MSC THESIS TASK DESCRIPTION

Zsófia Papp (HM1FMH)

candidate for MSc degree in Electrical Engineering

TDoA based indoor positioning over cellular 5G network

Mobile positioning makes possible to calculate the location of any mobile device connected to the cellular network. The greatest advantage of this method compared to other positioning methods is that it is widely available, reliable and device-agnostic, thanks to the 3GPP standards applied in the network. Mobile positioning is a highly requested feature in manufacturing, emergency services, IoT tracking and UE tracking applications, and <1m accuracy is fundamental for industrial applications, which can be reached with time-based positioning method.

This Thesis aims researching the theoretical background of TDoA positioning implementation over cellular network (especially 5G), collecting and evaluating timing data, and using this knowledge to achieve better TDoA accuracy.

Tasks to be performed by the student will include:

- Present the challenges of the indoor positioning in mobile networks.
- Study and analyze the current state-of-the-art solutions in 4G networks, and the possible new approaches in 5G networks.
- Create a novel hybrid TDoA based 3D indoor positioning algorithm, considering multipath mitigation, and relative time error (rTE) corrections.
- Design a test environment to compare the novel and the existing methods.
- Verify the positioning methods with real mobile network measurements and implement necessary changes to improve robustness and accuracy of positioning.

Supervisor at the department: Dr. Alija Pašić

External supervisor: Dániel Andrási, Ericsson

Budapest, 10 October 2020

/ Dr. Gábor Magyar /

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Zsófia Papp

TDOA BASED INDOOR POSITIONING OVER CELLULAR 5G NETWORK

DR. ALIJA PAŠIĆ

BUDAPEST, 2021

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HALLGATÓI NYILATKOZAT

Alulírott **Papp Zsófia**, szigorló hallgató kijelentem, hogy ezt a diplomatervet meg nem engedett segítség nélkül, saját magam készítettem, csak a megadott forrásokat (szakirodalom, eszközök stb.) használtam fel. Minden olyan részt, melyet szó szerint, vagy azonos értelemben, de átfogalmazva más forrásból átvettem, egyértelműen, a forrás megadásával megjelöltem.

Hozzájárulok, hogy a jelen munkám alapadatait (szerző, cím, angol és magyar nyelvű tartalmi kivonat, készítés éve, konzulens(ek) neve) a BME VIK nyilvánosan hozzáférhető elektronikus formában, a munka teljes szövegét pedig az egyetem belső hálózatán keresztül (vagy hitelesített felhasználók számára) közzétegye. Kijelentem, hogy a benyújtott munka és annak elektronikus verziója megegyezik. Dékáni engedéllyel titkosított diplomatervek esetén a dolgozat szövege csak 3 év eltelte után válik hozzáférhetővé.

Kelt: Budapest, 2021. 05. 23.

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Papp Zsófia

Bírálat

Papp Zsófia (HM1FMH) mérnökjelölt

TDoA Based Indoor Positioning over Cellular 5G Network

című diplomamunkájához

A jelölt dolgozata a beltéri helymeghatározás kérdéskörével foglalkozik 5G mobilhálózati környezetben. A dolgozat témája rendkívül időszerű az 5G hálózati megoldások egyre növekvő terjedésének és az általuk megvalósíthatóvá váló új alkalmazási területeknek köszönhetően.

A dolgozat az általános bevezetőt követően egy rendkívül részletes áttekintést ad a helymeghatározás során felmerülő problémákról és az azokhoz kapcsolódó megoldások hátteréről. Kiemelendő, hogy bár a vizsgált terület rendkívül sokrétű, a jelölt mégis képes közérthetően és összefüggően bemutatni a téma minden aspektusát.

A későbbiekben a jelölt a célul kitűzött pontossági paramétereket ismerteti és röviden összefoglalja a vizsgálatokhoz használt eszközöket és lépéseket. A vizsgálatok szimulációs környezetben kerültek elvégzésre, mely lehetővé tette nagy számú eset elemzését. A jelölt mélyrehatóan ismerteti a szimuláció során felhasznált hibamodelleket, többutas terjedési és jelerősségi modelleket, melyek implementációját az irodalomkutatás során feltárt ismeretekre alapozza. A szimuláció felhasználásával különböző pozicionálási algoritmusokat futtat, és elvégzi ezek összehasonlító elemzését. A többutas terjedés negatív hatásainak csökkentése érdekében részletes elemzést ad a RANSAC algoritmus futási eredményeiről is. A jelölt több önállóan felállított lehetőséget is megvizsgál a RANSAC algoritmus konfidenciájának értékelésére, annak érdekében, hogy ezek figyelembe vételével tovább tudja javítani az algoritmus kimenetének felhasználhatóságát. Ezen lehetőségek azonban, az adott feltételek mellett, nem érnek célt. A jelölt bemutat egy iteratív késleltetés kompenzációs algoritmust is, majd a korábban ismertetett algoritmusok és az értékelésük során kapott eredmények alapján ezek felhasználásával összeállít egy saját kombinált algoritmust. Ezzel átlagosan 25 cm-es javítást képes elérni a helymeghatározáskor és képes jelentősen javítani a pozicionálási hibát olyan esetekben is, ahol a közvetlen rálátással rendelkező hozzáférési pontok száma alacsony. A jelölt a szimulációs környezet paramétereinek változtatásával bemutatja, hogy a kidolgozott pozicionálási megoldás különböző környezetekben is hasonló eredményességgel képes viselkedni. Mivel a kapott pontossági eredmények nem érik el az előzetesen kitűzött célokat, a jelölt több területet is azonosít, melyek fejlesztésével további javítást lehet a jövőben elérni ezen a téren.

Sajnos a szimulációs eredmények összevetése nem történt meg valós környezetben végzett mérésekkel, mivel ez utóbbi környezet – a jelölt hibáján kívül – nem készült el a diplomamunka beadási határidejéig.

A dolgozat szerkezete könnyen átlátható és követhető, a használt megfogalmazások érthetőek és pontosak. Néhány kisebb elgépelésből és ábra szerkesztési hibából adódó problémától eltekintve a dolgozat rendkívül színvonalas és az említett hibák is csak kissé zavaróak. Néhány kiemelendő probléma: a 16. ábrán levágásra került a X tengely felirata, bizonyos ábráknál a címkék nehezen olvashatóak a kis betűméret miatt, a táblázatokat is ábraként tünteti fel. A dolgozatban jelentős számú rövidítés található, melyeket a jelölt az első említéskor old fel. Bizonyos esetekben a régebben használt rövidítések feloldását később is elvégzi ezzel is segítve a megértést. Tovább javíthatta volna ezen kifejezések érthetőségét, ha a jelölt a dolgozatot ellátta volna rövidítésjegyzékkel vagy a használt rövidítéseket egy adott fejezetben, szakaszban táblázatos formában is összefoglalta volna.

A dolgozathoz kapcsolódó kérdéseim a következőek:

- A dolgozatban többször is említésre kerül, hogy a pozicionálást a 3D térben végzi el, ugyanakkor a számításokhoz használt képletek csak 2D helymeghatározást mutatnak be. A 4.4.1 szakaszban a jelölt említést tesz arra, hogy a választott irodai környezetben a hozzáférési pontok elhelyezkedése miatt csak 2D helymeghatározás történik. A létrehozott algoritmus a jelenlegi formájában képes 3D helyzetmeghatározásra is, vagy csak kisebb módosítással tehető erre alkalmassá?
- A 27. ábra jobb oldalán szereplő értékek szerint 7 LOS Dot esetén a pozicionálási hiba jelentősen nagyobb, mint 5 ill. 6 LOS Dot esetén. Mi okozhatja ezt az eltérést?
- A 4.4.2.4 szakaszban ismertetett lehetséges konfidencia indikátorokon túl van-e ötlete más paraméterre, ami jobban jellemezheti a RANSAC algoritmus eredményének megbízhatóságát?

Értékelés

A dolgozat alapján úgy ítélem meg, hogy a mérnökjelölt a kiírásban kitűzött feladatokat megfelelő szinten végezte el. A szakterülethez kapcsolódó szakirodalmat és technológiákat kellő mélységben megismerte, azokat a gyakorlatban is alkalmazni képes. A dolgozatban bemutatott eredmények bizonyítják, hogy a jelölt képes önálló mérnöki munkát végezni.

A diplomamunkát elfogadásra javaslom. Javasolt érdemjegy: jeles (5)

Budapest, 2021. június 7.

Pelle István
okleveles mérnökinformatikus

Záróvizsga Bizottsági Ajánlás

a **Hírközlési és Informatikai Tudományos Egyesület** (HTE)
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Záróvizsgázó hallgató neve:

Papp Zsófia

Diplomaterv/szakdolgozat címe:

TDoA alapú leltéri helymeghatározás cellás 5G mobilhálózatban

Képzés szintje:

- ☐ BProf
- ☐ BSc
- ☒ MSc

Diplomaterv/szakdolgozat minősítése: jeles (5)

Diploma minősítése: kitüntetéses (4,77)

A fenti diplomatervnek/szakdolgozatnak a HTE diplomaterv/szakdolgozat pályázatra történő benyújtását a Záróvizsga Bizottság javasolja.

Dátum: 2021. 06 hó 16 nap

ZVB elnöke

*A kitöltött és aláírt **Záróvizsga Bizottsági ajánlást** szkennelve, **PDF formátumban a pályázat benyújtásakor, a pályázat egyéb dokumentumaival együtt kell feltölteni a pályázati portálon** (https://www.hte.hu/hte-diplomaterv-szakdolgozat-palyazat) **keresztül** az ott ismertetett módon!*

További információk: Dr. Farkas Károly, karoly.farkas@hte.hu, +36 1 371 2719

Összefoglaló

Az 5G hálózatok bevezetése és térhódítása várhatóan jelentős átalakulást fog eredményezni az élet számos területén. A nagyobb sávszélességnek, kis késleltetésnek és a rugalmas hálózati strukúrának köszönhetően olyan új alkalmazási területek kerülnek majd előtérbe, mint az Ipar 4.0, az önvezető járművek és az okos város, de az egészségügyben, a tömegközlekedésben, és az energiagazdálkodásban is radikális fejlődésre számíthatunk a mobilhálózatok új generációjának köszönhetően.

A felsorolt példák közül is számos esetben elengedhetetlen a mobilhálózathoz kapcsolódó eszközök pontos és megbízható helymeghatározása. Különösen összetett feladat a beltéri pozícionálás, ahol a legnagyobb kihívást a beltéri jelterjedési sajátosságok jelentik. Az ismeretlen helyzetű mobileszköz koordinátáinak meghatározása speciális referencia-jelek segítségével történik. Beltéri környezetben a jelterjedést gyakran nehezítik falak és egyéb akadályok, amik a referencia-jelek csillapítását, visszaverődését és szóródását okozzák. Ezek miatt a hátrányos hatások miatt nehéz olyan beltéri helymeghatározó rendszert alkotni, amely elfogadható telepítési és üzemeltetési költségek mellett képes az elvárt pontosságot biztosítani. Egy ígéretes megoldási alternatíva az 5G mobilhálózaton keresztül történő pozícionálás, mivel megbízható, eszközfüggetlen helymeghatározást tesz lehetővé járulékos telepítési költségek nélkül. Ebben az esetben a fő kérdés, hogy a pontossági követelményeknek képes-e megfelelni a redszerünk.

A diplomamunkámban bemutatom, hogy szoftveresen milyen lehetőségek vannak a pontosság növelésére, illetve milyen algoritmusokkal lehet ellensúlyozni a beltéri jelterjedésből adódó hátrányokat. Ezenkívül implementálok egy vételi időkülönbség (Time Difference of Arrival, TDOA) mérés szimulátort, amely figyelembe veszi a beltéri jelterjedés jellemzőit is, és más hatásokat, amik a TDOA alapú helymeghatározást befolyásolják. Ezt követően több különböző módszer kombinálásával megalkotok egy új pozícionáló algoritmust, és a saját készítésű szimulátor segítségével demonstrálom, hogy milyen pontosság érhető el ezzel az új technikával a különböző körülmények függvényében.

Abstract

The deployment and expansion of 5G mobile networks will bring a radical change in several aspects of our life. The higher bandwidth, low latency, and flexible network structure are key enablers for new use-cases, like Industry 4.0, autonomous vehicles, and smart cities. But substantial changes are expected in the field of healthcare, public transportation, and energy management as well.

Many of these applications require accurate location estimation of devices that are connected to the cellular network. Indoor positioning is a particularly complex problem, where indoor propagation properties are the greatest challenge. Positioning Reference Signals (PRS) are used to calculate the position estimate of a mobile device. Because of walls and other obstacles, these signals suffer from reflection, refraction, and attenuation. These impairments make it hard to construct an indoor positioning system, that is cost-effective and accurate at the same time. 5G network-based localization is a promising solution to this problem because it enables reliable, device-agnostic position estimation without additional installation costs. In this case, meeting accuracy requirements is the key challenge.

In my thesis work, I show how is it possible to enhance accuracy in the positioning software, including multipath and Non-Line-of-Sight mitigation algorithms. I implement a Time Difference of Arrival (TDOA) measurement simulator, considering indoor propagation characteristics and other impairments affecting the TDOA positioning. After that, I combine two different approaches to produce a novel positioning algorithm, that is robust to propagation challenges. Finally, I use this simulator to demonstrate the expected accuracy of the new positioning algorithm.

1 Introduction

1.1 Motivation

Mobile communication is undoubtfully one of the most popular technologies in the world: almost everybody is carrying around a cellphone in their pocket. They are part of our everyday life, making it more comfortable and connecting people since the very beginning of the mobile network evolution.

Nowadays not only people are connected through the mobile communication system, but thanks to the Internet of Things and Industry 4.0 more and more devices are getting involved. Many different sectors make use of this reliable, widely available, and ever-evolving service. The time around 2020 is considered as a breakthrough from a mobile technology point of view, because of the deployment of the first commercial 5G networks [1]. 5G is expected to bring radical changes in the telecommunications sector, enabling a whole bunch of new use-cases with its high data rate, low latency, and energy efficiency. Many of these use-cases require device positioning. This functionality is used for emergency call localization for a long time, but the demand for it has significantly increased in the last years [2]. Automated industries, location-based services, and traffic- and transport services show a high interest in being able to localize mobile equipment with the assistance of the mobile communication network.

The main advantages of this method compared to other popular positioning methods, like GPS (Global Positioning System) is wide availability and device agnosticism. This means, that mobile network-based positioning requires no special resources from the devices: it works with the simplest IoT device as well as high precision industrial robot arm. Besides, it can be used under such circumstances, where GPS is not available: indoors, underground, underwater, and dense-urban areas.

1.2 Problem statement

Accurate indoor positioning is a complex engineering problem [3], mainly because of the radio signal propagation challenges. Office buildings, factories full of metal objects, underground mines, and shopping malls are harsh environments: there are surfaces made of a wide range of materials, walls with different thicknesses, moving objects like people or machines, and typically many other devices transmitting radio signals. All these factors are causing severe multipath, shadowing, scattering, and interference, which makes mobile equipment positioning a challenging task.

Network-based positioning builds on different features of the radio waves: Time of Arrival (TOA), Angle of Arrival (AOA) or received signal strength. The problem is, these attributes have an erratic behavior due to the Non-Line of Sight (NLOS) propagation, in contrast to free-space propagation, where all of these characteristics can be described with simple models. Fortunately, there are many options for mitigating the NLOS effect on positioning, as I summarize in Chapter 2.6.

1.3 Current research

The research background of indoor positioning is abundant, a tremendous amount of studies can be found about this topic from the last 25 years, and new studies are published continuously to this day. Despite that, there is not a single solution that is widely spread and universally applicable to most of the indoor use-cases, like the GPS positioning is in an outdoor environment. Most of the proposed solutions are only applicable in specific circumstances.

The most popular technologies for indoor location estimation include UWB (Ultra-Wide Band radio), Bluetooth, and Mobile Network-based solutions [4]. UWB is known to be the most accurate method with centimeter-level accuracy, Bluetooth is the most affordable and easily available from the above-mentioned solutions, and Mobile Network positioning has the advantage that it can be deployed on the already built-out infrastructure.

