Seyed Mohsen Atefnia

Barycentric Interpolation Approach in Outdoor Cellular Positioning Based on Received Signal Strength

Metropolia University of Applied Sciences

Master of Engineering

Information Technology

Master’s Thesis

04 May 2024

PREFACE

Embarking on this thesis has been a significant milestone in my pursuit of a Master of Engineering degree in Information Technology at Metropolia University. The journey has been intellectually stimulating and immensely enlightening, shaping my understanding and appreciation of the complexities involved in outdoor cellular positioning. The process of researching and meticulously analyzing the Barycentric Interpolation method for cellular-antenna-based positioning not only challenged my analytical skills but also expanded my perspective on the potential and limitations of current positioning technologies in urban settings. This thesis not only represents a crucial academic achievement but also a personal voyage of discovery and growth. The knowledge and experiences gained through this endeavor have been invaluable, providing a solid foundation for my future career and academic pursuits in the field of Information Technology.

I would like to express my deepest gratitude to my advisors, Sami Sainio and Yaghoub Farjami. Their expertise, patience, and guidance have been crucial to my research. They provided me with academic and moral support throughout this journey, for which I am profoundly thankful.

Special thanks are also due to my sister, whose encouragement and belief in my abilities kept me motivated during the most demanding periods of this work. Her unwavering support and practical advice have been a cornerstone of my success.

I must also extend a heartfelt thank you to my mother, whose love and sacrifices have shaped me into the person I am today. Her endless optimism and nurturing nature have been my constant source of strength and inspiration.

This thesis would not have been possible without the support and encouragement from each of these remarkable individuals in my life. I am eternally grateful for their contributions and blessed to have them by my side.

Espoo, 04.05.2024
Seyed Mohsen Atefnia

Abstract

Author:	Seyed Mohsen Atefnia
Title:	Barycentric Interpolation Approach in Outdoor Cellular Positioning Based on Received Signal Strength
Number of Pages:	86 pages + 6 appendices
Date:	04 May 2024
Degree:	Master of Engineering
Degree Programme:	Information Technology
Professional Major:	Networking and Services
Supervisors:	Sami Sainio, Senior lecturer Yaghoub Farjami, Senior lecturer

This thesis investigates the use of the Barycentric Interpolation (BCS) computational method for outdoor positioning using cellular networks based on received signal strength (RSS) as an alternative to Global Navigation Satellite Systems (GNSS). GNSS often faces challenges in urban environments due to signal attenuation, multipath effects, and susceptibility to jamming. The study develops a positioning algorithm using the Barycentric Interpolation (BCS) method and employs data from cellular networks to assess its viability in Helsinki's urban setting. This algorithm utilizes positional data from scanned 2G cellular antennas obtained by a GSM-enabled device, along with corresponding RSS levels used as weights, to determine and evaluate the geographical coordinates of the user equipment (UE).

This algorithm does not rely on satellite signals, private data of cellular network infrastructure, internet connection, or specific antenna configurations, making it suitable for areas where GNSS is unreliable or vulnerable to jamming. While BCS does not surpass GNSS in accuracy, it offers significant benefits by utilizing public data from land-based cellular networks and functioning independently of internet connections and network operator support. This highlights its potential as a complementary or alternative positioning method in urban scenarios.

This work enhances the understanding of BCS applications in challenging environments. It also sets the stage for further advancements in integrating cellular signal data with interpolation methods to improve urban and autonomous navigation technologies without relying solely on the infrastructure of a specific network operator, leveraging the network infrastructure capacity of all available operators.

Keywords: Barycentric Interpolation, Cellular Positioning, Received Signal Strength (RSS), Outdoor Positioning, 2G Cellular Networks, 2G cellular antennas, User Equipment (UE), Geographical Data, BCS Positioning Algorithm, Positioning Accuracy, Mobile-based Positioning, Data Collection, Network Infrastructure, Geospatial Analysis, Urban Environments, Position Estimation

The originality of this thesis has been checked using Turnitin Originality Check service

Table of Contents

List of Abbreviations

2G	The Second-Generation Cellular Network
3G	The Third-Generation Cellular Network
3GPP	The 3rd Generation Partnership Project is an umbrella term for a few standards organizations which develop protocols for mobile telecommunications.
4G	The Fourth-Generation Cellular Network
5G	The Five-Generation Cellular Network
6G	The Six-Generation Cellular Network
AECID	Adaptive Enhanced Cell-ID
A-GPS	Assisted GPS
AIS	Automatic Identification System
AOA	Angle of Arrival
BCS	Barycentric Coordinate System
BP	Back-Propagation
BS	Base Station
BTS	Base Transceiver Station
CDMA	Code Division Multiple Access
CID	Cell ID: A unique identifier which is assigned to each cell antenna by a cellular network.
CIR	Channel Impulse Response
CTF	Channel Transfer Function
DGPS	Differential GPS
DL	Downlink
E-CID	Enhanced Cell ID
FCC	The Federal Communications Commission is an independent agency of the United States government that regulates communications by radio, television, wire, satellite, and cable across the United States.
FCF	Frequency Channel Coherence Function
FDMA	Frequency-division multiple access
GIS	Geographical Information Systems

GMSK	Gaussian Minimum Shift Keying
GNSS	Global Navigation Satellite Systems
GPS	Global Positioning System
GSM	Global System for Mobile communications
IEEE 802.1	802.11 is a standard that was developed by the Institute of Electrical and Electronic Engineers (IEEE)
LAI	Location area identity
IoT	Internet of Things
IPS	Indoor Positioning Systems
LBS	Location-Based Services
LOS	Line-of-Sight
LPP	LTE Positioning Protocol
LTE	Long-Term Evolution
MIMO	In radio, multiple-input and multiple-output is a method for multiplying the capacity of a radio link using multiple transmission and receiving antennas to exploit multipath propagation.
mMTC	Massive Machine-Type Communication
mmWave	Millimeter Wave is a wireless communication technology that uses high-frequency electromagnetic waves in the range of 30 to 300 GHz.
MS	Mobile Station
NAVSTAR	Satellite-Based Radio Navigation System
NB-IoT	Narrowband Internet of Things
N-LOS	Non-Line-of-Sight
OTDOA	Observed Time Difference of Arrival
PCA	Principal Component Analysis
QPS	Quantum Positioning Systems
RAKE	A rake receiver is a radio receiver designed to counter the effects of multipath fading.
RF	Radio Frequency
RFID	Radio Frequency Identification
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
RSTD	Reference Signal Time Difference

RTK	Real-Time Kinematic
RTT	Round-Trip Time
SRAM	Static random-access memory
TA	Timing Advance
TDMA	Time-Division Multiple Access
TDOA	Time Difference of Arrival
TOA	Time of Arrival
UAV	Unmanned aerial vehicle.
UE	User Equipment
UMTS	Universal Mobile Telecommunications System
UWB	Ultra-Wideband
WCDMA	Wideband Code Division Multiple Access
WLAN	Wireless Local Area Networks
WSN	Wireless Sensor Networks

