been studied in the literature [Gezici S., 2005] and [Dardari.D, 2009], for indoor positioning with UWB is the TOA technique. As mentioned before the time measurements can be very precise since UWB use a broad bandwidth. By applying some signal processing together with a matching filter the incoming signal can generate a fairly accurate time measurement which in turn gives accurate range estimations within a meter.

4.4.2 UWB with TDOA and Gauss Newton

Another UWB approach that has been proposed for accurate indoor positioning in [Jingjing Xia, 2010] is a two-step method that measures time. The first step uses TOA together with a closed-form LS estimation in order to calculate a rough position. The second step then uses the rough position estimation as an initial guess for the Gauss-Newton method that is based on TDOA measurements which recursively can improve the position estimation. By applying this method accuracy within 10-15 cm is possible to reach.

Table 4.4: *Characteristics for UWB Frequency, note that this is comparable only if both methods use similar bandwidth*

Frequency	Method	Accuracy	Latency	Cost
UWB	TOA	10-100 cm	Mid	High
UWB	TOA+LS and TDOA+NLS	10-15 cm	Mid/Slow	High/Very High

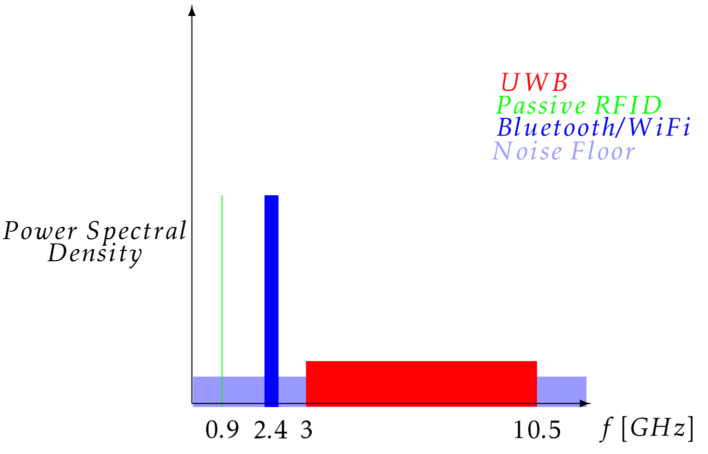

Figure 4.3: *Graph shows how the different radio-based methods relate their bandwidth to PSD. Note that there is more frequency band for RFID, Wi-Fi and Bluetooth that isn't shown in the graph.*

4.5 Summary

This chapter described the relation between accuracy and the radio-based techniques

- **Bluetooth**
- **Wi-FI**
- **RFID**
- **UWB**

were the accuracy were effected by enivronment, measurement technique and positioning method. Some of the presented results was achieved in NLOS/LOS scenarios which means that the accuracy sometimes are to optimistic/pessimistic, see comments associated with tables.

5

Comparisons

5.1 Comparisons between Measurement Techniques

This section presents a comparison between the different methods for measurements regarding positioning. It is difficult to choose one measurement technique over another since every method has its own advantages and disadvantages. Therefore a comparison between the existing solutions is necessary in order to understand what method suits which scenario. It is also relevant to understand what is respectively measurement technique's limitations and improvement possibilities.

5.1.1 Cell-ID

Cell-ID uses very simple and cheap measurements because the technique only detects if the target got coverage or no coverage. The accuracy for the method is therefore not the best and it is thus very dependent on the number of nodes. This means that improvement possibilities for cell-ID are limited by number of nodes.

5.1.2 RSSI

RSSI is a measurement technique that is very simple to use since it is possible to achieve measurements without any complicated hardware. Unfortunately is the technique very sensitive to many of the common errors like multipath, interference, distance and None Line Of Sight (NLOS) which means that the technique's accuracy is very limited by the surrounding environment.
Further is that the signal gives very unstable measurement values which means that filtering can improve both the robustness together with the accuracy.

5.1.3 One-Way TOA Ranging

One-Way TOA Ranging is a technique that can achieve very high accuracy if the time measurements are close to exact. Since the radio waves' propagation velocity moves at the speed of light the time measurements needs to have very small errors. Therefore, this technique will demand expensive equipment (very accurate atomic clocks) with very high frequency and well synchronized between an observer and a target.