Wireless target location estimation is a two-step process. In the first step, received signal strength, TOA, or AOA measurements are gathered. After that, the measurements are processed to determine the position. Various positioning methods are available for all kinds of measurement inputs.

1.4 Scope

Implementing a complete indoor location estimation system, that is generally applicable, reliable, and accurate enough is a yet unresolved challenge.

In this Thesis work, I aim to contribute to deploying such a system on a small cell 5G mobile network. The localization is based on Time Difference of Arrival (TDOA) measurements, and it is device-agnostic, which means it applies to every standard 5G mobile equipment right out of the box.

To achieve notably good accuracy, relative timing error (rTE) corrections and multipath mitigation is applied to TDOA measurements. The system is intended to provide high accuracy position estimates in a wide variety of environments, but the prototype system will be deployed in a semi-open office area. The goal is setting up a functional prototype as an end-to-end solution, being able to present the capabilities of the system and provide a blueprint for future implementation of a commercial-grade, scalable solution.

1.5 Approach

Setting up a mobile equipment localization system on a 5G network is a highly collaborative task, including lots of different knowledge areas, like signal propagation, signal processing, telecommunication standards, system integration, and positioning algorithms.

To deploying a prototype as quickly as possible, fulfilling all the requirements, effective teamwork is fundamental. While every developer taking part in this project has his and her specific knowledge, an overall understanding of the whole system is also necessary to bind the different aspects into a working solution.

My primary knowledge area in this project is positioning methods, which means I'm responsible for implementing the location estimation algorithm, including NLOS mitigation. My part also includes some integration, propagation, and synchronization aspects. Integration is required to insert my location estimation algorithm as a component in the network positioning system. Synchronization insights are necessary for being able to understand and apply relative Time Error (rTE) corrections to the TDOA measurements. I also need to build competence in the radio signal propagation properties field, to better understand multipath and NLOS conditions.

The position estimation algorithm is developed based on simulated TDOA measurements and it is going to be verified with real network measurements in 2021. Based on 5G live network measurement results, improvements might be needed, and experiences can be drawn.

1.6 Thesis Organization

The remainder of this thesis is organized into 5 Chapters. My research begins by investigating current time-based positioning methods, network synchronization methods, and indoor propagation environment properties including NLOS simulation and elimination methods.

Then I present the solution architecture, system information, limitations, and the detailed task specification with the requirements in Chapter 3.

In Chapter 4 I focus on the main problem: implementing a time-based, indoor, 3D positioning algorithm, which is robust to NLOS conditions and applies rTE corrections to improve accuracy. In this Chapter, I rely on previously studied theories and combine them for a reliable, accurate mobile equipment localization. In the first part of my work, I'm using simulated TDOA measurements as input for my location estimation algorithm.

In Chapter 5 I evaluate the positioning performance of the developed positioning method. I investigate the robustness to changes in the propagation environment, and I analyze the possibilities to improve accuracy.

Finally, I summarize my work in Chapter 6 and present my plans regarding future work.

2 Background

In Chapter 2 I summarize the theoretical background knowledge that I gathered in the research phase of my thesis work. In the latter part of this Thesis, I am going to rely on the information and references collected here.

2.1 Time-based localization techniques

There is a wide variety of network-based localization techniques, and one possible classification of them is based on the type of the measurement input. Radio signals have three main features that can be measured in the receiver: received signal strength (also called RSSI, Received Signal Strength Indicator), Time of Arrival (TOA), and Angle of Arrival (AOA). The location of a target device with an unknown position can be determined based on these measurements.

In this paper, I only consider the category of time-based positioning methods [5], because my assignment is to implement such a method, see Chapters 3 and 4. This choice is based on the fact, that time-based position estimation is a good trade-off between accuracy and complexity: typically, more accurate than power-based methods, and less complex than angle-based methods. They are also suitable for indoor positioning because of the relatively high NLOS error tolerance.

The basic methods I describe in this chapter, are independent of the network type: they are applicable to Wi-Fi, Bluetooth, UWB, or any other radio network, however, the position estimator algorithms might be different depending on the characteristics of the network, as I explain later in Chapter 2.2 and 2.6.

The subject of my Thesis is the cellular mobile network, so for the sake of analogy with the next parts of this paper, I’m going to use the mobile network terminology.

2.1.1 TOA-based positioning

Time of Arrival can be measured by the receiver antenna, as shown in Figure 1. The location of a mobile device with an unknown position can be estimated based on TOA measurements with the following fundamental method [5].

Time-synchronization between the network and the target device is mandatory for TOA-based positioning, so the Time of Departure (TOD) of the positioning signal can be measured as well. The Time of Flight (TOF) can be calculated as the difference between TOD and TOA, see Equation (1). Assuming that signals propagate at the speed of light in air, the length of the actual propagation path between transmitter and receiver can be determined, see Equation (2).

$$\mathbf{TOF = TOA - TOD} \tag{1}$$

$$\mathbf{d = c * TOF} \tag{2}$$

Where *d* stands for the length of the propagation path, and *c* is the speed of light. In ideal, free-space propagation *d* is equal to the Euclidean distance between the transmitter and receiver. Three TOA measurements yield three distances, and the unknown UE position can be calculated as the intersection point of three (or more) circles.

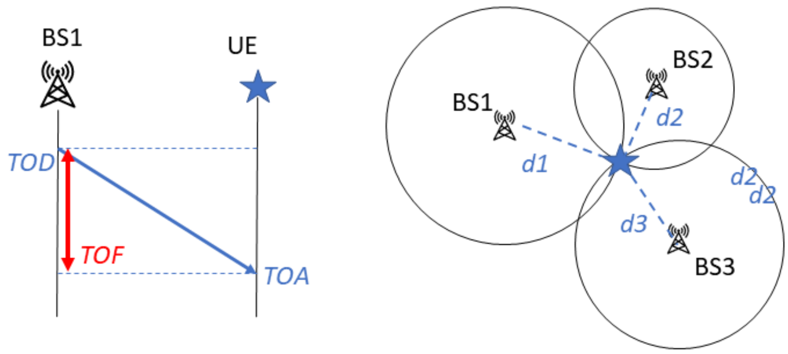

Figure 1: TOA-based positioning illustration

However, in an indoor propagation environment, the direct path is often blocked by an obstacle, and a reflected path might become dominant, which results in an elongated propagation path, as shown in Figure 2. As a consequence, the circles don't intersect in a single point anymore. In this case, the position estimate can be calculated as the optimal solution of a cost function minimalization, see Chapter 2.2 for details.

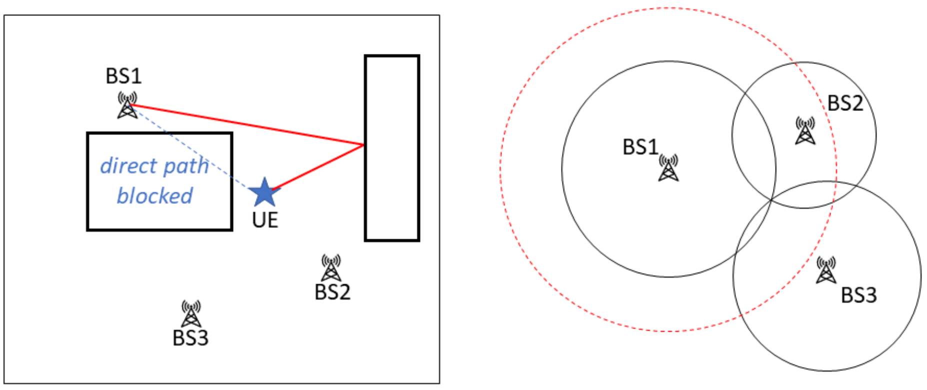

Figure 2. Direct path blockage, and a dominant reflected path's effect on TOA-based positioning

2.1.2 TDOA-based positioning

Synchronization between the cellular network base stations and the target User Equipment (UE) is usually not feasible. If that is the case, the Time Difference of Arrival (TDOA) can be measured instead of TOA, see Figure 3.

A TDOA measurement can be derived from the difference of two TOA measurements. This way, the unmeasurable TOD can be eliminated. Usually, the serving BS is selected as reference BS, and their TOA measurement is subtracted from all the other TOA measurements.

$$\boldsymbol{TOF_i = TOA_i - TOD} \tag{3}$$

$$\boldsymbol{TDOA_{i,ref} = TOF_i - TOF_{ref} = TOA_i - TOA_{ref}} \tag{4}$$

It can be seen from the above equations as well, that the Antenna Reference Points (ARPs) must be time-synchronized for TDOA-based positioning as well, so the TOD can be the same for all of them. The TDOA can be measured by the UE, without being synchronized with the network.

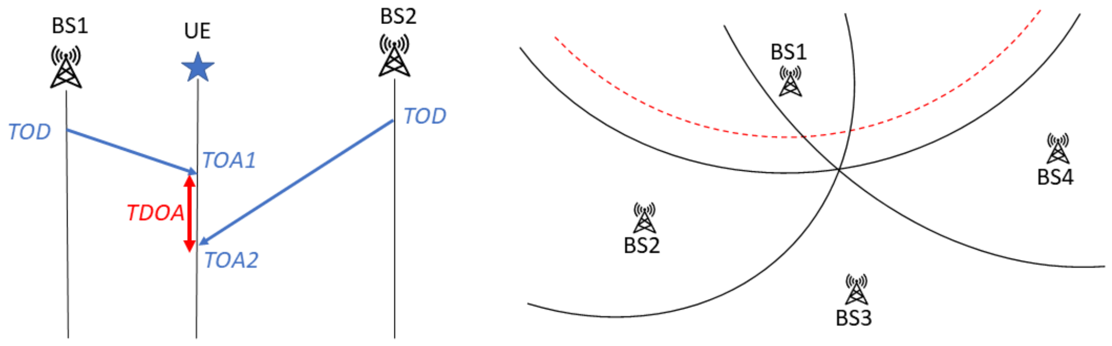

Figure 3: TDOA positioning illustration

In this case, the location of the UE can be determined as the intersection point of two (or more) hyperbolas. The direct path blockage affects the TDOA positioning the same way as I showed in Figure 2: if one of the ARP's direct paths is blocked, the hyperbola illustrating the TDOA measurement is shifted.

2.2 Solution of the TDOA localization problem

2.2.1 Problem formulation

The *(x,y,z)* coordinates of an unknown UE can be calculated as the solution of a system of nonlinear equations based on TDOA measurements, assuming that the ARP coordinates (x_i, y_i, z_i) are known. This system of equations can be formulated as follows:

$$\boldsymbol{c * TDOA_{i,ref} = c * TOF_i - c * TOF_{ref} = d_i - d_{ref}} \quad (5)$$

$$\boldsymbol{d_i = d_{ref} + c * TDOA_{i,j}} \quad (6)$$

$$\boldsymbol{d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2}} \quad (7)$$

$$\boldsymbol{(d_{ref} + c * TDOA_{i,ref})^2 = (x - x_i)^2 + (y - y_i)^2} \quad (8)$$

Where d_i denotes the distance between the UE and *i-th* BS, where *i* goes from 1 to *n*, where n is the number of BSs. This way, we have a system of *n* nonlinear equations in the form of (8), where the unknowns are the UE coordinates.

From here, it is straightforward, that at least 2 TDOA measurements are required for a 2D position estimate because it means we have 2 unknown variables: x and y. However, solving this set of nonlinear equations is difficult, but there are multiple solutions proposed for this problem.

2.2.2 Taylor-series linearization solution

One possible way to do it is by linearization of the (8) equations with the Taylor series method [6], and then iteratively calculating the optimal solution estimate by the local least squares (LS) solutions [7]. This method obtains a precise position estimate at reasonable noise levels but suffers from initial condition sensitivity and convergence difficulty [8]. Weighted least squares (WLS) is a generalized variant of traditional least square regression. It makes use of the knowledge of the variance of measurements, as it is used as a weighting factor.

2.2.3 Maximum-likelihood estimation

ML estimators [9] [8] provide a closed-form solution; thus, they are less computation-intensive than iterative methods, but usually, they can't make use of additional TDOA measurements to improve solution accuracy [10].

In 1994, Chan proposed a simple and efficient estimator for the TDOA localization problem [9], which is widely used to this day, even in 5G positioning simulations [11].

2.3 TDOA measurement technique

In this chapter, I summarize shortly how TOA measurements are carried out. As I derived in Equation (4), a TDOA measurement equals the difference between two TOA measurements.

Positioning Reference Signals (PRS) are transmitted by the ARPs, and the TOA of the signal is determined based on the received Power Delay Profile (PDP), which is produced by sampling the received signal strength. The goal is to find the exact time when the transmitted signal reached the receiver.

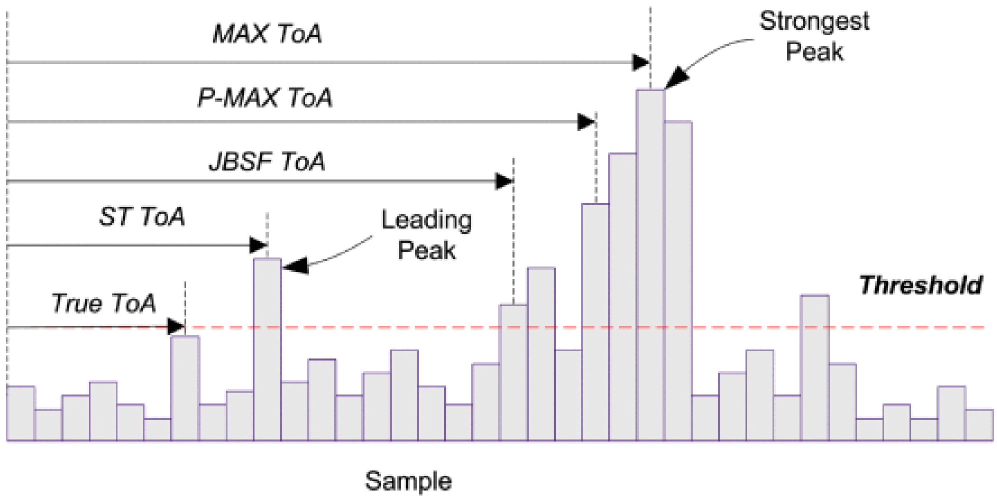

Figure 4. Illustration for different methods determining the TOA based on the PDP (source: [12])

There are multiple ways to this, as illustrated in Figure 4, but the most common method is choosing the sample with the highest received power. Technically, this is done by correlating the received signals [10], see Figure 5 for illustration. The cross-correlation function can be written as

$$\hat{R}_{xy}(\tau) = \frac{1}{T-\tau}\int_{\tau}^{T} y_1(t)y_2(t-\tau)dt \tag{9}$$

where T is the observed interval, and we are looking for the τ that maximizes $\hat{R}_{xy}(\tau)$ value as it is the measured TDOA.

PRSs defined by 3GPP standards were chosen for having good correlation properties. However, under severe multipath propagation caused by good reflectors, it can be difficult to determine the reception time, because of the many multipath components it is impossible to distinguish the LOS (Line of Sight) path from NLOS (Non-LOS) paths.

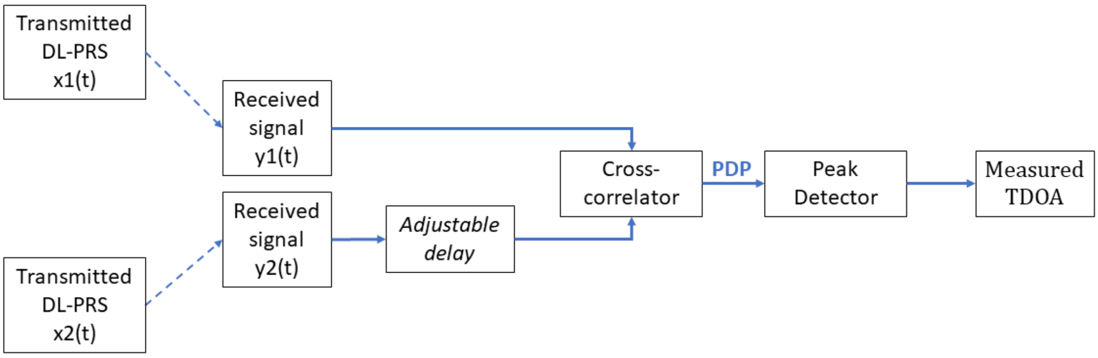

Figure 5: TDOA measurement estimator block diagram

2.4 Network synchronization

As mentioned in Chapter 2.1, time synchronization between ARPs is mandatory for TDOA, and requirements are more stringent for localization than they are for communication purposes. [13]

According to the 3GPP standard, TDD (Time Division Duplex) operation using a guard period between UL and DL transmissions: the network synchronization inaccuracy is 3 microseconds between any two radios [14]. Assuming that radio wave propagation speed equals the speed of light, a rule of thumb can be calculated, that 1ns error in timing causes 30cm error in positioning, so 3 microseconds synchronization error equals to 900 meters error in positioning, which is unacceptable in indoor localization. Therefore, accurate and stable clock synchronization is essential for high accuracy TDOA positioning.