1 Introduction

1.1 Background and Context

In general, positioning technologies can be classified into two primary types: satellite-based, and wireless network-based [113]. Wireless positioning technologies refer to determining the position of a mobile device such as a sensor, computer, radar, or cell phone connected to wireless networks such as wireless sensor networks (WSN), wireless local-area network (WLAN), and cellular networks [114]. Alternatively, satellite-based positioning relies on Global Navigation Satellite Systems (GNSS) such as global positioning system (GPS) or Galileo, using signals from satellites orbiting the Earth to determine a mobile object's position precisely. Essentially, positioning is categorized into two types: outdoor positioning and indoor positioning. The position can be represented in two or three dimensions, and typically the position information is given in latitude and longitude form [15-16]

The positioning technologies underpin various applications such as navigation, asset tracking, and location-based services (LBS). In the past, the positioning techniques were only developed for military intentions [115]. However, with the growth in the number of mobile devices and technology, the need for location-based services for people and industries has increased. Therefore, the key factor for positioning is precision which highlights the need for further research and development in this specific domain [115].

GNSS is perhaps the best known of positioning technologies and it relies on a constellation of satellites orbiting the Earth to provide coverage of the entire globe [15]. By measuring the time, it takes for signals from these satellites to reach a mobile device, its location can be found to within a matter of meters [15]. Widely used by navigation applications the world over, whether inbuilt into vehicles as a GPS system, or app-based for hikers and pilots, the positioning technology enables users to locate themselves and their destination and plan their route [17].

Cellular-based positioning, one of the most crucial wireless positioning technologies, leverages the extensive coverage of existing mobile networks, spanning from 2G to the latest 5G technology, to pinpoint the position of mobile devices. By analysing signal strength and timing differences between base stations (BS), cellular positioning can provide coarse to fine-grained position information within an indoor or outdoor environment [24].

There are two main approaches to cellular positioning: mobile-based and network-based methods [24]. Mobile-based methods depend on the device itself to determine its position, usually by actively emitting or receiving wireless signals and processing the received signal information [24]. In contrast, network-based methods involve a network of base stations or sensors to locate a device, typically with the device passively transmitting or receiving signals that can be tracked by the network [24]. Network-based methods are employed by carriers due to their extensive infrastructure capable of collecting and processing signal data from their network of base stations. Therefore, in mobile-based positioning techniques, access to network information is impossible, and independent and accessible databases are employed for positioning [24].

Indoor environments, however, pose a challenge for GNSS, as satellite signals are often obstructed by buildings and structures [62]. This is where indoor positioning systems (IPS) steps in, providing accurate positioning within limited indoor spaces [62]. IPS technologies utilize a variety of methods, such as WLAN signal strength fingerprinting, Ultra-Wideband (UWB) signal propagation delay measurements, and Bluetooth beacons, along with cellular network signal analysis, to determine the location of devices within buildings [62].

The significance of accurate positioning goes beyond applications in navigation or tracking [24]. For autonomous systems, such as self-driving vehicles and drones, the exact position must be computed for the correct and controlled operation [116]. For instance, positioning data is essential for autonomous vehicles in that they need to move or drive through complicated environments, avoid obstacles, and make sound well-informed decisions for safe and precise driving [117].

Another field where accurate positioning has a very critical contribution is that of monitoring the critical infrastructure [118]. In such cases of the location of pipelines, power grids, or even communication towers, the tracking of asset location allows operations to become proactive in predicting and preparing for possible failures or disturbances, therefore keeping them in such a way that operational efficiency is intact, and downtime is at a minimum [118].

In general, asset management is a broader area that incorporates tracing and management of physical assets in different industries [119]. The positioning technologies enable firms to track and optimize the movement of assets and it helps them indirectly to ensure that they are safe. This is essential for high-value assets, including vehicles and other forms of machinery, and inventories [119].

As technology keeps improving, the current positioning systems are evolving to be more sophisticated and finally integrated into our daily undertakings. Pedestrian navigation apps, asset-tracking solutions, and autonomous vehicles are only some of the examples that represent the great effect of these technologies in growing. Positioning systems in the future of transportation, logistics, and smart cities are bound to shape or position with real-time information about location [120].

1.2 Aim and Scope of the Study

Despite providing extensive global coverage, the GNSSs encounter limitations in urban environments characterized by dense obstructions, such as tall buildings, and deep valleys. Moreover, intentional signal manipulation techniques such as spoofing and jamming jeopardize their integrity due to the absence of signal authentication and encryption. While extensive research aims to mitigate these challenges, they remain persistent, underscoring the critical need for alternative positioning methods in scenarios where GNSS is unavailable, unreliable, or susceptible to manipulation [19] [30].

The expansion of wireless networks has made it possible to utilize cellular positioning technology as a desirable alternative in urban and indoor environments, where obstructions often compromise satellite signal integrity. This approach leverages the widespread availability of existing cellular networks, thereby providing a cost-effective solution without the need for new infrastructure [121-123].

Cellular positioning is known for its faster position determination and lower power consumption compared to its satellite counterparts, increasing its suitability for mobile devices [123]. However, this technology is not without its limitations. The conventional cellular positioning techniques, such as angle of arrival (AOA), time difference of arrival (TDOA), and Triangulation / Multilateration, for determining location coordinates need access to precise private data of cellular network infrastructure, the necessity for accurate time synchronization among cell towers, or dependency on cellular antenna configuration, signal frequency, and data internet connection which delimits them to be leveraged by only in network-based positioning method compared to mobile-based [124-125].

To address these constraints, this research proposed leveraging the Barycentric interpolation algorithm based on received signal strength (RSS) for outdoor cellular positioning. This algorithm is also known as the Barycentric coordinate system (BCS), which is used throughout this work for simplicity. Utilizing the geometry and data of cellular antennas' (which are considered as public data of cellular network infrastructure), BCS offers a promising approach to estimate the user equipment's (UE) position when there is no accessibility to GPS, internet data connection, private data of cellular network infrastructure, cell antenna configuration, or synchronization among cell towers. Its methodology, involving assigning weights to cellular antennas based on their positions and signal strengths, presents a novel solution to the limitations of traditional cellular positioning methods.

This thesis aims to develop and evaluate an Outdoor-RSS-based positioning algorithm employing the BCS method in urban area with a high concentration of 2G cellular towers.

The study focused on determining the position of an active user equipment (UE) using the mobile-based positioning approach within a two-dimensional latitude/longitude grid over a 1 km radius of the city center area.

1.3 Methodology

This research employed a mobile-based positioning approach to develop a BCS algorithm based on RSS measurements, to achieve the maximum possible accuracy on outdoor cellular positioning in urban environments using 2G cellular networks. The methodology consisted of the following key steps:

- The data collection points were pinpointed on the Google map based on varying conditions, including 2G cell density, terrain, and the presence of urban structures. This was conducted to challenge and evaluate the BCS algorithm in the further sections.