5.1.4 Two-Way TOA Ranging

Two-Way TOA Ranging is very similar to the earlier mentioned one-way TOA both with its limitations and its possibilities for improvements, however differences exists. One advantage with the two-way TOA ranging is the non existing synchronization problem, instead accuracy of two-way TOA depends on both the response delay from the observer that reflects the signal back to the target and to the relative clock offset between the target and the observer.
This means that the accuracy can be improved by the adoption of high-precision oscillators and rapid synchronization techniques for the physical layer.

5.1.5 TDOA

TDOA is as mentioned in the earlier two time measurement techniques, very sensitive to precise measurements for accurate positioning.
Since the positioning estimation only depends on the time differences in received signals a synchronization between the target and the observers is not necessary, neither is for the target to have a high clock frequency. Instead it is of a big importance that all the observers have well synchronized clocks to achieve accurate measurement and positioning estimations.

5.1.6 AOA

AOA is in general a bad technique for indoor positioning, mainly because the method involves expensive angle measurements. Other problems that are significant for AOA is that the solution depends on straight lines between the observers and the target which means that areas affected by NLOS and multipath will reduce the accuracy a lot.

5.1.7 Probability Detection

Probability Detection is a fairly cheap method that bases its positioning accuracy on how well probability detections are related to real distances. Since longer distances generate greater uncertainties in the probability measurements, the positioning accuracy is limited.
The positioning accuracy can get improved by adding a greater number of nodes in the positioning area together with filtering to achieve more robust probability detections.

5.2 Comparisons between Positioning Methods

Since there are many different types of measurements with various strengths and weaknesses a determination of one superior positioning method therefore isn't possible. Instead a comparison between the existing solutions is needed. One way to make fair collation between all the methods is to list them after how advanced they are. A general approach (not an absolut truth) for positioning methods are, more advance methods demands better measurements and achieves more satisfying accuracies at a higher cost.

5.2.1 Cell-ID

The least advanced method in this report is Cell-ID, since the method is very cheap and demands a short range between a target and a node. To make this approach effective for positioning a high density of nodes is necessary, further is that the method is very fast since it barely need to do any calculations. As mentioned earlier this procedure doesn't give the best accuracy.

5.2.2 Weighted Centroid

The next method to be evaluated is the weighted centroid which is a very cheap method for positioning. The method uses unstable measurement techniques for example RSSI or probability detection. This means that a higher number of scans in combination with filtering are necessary to achieve satisfying accuracies. Similar to cell-ID the method doesn't provide the best accuracy, but there are possibilities to improve the precision by adding more nodes in the positioning area.

5.2.3 Fingerprinting

A third approach to be evaluated is the fingerprinting method. This algorithm requires an offline phase that determines all the different fingerprints which makes the method more expensive than the earlier mentioned approaches. Fingerprints can be created by both short range and long range radio-based techniques which make the method possible to apply at many different areas.
Because the technique doesn't calculate a position based on distance estimations, but rather matching measurement values, the possibility for acceptable positioning accuracy in NLOS areas are advantageous, however is the system is sensitive to changes in the deployment area. In order to make robust fingerprint estimations a fair amount of scans is necessary. Finally there will also take some extra time for calculations compared to earlier methods since the online data has to be matched with the fingerprints.

5.2.4 LS

LS estimation is one algorithm that differs from earlier mentioned estimations since the position is determined by relating measurements to a linear model that subsequently can estimate a position. This means that the accuracy for LS estimation can vary depending on which type of measurement data (RSSI, AOA, TDOA, TOA) that is obtained. Since all these four measurement types use nonlinear models for relating measurements to positions, a transformation from nonlinear to linear problems (trilateration or triangulation) needs to be done. By doing so the LS can achieve a positioning estimation without more complex and expensive methods that involves solving iterative optimization problems.

5.2.5 WLS

One way to improve accuracy for LS estimations is to use WLS since this solution measure the standard deviation for the different observers in an offline phase. Due to this offline phase the cost for the system will be higher together with a better achieved accuracy since the different observers gets different weighting factors.

5.2.6 NLS

NLS is a similar method as the aforementioned LS estimation; the difference is that instead of a linear model that is getting matched to measurement data a nonlinear model is used. Since the model is more related to a real environment, a better (the best) match to real measurements is possible which means a more accurate positioning estimation at a higher cost.
Unfortunately this approach demands an iterative solution in order to find the best solution for the loss function which means that an initial guess at the true position is needed. It is important that this guess is sufficiently accurate since convergence to the true value is necessary. This initial value can get determined by the less advanced LS, unfortunately this makes the NLS algorithm even more expensive.