Three common methods for clock synchronization are GNSS (Global Navigation Satellite System), PTP (Precision Time Protocol, standardized in IEEE 1588), and Network Listening, which is a 3GPP standard for synchronizing eNodeBs.

2.4.1 Clock drift and offset

In mobile positioning, every ARPs have a clock equipped with a disciplined oscillator that is regulated by a synchronization reference (e.g. GNSS or PTP). The local time in an ARP can be expressed as:

$$\boldsymbol{C(t) = (1 + \delta)t + \mu} \tag{10}$$

where δ is the clock drift (frequency difference from real value), and μ is the clock offset (time difference from real-time), both being 0 in an ideal clock, however, they are nonzero in real clocks. Clock offset that is adequate for communications is generally assumed to be inadequate for purposes of positioning, so it should be corrected periodically with a synchronization technique.

2.4.2 Network Listening

Network Listening is a fairly new approach for clock synchronization in cellular mobile networks, defined in 3GPP TR 36.922 [15]. It can be used in scenarios where GPS and PTP are not applicable: a typical use-case for Network Listening is indoor macro-cells synchronization.

Indoor eNodeBs obtain their clock synchronization from the so-called Sync eNodeB, which is an outdoor radio equipped with a GNSS synchronization reference. Indoor eNodeBs periodically track synchronization signals from the Sync eNodeB to maintain synchronization. However, because of the nonidealities in the cellular network, the synchronization between eNodeBs contains Relative Timing Error (rTE), which impacts TDOA timing measurements, and thus indoor positioning accuracy.

Relative timing errors can be monitored transparently, without affecting the clock control [16]. The method is based on the assumption, that the radio link between two RDs is symmetrical, even in NLOS indoor environment, so any asymmetries experienced between double-directional propagation channels are the result of rTE between eNodeB clocks.

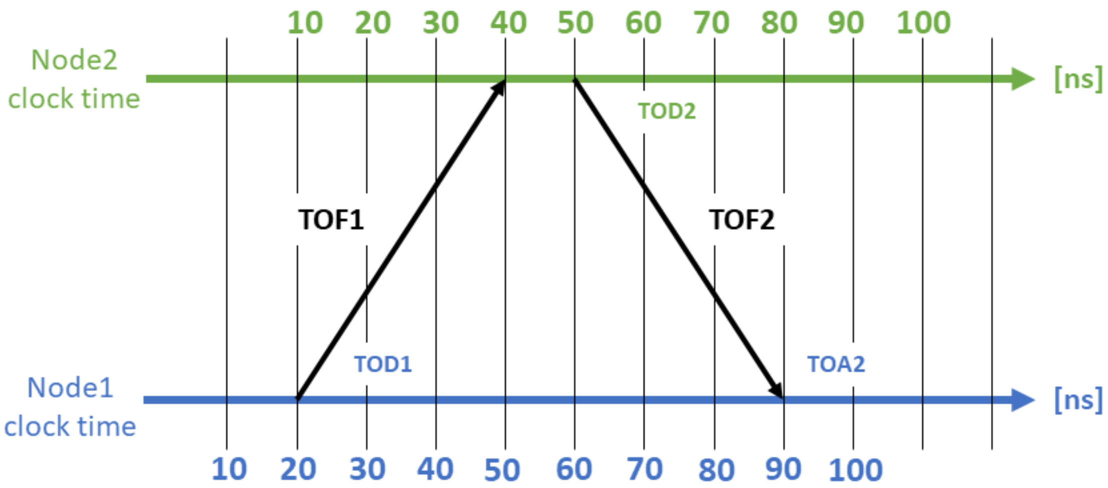

Figure 6. Clock synchronization, and rTE effect on TDOA measurements

The rTE correction observation process consists following steps (see Figure 6 for illustration):

Node1 initiates TOA measurement to determine Time-of-Flight (TOF_1) to Node2.

After that, TOF_2 is measured in the opposite direction, from Node2 to Node1. Because of the channel symmetry, ToF_1 is assumed to be equal to TOF_2 . Any difference between them is due to the relative timing error between the two nodes.

Based on the difference between the two ToF measurements, the relative time error between Node1 and Node2 clock can be determined, see Equation (11-13)

TDOA measurement impairments caused by this relative timing error can be compensated by subtracting the observed rTE value from the measured TDOA, see Equation (13).

$$\boldsymbol{TOF_1 = 40ns - 20ns = 20ns} \qquad \boldsymbol{TOF_2 = 90ns - 50ns = 40ns} \tag{11}$$

$$\boldsymbol{rTE_{12} = TOF_1 - TOF_2} = 20ns \tag{12}$$

$$\boldsymbol{TDOA_{12(corrected)} = TDOA_{12(measured)} - rTE_{12}} \tag{13}$$

Using these corrected TDOA measurements in the position estimation enables better positioning accuracy.

2.5 Indoor propagation environment

In this chapter I introduce some results of measurement studies, to better understand why is indoor propagation environment so challenging from a positioning point of view. After that, I give a short description of how to use channel modeling in multipath propagation simulations.

2.5.1 Multipath propagation

Indoor environments are very complex compared to outdoor propagation environments. Walls and other obstacles result in direct path (DP) blockage, and the wide variety of materials, especially good reflectors like metal objects and flat surfaces lead to multipath signal propagation. Both of these incidents affect the link between transmitter and receiver antennas, therefore they contribute to errors in the TOA measurements, and thus the TDOA measurements. In Figure 7 I provide an overview of one possible link classification, and the TOA error sources related to different types of links.

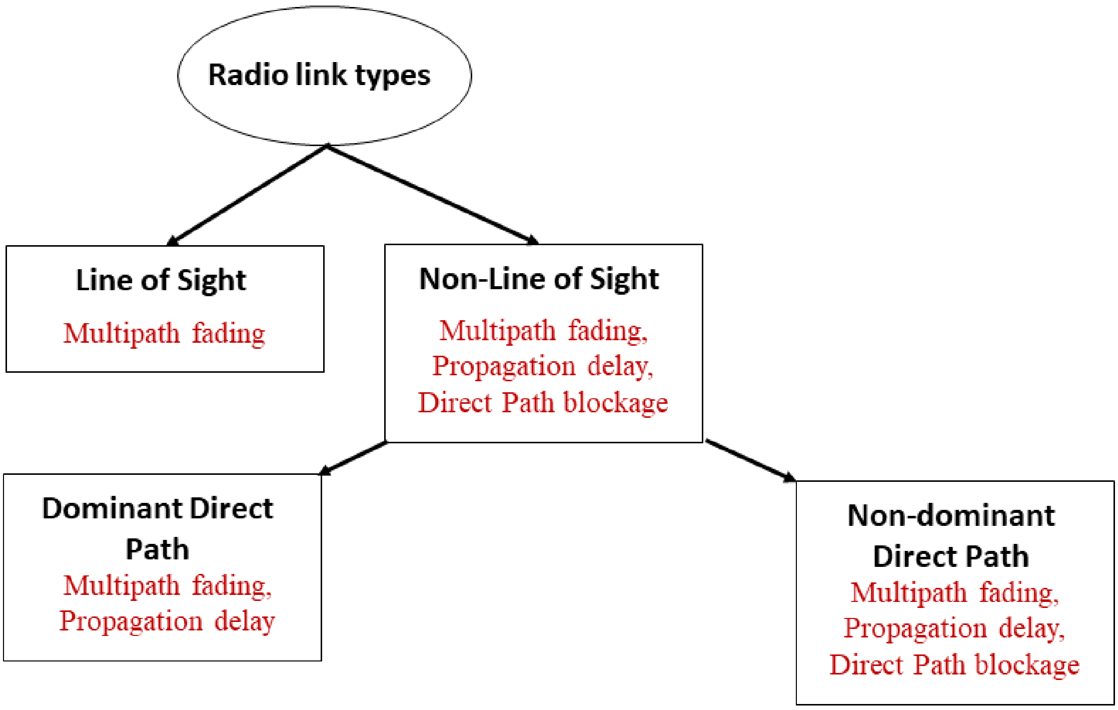

Figure 7. Radio link classification, and the related TOA error sources (based on [17])

For designing an effective NLOS mitigation algorithm, it is important to have a concept about how radio signals behave in indoor environments. Exhaustive measurement campaign results with good illustrations and datasets are presented in the following studies: [18] [19] [20]. I include a short extract of them below.

Typical NLOS anomalies can be observed in Figure 8. TX5 and the lower receiver antenna present NLOS-DP propagation: the LOS is blocked by the wall, but the DP is still dominant over other NDPs. This type of NLOS propagation causes only small errors in the TOA measurements.

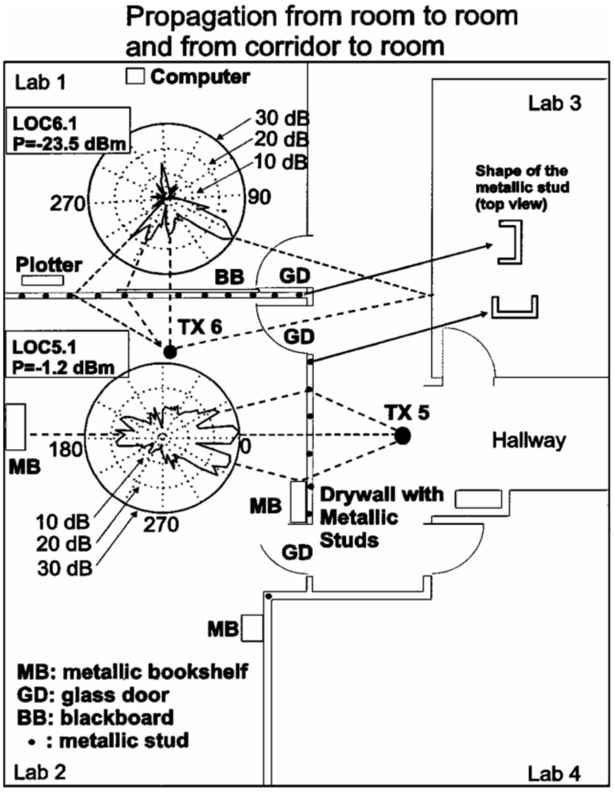

Figure 8: Illustration of NLOS-DP and NLOS-NDP propagation (figure source: [18])

On the other hand, TX6 and the upper receiver antenna show an NLOS-NDP propagation: the reflected path has a stronger received power than the DP attenuated by the wall. This is very harmful to the TOA measurements: the TOF increased significantly compared to the DP TOF because the reflected path is almost 3 times longer than the DP. From a positioning point of view, this introduces a large error to the calculations, as explained earlier in Figure 2 and Figure 3.

Another source of errors in TOA measurement is caused by multipath fading [21]. This anomaly occurs in LOS and NLOS propagation as well. Good reflectors like metal objects and very flat surfaces (whiteboards, floor tiles, etc.) can reflect the radio signals almost perfectly, with a very small loss. This might be problematic because these strong reflected waves reach the receiver, and make it hard to determine the exact reception time of the real LOS signal. The TOA error caused by multipath fading is usually smaller than the NDP error, but it is the dominant propagation factor for LOS radio links operating at frequencies below 10GHz [22].

2.5.2 Channel modeling

Channel modeling is a statistical approach to describe physical propagation channel properties. It is frequently used in radio simulations for system designing or algorithm testing. [19] Channel models can be constructed based on real-life measurements [23], or raytracing [24]. Deterministic channel models are consistent in space, time, and frequency. They have different types, for example, LOS probability models, fast-fading models, penetration models, and multipath models [25].

There are many detailed studies and standards about channel models [19] for different propagation environments both outdoor and indoor. In this thesis, the latter type is relevant, especially LOS probability and multipath channel models.

An exhaustive, 11-step channel coefficient generation procedure is described in [25]. This is considered as the state-of-the-art documentation for 5G channel modeling and is widely used for 5G positioning simulations (see Figure 10 and Figure 11 later in 2.7.2). Distance- and frequency-dependent pathloss models and NLOS probability models are given here for both indoor and outdoor scenarios.

2.6 Multipath mitigation methods

As I explained earlier, the NLOS propagation and the multipath fading can significantly increase positioning error in TOA and TDOA-based positioning methods. This damaging effect can be reduced by different multipath mitigation methods, which can be divided into two main categories. The other group of NLOS mitigation techniques overcomes the NLOS error in one step, without identifying the NLOS links.

2.6.1 NLOS link identification and compensation

The first category includes methods, where NLOS mitigation is carried out in two steps: NLOS link identification and NLOS effect suppression. Successfully identified NLOS links can be discarded from the position estimation process if there are enough LOS links to calculate the position estimate. However, correcting NLOS induced errors might be a better option.

2.6.1.1 CIR-based NLOS identification

NLOS link detection can be performed before the position estimation process, based on the received Power Delay Profile (PDP), also called the Channel Impulse Response (CIR) in signal processing.

CIR features, like kurtosis, root-mean-square delay spread, rise time, normalized strongest path energy, and total energy can be used as metrics in link classification, as proposed in [12] and [26]. The advantage of these methods is that they are completely environment independent, and proved to work well even in harsh environments. A further advantage is that the analysis of CIR features can tell not only the LOS/NLOS classification, but it can indicate how serious the NLOS error is [26].

Therefore CIR-based NLOS identification is a promising approach, especially with the recent advancements applying Machine Learning methods [27] [28].

2.6.1.2 Location-based NLOS identification

Another option is to perform the LOS/NLOS classification after calculating the position estimate. A common technique is to calculate candidate estimates based on different subsets of Antenna Reference Points and looking for clusters among the preliminary estimated positions because those estimates were presumably produced by LOS links [10]. The limitation of this method is that it only works properly if there are redundant LOS reference nodes available.

2.6.1.3 NLOS compensation

If a radio link was classified as NLOS by one of the previously mentioned methods, the TOA measurement on that link contains a portion of error due to NLOS propagation. The magnitude of this error can be determined either based on a propagation model [29] or from the residuals based on a preliminary position estimate [30].

2.6.2 Direct NLOS mitigation

2.6.2.1 Fingerprinting

The fingerprint-based positioning method [31] consists of two stages: the offline measurement collection phase, and the online positioning phase. In the offline phase, on-site measurement samples are collected and stored in a so-called fingerprint database. In the online phase, the archived measurements can be used to compare to the real-time measurements, and based on similarity, the actual target position can be estimated.

Fingerprint-based positioning provides good accuracy in the online phase and it can handle static NLOS errors well. However, the measurement collection in the offline phase is a long and costly process, which is hard to automate in indoor environments.

2.6.2.2 Filtering

Particle [32] and Kalman [33] filters can be utilized in position estimation if the target device with the unknown location is moving. These methods make use of the fact, that during movement, the variance of TOA measurements over an NLOS link is significantly higher than LOS links. This is caused by the multipath components (MPCs) fast-changing nature, which means, they can greatly vary by small spatial difference.

2.6.2.3 Robust estimators

Linear regression methods (like WLS) are sensitive to outliers in the data. A robust WLS algorithm has been proposed in [34], where an iterative reweighted least squares regression of the bi-square cost function is applied.

Another robust estimator was proposed in [26] where an equality constraint is defined to the optimization problem which makes this method resilient even to a large number of NLOS affected observations.

2.6.2.4 Map-based NLOS mitigation

There is another NLOS mitigation method proposed in [35] [36] that applies to buildings with many closed rooms, like hospitals, schools, and traditional closed offices. In such venues, wall attenuation is a common source of errors in TOA measurements. In a closed room, there is usually not a single LOS link available, which is troublesome for methods that rely on LOS-NLOS classification.