- The offline database file in a CSV format containing cellular towers' data associated with Finland area was collected from the opencellid.org website which is the largest open database of cellular towers in the world.

- The data scanning and storing program was developed by Arduino C programming language, and then an Arduino GSM-enabled IoT module was programmed by the program for the cellular antennas' scanning process. The procedure of this sketch begins by scanning available 2G cellular antennas to collect data and then store them in a file in CSV format.

- The BCS positioning algorithm was developed by leveraging M programming language and Power Query tool to determine UE's geographical position based on nearby 2G cellular antennas' coordinates and RSS level. The algorithm procedure begins by loading the UE’s neighbouring scanned cellular antennas’ data files based on each data point and the cell towers’ information database file to process data and ends with UE’s position estimation, storing and accuracy evaluation.

- The data collection process consisted of two steps. First, a GPS-enabled device (mobile phone) was used to determine the geographical coordinates of UE based on each pre-pinpointed data point on the map. Then, the Arduino module scanned 2G cellular networks around the pre-pinpointed data points to collect data on available 2G cellular antennas. The process was repeated for all 12 pre-selected data points in four distinct directions, resulting in a total of 48 samples for algorithm evaluation.

In the final step, the data collected by both the GPS and the module were processed using the BCS positioning algorithm program to calculate the UE’s position for each data point. The accuracy of this estimation was then evaluated by comparing it to the UE’s position obtained by GPS, which serves as reference coordinates.

This methodological framework set the foundation for a comprehensive evaluation of the proposed positioning algorithm, with a particular focus on its validation in the Finland area within Helsinki city center, encompassing a maximum 1 km radius from the Kamppi shopping mall.

1.4 Significance of the Study

This thesis holds significance in two key aspects. Primarily, it introduces a novel outdoor cellular-positioning algorithm based on the Barycentric interpolation technique for determining the two-dimensional coordinates of a user equipment (UE). This method’s accuracy is compared with the GPS system, one of the world’s most precise satellite positioning systems, thereby examining the precision and limitations of the Barycentric interpolation technique in outdoor positioning. Such a contribution is pivotal in advancing outdoor positioning technologies using cellular tower information.

The secondary significance of this work lies in the feasibility of outdoor positioning by UE itself without relying on the Internet, satellite systems, time synchronization among cell towers, or dependency on antenna configuration and signal frequency. Unlike mobile network operators, who are limited to using their own private/public data of cellular network infrastructure in the positioning process, this study leverages public cellular data of networks belonging to distinct operators. This approach leads to a larger dataset incorporation in interpolation calculations, potentially enhancing positioning accuracy. Therefore, this study offers valuable insights into enhancing mobile-based positioning accuracy different from the conventional scope of cellular network-based methodologies.

1.5 Structure of the Thesis

The structure of this thesis is delineated into six main chapters. It begins with Chapter 1, introducing the study’s background, objectives, methodology, and its significance. Chapter 2 delves into the nuances of wireless positioning technologies, exploring their development, the constraints associated with GNSS, and the advantages inherent in cellular networks, with an emphasis on Barycentric interpolation method. The third chapter, ‘Methodology’ elaborates on the Data collection points, the procedural approach of the algorithm, and the positioning scenario examined in this research. Chapter 4 is dedicated to the results of the study, showcasing the estimations, validation processes of the BCS algorithm, and comparative analyses. Discussions on the findings, the inherent limitations, and ways for future inquiries are broached in Chapter 5. The thesis concludes with Chapter 6, providing a summary of the significant discoveries and contributions to the domain of outdoor cellular positioning.

2 Overview of Wireless Positioning Technologies and Methods

2.1 Introduction

This chapter reviews the literature relevant to wireless positioning, focusing on the evolution and challenges of cellular-based methods and the innovative application of BCS for outdoor positioning. Amidst the advancements in GNSS and cellular network infrastructures, the pursuit of enhanced accuracy, reliability, and security in positioning remains paramount. This review examines the progression from GNSS to cellular positioning techniques, emphasizing the need for improved solutions due to challenges such as radio jamming and environmental constraints.

The literature is explored systematically, beginning with the background of wireless positioning technologies, followed by discussions on the limitations of GNSS and the potential of cellular networks. Special attention is dedicated to BCS, analysing its theoretical basis, applications, and promise for urban outdoor positioning.

By synthesizing the literature, this review establishes the context for this thesis, identifying knowledge gaps and laying the groundwork for the subsequent research on a BCS-based positioning algorithm and its prospective contributions to outdoor positioning technologies.

2.2 Background on Wireless Positioning Technologies

2.2.1 Early Developments in Wireless Positioning

Wireless positioning technologies have undergone a continuous journey of innovation and evolution, fundamentally transforming how people navigate and comprehend their surroundings. This progression can be traced from the early radio navigation systems of the 1960s to the sophisticated multi-sensor systems of the 2020s [1] [2].

The advent of Loran (Long-Range Navigation) and Decca in the mid-20th century heralded a new era in radio navigation. Developed in the 1940s during World War II, Loran was initially vital for transatlantic ship navigation and later for long-distance aircraft. Its core principle relied on the time difference of arrival (TDOA) of signals, using synchronized radio signals from multiple stations; the time delay between receiving these signals at a specific location was then calculated to determine the position with an accuracy in the order of tens to hundreds of fees[1]. Loran-C, an advanced version, offered enhanced range and precision, making it a cornerstone of navigation during that era. Figure 1 shows the layout of Loran’s transmitter stations and the concept of time difference of arrival (TDOA).

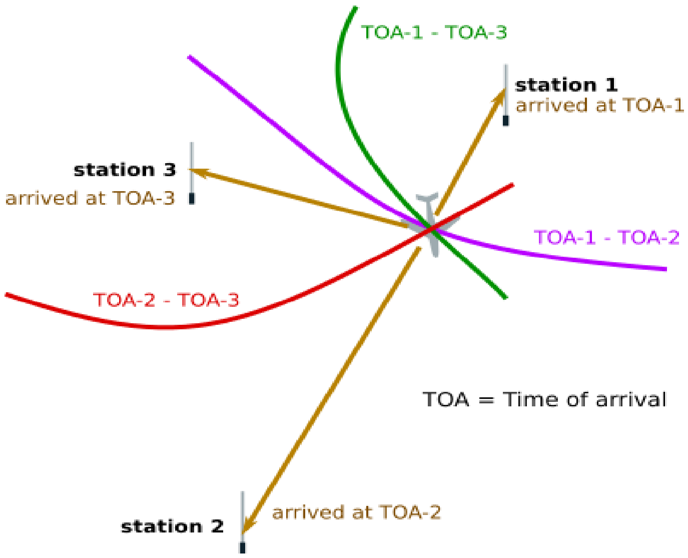

Figure 1. LORAN hyperbolic grid lines. [2]

Concurrently, the Decca Navigator System, with conceptual beginnings in the 1920s, emerged as a significant innovation in precise navigation. Developed and refined during World War II, largely due to the efforts of W. J. “Bill” O’Brien, Decca utilized synchronized radio signals between stations for accurate hyperbolic position fixing [3][4]. This system became an essential tool for maritime and aerial navigation in the post-war period. Both Loran and Decca laid the groundwork for modern navigational technologies, signifying a crucial transition from traditional to electronic navigation methods.