5.2.7 WNLS

WNLS is a method that creates better accuracy to a higher cost. As for the WLS case an extra offline phase is necessary to measure the standard deviation for the different nodes. This deviation can be used as a weighting factor for the various observers in order to improve the accuracy.

5.2.8 ML

The ML approach gives a very efficient positioning estimation when the error probability distribution is known. An example is when the noise is Gaussian distributed with a positioning dependent covariance. This will create a Gaussian Maximum Likelihood (GML) estimation which is close to an ordinary WNLS estimation. The only difference is that the loss function for GML will have an extra noise dependent term that reduces errors from large uncertainties.
ML is in general the most optimal location estimation, unfortunately is the method more complex than earlier mentioned methods. As for NLS estimations, ML requires iterative algorithms to calculate a final position estimation which also makes the method more complex.

5.3 Comparisons between Radio-Based Methods

Since there are many types of different radio-based techniques that is used for positioning estimations a comparison between the existing solutions is needed in order to understand their strengths and weaknesses. A general approach is that a more expensive radio-based solution can generate a more accurate positioning estimation. Table 5.1 shows an approximate comparison between the different radio-based methods.
Unfortunately these results are not an absolute truth since the accuracy, latency and cost are very dependent on the environment together with the creation of the positioning system and the number of nodes.

5.3.1 Bluetooth

Bluetooth, from table 5.1 can be seen that Bluetooth doesn't achieve the best accuracy compared to the other radio-based methods. One of the main reasons for this is that the cheap technique doesn't provide accurate time measurements which are in general the best approach for accurate positioning estimations. Even so, there are other possibilities for fairly exact positioning estimations. One method that has given promising results is the filtered RSSI with trilateration. What's unfortunate with this method and positioning methods for Bluetooth in general, is the high latency.
This means that a tracking system with Bluetooth signals, as the only source of information, would have difficulties to keep track of a moving object.
Other properties with Bluetooth are the use of frequency-hopping which means that a Bluetooth device hop through more than a thousand frequency channels every second.
By applying this strategy the Bluetooth technique gets very robust against noisy channels in combination with the possibility of sharing frequency spectra with other radio-based methods. One example is when there are nearby Wi-Fi transmitters with approximately the same frequency as the Bluetooth. The Bluetooth technique can discover which frequency channels that interfere with the Wi-Fi and prevent the noise by skipping to send over these channels.
More advantages with the Bluetooth approach is that the technique exists in almost every cell phone which makes it possible to create a positioning area for persons only by adding a couple of Bluetooth transmitters.
Another big asset for the Bluetooth technique in cell phones is the possibility to use its other powerful sensors in a combination with the Bluetooth. So by fusing the different measurement data from the gyroscope, accelerometer and magnetometer together with the Bluetooth positioning system a lot more accurate estimation for the positioning is possible.

5.3.2 Wi-Fi

The Wi-Fi based positioning technique doesn't attain the best accuracy, as can be seen in table 5.1. One reason for this is that the fairly cheap technique doesn't provide exact time measurements. Further is that the Wi-Fi technique use mid to long detection range which means that the method is very sensitive to NLOS, interference, cancellation and other radio wave related errors.
However, there are some advantages with Wi-Fi. One of the method's biggest strengths is the large spread of existing infrastructure; this means that positioning with Wi-Fi in connection to malls, hospitals and other public areas are very economically advantageous.
Unfortunately many of these locations are exposed for constant changes in the measurement data by people's movements which mean that accurate positioning estimations are difficult. It is also common with a low node density in the environment that makes the positioning even harder.
One way to improve the accuracy for many of these existing infrastructures are to add more nodes or as for the Bluetooth case combine the Wi-Fi measurements with a cell phones existing sensors like gyroscope, accelerometer and magnetometer for a more accurate positioning estimation.