Given the assumption that the relative permittivity is approximately the same for all walls, and that room-level location accuracy is achievable through-the-wall (TTW) bias can be estimated and compensated as described in [35] [36]. The drawback of this method is, that it requires a 2-dimensional floor map of the building, including the walls.

2.7 User Equipment positioning in 4G and 5G mobile networks

2.7.1 4G standards and UE positioning solutions

User Equipment (UE) positioning is a long-known functionality provided by the cellular mobile network. Until 4G it was almost exclusively used for localizing emergency calls, so the accuracy requirements were determined by the Federal Communications Commission of the United States (FCC).

However, this trend started to change in 4G, because the achievable positioning accuracy reached a level that is sufficient for other use-cases. In the 3rd Generation Partnership Project (3GPP) Release 13 a new study item has been completed about indoor positioning enhancements for LTE [37], which is a major milestone in indoor positioning over the cellular network.

In [38] a simulation study is presented about indoor positioning, based on the key scenarios defined in the aforementioned 3GPP release. One of these scenarios includes microcells installed inside the building. With this improvement, the horizontal accuracy of positioning increased significantly, compared to other indoor positioning scenarios utilizing only the outdoor macrocell network for position estimation. It is worth noting, that the results shown in Figure 9 were achieved by only installing 4 small cells inside a 50m×120m building. As suggested by [39], increasing the number of Antenna Reference Points improves positioning accuracy.

Scenario	**Method**	**50% error [m]**	**70% error**	**90% error**
Indoor	OTDOA	6 m	9 m	16 m
Indoor	CID	15 m	20 m	31 m

Figure 9. Indoor positioning accuracy in LTE,
based on scenarios recommended in Release 13 study (source: [38])

Another experimental indoor positioning system was constructed and tested in [40]. They installed 11 indoor base stations inside a 30m×40m office area and managed to present an average localization error of around 3m. This was achieved with a fingerprint-based positioning algorithm.

2.7.2 5G standards and UE positioning solutions

5G will be a huge leap in mobile communication technology, and mobile network positioning is also going through important changes. These changes are driven by the increasing demand for UE location estimation in a wide range of industrial and commercial use cases [41].

In the latest official 3GPP release (Release 16) the LTE positioning feature is extended with new techniques which are favorable for 5G positioning [42], such as wideband signals, higher frequencies, and flexible architecture.

Another fundamental feature is the support of a massive number of antenna elements for both transmission and reception, enabling massive MIMO (multiple-input, multiple-output) and advanced beamforming functionalities [43]. Massive MIMO antenna systems can provide enhanced accuracy by utilizing angular properties of propagation combined with time measurements [11]. Beamforming can be used in positioning as well, and it can greatly reduce the harmful effect of multipath components.

In 4G, the number of reference symbol signals for performing RSTD (received signal time difference, basically the same as TDOA) measurements was limited [44]. In 5G, this issue is resolved by the repeated transmission of PRS resources, since it allows a much denser measurement collection, as explained in [42]. The increased number of measurements improves the timing and position estimations.

At the time of writing this thesis, not many 5G indoor positioning systems were available. Huawei claims to be the first to verify a 5G indoor positioning on a live network [45]. Very little information was shared about the deployment setup, only the positioning precision was stated in 3 to 5 m in 90% of the test area.

Apart from that, simulations are available to 5G positioning, for both indoor and outdoor scenarios. A 3GPP study was made about the simulation results [11], which can be considered as a reference for 5G positioning systems. Many different cases were investigated, so I have selected some of them, that have similar parameters to the prototype network I was working on in the latter part of my Thesis work. The most important parameters are summarized in Figure 10.

Parameter	Case 1	Case 2	Case 3	Case 4
Number of ARPs	12	12	12	12
Simulation area	120m×50m	120m×50m	120m×50m	120m×50m
Inter gNB distance	20m	20m	20m	20m
Carrier frequency	4GHz	4GHz	2GHz	2GHz
PRS bandwidth	100MHz	50MHz	50MHz	5MHz

Figure 10. Most important simulation parameters for indoor office 5G positioning simulations [11]

The position estimates were determined with the Gauss-Newton algorithm, and the achieved positioning accuracy is shown in Figure 11. Cases 1-3 show significantly better precision, compared to the 4G indoor positioning methods demonstrated in the previous section. However, Case 4 simulation results are not better than 4G OTDOA with only 4 indoor ARPs, so 5G does not automatically mean higher accuracy. It depends on the deployment characteristics and the position estimator algorithm.

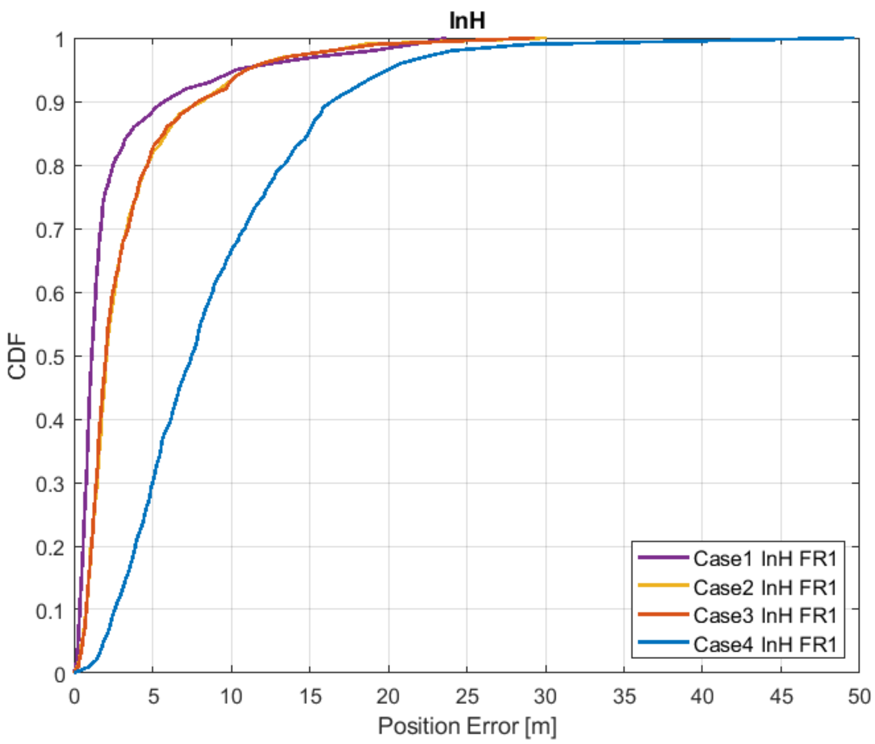

Figure 11. Positioning error CDFs for indoor 5G positioning [11]

3 Solution Architecture

The purpose of the design and development work I've carried out in this thesis is to create a software component, which provides a location estimate of a target device with an unknown position in a 5G network. In other words, the component takes measurements and network-related information as input and performs processing and calculations to determine the UE position. It is essential, that the final solution fits well into the 5G system, utilizes the strengths, and compensates the weaknesses to achieve the expected performance.

In this chapter, I give an overview of the mobile network environment, which serves as a frame to the planned solution, and sets up limitations for it as well. After that, I elaborate on the task specification and describe the actions that are part of the workflow to create a positioning estimator component. I also specify the most important requirements the solution must meet, and finally, I explain the solution plan I've been following through the implementation process.

3.1 Overview

The position estimation will happen over the 5G mobile network. More specifically, it is intended to be used in Ericsson's indoor 5G microcell network, the Radio Dot System (RDS) [46]. In RDS, the Radio Access Network (RAN) nodes are called Radio Dots (RDs, see Figure 12), and 8 of them are connected to an Indoor Radio Unit (IRU). This is a strict boundary for the number of Dots per deployment because adding more IRU's to a system is not practical from a network coverage point of view, and the main purpose of the Radio Dot System is to provide conventional cellular network functionality. On top of that, a new feature is under development, which will enable device-agnostic high precision indoor localization over RDS.

Figure 12. Radio Dot, mounted on the ceiling (source: [46])

Building up a solution like this consists of multiple development phases. The protocols and standards must be worked out, which define the functions and roles of the different network components and the message flow between them. Apart from that, the measurement technique must be implemented in the RAN, to gather information about the UE and provide it as input for the UE position estimator algorithm. And of course, the positioning method itself must be developed. For companies like Ericsson, it is important to bring the end-to-end (E2E) solution to the market as soon as possible, therefore the different development processes are usually overlapped in time. It is also common practice to build prototypes first, as a "proof of concept", to get an insight into the expected performance and characteristics of the new feature.

The UE positioning system prototype consists of the following components:

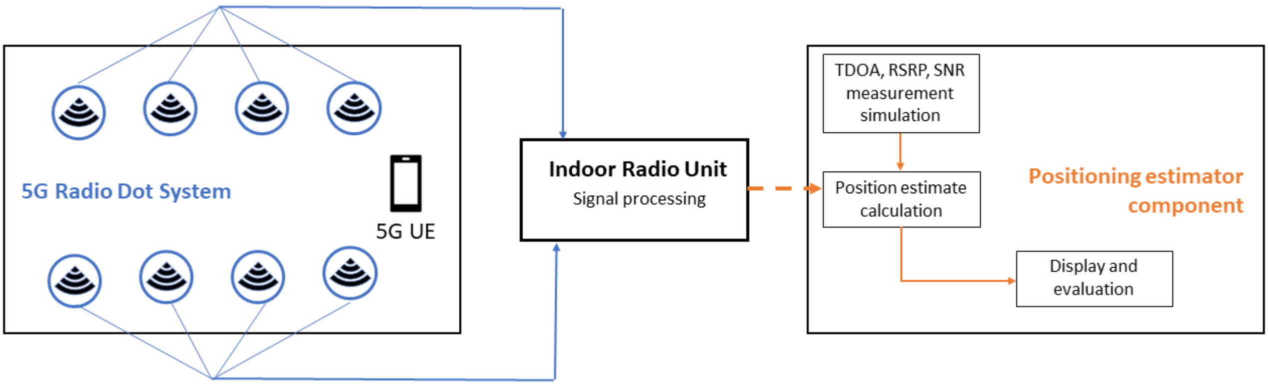

Figure 13: End-to-End solution prototype block diagram

The signal processing unit, implemented in the IRU is responsible for making TDOA measurements, and also contributes to synchronization between Dots. The measured TDOA values and timing corrections are forwarded via Ethernet port. The UE location estimate is calculated by the Positioning Estimator (PE) component, which is a prototype implementing the functionality of the Location Management Function (LMF).

The Radio DOTs (RDs) also have their computation unit, which is taking part in the time synchronization process. RDs are omnidirectional 5G microcells. They are transmitting on 1800MHz carrier frequency, with a bandwidth of 20MHz.

The mobile equipment with an unknown position can be any standard 5G mobile device.

3.2 Task specification

The focal point of my thesis work is implementing a Position Estimator Component (PEC) which fits into the system described in 3.1, and optimizing it in terms of positioning accuracy. The component takes network measurements as input and provides the estimated UE position and the confidence indicator of the estimate on the output. This component is expected to overcome the challenges of indoor propagation summarized in Chapter 120, and it is expected to work environment-independently, so robustness tests to parameter changes are an essential part of the development process as well.

Apart from the position estimator algorithm implementation and verification, realistic simulation of TDOA and RSRP measurements must be performed, including the impairments, which affect the accuracy, like multipath propagation and time synchronization error. There are multiple reasons behind this decision. The first one is, that the real network measurements were not available yet, when I began the formulation of the location estimation process, so I had to work with simulated measurements in the beginning. According to the plans, the simulated measurements will be replaced with real measurements as soon as the network deployment is ready. But the ability of simulation will be useful even after reaching this major milestone because extensive measurement collection is costly in terms of time and resources, so testing algorithm improvements is more effective through simulations.

The result of the development carried out in this thesis work is not only the position estimator component implementation but the overall understanding of the factors that contribute to the accuracy of the final estimate. A functional prototype is expected, and the conclusions about what areas of it need further improvements in the future, to achieve the accuracy goals are summarized in 3.3.

The following questions should be answered based on simulations:

- What is the expected positioning error in the planned system?
- Is the developed position estimation robust to changes in the environment or the system?
- What improvements are needed in the future to achieve sub-meter accuracy?

When I started my thesis work which includes the development of a position estimator algorithm, the 3rd Generation Partnership Project (3GPP) Release 16 containing 5G standards was completed, and the measurement collection implementation in the RAN was almost finalized. I had to make research to build up knowledge first, and I began the implementation parallel with the measurement process verification.

3.3 Requirements

The requirements for 5G positioning use-cases are summarized in the following 3GPP Technical reviews [41] [11]. Our long-term goal is to implement a positioning system that meets these requirements, so it is important to keep them in mind during the development.

My task was the implementation of the position estimation process, so the accuracy requirements are the most relevant for this thesis work. Update rate and latency are primarily determined by the network setup, but the positioning algorithm should not take too long to compute the location estimate. I've collected the most popular indoor use-cases, and their requirements in Figure 14.

Use-case	Horizontal accuracy	Vertical accuracy	Latency	Availability
Wearables	2 m	1-3 m	1 s	90-99%
Advertisement push	3 m	3 m	60 s	90%
Medical equipment	3 m	2 m	60 s	99%
Industrial equipment	0.5 m	1-3m	20 ms	99%
First responders (emergency)	1 m	2 m	1 s	95%

Figure 14. Requirements for indoor 5G positioning use-cases [41]

Since the system is just in the prototype phase, the positioning estimation is not expected to satisfy all of the listed requirements right now. However, we need to make a plan to eventually getting there in the future, so it is important to ramp up knowledge and develop an understanding of the factors that are required to make it feasible.

3.4 Solution plan

For implementing the position estimator component with the functionality described in previous sections, I used the MATLAB platform. This was a straightforward choice because the rest of the End-to-End prototype was written in MATLAB as well, and it is the long-established development environment for research and innovative prototype implementation within the company.

The development work consists of 3 phases:

1. Input measurement simulation
2. Basic position estimation
3. Multipath mitigation

The first two steps build up a test environment for the third step. Based on research I made in the first part of this thesis, multipath-related errors cause the biggest degradation in indoor positioning accuracy, therefore this issue is foreseen as the greatest obstacle on the way to sub-meter accuracy.

Multipath mitigation is planned to be carried out in multiple improvement cycles because coming up with the optimal solution at once is unrealistic in case of such a complex problem. A more feasible approach is to start with a crude solution, see how it works, evaluate the strengths and weaknesses. Meanwhile, I can gain experience about the issue and improve the method step-by-step accordingly.

The developed solution will be used in a real system, robustness analysis is a meaningful part of the workflow. It is not enough to find a solution that works well with a specific setup, testing the solution's sensitivity to changes in the network environment is also very important because we want to build a system that works well in any indoor deployment scenario.

4 Positioning estimator component implementation

The positioning estimator component is a core part of the E2E system which enables UE position estimation over the 5G network. It is a software component, running on a server, receiving radio measurement data on their input, and providing the estimated UE location on their output interface.

4.1 Simulation workflow

I refer to the positioning algorithm and the input measurement simulation as the *TDOA positioning simulator*, because together they enable the simulation of the complete TDOA-based positioning estimation process. This is a favorable workflow for prototype development because this way I could go on with the positioning algorithm research and development without depending on the availability of real-life measurements.

In this chapter, I introduce the simulation workflow of positioning estimation step by step. I begin with the options and input parameters I have added to the code to make the TDOA simulator customizable and I show how the network deployment can be defined. After that, I describe how the position estimates are calculated, and how the results are displayed to help the algorithm development.

4.1.1 Input parameters

In Figure 10 I summarize the input parameters that can be specified by the user for setting up the desired simulation options.