In the 1970s, the concept of GNSS emerged, notably with the United States launching the initial satellites for the NAVSTAR system, which evolved into the GPS. This satellite-based system significantly advanced the capabilities of wireless positioning, offering worldwide coverage and high accuracy [5].

The 1980s saw the proliferation of cellular networks, introducing another dimension to wireless positioning. Techniques such as Cell ID determination estimated a device’s location based on signal strength from nearby base stations, providing a simple and cost-effective method for positioning [6-7].

The 1990s marked a leap in GNSS accuracy with Assisted GPS (A-GPS), which utilized cellular networks to enhance positioning accuracy, especially in environments where GPS signals alone were inadequate. This decade also saw the focus shifting to indoor positioning systems (IPS) with the emergence of Wi-Fi fingerprinting, a popular technique for estimating positions indoors where GPS signals were typically weak or unavailable [8-9].

The proliferation of smartphones and the rise of the Internet of Things (IoT) in the 2010s led to further advancements in wireless positioning. New techniques such as Ultra-Wideband (UWB) and Bluetooth Beacons emerged, offering enhanced accuracy and scalability [10-11].

The 2020s have been characterized by the convergence of various positioning technologies, leading to the development of multi-sensor positioning systems. These systems combine data from multiple sources to provide more accurate and reliable positioning, especially in challenging environments such as urban canyons, dense forests, and indoor or underground spaces where direct line-of-sight to satellites is compromised [12].

Looking forward, emerging technologies such as millimeter wave (mmWave) positioning and quantum positioning systems (QPS) hold promise for further advancements in accuracy and precision. The integration of wireless positioning with Internet of things (IoT) is also creating new opportunities for applications ranging from smart cities to logistics management [13-14].

2.2.2 Global Navigation Satellite Systems (GNSS)

Global Navigation Satellite Systems (GNSS) are constellations of satellites that provide precise positioning, navigation, and timing information worldwide. The four major GNSS systems in operation are GPS (United States), GLONASS (Russia), Galileo (European Union), and Bei Dou (China) [15].

GPS, the first and most widely used GNSS, employs a constellation of 31 satellites to offer unparalleled accuracy and global coverage. GLONASS, Russia’s counterpart, utilizes a constellation of 31 satellites known for its robustness and resilience to interference. Galileo, Europe’s response to US dominance, aims to enhance accuracy, availability, and security with its constellation of 30 satellites. Bei Dou, China’s emerging GNSS power, employs a constellation of 35 satellites, particularly strong in Asia [15-16].

The emergence of multi-GNSS constellations, capable of receiving signals from multiple systems, offers enhanced accuracy, resilience, and extended coverage. As GNSS technology advances, multi-GNSS will become increasingly important for reliable and secure positioning across a wide range of applications [17-18].

At the heart of GNSS technology lies the concept of signal time delay, where the duration taken for a signal to travel from a satellite to a receiver is precisely measured. This measurement is crucial as it directly reflects the distance between the satellite and the receiver, assuming the signal propagates at the speed of light [19]. GNSS's effectiveness hinges on trilateration, a mathematical technique that pinpoints a precise location by determining distances from multiple satellites. GNSS receivers, equipped with antennas that capture satellite signals, utilize this spatial information to calculate their exact position on Earth. The trilateration process involves the intersection of spherical distances derived from at least four satellites. This intersection not only determines latitude and longitude, but also altitude, enabling three-dimensional positioning [19].

To enhance the accuracy and reliability of GNSS positioning, reference stations and GPS rover receivers play a pivotal role. Reference stations, strategically positioned on the Earth's surface, continuously monitor the precise location of orbiting satellites. These stations collect and transmit correction data, including atmospheric delay corrections and satellite ephemeris data, to nearby GPS rover receivers [20].

GPS rover receivers, handheld or embedded devices that can receive GNSS signals, utilize these corrections to refine their positioning estimates. This process, known as Differential GPS (DGPS), significantly improves accuracy, particularly in challenging environments where satellite signals are weak or obstructed [21]. In addition to DGPS, Real-Time Kinematic (RTK) further elevates GNSS positioning accuracy. RTK utilizes a network of reference stations to provide real-time corrections to rover receivers, enabling centimetre-level accuracy for applications such as surveying, precision agriculture, and autonomous vehicles. Figure 2 precision positioning through satellite Corrections [21].

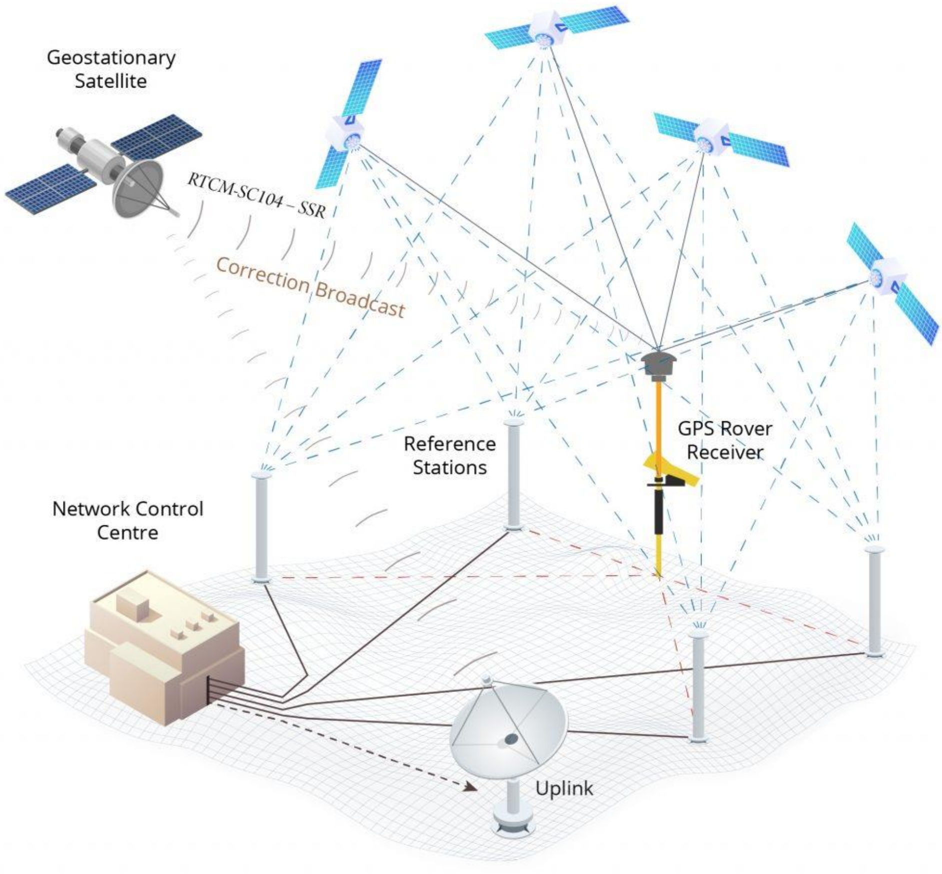

Figure 2. Precision Positioning through Satellite Corrections. [22]

The integration of reference stations, GPS rover receivers, and DGPS/RTK technology has transformed GNSS into an indispensable tool for precise positioning, enhancing the efficiency and safety of a wide range of applications [22] [23]. In recent years, there is a disparity in the distribution of GPS rover receivers and reference stations between developed and developing countries. This disparity has a direct impact on the accuracy of positioning data in developing countries, as the lack of these devices limits the ability to obtain reliable and accurate positioning information [23].