5.3.3 RFID

RFID based positioning can achieve quite accurate positioning estimation to a low cost according to table 5.1. The reason is that the RFID positioning system uses very cheap passive tags with short detection range. So by having a high density of low cost tags at the positioning area, a position estimation can obtain a decent accuracy. This also means that an increase of nodes in positioning area also improves the accuracy.
Since the passive RFID tags have short detection range combined with very fast measurements, the effects from many of the environmental disturbances related to radio waves is reduced.
In comparison with the earlier mentioned radio-based methods, Bluetooth and Wi-Fi, the RFID technique is more suitable for positioning estimations in areas where there is no existing infrastructure to use. This is mainly because the cheap cost for the passive tags, but also for the method's ability to penetrate obstacles at close range and fast measurements. Since RFID doesn't need LOS to function correctly the method is especially suited for harsh areas.
Further is the RFID technique doesn't exist in cell phones like Bluetooth and Wi-Fi which means that it becomes more difficult and expensive to fuse the positioning data with other sensor data in order to achieve a higher accuracy.
However as mentioned earlier, one way to increase the positioning accuracy is to increase the density of the passive tags, but there are more possibilities. Another approach is to place some active reference tags in the positioning area to make track of environmental changes that occurs or improve the placements of the different tags.

5.3.4 UWB

As can be seen in table 5.1 UWB is the best approach for accurate positioning. The main reasons for this are the wide bandwidth together with the short pulses at different wavelengths. These characteristics can then be associated with a lower PSD which means less interference with other systems, a higher reliability for both penetration of obstacles and the possibility to go around objects.
Further is that UWB solves many of the problems (but not all of them) with multipath, NLOS and cancellation due to the short pulses. Other advantages are the long range detection and the possibility for to transfer large amounts of data and still consuming a very little transmit energy.
Unfortunately the UWB technique is expensive and there isn't any existing infrastructure. Therefore, a difficult position area with high demands of precision is needed in order to make UWB cost efficient. As for RFID, the UWB technique doesn't exist in any cell-phones which mean that tracking possibilities with other powerful sensors are limited.

Table 5.1: *Characteristics for Different Radio-Based Methods. These results should not be interpreted as an absolute truth since the accuracy, latency and cost all depends on the positioning systems design in combination with the environment. For example, RSSI has achieved very optimistic results and fingerprinting has achieved pessimistic results.*

Frequency	Method	Accuracy	Latency	Cost
Bluetooth	RSSI+LS	1-2 Meters	Very Slow	Low
Bluetooth	RSSI+FP	3-5 Meters	Very Slow	Mid
Bluetooth	Cell-ID	3-10 Meters	Slow/Mid	Low
RFID	PD+WC	1-2 Meters	Fast	Low
RFID	Cell-ID	1-2 Meters	Fast	Low
RFID	PD+LS	1-3 Meters	Mid/Fast	Low/Mid
RFID	RSSI+LS	0.5-1 Meters	Mid	Low/Mid
RFID	RSSI+FP	1-2 Meters	Mid	Mid
Wi-Fi	RSSI+FP	5-10 Meters	Mid	Mid/High
Wi-Fi	RSSI + LS	1-5 Meters	Mid	Mid
Wi-Fi	TOA	1-5 Meters	Mid	Mid
UWB	TOA	10-100 cm	Mid	High
UWB	TOA+LS and TDOA+NLS	10-15 cm	Mid/Slow	High/Very High

6
Conclusions and Future Work

This chapter presents the most important conclusions of the thesis, along with recommendations for future work on the subject.

6.1 Conclusions

The main contributions of this work, an overall comparison between the existing radio-based indoor positioning systems, analysis of why the choice of positioning method is difficult, analysis of the connection between cost and accuracy, a simplification to select and adapt accurate positioning systems to real problems.

6.1.1 Different Measurement Methods

As mentioned earlier in the comparison chapter there is no measurement technique that works for all possible scenarios, instead the right method needs to be selected to the correct positioning problem.
In this report six different methods have been investigated, AOA, RSSI, TDOA, TOA, probability detection and cell-ID, these solutions can be divided into two different groups.

The first group consists of probability detection and cell-ID, they performs best when shorter ranged radio-based methods are used. The main reason for this is that the positioning method's accuracy is directly dependent on the number of nodes and not the accuracy of the measurements due to the low cost. This means that very cheap nodes are necessary in order to make this approach viable.
It is also possible to add RSSI to this group of measurement techniques, but the method generally demands a more complex positioning method like FP or LS without adding significantly better results.