Measurement simulation parameters		
flag_NDP_propagation	true, false	NDP propagation error on/off
flag_multipath_fading	true, false	multipath fading error on/off
flag_TDOA_observation_error	true, false	TDOA obs. error on/off
flag_rTE_error	true, false	relative timing error on/off
flag_Dot_coordinate_error	true, false	Dot coord. error on/off
simulation_mode	local, overall	(see 4.1.2)
DOT_number	3…8	number of Dots
DOT_coordinates	-	(x_i,y_i,z_i) coordinates for each Dot
UE_position_envelope	-	(x_{center},y_{center},range)
trial_number	-	number of trials executed

Position estimation parameters		
positioning_dimensions	2, 3	dimension of pos. estimate
flag_RANSAC	true, false	RANSAC method on/off
flag_IDC	true, false	IDC method on/off
flag_combined	true, false	Combined method on/off

Figure 15. Most important parameters in the TDOA simulator

Only the most important parameters were listed above, there are other parameters for activating or deactivating different methods I tried during the algorithm development and some parameters related to displaying output graphs.

4.1.2 Measurement error simulation

There are two types of simulation modes to choose from: `overall` and `local`. The main difference between the two modes is in the measurement error simulation.

In the `local` mode, one specific measurement input is evaluated in one specific UE location, thus the measurement error is generated in the setup part, and the same errors are used in every location estimation cycle, just a small variation is added to the errors in every iteration. In this case, a small UE envelope is chosen (fixed to 50cm×50cm) because it is a reasonable area to assume that the measurement error is stable.

On the other hand, in the `overall` mode, the measurement errors are re-generated for every positioning estimation loop, and typically a bigger UE envelope is chosen.

TDOA and SINR measurements are being simulated. Simulation is implemented by a statistical approach, where random errors are described with probability distributions. Details about the different error types and distribution parameters are explained later, in 4.2.

4.1.3 Position estimation

The position estimation process consists of a setup part and a looping part, where a given number of position estimation cycles (shortly called trials) are executed with the parameter setup defined in the setup part.

The purpose of the `overall` mode is to an overall image of the position estimator algorithm's expected accuracy. On the other hand and `local` mode is useful for low-level algorithm debugging. In this Thesis, I only show results generated by `overall` mode, but I used the `local` mode during the development phase several times to investigate anomalies.

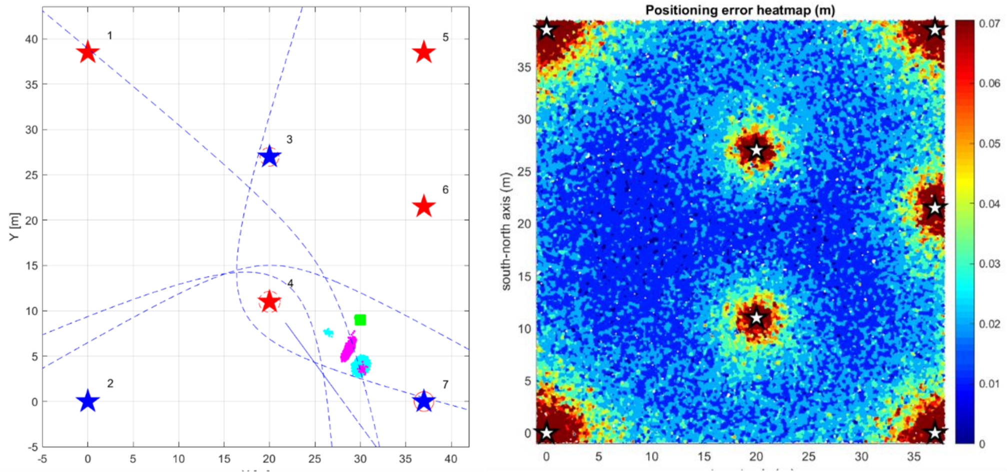

Figure 16. Output graph for the two simulation modes (left: `local`, right: `overall`)

4.1.4 Result evaluation

In every trial loop, the calculated position estimate is stored in an array, along with other information related to the position estimation process, and they are evaluated as the final step of the simulation workflow. Different kinds of output graphs and plots are used, depending on the relevant information the user wants to investigate: CDFs, PDFs, heatmaps, graphs, etc.

The typical visual outputs in the two different modes are shown in Figure 16. In local mode, the Dot placement is illustrated by stars, the UE's true locations, and estimated locations are shown with colorful point clouds, and the hyperbolas illustrating the TDOA measurements are plotted as well. In overall mode, the positioning error is plotted on a heatmap.

4.2 Input measurement simulation

The end-to-end prototype was not functional yet when I began to implement the position estimator component, so real radio measurements were not yet available. That is why simulating the input measurements was an essential part of my work. The planned measurement input consists of the following data:

- Time difference of arrival (TDOA) measurements

- Received signal strength (RSRP) measurements
- and the complete power delay profile (PDP)

These measurements are used for calculating the position estimate. The planned positioning method is primarily based on TDOA measurements so this is the input I spent the most time on modeling and verifying. I also performed RSRP measurement simulation, although it is more of a complementary input. The CIR was not simulated, because it would have been more difficult to carry out, and it does not worth the effort, details are described in Chapter 4.2.4.

Assuming free-space propagation, TOA and RSRP measurements are the function of the distance between transmitter and receiver (in our case Radio Dot-Mobile Equipment), because radio signals travel on the shortest path, with the speed of light. However, in indoor environments, there are different sources of impairments to be considered. In the next sections, I identify these error sources and determine statistical distributions to describe their nominal values in our specific system.

4.2.1 TDOA simulation

The TDOA simulation is carried out as the difference of two simulated TOA measurements because a TOA measurement is the function of RD-UE distance, so a base value can be easily calculated with the following equation.

$$TOA_i = \sqrt{(RD_{xi} - UE_x)^2 + \left(RD_{yi} - UE_y\right)^2} * c \qquad (14)$$

Where c is the speed of light, and TOD is assumed to be 0s for all Dots. The different errors, caused by the non-ideal conditions in the system, are added to this equation. First I had to identify the relevant error sources, affecting TOA measurements. The next step was finding random variable distributions, which are a realistic representation of the expected error. For completing this task, I relied partially on signal propagation properties introduced in chapter 2.5, and I also took into consideration the measurement errors we experienced while verifying the synchronization requirements for positioning. Based on these, I found 4 error sources to consider in TDOA simulation:

1. Radio Dot (RD) coordinate error
2. Relative Time Error (rTE)
3. TDOA observation error

4. TOF error due to NLOS and multipath propagation

4.2.1.1 Radio Dot coordinate error

Before installing Radio Dots into a building, a detailed deployment plan is made with Ericsson Indoor Planner software. This plan includes the recommended placement of Dots, but it can't be straightforwardly used as ground truth for positioning algorithms for multiple reasons.

Some Dots might be moved away from the planned location, because of the infrastructural boundaries (for example lamps, or wires), or other reasons. Even if the Dot is mounted according to the plan, the placement is usually measured by hand, which brings some uncertainty to the x and y coordinates. Z plane error is considered negligible since these devices are mostly ceiling mounted, and the height of the ceiling is known.

This uncertainty in the x and y coordinates is characterized by two independent, normally distributed random variable, with the following parameters:

- Standard deviation: 0.1m
- Expected value: 0 m

4.2.1.2 Relative time error

Time synchronization between Radio Dots is essential for accurate TDOA-based positioning, as explained in Chapter 2.4. The End-to-End prototype developed in this project includes innovative solutions to minimize synchronization error, but the Dot clocks can't be synchronized perfectly. There is still some residual time error to deal with, which I simulated with a standard normal distribution with parameters based on preliminary timing measurements in our system:

- Standard deviation: in the order of 10ns
- Expected value: 0ns

4.2.1.3 TDOA observation error

A high-level description of the TDOA measurement technique was given in 2.3. Such a correlation method is implemented in Radio Dot's processing unit, but the technique is still under development. Unfortunately, we experienced a quite significant TDOA observation error, falling in the range of 10ns. It is suspected to be caused by a miscalculation and expected to be reduced in the order of 1ns shortly.

According to the current state, I modeled this error source with a uniformly distributed random variable in the order of 10ns.

4.2.1.4 TOF error due to model

The most obvious and the most challenging error source in an indoor radio environment is the multipath propagation, which includes reflection, refraction, diffraction of the transmitted signal, and results in excess values to the TOA measurements compared to a free space propagation.

One way to produce realistic simulations to this complex error type is raytracing. The drawback of this method is that it requires a precise 3D model of the environment, which is difficult to produce. Apart from that, it might not be the best way to rely on just one site's information, when developing location estimation algorithms.

Although the error value strongly depends on the actual environment, it is possible to construct statistical multipath models which describe the general features of different buildings and hence can be used for simulations easily and effectively. The advantage of this approach is that such models can be modified and changed quickly, which gives a lot of freedom in the development process to test the sensitivity and robustness of the location estimation algorithm to different models.

The question is: how to construct such a multipath model? I proposed a simple solution, the details in Chapter 4.2.2.

4.2.2 Multipath modeling

Multipath modeling is a method used in radio network planning and simulation. Multiple standards include different multipath model recommendations for different mobile network deployment scenarios, like urban, suburban, rural, or indoor.

Most of these models follow the recommendations given in [25] about channel modeling. This model is complex and would have taken too much time to implement every aspect of it in the TDOA simulator. So instead of that, I made a simplified model, containing only the most important parts to simulate additional pathloss and excess TOA in a multipath environment. Based on [25], both of these values depend on the BS-UE distance.

4.2.2.1 Dataset

I received an indoor measurement dataset, which was taken in a similar radio system to RDS, in an office environment [20]. The dataset included 35 measurement points across the building, which was a modern semi-open office (similarly to Ericsson House Budapest) area with a wide variety of materials.

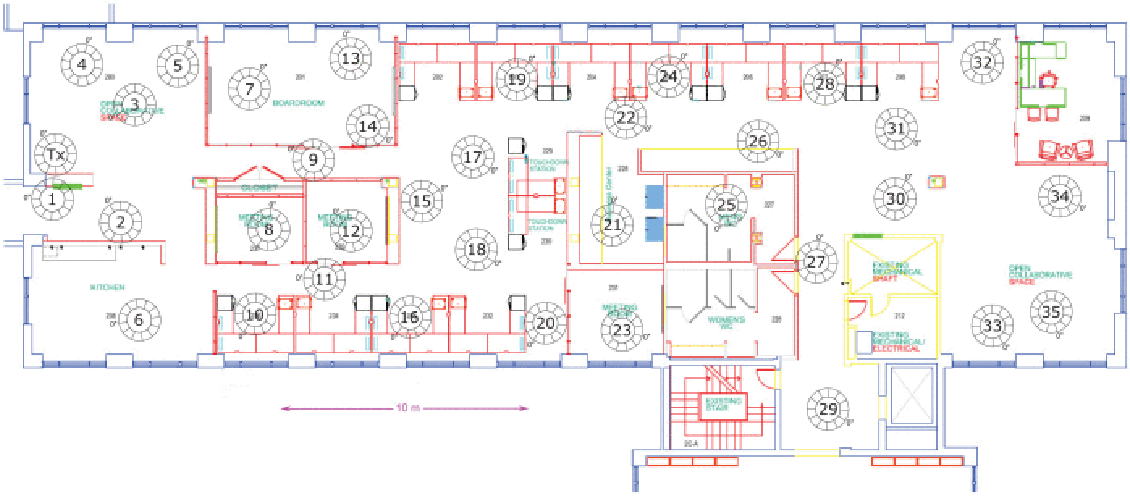

Figure 17. Indoor propagation measurement setup, with 35 RX points (source: [20])

4.2.2.2 Data processing steps

The data was given to me in a form of 35 Power Delay Profiles (PDPs). The TX and RX coordinates, and hence the TX-RX distances were known as well. I wrote a MATLAB script which is processing the PDPs through the following steps.

First, it is extracting the 5 strongest multipath components, their reception times, and the received powers. Then it determines the theoretical "LOS" reception time, based on TX and RX distance. After that, it calculates the excess TOA value on the top of "LOS" TOA with the following equation.

$$TOA_{excess} = TOA_{reception} - TOA_{LOS} \tag{15}$$

At this point, I have 5 excess TOA values and 5 received powers per measurement point. In the next step, I determined the probability of a dominant NLOS path with the following method. I calculated the empirical mean and standard deviation of the received powers, but I linearized them before doing so. I calculated the mean and standard deviation of the excess TOA values as well. Now I have all the information I used to construct the multipath model.

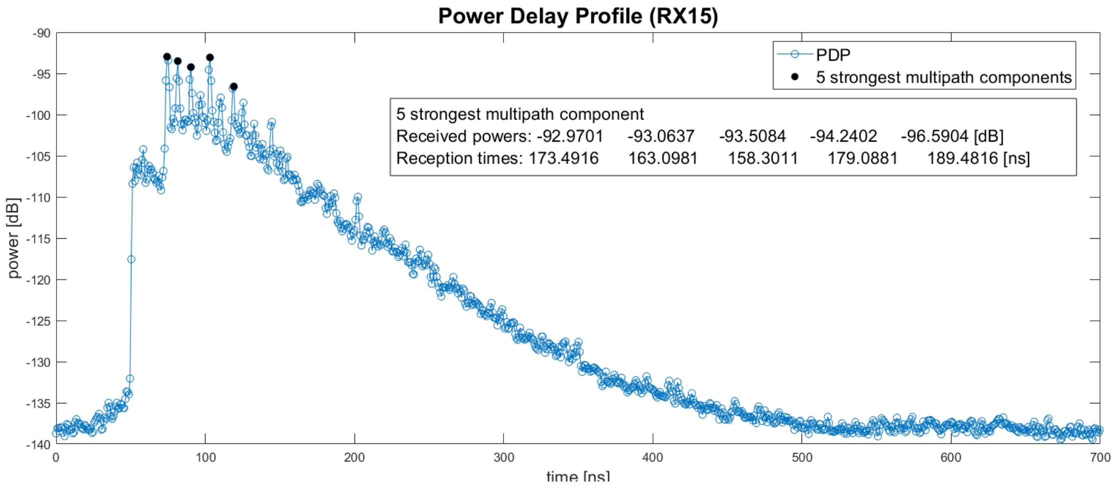

Figure 18: Power Delay Profile (PDP) in measurement location 15 (TX-RX distance is 15m)

Based on the 3GPP study about channel models [25], NLOS probability increases proportionally with the Dot-UE distance, so I created the following distance categories:

- DOT-UE distance below 3m: the UE is right under the Dot, or very close to it, so no NLOS propagation is expected.
- DOT-UE distance between 3m and 8m (or 10m): this is the estimated distance of open areas in the office, so a smaller value on NLOS probability is expected. It is around half of the ISD.
- DOT-UE distance between 8m and 25m: this is a distance, where I expect a couple of walls between the Dot and the UE. It is around the ISD.
- DOT-UE distance above 25m: this distance is usually above ISD, so if the UE is this far away from one DOT, it is presumably close to another one, so the probability of NLOS propagation path from the further DOT increases drastically.

I classified every measurement point into these regions, and I took the average of the values in the same region. This way, I was able to define one standard deviation per distance zone, which I used to simulate the expected excess TOA values.

To calculate the dominant NLOS path probability I used the following technique. Based on the expected value and standard deviation of the linearized power values, I generated a probability density function (PDF), as shown in Figure 19. Finally, I used this PDF to calculate the NLOS probability by determining the place of LOS power, and the probability of the power is higher than that is the probability of a dominant NLOS component. Visually, it is the area under the normal distributions Gauss-curve, from the LOS power to infinity, see Figure 19.

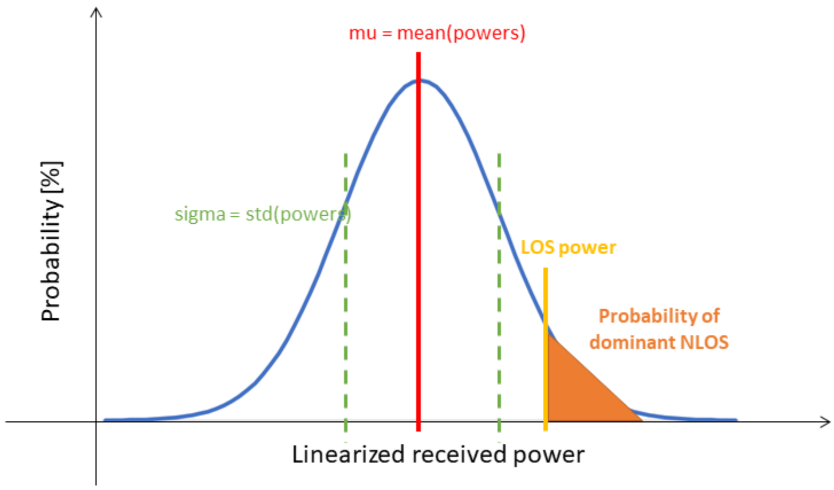

Figure 19: Normal distribution of linearized received powers for 5 strongest multipath components in one measurement point

4.2.2.3 Constructed multipath models

After the data processing steps, the following NLOS model came out as a result. This model accounts only for TOA errors caused by a dominant NPD propagation, doesn't include multipath fading errors occurring when the data processing unit can't identify the strongest signal reception time precisely.