2.2.3 Basics of Cellular Positioning Technologies

Cellular networks have transcended their initial role of facilitating voice communication, evolving into ubiquitous platforms for data transmission and location-based services. Underpinning this transformation lies cellular positioning, a suite of technologies enabling the estimation of a mobile device's location by leveraging the cellular network infrastructure. This overview delves into the foundational aspects of cellular positioning, tracing its evolution from the nascent stages of 2G to the burgeoning era of 5G technologies.

2.2.3.1 The 2G Era and Cell-ID: Early Foundations

The second generation (2G) of cellular networks, such as Global system for mobile communications (GSM) and code division multiple access (CDMA), laid the groundwork for cellular positioning. The basic Cell-ID method utilizes the unique identifier of each BS, providing location estimates within the cell's coverage area, typically ranging from hundreds of meters to kilometres. While simple and widely implemented, Cell-ID offers limited accuracy, particularly in densely populated urban environments or situations with signal obstructions [24].

2.2.3.2 Evolving Techniques: 3G and Beyond

The arrival of 3G technologies such as Code Division Multiple Access (WCDMA) and Universal Mobile Telecommunications System (UMTS) significantly improved the capabilities of cellular positioning. WCDMA introduced innovative technique Angle of Arrival (AOA), which analysed the signal's direction from multiple BSs. This enabled more precise location estimates within the cell, especially in urban environments with dense cell deployments. Furthermore, 3G witnessed the implementation of time-based methods such as Time of Arrival (TOA) and Time Difference of Arrival (TDOA) [24]. These techniques measured the signal propagation time between the mobile device and BSs to estimate distance and location. While offering better accuracy than Cell-ID, TOA and TDOA were susceptible to synchronization errors and signal propagation delays, particularly in non-line-of-sight (NLOS) scenarios. These limitations could impact accuracy, especially in urban canyons or areas with dense foliage [24].

The fourth generation (4G) of cellular networks, spearheaded by Long-Term Evolution (LTE), ushered in significant advancements in both positioning accuracy and network-based positioning capabilities. One key innovation was Assisted-GPS (A-GPS), which integrated GPS data with cellular network information. This hybrid approach addressed a fundamental limitation of standalone GPS in mobile devices, namely the slow acquisition time due to the need to synchronize with multiple satellites. By leveraging BS data such as ephemeris (satellite orbit information) and almanac (satellite visibility data) stored on the network, A-GPS significantly mitigated acquisition time, especially indoors where direct satellite visibility is often limited. Furthermore, 4G introduced enhanced Cell-ID techniques that incorporated information from neighbouring BSs alongside the traditionally used serving cell. This enhanced accuracy, particularly at cell borders where location estimates based on a single cell can be ambiguous. By analysing signal strengths and timing measurements from multiple surrounding cells, these techniques offered improved location granularity within the cell coverage area [24].

2.2.3.3 Emerging Technologies: NB-IoT and LTE-M

Narrowband Internet of Things (NB-IoT) and LTE-M are cellular network technologies specifically designed for low-power, wide-area connectivity. While primarily focused on machine-to-machine communication, they also offer potential for positioning applications, particularly in asset tracking and environmental monitoring. NB-IoT, with its extended range and low power consumption, is suitable for tracking devices in remote areas or within buildings. LTE-M, offering higher data rates and wider coverage, can be used for real-time tracking of assets requiring more frequent location updates. Both technologies are still evolving, and their role in cellular positioning is expected to grow in the coming years [25-27].

2.2.3.4 The 5G Positioning Landscape

The fifth generation (5G) of cellular networks promises a paradigm shift in positioning capabilities. New features like higher bandwidth, improved signal propagation, and massive machine-type communication (mMTC) pave the way for more precise and diverse positioning applications. Enhanced timing measurements, coupled with advanced algorithms, are expected to deliver sub-meter accuracy, enabling centimetre-level positioning in specific scenarios. Additionally, Non-Line-of-Sight (NLOS) performance, crucial for indoor and urban environments, is anticipated to see significant improvements due to features such as multipath propagation analysis and fingerprinting techniques [28-29].

As cellular positioning continues to evolve, particularly for outdoor environments, understanding the underlying techniques becomes increasingly important. In section 2.5 delves deeper into the various cellular positioning methods, exploring their principles, operation, and performance characteristics in more detail.

2.3 Vulnerabilities in GNSS Positioning

This section explores GNSS vulnerabilities, categorizing them into two primary groups: intentional threats, such as jamming and spoofing, and accidental threats, which stem from environmental and technical factors. Detailed discussions follow, highlighting the impact of these vulnerabilities on GNSS systems and underscoring the need for alternative positioning solutions. Additionally, it addresses recent real-world examples of intentional threats.

2.3.1 Accidental threats

2.3.1.1 Urban Environment Challenges

In urban settings, GNSS systems are subjected to two primary phenomena that degrade signal integrity and positioning accuracy: signal attenuation and multipath errors. Signal attenuation, a consequence of urban infrastructure, diminishes the strength and clarity of GNSS signals, compromising the system's ability to accurately determine positions. This effect is particularly pronounced in densely built areas where buildings act as barriers to signal propagation [19] [30].

Simultaneously, urban environments contribute to multipath errors, a condition where GNSS signals reflect off surfaces such as buildings and vehicles before reaching the receiver. These reflections introduce delays and distortions to the signal, complicating the task of accurate signal interpretation by GNSS receivers. The presence of multiple reflected signals can lead to erroneous positioning information due to the receiver's difficulty in discerning the direct signal path from the reflected ones [19] [30]. Figure 3 visualizes the effect of multipath error and signal blockage on GNSS positioning accuracy. These urban-specific challenges highlight the need for adaptive GNSS technologies or supplementary positioning systems.