The second group performs best when the measurements are more accurate and better related to a distance, which means long ranged radio-based techniques. This group includes AOA, RSSI, TDOA and AOA, however it is possible to ignore AOA since the method is both expensive and very sensitive to harsh areas where NLOS exists.
Another method that also struggles with accurate positioning is the RSSI due to the instability in the measurements, both for environments with LOS and the more difficult areas with NLOS. However, this method is still very useful for scenarios where the accuracy doesn't need to be so precise but rather cheap.
This is due to many of the radio-based methods with longer ranges have relatively cheap systems which means that other longer range approaches like TOA and TDOA doesn't give better positioning estimations since the time measurements are to inaccurate.

The last two methods, TOA and TDOA, have as mentioned before the best possibility for accurate positioning as long as the time measurements are sufficiently precise. This precision mainly depends on two different factors, clock frequency and environment.
The clock frequency needs to be in the order of nano seconds to achieve accuracies within a meter, this also means that synchronization between the target and the observers, depending on TOA or TDOA, needs to be very exact.
The accuracy of the positioning system is also very dependent on the environment, which means that LOS is preferably for accurate positioning. Unfortunately this is an unusual event meaning that the radio-based method needs complex solutions to handle issues like multipath, NLOS and interference. This means that a precise system that utilizes time measurements require much thought in the design and will be more expensive.

6.1.2 Different Positioning methods

As mentioned in the comparison chapter, the choice of positioning method is dependent on which case to be solved together with the used measurement method that has been used. One way to simplify this choice is to continue with the last part's division, long detection range and short detection range.

For short range measurement techniques like PD and cell-ID a simple positioning method like WC or cell-ID is most suitable. This is mainly because the measurements are inaccurate and the precision is very dependent on the node density. This means that even if a more advanced method like LS or FP is applied the positioning result's accuracy won't improve significantly. So by keeping the positioning method simple the system's cost can be reduced.

For longer detection ranges other methods like FP, LS, NLS and ML generally achieves better precision. This is because the methods WC or cell-ID need positioning areas with a high density of nodes to attain sufficient accuracy.
FP is a method that in most cases uses RSSI as its measurement technique which

means that the accuracy is limited. This is due to the other long detection range measurement techniques like TOA and TDOA demands complex and expensive time measurements which mainly use other positioning methods and achieve higher precision then what is possible for FP. Nevertheless, it is possible to combine it with other methods like TOA or UWB impulse responses and achieve much better accuracy.
However, there are possibilities with cheap measurement techniques associated with FP and positioning areas. When the positioning area suffers from NLOS and the existing measurement technique is RSSI, then FP can achieve satisfying results. In general, FP can obtain decent accuracy from cheap measurement techniques like RSSI, in rough NLOS areas, to a high cost.

The last types of methods are thus LS, NLS and ML which also have the possibilities to generate the best positioning estimations for distance measurements. For measurement techniques with a higher uncertainty like RSSI, the LS estimation is sufficient since a more complex and more expensive method like NLS and ML doesn't improve the result significantly.
If there instead is a more expensive and more accurate radio-based method that use time measurement techniques, the possibility for precise positioning increases with a more advanced positioning method like NLS, which is most accurate, or ML.
However, since both NLS and ML demand an iterative solution to minimize a loss function, a combination of both LS and NLS or LS and ML perhaps gives the best and most robust result, since the LS estimation can be used to find a good initial "guess" for the target's position.

6.1.3 Radio-Based Methods

The choice of radio-based method is dependent on the positioning area's environment in combination with the accuracy requirements. From the comparison chapter, differences, similarities and advantages are explained and thus are a basis for which use the different radio-based methods have.
The four techniques that have been treated in this report are Bluetooth, Wi-Fi, RFID and UWB. As earlier these can be divided into groups after their different properties.

RFID is the first group to be evaluated since it is characterized by its short detection range. As mentioned earlier RFID gathers relatively primitive measurements which means that the technique fits very well together with simple measurement- and positioning methods like cell-ID, PD and WC.
Since RFID has very low response times both cell-ID and PD gathers data sufficiently fast for a positioning estimation in a tracking scenario. This means that PD and WC can be used as the positioning method for RFID because it is more accurate then cell-ID.