RD-UE distance	Excess TOA value due to a dominant NDP path [m]	Probability of dominant NDP path
0-3m	-	0%
3-8m	$\mu = 3.8m, \sigma$=3.2m	12.3%
8-25m	$\mu = 5.1m, \sigma$=2m	20%
>25m	$\mu = 10.6m, \sigma$=2.4m	71.2%

Figure 20: Model for excess ToF due to NDP propagation

I constructed another model for simulating the influence of multipath fading on TDOA positioning, which is independent of the previous model, and as shown in Figure 21. It is worth noting, that multipath fading can add a negative impairment to the TDOA measurements because of constructive interference.

RD-UE distance	Multipath fading bias [m]	Probability of dominant NDP path
0-2m	$\mu = 0m, \sigma = 1m$	10%
>2m	$\mu = 0m, \sigma = 1m$	50%

Figure 21. Model for multipath fading

The values in Figure 21 were determined based on studies [21] [47]about multipath fading, because of lack of real measurements. The values in Figure 20 were calculated from real measurement data, and they align with the studies and standards introduced in 2.5.1.

It is important to keep in mind, that the dataset I used for building up the models was limited. I plan to refine them in the future, as soon as real-life TDOA measurements will be available in our system. The MATLAB script I have written for model construction is prepared for handling any size of the input dataset, so I will be able to generate refinements quickly by using the same script.

4.2.3 RSRP simulation

Although the developed position estimator method is based on TDOA measurements, it is still worth including received power, and signal to interference-plus-noise-ratio (SINR) measurements into the location estimation process, because they are tightly correlated to NLOS errors [25], and thus provide additional information which could be used to further improve accuracy. For example, the measured SINR values can be used for weighting the TDOA measurements in the location estimation process, because lower SINR indicates that the given TDOA measurement is less reliable, which is often caused by direct path blockage. Considering these measurements with less weight in the position estimate calculation results in robustness to TDOA errors, although it doesn’t eliminate the errors completely.

For simulating RSRP measurements, and SINR values I made the following assumptions. The received power can be calculated as the sum of transmitted power and pathloss. Assuming free-space propagation, the pathloss value depends only on the transmitter-receiver distance. In an indoor environment, additional pathloss occurs due to the obstacles in the propagation path, so the simulated received power can be described by the following equations [48]:

$$PL_{free-space} = 20 * log\left(\frac{4\pi d}{\lambda}\right) \tag{16}$$

$$P_{received} = P_{transmitted} - PL_{free-space} - PL_{additional-NLOS} \tag{17}$$

where the powers and path losses are given in dBm, d stands for the transmitter-receiver (or Dot-UE) distance and λ is the wavelength of the signal.

I constructed a similar distance-dependent model as in Figure 20, with the same distance regions. I determined the expected values and standard deviations of the additional pathloss based on the same measurement dataset, that I used for excess TOA values (see 4.2.2). I calculated the LOS probability based on an indoor LOS probability model that was presented in [25]:

$$\mathrm{Pr}_{\mathrm{LOS}} = \begin{cases} 1 & , d_{\text{2D-in}} \leq 1.2\mathrm{m} \\ \exp\left(-\frac{d_{\text{2D-in}} - 1.2}{4.7}\right) & , 1.2\mathrm{m} < d_{\text{2D-in}} < 6.5\mathrm{m} \\ \exp\left(-\frac{d_{\text{2D-in}} - 6.5}{32.6}\right) \cdot 0.32 & , 6.5\mathrm{m} \leq d_{\text{2D-in}} \end{cases} \tag{18}$$

$$P_{rNLOS} = 1 - Pr_{LOS} \tag{19}$$

The LOS probability is the function of the 2-dimensional BS-UE distance ($d_{2\text{-}indoor}$), so instead of defining a fixed probability for a distance region, the probability can be calculated individually, for every measurement simulation.

RD-UE distance	**Additional pathloss due to NLOS propagation [dB]**	**Probability of dominant NDP path**
0-3m	-	according to (19)
3-8m	$\mu = 8dB, \sigma = 2dB$	according to (19)
8-25m	$\mu = 15dB, \sigma = 5dB$	according to (19)
>25m	$\mu = 22dB, \sigma = 5dB$	according to (19)

Figure 22: Additional pathloss due to NLOS propagation model used in received power simulations

To calculate the SINR based on the received signal strength, I had to determine the noise floor and the interference level. The noise floor is determined by Equation (20). Interference could possibly occur due to the outdoor macro-cells, but that is not relevant to our system, so the interference level is negligible.

$$\text{Noise floor}_{\text{dBm}} = 10\log_{10}(k \times T_0 \times 1000) + \text{NF} + 10\log_{10}\text{BW}. \tag{20}$$

$$\boldsymbol{SINR_{dBm} = P_{received,dBm} - Noise\ floor_{dBm} - P_{interference,dBm}} \tag{21}$$

4.2.4 CIR simulation

The CIR is intended to be used in the multipath component evaluation and multipath error mitigation, but simulating complete realistic channel impulse responses would have been required a ray-tracing approach, which is a significant development effort. I decided not to do it because the CIR-based link classification method implementation was scheduled later when there will be real measurements available.

4.3 Position estimation algorithms

The UE's estimated position can be determined with different algorithms, as I introduced earlier in 2.2. At the beginning of the development process, I opted for including multiple position estimators, because I wanted to make a comparison in terms of accuracy and computation complexity. This led to having 3 different solvers implemented in the positioning component:

1. Linearized Least Squares (called LLS)
2. Weighed Least Squares (called WLS)
3. Robust Weighted Least Squares (called RWLS)

4.3.1 LLS positioning

This is a quick and simple closed-form solution for the TDOA localization problem, which is perfect to calculate a rough position estimate to be used as an initial position in iterative methods, like the WLS and RWLS. The disadvantage of this mechanism is the sensitivity to NLOS and other error sources, see Figure 23. The achievable accuracy in nonideal environments is much lower than the other two methods, as shown later in the comparison. The solution was implemented based on [6].

4.3.2 WLS positioning

Ericsson has a 4G legacy OTDOA positioning algorithm, which I have reconstructed based on the functional specification to fit into this new system. This is an iterative optimal solver, using the SINR measurements as weights.

4.3.3 Robust WLS positioning

At a later stage of development an improved, robust WLS solver was implemented and handed over for me to integrate into my TDOA positioning simulator as a third position estimator algorithm.

The robustness of this method comes from the iterative reweighting, and the application of a bi-square cost function, which assigns a smaller weight to those measurements that are separated from other measurements, thus assumed to be outliers.

My task was to integrate this new solution as a third option into the simulator and compare it to the previous two methods with different network setups and error values, to find out which one gives the best positioning accuracy.

Integration work I carried out included aligning the simulator's output interface to the algorithm's input interface and verifying functionality. For verification, the positioning algorithm was given different inputs, and the position estimate was calculated and visualized from different aspects: positioning error CDF, positioning error and Dot layout, the spatial distribution of position estimates in different locations.

4.3.4 Comparison

The difference between the three positioning estimator algorithms does not really appear under ideal conditions, assuming free-space propagation and no multipath errors.

However, after I constructed the multipath model and rTE and TDOA error models, and I included these errors in the TDOA measurement simulations, it became clear, that RWLS is more resistant to this kind of impairment than the other methods. After comparing the errors of position estimates, I decided to discard WLS, because RWLS has significantly better accuracy in nonideal propagation conditions (see Figure 4).

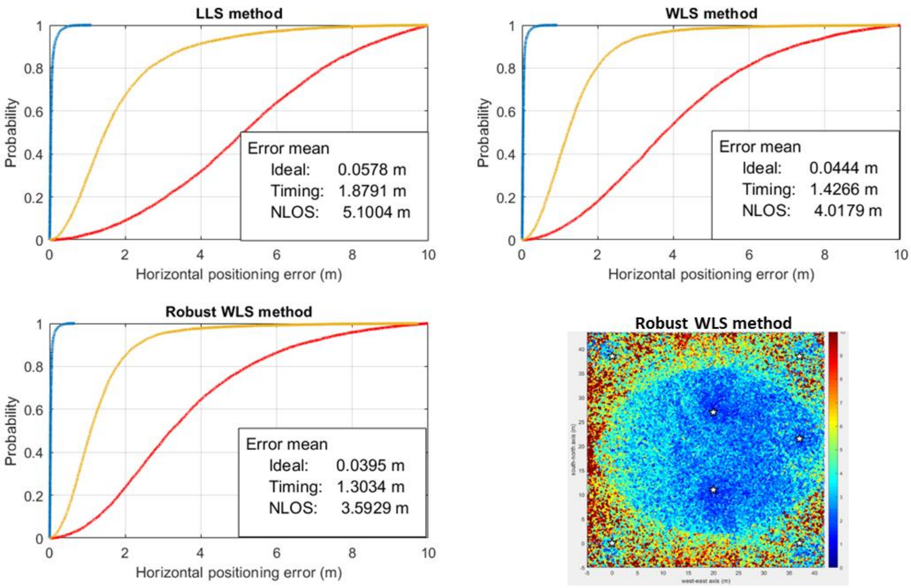

Figure 23. Comparison of the 3 different position estimator algorithms positioning error CDfs. (3 different error setup was simulated: no error, rTE+TDOA error, rTE+TDOA+NLOS error)

4.4 Multipath mitigation algorithms

As shown in Chapter 2.5, the indoor radio environment is strongly affected by NLOS-NDP propagation and multipath fading. This results in the degradation of positioning accuracy, see Figure 23. It is important to know and separate the factors that are causing error in the position estimate, to be able to mitigate them effectively. In Chapter 4.2.1 I introduced the development of the TDOA error model.

The listed impairments add to the location error, and they can be mitigated with different methods. Timing and measurement errors are handled by the RAN (Radio Access Network), and Dot coordinate error is negligible compared to the other errors. The positioning errors caused by multipath propagation can be handled in the Position Estimator component, and there are several ways to do it, as described in Chapter 2.6.

In this chapter, I summarize the development steps I made in the PE component to reduce multipath errors.

4.4.1 Multipath error assessment

First, I had to choose what kind of algorithm I would like to use for multipath mitigation. I have collected a lot of different approaches in 2.6. To make a good decision, it was essential, that I know the Radio Dot System's characteristics and limitations. The following factors were considered in my decision: the time for implementation, the complexity of the solution, the number and characteristics of base stations (DOTs), indoor propagation properties.

Before I have seen any real-life measurement, I assumed, that in a typical office building the number of Line-of-Sight DOTs will be very low, since the Radio Dot System is constructed in a way, where typically 8 Dots are installed on a floor, so ISD is in order of 20m or more. This means a very sparse deployment, compared to other TDOA-based positioning systems, like UWB or Bluetooth.

But after evaluating the real PDP measurements and constructing the multipath models based on the results (see details in 4.2.2), it turned out, that having obstacles or even thin walls between the transmitter and receiver not necessarily results in big excess TOA values. This was surprising to me, although the propagation studies introduced in 2.5.1 were showing the same outcome, see Figure 8, where the signal received through the wall was attenuated, but still the strongest multipath component. The conclusion is: TOA (and TDOA) measurement are somewhat robust to LOS path blockage. This results in an increased number of DOTs, where the measured TDOA value is not biased by a large NLOS error, meaning that the measurement error is in the order of LOS measurements.

This is an important consequence since the number of LOS DOTs is essential in TDOA-based positioning: having 3 good quality LOS TOA measurements is enough for accurate position estimation in 2D. For the 3D position estimate, 4 LOS TOA measurements are required. In the so-called Office scenario, all the DOTs are ceiling mounted, so a 2-dimensional location estimate of the UE is determined.

My simulations showed, that if the channel models constructed in 4.2.2 are not far from reality, at least 3 “LOS” DOTs will be available over 80% of the coverage area.

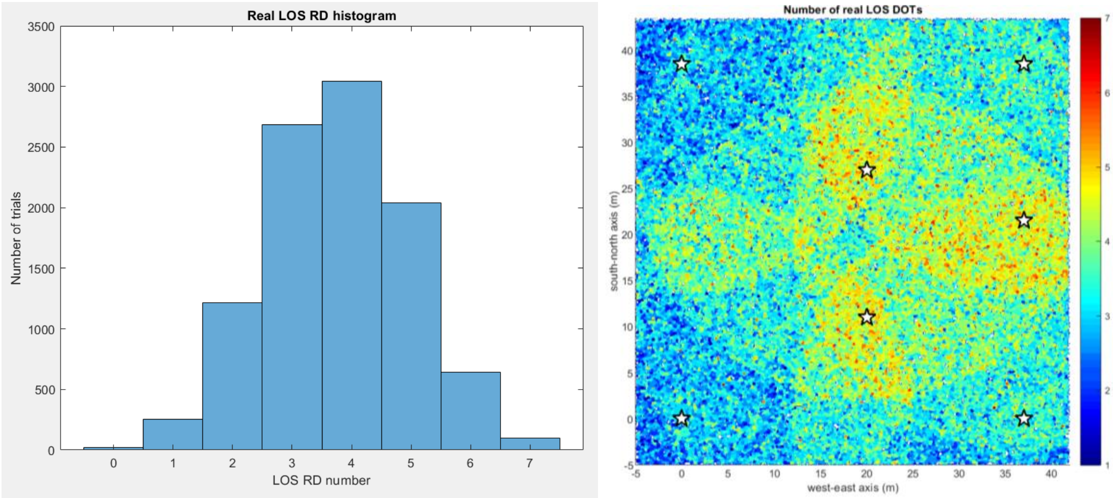

Figure 24: Expected number of LOS DOTs
(on the left: distribution, on the right: spatial characteristics of the number of LOS Dots based on 10,000 measurement simulations)

Based on this result, I assumed that detecting TDOA measurements with a large error, and simply throwing them away will improve the location estimation accuracy significantly. This mechanism is called outlier detection, and there are several algorithms for performing it.

4.4.2 Outlier detection with RANSAC algorithm

RANSAC is a widely used outlier detection technique. It works the best with a high number of samples, but in our system, there are only 7 or 8 samples available because of the limited number of DOTs, but I still decided to try the RANSAC algorithm in this case, because I received an internal Ericsson implementation for it, which I could integrate into my position estimator component. The integration itself was fairly straightforward, but it took quite some effort for me to figure out the best parameters to use for RANSAC algorithm. Doing the parameter tuning, I also wanted to make sure that I am not over-optimizing the solution, so I monitored the robustness to different error sources and scenarios.

4.4.2.1 Candidate solution calculation

In the RANSAC algorithm, multiple candidate solutions are processed, and the best candidate solution is selected as the final solution. Different scoring methods can be used to assign metrics to how good a candidate solution is, as explained in 4.4.2.2.

In the internal RANSAC implementation I used in my positioning component, the solution candidates are determined based on Dot-triplets: position estimates are calculated for all possible triplets. This means $\binom{7}{3} = 35$ or $\binom{8}{3} = 56$ candidates. 3 Dots give 2 TDOA measurements, and the analytic solution of the localization problem can be visualized as intersections of two hyperbolas, so there might be 0,1 or 2 solutions for every candidate. These solutions go through a sanity check, and the irrealistic ones are discarded. The surviving position estimates are used to calculate the TOA residuals for every measurement. A residual equals the difference between the measured TOA and the theoretical TOA which can be calculated from the estimated Dot-UE distance.