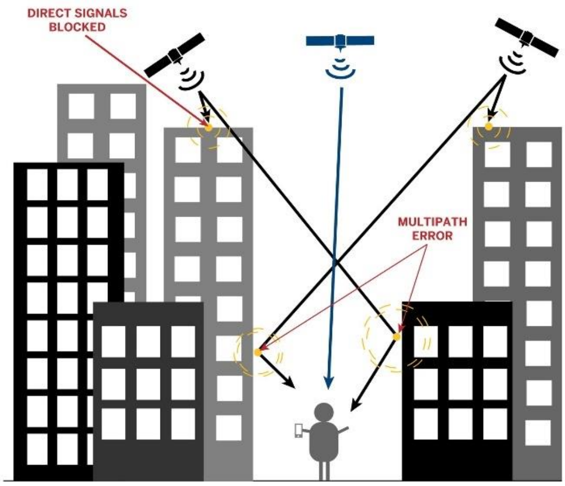

Figure 3. Multipath error and Signal blockage. [35]

For instance, authors in [31] proposed a hybrid scheme combining GNSS and cellular network data (using TDOA technique) to improve location accuracy in urban scenarios where GNSS signals are often inadequate.

This study [32] analysed the limitations of GNSS in urban environments and proposed using cellular signals (LTE/5G) and UWB ranging as alternatives. It focused on improving TOA-based navigation systems in conditions where GNSS signals are compromised, such as in deep urban canyons or indoors.

In [33], the authors proposed using standard long-term evolution (LTE) signalling for high accuracy positioning estimation, specifically targeting the limitations of GNSS in dense urban environments. This technique was inspired by the human sound localization system and validated in a dense urban city, aiming to meet the Federal Communications Commission (FCC) requirements.

2.3.1.2 Environmental and Technological Threats

Environmental factors such as ionospheric and tropospheric delays play a crucial role in affecting GNSS signal precision. These atmospheric conditions can alter the speed and trajectory of GNSS signals, leading to errors in time-of-arrival calculations essential for accurate positioning [34]. Figure 4 represents the trajectory of a GPS signal encountering the ionosphere, approximately 1000 kilometres above Earth’s surface. Due to solar radiation, this region contains ionized gases that dynamically alter the signal’s refractive index (RI). This variability in RI directly impacts the signal’s transit time, contributing to fluctuations in GPS accuracy [34]. Technological threats extend beyond signal interference from RF sources, encompassing the broader spectrum of electromagnetic pollution in our increasingly digital world. This includes interference from broadcast towers, mobile networks, and even satellite constellations themselves, which can crowd the frequencies GNSS systems rely on [30] [34].

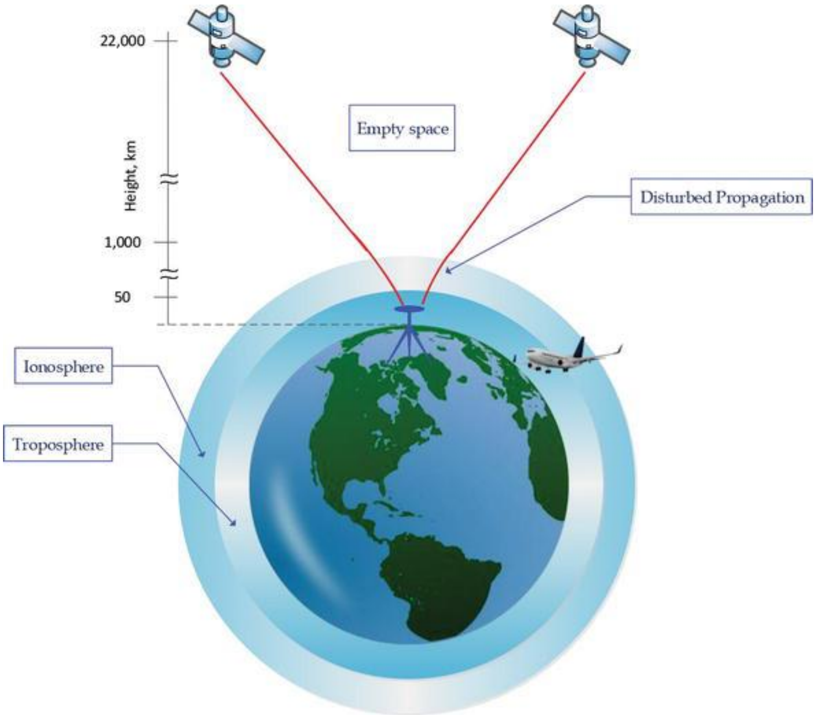

Figure 4. GPS signals disruption by solar-driven ionosphere. [34]

2.3.2 Intentional threats

Expanding on the vulnerabilities to intentional disruptions, jamming and spoofing pose substantial risks to GNSS systems. Jamming, by emitting noise or signals at GNSS frequencies, can obscure or entirely block satellite signals, severely disrupting navigation, and timing services. Spoofing, more sophisticated, involves broadcasting counterfeit GNSS signals. These fake signals, particularly dangerous because GNSS data is often unencrypted, can be made to appear as legitimate satellite signals, leading receivers astray. The unencrypted nature of GNSS signals leaves them exposed to spoofing, as attackers can easily mimic the signal structure to deceive GNSS receivers as it is shown in Figure 4 [30] [36]. This vulnerability underscores the critical need for incorporating signal authentication and encryption in GNSS protocols to mitigate spoofing risks, alongside advanced detection mechanisms to identify and counteract jamming attempts or investigate other positioning methods as alternatives to GNSS.

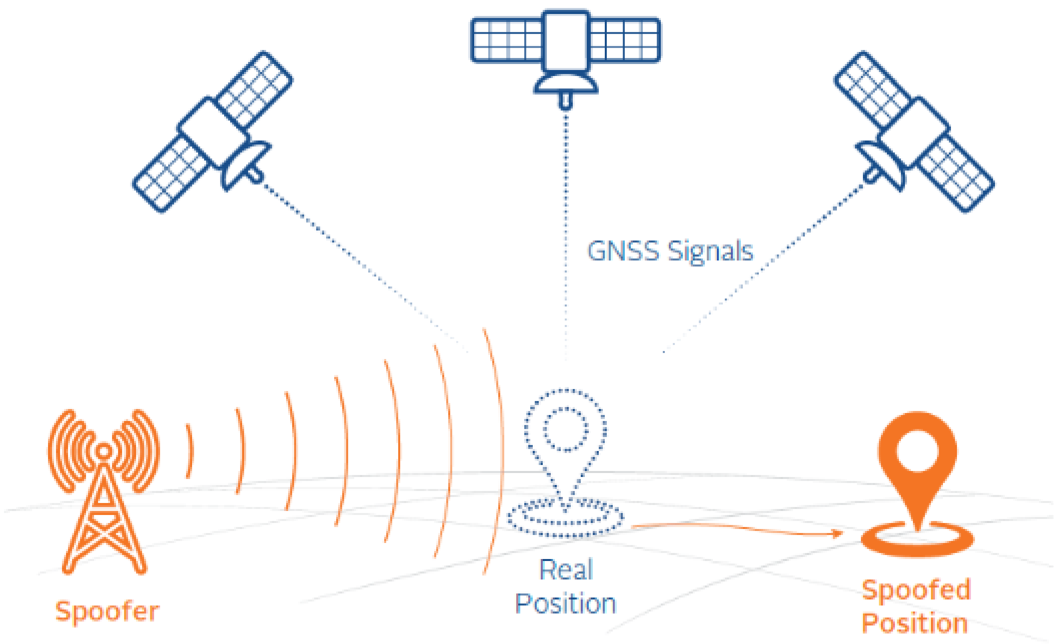

Figure 5. Impact of GNSS signal spoofing on the receiver. [37]

This paper [38] discusses approaches to mitigate GNSS disruption caused by jamming, including the use of inertial systems, filtering in spatial and time-frequency domains, and vector tracking of GNSS signals.