The Bluetooth is a radio-based method that use fairly short detection ranges, longer then RFID and for the most cases shorter than Wi-Fi and UWB. As men-

tioned earlier, the Bluetooth technique is cheap and can't achieve accurate measurements which mean that AOA, TOA and TDOA don't perform so well. Further is that the measurements are very slow which means that it takes a long time to make enough scans for accurate PD.
As can be seen in table 5.1 RSSI is the measurement technique that has been giving the best accuracy for a positioning estimation with Bluetooth. However, this was achieved in conjunction with filtering which causes a much reduced latency and the possibility for tracking an object a lot more difficult.
Instead the less accurate and much faster measurement and positioning method cell-ID can be used for tracking applications. As mentioned earlier an increase of accuracy can be achieved by adding a number of extra nodes in the positioning area.

The Wi-Fi technique is characterized by mid to long detection ranges in combination with low density of nodes which means that methods like cell-ID and PB will have difficulties to generate precise results.
Instead the longer detection range methods like RSSI, TOA and TDOA are more interesting. Unfortunately most of the Wi-Fi techniques are rather cheap which means that accurate time measurements becomes difficult, this indicates that RSSI is a better approach for positioning estimations since it is suitable for low cost and longer detection ranges.
Wi-Fi can also collect measurement data fairly quick which means that the possibility for gathering data and filtering to get more robust data is possible. As can be seen in table 5.1, RSSI in combination with LS is one of the solutions that have achieved the best accuracy for Wi-Fi. However, this result was achieved in relatively light conditions since the positioning estimation were calculated during a constant positioning area.
For more relevant scenarios when the environment is constantly changing, reference nodes can be placed all over the positioning area and measure how the RSSI varies for more accurate results. This approach is possible for both FP and LS solutions which also is two of the most suited methods for positioning with Wi-Fi and RSSI. However, FP should be used for the most accurate positioning estimation.

Earlier in this report it was shown how wider band for TOA estimations improves the CRLB inequality and therefore also the ranging accuracy.
This is also the reason why RSSI isn't used as accurate positioning estimation for the UWB technique, because the CRLB inequality for RSSI doesn't improve by increasing SNR or the effective signal bandwidth.
Since UWB is a radio-based method with fairly long detection range the other measurement approaches like probability detection and cell-ID are less useful.
UWB is without any doubt both the best positioning method and the most complex one. As for RFID the UWB technique doesn't exist in any cell-phones and the infrastructure for a positioning area needs to be built. Therefore, a difficult position area with high demands of precision is needed in order to make UWB to a viable solution. This also means that the most advanced methods for posi-

tioning should be used, namely TOA or TDOA in a combination with LS, NLS or ML.

6.1.4 How to Chose the Correct Positioning System?

To chose a positioning system for a certain environment is a difficult problem since there are many factors that affects the decision. One general approach is to choose the least expensive positioning solution that still satisfies the accuracy demands of the system. This means, in order to create a successful and effective system to a low cost, a number of factors needs to be treated.

The factors are: environment, LOS/NLOS condition, track people or objects, environmental changes or stability, existence of infrastructure, required accuracy, required latency, improvement possibilities, existence of external sensors, communication cost, robustness to failures and computational power.

A survey based on these factors can serve as a foundation for which positioning method to use. Unfortunately, this also means that there is no general solution that works for all different cases, instead each positioning problem needs its own solution that is adapted to the specific environment.

6.2 Future Work

This section presents some suggestions of future work in the area of indoor positioning.

Data Fusion
The positioning methods proposed in this thesis are UWB, Wi-Fi, Bluetooth and RFID. These have all been analyzed by their strengths and weaknesses in combination with their respective positioning result. With sensor fusion between the different radio-based methods, it should be possible to increase the accuracy in the positioning estimations. Another possibility that could be considered are fusing between different measurement methods for a more accurate and robust result.

Tracking/Motion Models
This thesis main priority has been indoor positioning methods, but for many real applications a tracking with motion models are to endeavor. By adding accelerometer, gyroscope and magnetometer, the possibility for velocity estimations in all directions can be received. This means that a more accurate positioning estimation should be possible. Note that there already is a lot of literature on this area

Antenna Placements
One aspect that hasn't been taken into account in this thesis is the placement of the different radio-based methods' antennas. By studying the most common error sources in combination with the wave propagation, increasing measurement

accuracy should be possible.

Other Indoor Positioning Methods
This work has investigated measurement techniques and positioning methods for four different radio-based methods. A future investigation of other radio-based positioning methods like Terrestrial Trunked Radio (TETRA) could use these results for a first evaluation. It is also possible to investigate non radio-based methods like ultrasonic, magnetometer, cameras and barometers.

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