It is worth mentioning here, that this RANSAC implementation was originally developed for TOA measurements, but it can be applied to TDOA measurements without modifications, based on the following considerations. The “TOA model with unknown UE-network time offset” (7) and the “TDOA model with a dummy variable extension” (8,9) are actually the same models in the structure.

$$\boldsymbol{TOA_i} = \frac{\sqrt{(\boldsymbol{x_i} - \boldsymbol{\hat{X}})^2 + (\boldsymbol{y_i} - \boldsymbol{\hat{Y}})^2}}{\boldsymbol{c}} + \boldsymbol{TOD} \tag{22}$$

$$\boldsymbol{TDOA_i} = \frac{\sqrt{(\boldsymbol{x_i} - \boldsymbol{\hat{X}})^2 + (\boldsymbol{y_i} - \boldsymbol{\hat{Y}})^2}}{\boldsymbol{c}} + \boldsymbol{m} \tag{23}$$

$$\boldsymbol{m} = -\frac{\sqrt{(\boldsymbol{x_1} - \boldsymbol{\hat{X}})^2 + (\boldsymbol{y_1} - \boldsymbol{\hat{Y}})^2}}{\boldsymbol{c}} \tag{24}$$

Where (x_i, y_i) are the Dot coordinates, i=1 is the reference Dot in TDOA measurements, $(\hat{X}, \hat{Y})$ are the UE estimated coordinates and c is the speed of light. The only difference is that with TOA measurements, the UE-network offset (*TOD*, time of departure) can be estimated by RANSAC. For TDOA measurements a dummy variable (*m*) is estimated instead, which will be thrown away.

4.4.2.2 Different scoring methods

The RANSAC implementation I used contains two different score modes: a simple threshold-based scoring, and a more advanced probability-based scoring. The former one uses only a threshold value for LOS TOA residuals, and every measurement that has a residual above this threshold is classified as NLOS. This method is problematic because it can’t differentiate between candidates with the same number of LOS Dots: it simply chooses the first candidate in the array, which has the highest number of inliers.

The advanced scoring mechanism makes use of the a-priori knowledge about LOS and NLOS error distributions. Methods requiring a-priori knowledge are generally not preferred, because the given knowledge might be too specific, and what works well in one setup, might be much worse on another site. In other words, the method should not be sensitive to the chosen LOS and NLOS distributions, as long as they are reasonable.

I performed a profound sensitivity analysis to investigate this concern. First I calculated the excess TOA value distribution for LOS and NLOS Dots, based on the simulated TDOA measurements, to see what would the "ideal" distributions look like in this deployment. Then I tried different distributions and checked the positioning errors with simulations. Based on the results I confirmed, that the score mode is not sensitive to the given distributions, assuming that they align with the general characteristics of LOS and NLOS TOA excess values, namely that the LOS TOA excess values yield a zero-mean Gaussian distribution, and the NLOS TOA excess values yield a distribution which is shifted towards the positive range and has a lognormal form.

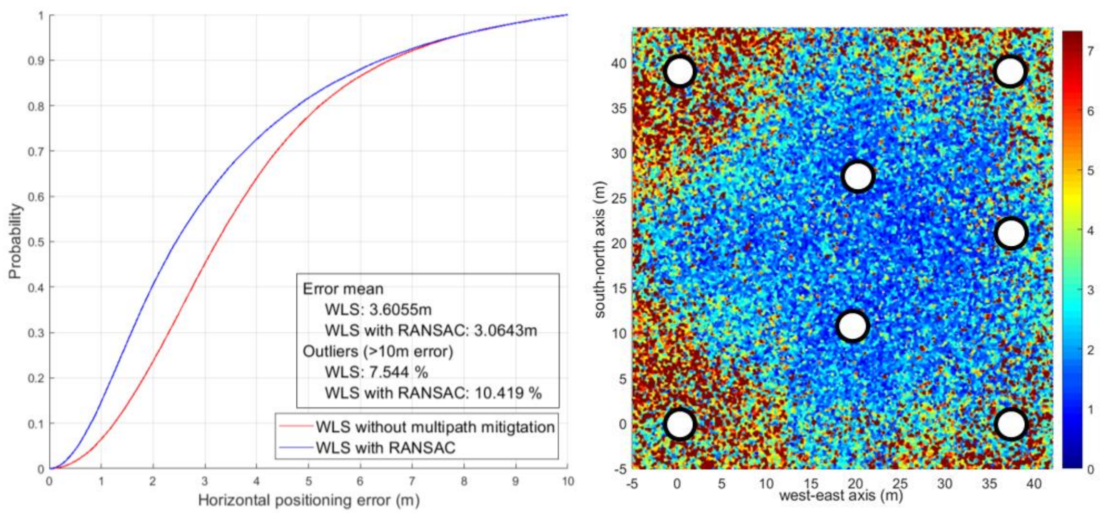

Figure 25. Simulation results for RANSAC outlier detection method: CDF compared to basic RWLS on the left, and positioning accuracy heatmap on the right.

4.4.2.3 LOS-NLOS classification reliability

Although RANSAC decreased the overall positioning error mean by 0.5m, which is a significant improvement, I noticed that in around 35% of trials the positioning error actually increased, compared to the position estimate calculated without RANSAC given the same TDOA input measurements. In other words, in roughly one-third of the positioning records, turning on RANSAC makes more harm, than good.

To find out the reason behind the accuracy degradation in those cases, I inspected the LOS-NLOS classification determined by the RANSAC algorithm, because a faulty classification might be damaging to the position estimation error. RANSAC multipath mitigation discards the measurements of Dots that were classified as NLOS, so if a LOS link is falsely detected as NLOS, that has a negative impact on the accuracy, especially when there are not enough correctly detected LOS Dots to calculate a good 2D position estimate.

On the other hand, an NLOS link classified as LOS by RANSAC is also harmful, because it means that an NLOS measurement with a possibly big error is included in the position estimation process. However, as shown in Figure 24 histogram, around 15% of the measurement contains less than 3 LOS links, but RANSAC always gives back at least 3 Dots classified as inliers because of the algorithm's underlying logic explained in 4.4.2.1. So in these cases, it is unavoidable to have at least one "false positive" LOS indication in the classification output, which might not be favorable. I will come back to the corner case of less than 3 LOS measurements later.

Comparing Figure 24 and Figure 25 it is clear, that big positioning errors are correlated to the low number of LOS Dots, especially when there are less than 3 of them. In those cases, positioning error often goes above 10 meters, and such a position estimate is considered as an outlier. That is why the number of outliers is so large with RANSAC. Considering Figure 23. with the positioning error heatmap of estimates provided by standalone RWLS, it is reasonable to say, that it would be better not to run RANSAC at all when there are less than 3 LOS Dots available, because the RWLS generally gives a better position estimate in these cases, with much quicker computation time.

The problem is, the number of real LOS Dots is unknown, it is just because of the simulated measurement input, that I have an insight into this aspect. Link classification is viable based on the PDP, as suggested in 2.6.1.1 but at the time I don't have that available as an option. As an alternative, I thought about calculating a confidence indicator that could reveal when the outcome of RANSAC is less reliable. Then a threshold value could be determined, when it is better to fall back to a simple RWLS position estimation, without RANSAC.

There is another factor to be considered when talking about position estimates produced by a limited set of Dots, because of RANSAC: the Geometric Dilution of Precision. [13] GDOP is an indicator of the goodness of Dot placement from a positioning point of view: the smaller GDOP is, the better the spatial distribution is. RANSAC necessarily introduces GDOP problems in some cases, when it throws away some measurements completely. To phase out this effect, it might be favorable not completely discarding the NLOS measurements from the location estimation, but incorporating them with a small weight instead.

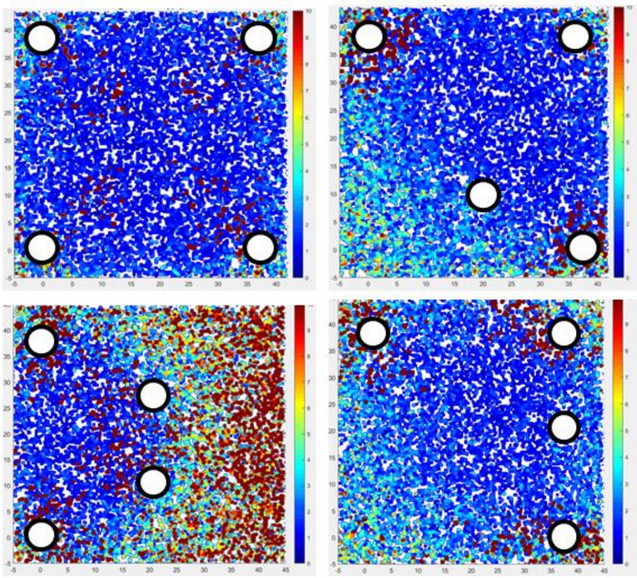

Figure 26. Illustration of GDOP effect with the different geometrical placement of 4 Dots (NLOS error was deactivated for these simulations, other errors were active)

4.4.2.4 Confidence indication

The idea of a confidence indicator came up in the previous section first, where I intended to use this indicator for filtering out measurements with too few LOS links for RANSAC to be efficient, and applying a fallback positioning method to them instead. The question is, how to implement such a confidence indicator in the RANSAC algorithm?

Knowing the principle working mechanism of this internal RANSAC implementation (explained in 4.4.2.1), it is reasonable to assume that such a confidence indicator should be able to be determined: I assumed that such a non-ideal condition, like not enough LOS measurements, should appear in candidate solutions, residuals or scores. I planned to evaluate these details in connection with poor positioning accuracy, and find the analogy between them. I came up with 4 ideas in the beginning and investigated each one of them. Unfortunately, none of them showed correlation with the number of NLOS Dots in itself, so they can’t be used as a confidence indicator alone.

1. <u>Number of detected LOS Dots as a confidence indicator</u>

A very simple confidence indicator could be the number of detected LOS Dots according to RANSAC. I noticed that there is a correlation between the number of Dots classified as LOS and positioning accuracy, see Figure 27. On the right picture, from the separated CDFs it is clear, that measurements with 3 and 4 assumed LOS Dots have a worse accuracy than those with 5 or 6.

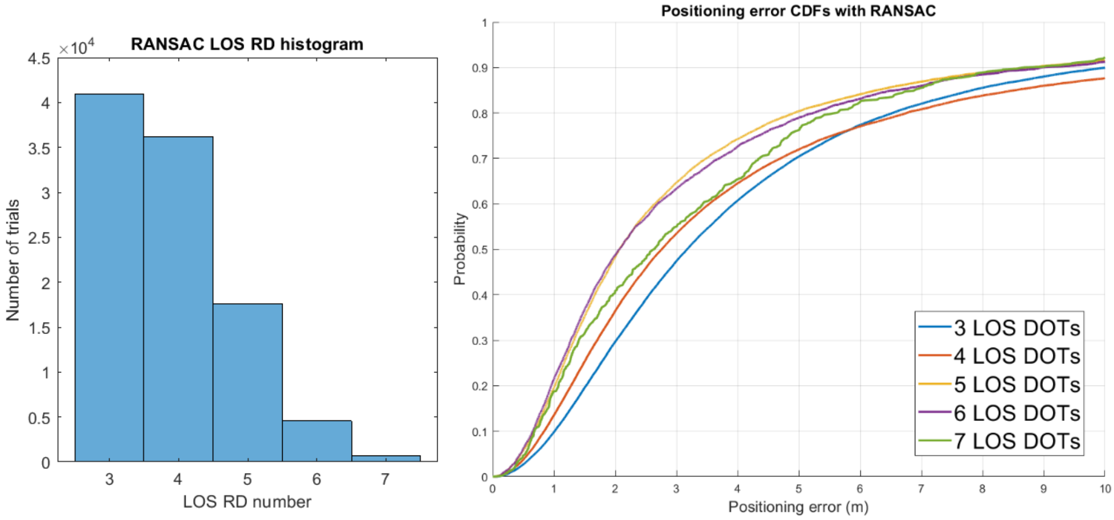

Figure 27. Number of Dots classified as LOS (inliers) by RANSAC on the left. Positioning error CDFs, separated by the number of LOS Dots detected by RANSAC

So the number of detected LOS Dots might be useful as a rough accuracy indicator, however, it doesn't provide enough information to be useful for fallback method triggering. I tried throwing away all RANSAC estimates with 3 and 4 detected LOS Dots and using the basic RWLS algorithm to calculate UE position instead. It turned out not to be an effective way for improving positioning accuracy because it ignores a lot of good estimates as well. It should be possible to differentiate between "good quality" and "bad quality" estimates, and therefore a refinement is needed in the confidence indication mechanism.

2. <u>Candidate solutions and scores as a confidence indicator</u>

I had another idea, that a more sophisticated confidence indicator could be developed based on the scoring system in RANSAC. I assumed, that the scoring of candidate solutions might be correlated to the reliability of outlier detection and the overall measurement quality.

Under measurement quality, I understand the errors in the elements of a TDOA measurement set, and thus the number of Dots with relatively small error, which can be labeled as LOS.

To prove my impression, I examined the scores of candidate solutions thoroughly. As I mentioned earlier, the baseline RANSAC implementation only chooses the candidate with the highest score as the final solution and doesn't care about the rest of the scores. I had the impression, that this is a potential field for improvement: and I examined the scores based on the following properties.

- Value of the highest and lowest score.
- Score distribution, score clusters. (By a cluster, I mean score values that are very close to each other, and well-separated from other scores not belonging to the specific cluster.)

But it turned out, that these values are not indicative of the quality (and accuracy) of position estimates calculated with RANSAC.

3. <u>Sum of residuals as a confidence indicator</u>

I supposed that when a candidate position estimate is calculated from a triplet, which includes 2 LOS and 1 NLOS measurement, the sum of residuals will be significantly larger than for a triplet which includes 3 LOS measurements. Based on this assumption, I thought I will be able to identify measurements with only 2 LOS Dots.

Unfortunately, my simulations proved that this approach doesn’t work as I expected: I found no correlation between the sum of residuals and the number of Dots with NDP propagation. This means, that the sum of residuals in itself is not suitable for confidence indication.

4. <u>GDOP of detected LOS Dots as a confidence indicator</u>

My fourth idea was to consider the GDOP factor in the confidence indication. To confirm this approach, I checked if there is any correlation between bad GDOP and bad position estimates, but according to my simulations, I couldn’t find any. There were very bad estimates with good GDOP and very good estimates with bad GDOP. My conclusion based on these results is that GDOP’s impact on the positioning error is minimal, compared to other factors like LOD Dot number, and TDOA measurement error.

4.4.3 Excess delay compensation

Another way to mitigate the NLOS effect on the UE localization is to compensate for the excess TOA values caused by elongated propagation paths. One simple way to do this was proposed in [30]. I adopted this mechanism in my implementation, but I used the RWLS method instead of the Newton algorithm to calculate an initial position estimate. This initial estimate has an important role in excess delay compensation because the TOA corrections are determined accordingly, and the more accurate the position estimate is, the better the delay compensation will be.

The core of the proposed method is to correct the errors gradually, starting with the biggest ones, instead of correcting every measurement at once. The latter would affect not only the NLOS but also the LOS measurements, which is undesirable and would damage the accuracy.

To implement such an iterative compensation, a delay compensation function (DCF) was defined in [30] which applies a reference value as follows.

$$D_i^{comp} = D_i - D_{reference} \tag{12}$$

D_i is the residual error, calculated as the difference between the measured and estimated TOA (or TDOA) value. Negative D_i^{comp} compensation values are discarded, so authors of [30] recommend choosing a $D_{reference}$ close to the maximal residual error in the first iterations to only compensate for the large errors in the beginning. In later iterations $D_{reference}$ can be decreased, so that smaller errors will be compensated as well.

Adding another iterative method to the position estimation process might raise concerns regarding computation complexity. The authors of [30] concluded that keeping the number of iterations around 5 was optimal in their setup, so I used the same value as a starting point in my implementation.

My simulation results show, that iterative delay compensation (IDC) can improve the positioning errors to the same level as RANSAC, but achieves this with fewer outliers (see Figure 25 for comparison), and less computation time: 10 000 trials took only 74s for IDC, and 102s for RANSAC.