In [39] authors Proposes a technique for GNSS receivers to detect spoofing and jamming using observations of received power and correlation function distortion, potentially enhancing receiver resilience without requiring additional hardware.

Authors in [40] explored the use of Android network positioning as a viable alternative to GNSS for drone navigation, especially in contexts where GNSS is unreliable or unavailable due to jamming. This research highlights the potential of cellular and network-based positioning technologies in supporting drone operations, offering a complementary solution to GNSS.

2.3.3 Recent Real-world Incidents

Real-world incidents underscore the threats mentioned earlier vividly. This section addresses the most notable incidents of GNSS jamming and spoofing worldwide, categorized by region.

Europe:

- Newsweek on January 18, 2024, reported on the deployment of GPS jammers near Kaliningrad, Russia, an incident that had a profound impact on the navigation systems of cities in Poland, demonstrating the strategic use of such technologies in geopolitical scenarios and their far-reaching effects. Additionally, similar GPS jamming issues were reported in January 2024 in eastern and southeastern parts of Finland [41].

- In late June 2017, an incident in the Black Sea involving over 20 ships highlighted significant vulnerabilities in maritime navigation systems due to GPS spoofing. These ships reported discrepancies in their GPS-based navigation, erroneously indicating their positions at airports, distant from their actual maritime locations. One report detailed a vessel experiencing intermittent GPS signal reception issues upon approaching the coast of Novorossiysk, Russia, later showing a highly accurate but incorrect location 25 nautical miles displaced [42].

- In June 2017, the far north of Norway experienced significant GPS jamming incidents close to the Russian border, disrupting services from ambulances to personal safety alarms. This situation highlighted the vulnerability of civil GNSS to RF interference, with local police reporting similar jamming incidents since 2017. Additionally, in August 2017, a drone crash in the UK further illustrated the safety risks associated with GNSS jamming and spoofing. A 25lb survey drone lost GPS reception due to RF interference at the survey site, leading to its unintended drift and crash into a residential property [43].

- In 2010, at Hannover Airport in Germany, an unauthorized GPS repeater used within a hangar for testing business jets caused significant GNSS interference, misleading taxiing planes about the runway threshold's location. This interference, emanating from less than 1000 meters away from the runway, triggered erroneous warning alarms and positioning alerts in the aircraft. The incident underscored the vital importance of GNSS/GPS precision in aviation, where accuracy is crucial for the safety of take-offs and landings [44].

North America:

- In a technical exploration of automotive cybersecurity vulnerabilities In June 2019, a spoofing attack on a Tesla Model 3 was conducted to assess the impact on its navigation system. Researchers successfully transmitted simulated GPS signals, misleading the vehicle’s positioning system. This led to an unintended deviation from the intended route, demonstrating the susceptibility of advanced driver-assistance systems to GPS spoofing [45].

- The Portland Spoofing Incident at the ION GNSS+ Conference in 2017 demonstrated the inadvertent role of GNSS spoofing when a GNSS simulator, intended for demonstration, emitted signals that disrupted mobile phones within the vicinity. This incident inadvertently mimicked spoofing effects, showing how even non-malicious use of GNSS simulation technology can lead to significant disruptions in GNSS-dependent devices. The unintended signal interference altered the devices' perceived time and location, illustrating the potential consequences of GNSS spoofing where devices receive manipulated signals, leading to inaccurate positioning and timing. This serves as a critical example for research on GNSS security, emphasizing the need for awareness and preventive measures against both unintentional and deliberate spoofing activities [46].

Middle east and Asia:

- In a notable spoofing incident in 2023 the Middle East, OpsGroup reported navigational failures across 12 aircraft due to false GPS signals, including a significant event involving a Boeing 777. Flying near southeastern Iraq toward Baghdad, the aircraft lost GPS functionality, leaving the crew to rely on air traffic control for basic location and time information. This incident, part of a series of sophisticated spoofing operations near Iran, represents the increasing electronic warfare threats in the region, highlighting the need for enhanced countermeasures in aviation navigation systems to mitigate the risks associated with such malicious activities [47].

- In December 2019, SkyTruth reported GNSS disruptions near Chinese coast oil terminals, observed through automatic identification system (AIS) tracking anomalies and corroborated by Strava fitness tracker data. These disruptions, extending to cities such as Shanghai and Dalian, were attributed to GPS spoofing, where signals are manipulated to falsify location data. Further investigation revealed a distinct pattern of spoofing above Point Reyes, California, with vessels' reported locations being thousands of miles away from their actual positions. This pattern, differing from the one near the Chinese coast, suggested a sophisticated spoofing operation without a clear link between all affected areas [48].

- In 2016, significant GPS disruptions were detected around the Kremlin in Moscow, with civilian GPS signals showing incorrect locations, notably diverting to an airport nearly 20 miles away. This phenomenon was notably observed during the peak popularity of an augmented reality game. Investigations suggested the presence of a powerful transmitter capable of altering GPS signals within the Kremlin area, speculated to prevent unauthorized drone flights. Official responses to these findings were not provided, highlighting the intricacies and potential vulnerabilities in satellite navigation systems [49].

- On December 5, 2011, the RQ-170 Sentinel, a stealth drone developed by Lockheed Martin for the U.S. Air Force, was intercepted by Iranian forces approximately 140 miles from the Afghanistan border. Iran claimed the drone was brought down through cyber-espionage methods with minimal damage, suggesting a sophisticated level of cyber warfare capability. This event underscored the vulnerability of Unmanned aerial vehicles (UAV) to spoofing attacks, where false signals misguide the navigation systems of drones [50].

2.4 Signal Degradation in Cellular Positioning

Exploring the intricacies of signal degradation is crucial within the domain of cellular positioning research. This section aims to dissect the principal elements contributing to signal attenuation and distortion, which compromise the precision and consistency of location determinations. A thorough understanding of these degradation mechanisms is vital for the advancement of cellular positioning technologies that are both resilient and accurate.

2.4.1 Path Loss

The phenomenon of path loss plays a pivotal role in determining the accuracy and efficiency of cellular positioning systems. As the signal traverses the environment from the transmitter to the receiver, it undergoes attenuation primarily due to the distance it covers, along with various obstacles it encounters, such as buildings, trees, and other forms of interference. This degradation not only affects the strength of the received signal but also impacts the precision of location estimation algorithms that rely on signal metrics. Recent scholarly discussions have delved into the various models and factors influencing path loss, highlighting its critical nature in determining precise location information. Among the most examined models, the Hata-Okumura and the COST-231 models stand out for their applicability in urban, suburban, and rural environments. These models, which have been extensively validated through empirical data, provide a framework for estimating path loss over different terrains and conditions [51].