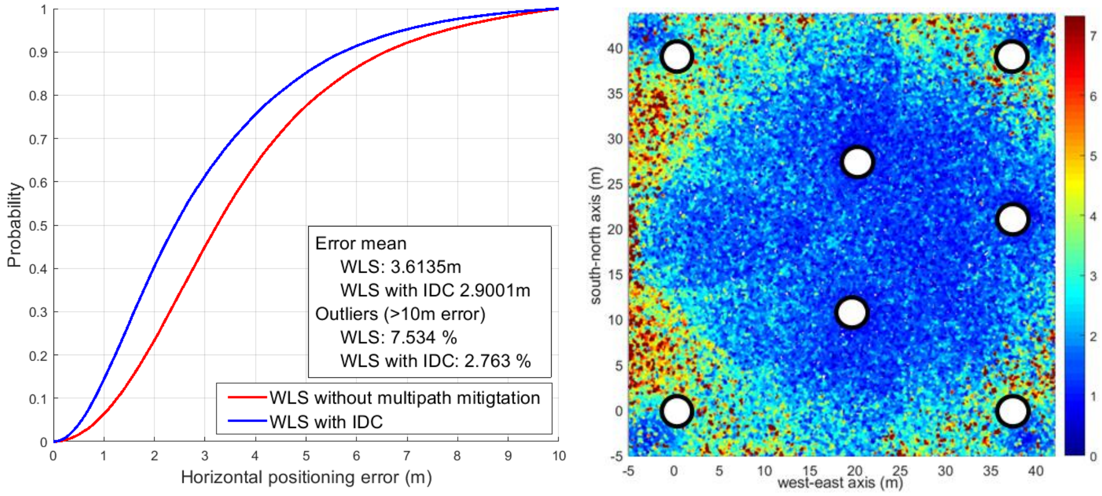

Figure 28: Simulation results for IDC method: CDF compared to basic RWLS on the left, and positioning accuracy heatmap on the right.

4.4.4 Combined multipath mitigation algorithm

After evaluating the results of outlier detection, and delay compensation, I came to the conclusion that a thoughtful combination of the two approaches might lead to improved positioning accuracy.

Based on my simulation results, RANSAC is very effective in eliminating NLOS errors when the number of Dots classified as LOS exceeds 4. However, the NLOS mitigation, and thus the positioning accuracy is not as good otherwise, as I showed in Figure 27 CDFs.

To further improve the positioning accuracy, I came up with the following combined logic. First, I calculate the position estimate with RWLS and with RWLS+RANSAC as well. Then I examine the classification output of the RANSAC algorithm. If the number of LOS Dots is 5 or more, the final position estimate is the one that was calculated by RANSAC, because based on Figure 27 CDFs, it is presumably a good estimate, with a small error.

Otherwise, in case less than 5 Dots were classified as LOS according to RANSAC, I apply the iterative delay compensation method, but with a slightly modified approach to make use of the RANSAC classification output. I use this output as a filter in the IDC method: the TDOA values that belong to a seemingly LOS Dot, are fixed. Corrections are only applied to the NLOS Dots. This is beneficial because this way, the risk of unintentionally "correcting" the LOS measurements is eliminated.

The iterative delay compensation method needs an initial position estimate as well to calculate the corrections. Here I use the estimate that was calculated by standalone RWLS, without RANSAC, because it is generally more reliable, as it can be seen on Figure 23 it is more homogenous compared to Figure 25, where the positioning errors are from a wide variety, with a noticeable number of very bad ones.

With the aforementioned technique, I was able to get an overall positioning accuracy, which is slightly better than RANSAC or IDC applied separately: the mean of positioning errors improved by 25cm.

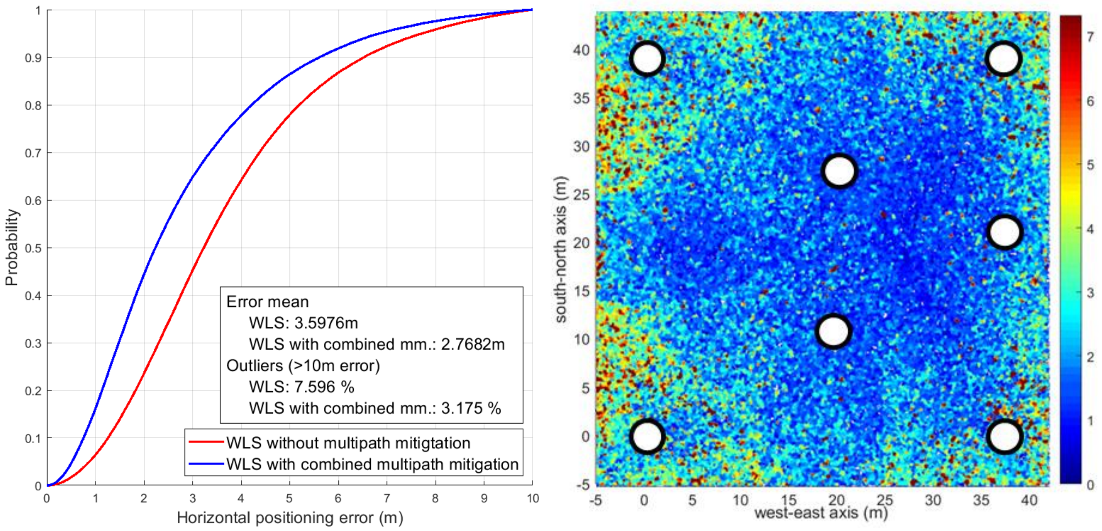

Figure 29. Simulation results for the combined multipath mitigation method: CDF compared to basic RWLS on the left, and positioning accuracy heatmap on the right.

Comparing Figure 28 and Figure 29 it is noticeable that the accuracy improved significantly in the problematic outer areas, where the number of LOS Dots is typically low, so this is a remarkable result. On the other hand, the overall accuracy got a bit worse in the inner areas, so apparently, there is some space to further refinements in the multipath mitigation algorithm.

5 Positioning performance evaluation

Looking back at the results presented in Chapters 4.4.2, 4.4.3, and 4.4.4, it is clear that even with the most effective multipath method, the accuracy requirements defined in Chapter 3.3 were not met: the positioning error is in the range of 4 meters for 80% of the positioning trials, instead of 1 meter.

So with the current system properties and positioning algorithms, sub-meter accuracy is not feasible. In this chapter, I explain what needs to be improved to reach our accuracy goal. As a part of this, I evaluate the performance of the developed positioning algorithm from different aspects.

5.1 Evaluation of the propagation environment

Positioning performance strongly depends on the actual propagation environment. The same position estimator algorithm might provide very different overall accuracy on different sites. Therefore, it is important to examine the robustness of the developed algorithm to changes in the channel model. The dataset I used for the model construction in 4.2.2 was limited. I believe that this model is not far from reality, assuming an open-office environment, but this needs to be verified with real measurements.

In other environments, like an industry hall or a theatre, this model is presumably not applicable. Anyways, the positioning method was created to be resilient to these changes, unless they are extreme. In Chapter 4 I used the same channel models (see Figure 20 and Figure 21) for all the simulations performed. In this section, I try 4 different modifications of these models, to prove that the developed method is resilient to reasonable changes in the propagation environment.

RD-UE Distance	Default **(**Figure 20**)**	Case 1 (μ, σ, p)	Case 2 (μ, σ, p)	Case 3 (μ, σ, p)	Case 4 (μ, σ, p)
0-3m	0,0,0	0,0,0	0,0,0	0,0,0	0,0,0
3-8m	3.8,3.2,12	3.8,3.2,20	3.8,3.2,5	8,4,12	2,1,12
8-25m	5.1,2,20	5.1,2,50	5.1,2,10	10,5,20	3,1,20
>25m	10.6,2.4,71.2	10.6,2.4,90	10.6,2.4,50	20,5,71.2	5,2,71.2

Figure 30. Modifications in the excess TOA model for positioning algorithm robustness test (modified values are highlighted, red means worse, green means better than default)

I choose these four modifications based on the following logic: I changed the normal distribution parameters (μ, σ) in two of them while leaving the p probabilities untouched. I tried a more optimistic and a more pessimistic situation, compared to the default one. Then I did the same for the other two cases, but I changed the probabilities this time.

I have run simulations with the 5 different excess TOA models, with all three multipath mitigation algorithms (RANSAC, IDC, and Combined). In 4.4, with the default model, the Combined method came out as the best one in terms of positioning accuracy, and it remained to be the best in the other 4 cases as well. The positioning error did not change much, as illustrated by CDFs in Figure 31. This indicates, that the proposed combined multipath mitigation method is insensitive to changes in the propagation environment.

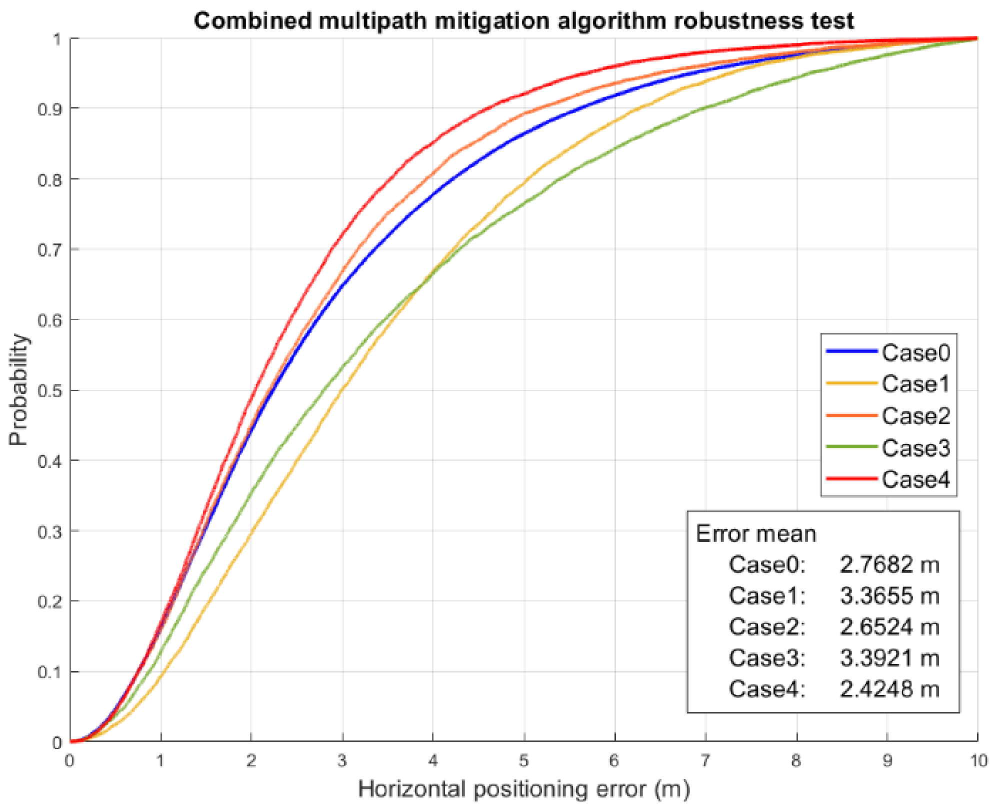

Figure 31. Comparison of positioning errors assuming different models for excess TOA value due to dominant NLOS propagation

I have tested the other model that I have created for simulating the multipath fading (Figure 21) effect on the TOA measurements similarly. In Chapter 4 I used the same $\sigma = 1m$ standard deviation, so this time I tried 3 modified values: $\sigma = 0.5m, 0.2m, 0.1m$, while keeping the probability of fading the same.

I have run simulations with the 3 different multipath mitigation algorithms given the above standard deviation values for multipath fading, but the positioning error results stayed exactly the same as with $\sigma = 1m$. Two conclusions can be drawn based on these simulation results: all methods are resilient to multipath fading, and other error sources (e. g. rTE, TDOA observation error) are dominant over the multipath fading error.

5.2 Evaluation of Radio Dot System properties

The features of the Radio Dot System also have an impact on the position estimation accuracy, including the number and placement of Radio Dots, and the TDOA and rTE measurement technique and errors. I used 7 Dots and the experienced TDOA and rTE error values (defined in 4.2.1.2 and 4.2.1.3) for all the simulations in Chapter 4. These errors are planned to be reduced by the improvements made to the measurement technique. If I run simulations with the optimistic, reduced TDOA observation error and relative timing error, the mean of the positioning error is reduced to 2m with the combined multipath mitigation approach. We could have added an extra Dot, but according to my simulation results, it would not bring a significant improvement in positioning accuracy.

5.3 Evaluation of the position estimator algorithm

Since I had limited time for positioning estimation and multipath mitigation algorithm development, I couldn’t include any kind of filtering in the UE position calculation process. PDP-based link classification was also not included, and I was not able to find a proper method for RANSAC confidence indication yet. These techniques would presumably improve the positioning accuracy, but they require significant effort to implement.

5.4 Evaluation of the computation complexity

During the algorithm development, I had to pay attention, that computation times don’t get too long for any algorithm because there is a stringent latency requirement for 5G indoor positioning use cases. I did the performance analysis on my company notebook, so the results were slightly influenced by other applications running on my machine and taking resources like RAM and CPU.

I investigated the computation complexity for 10 000 trials, and it turned out that RANSAC, IDC, and the combined multipath mitigation method cause significant overhead in the processing time, compared to the case when no multipath mitigation is carried out. The increased computation times are still well under the feasibility limit for 5G latency requirements, so that is not an issue: even with the combined mechanism, the execution time for 10 000 trials stays below 150s, which means roughly 15ms per position estimation.

6 Summary

6.1 Completed tasks

As a part of my Thesis work, I ramped up knowledge about different aspects of indoor 5G TDOA positioning to better understand the problem. I investigated indoor propagation properties by examining real measurement datasets and channel models, to find out how the position estimation process is affected by them. I collected many different multipath mitigation algorithms.

I have implemented a stochastic, system-level TDOA positioning simulator, including measurement error simulation. I created my customized channel model based on real measurement data and successfully applied this channel model in positioning algorithm development.

I thoroughly evaluated the performance of the RANSAC outlier detection algorithm: I analyzed the reliability of NLOS detection under various conditions, found the weaknesses of RANSAC, and came up with solution plans to overcome them. I tried to create a confidence indicator based on RANSAC algorithm details, but I did not find a solution to this problem yet.

I have chosen and implemented another NLOS mitigation algorithm, which enables compensating measurement errors, thus it is a good extension to RANSAC, and I proved that an improved positioning performance can be achieved by a thoughtful combination of the two methods.

I tested the robustness of the proposed combined multipath mitigation algorithm with multiple simulations and showed that it is insensitive to changes in the channel model, therefore it is a good candidate positioning solution for a prototype system.

Unfortunately, the RDS 5G system deployment was delayed a bit, so I didn't have the chance to verify my customized channel model and positioning algorithm with real measurement data from RDS yet. The positioning component I have implemented is ready to receive real measurements instead of simulated ones, so the verification can start instantly, as soon as data will be available. On top of that, I made a lot of different simulations, so I have concepts about what can go wrong in the positioning process, thus hopefully I will be able to find the problems more quickly.

6.2 Conclusions

While completing my MSc Thesis, I gained insights into the prototype development aspects of 5G technology and experienced what the first steps of deploying a completely new positioning method look like in production. I learned how to adapt to the changing plans and expectations, how to prioritize tasks to help the collaboration between different aspects of the development, and get the assigned tasks done until the due date at the same time. Participating in this prototype development collaboration and writing this thesis about it was the most challenging work I've done so far. It was especially hard in the beginning because there are so many aspects of such an end-to-end system. There is still so much left to learn and improve, and I am looking forward to it.

6.3 Future work

The positioning estimator algorithm I have implemented is planned to be used in the prototype system, as soon as it is functional. When real measurement data will be available in our system, I will verify the channel models I have created, and refine them when needed.

Another important step will be verifying the complete positioning method by real measurements. Real and simulated positioning results will be compared, and hopefully, the difference between the two will be minimal.

The positioning accuracy must be further improved in the future to meet 5G requirements, and my simulator is a useful tool for quickly implementing, testing, and comparing different positioning method improvements. Including some kind of filtering algorithm in the position estimation method would be certainly beneficial for accuracy. PDP-based link classification should be implemented and included as well since the studies about this topic show very encouraging results.

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