In [52], the authors analyzed the accuracy of different path loss prediction models, including Okumura-Hata and COST231-Hata, for cell design in mobile communication systems. They illustrate the importance of considering specific environmental characteristics such as building height. And street width to enhance the reliability of path loss estimations in various propagation environments. Also, authors in [53] emphasized the significance of accurate path-loss estimation in cellular networks for performance improvement and financial feasibility, highlighting the Okumura/Hata model's suitability across different environments and its ability to provide more accurate estimations by considering additional correction factors like antenna heights. Furthermore, in [54] the authors discussed positioning based on noise-limited censored path loss data, emphasizing how path loss data, limited by measurement noise, affects positioning accuracy. The study demonstrates the significant role of path loss in determining the accuracy of wireless positioning systems.

2.4.2 Multipath Propagation

The multipath effects, especially in 2G networks, arises when a transmitted signal reaches the receiver through multiple paths due to reflection, diffraction, or scattering. This phenomenon not only distorts the signal's original properties but also complicates the accurate determination of a mobile device's position. In 2G cellular networks, characterized by their reliance on Time-Division Multiple Access (TDMA) and frequency-division multiple access (FDMA) technologies, the multipath effects can severely degrade positioning precision. The reflections from various objects, such as buildings and vehicles, lead to multipath-induced errors, which are particularly problematic in urban environments where such obstacles are prevalent. Figure 9 represents the reflection, diffraction, or scattering effects on the signal [51] [55].

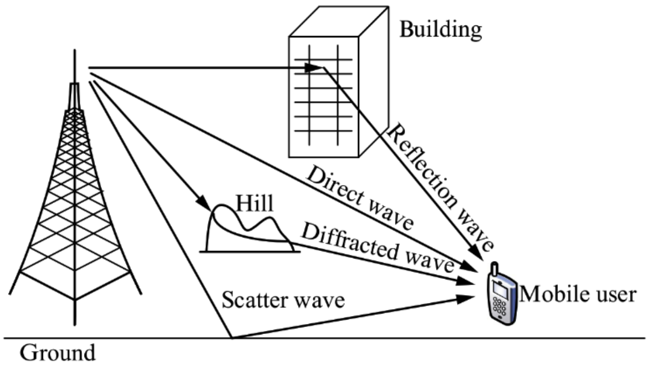

Figure 6. Multipath Effects. [56]

To address the challenges posed by the multipath effect in cellular positioning, have been developed several mitigation strategies. Adaptive filtering techniques, for example, have been employed to distinguish between the direct path signal and the reflections, thereby improving the accuracy of TOA and AOA measurements. Furthermore, the implementation of advanced algorithms, such as RAKE receivers, which can combine multipath signals constructively, has shown potential in counteracting the adverse impacts of this phenomenon. Additionally, the transition towards more advanced cellular technologies, such as 3G and 4G, which incorporate better error correction and signal processing capabilities, offers indirect solutions to the multipath problem initially faced in 2G networks. Nonetheless, understanding and mitigating the multipath effect remains crucial for enhancing the reliability and precision of cellular positioning systems across all generations of network technology [56-58].

2.4.3 Channel Effects

The channel effect significantly influences signal propagation and, consequently, cellular positioning accuracy within 2G networks. Characterized by various phenomena such as fading, shadowing, and the aforementioned multipath effects, the channel environment can drastically alter the transmitted signal before it reaches the receiver. In 2G networks, which predominantly operate based on Gaussian minimum shift keying (GMSK) modulation within GSM framework, the channel effect can lead to notable discrepancies between the expected and actual signal characteristics. This discrepancy primarily arises due to the environmental context—urban settings with dense infrastructures versus open rural areas—resulting in a varying degree of signal attenuation and distortion. These alterations can severely impact the system's ability to accurately triangulate a device's position,27 simulations when relying on methodologies such as TOA and RSSI, which are fundamental to cellular positioning [59-60].

To mitigate the adverse effects of channel conditions on cellular signals, especially in 2G networks, several corrective measures have been explored. Adaptive channel equalization techniques stand out for their ability to compensate for signal distortion by dynamically adjusting the processing based on the current channel conditions. Additionally, diversity schemes, such as spatial, frequency, and polarization diversities, are employed to enhance signal robustness against fading and shadowing effects. Network-based solutions, including advanced base station algorithms that account for varying channel conditions in real-time, also contribute to improved positioning accuracy [59-60].

2.5 Cellular Positioning: Principles and Methods

2.5.1 Fundamental Principles

Cellular positioning techniques are fundamentally underpinned by two methods: Multilateration and triangulation. Multilateration determines the UE's location by calculating the distance from multiple BSs. This technique necessitates at least three BSs for accurate positioning, using signal strength measurements and propagation models to estimate distances. Conversely, triangulation relies on estimating the signal's direction from the UE, requiring at least two BSs. This method utilizes the directionality of received signals to pinpoint the UE's location. While these methods independently offer a robust framework for calculating the position of the UE, the integration of other positioning techniques can significantly enhance the precision and dependability of the resultant position estimations [24] [61].

2.5.2 Positioning techniques

There are two main approaches to employ positioning techniques or methods: network-based or mobile-based. Mobile-based positioning utilizes onboard device technologies, such as Cellular Connectivity, GPS receivers, Wi-Fi scanners, or Bluetooth beacons, to independently estimate its location. Unlike network-based methods relying on external infrastructure, this approach empowers devices to actively emit or passively receive signals and process the received information to determine their position. Mobile-based methods offer advantages such as self-reliance in remote areas, low reliance on external infrastructure, and potentially high accuracy depending on the technology used [24] [62].

Network-based positioning leverages infrastructure networks, such as cellular, Wi-Fi, or sensor arrays, to estimate the location of a device, typically implemented and controlled by network operators rather than directly by individual devices or users. Unlike mobile-based methods where the device performs its own location estimation, network-based approaches rely on data collected from multiple network elements such as base stations, access points, or sensors. This data, encompassing signal strength, timing information, or angle of arrival, is processed, and analyzed by central algorithms owned and operated by the network operator, ultimately estimating the device's position within a defined coordinate system. While offering advantages such as widespread coverage, reduced dependence on device capabilities, and potential for high accuracy under specific conditions, network-based methods can be susceptible to limitations such as dependence on operator infrastructure availability, complex propagation environments, and computational demands for real-time processing [24] [62].

Subsequent sections examine each technique, explaining their underlying principles and functionalities that could be applied in both approaches. These techniques can be classified according to their functional essence as follows.

2.5.2.1 Proximity Information

Cell ID (CID) and Enhanced Cell ID (ECID)

The Cell ID (CID) positioning method, also referred to as the cell of origin (COO), is a foundational technique in cellular positioning, relying on the proximity of the mobile station (MS) to the nearest serving cell. It estimates the mobile station (MS) location by associating it with the geographic coordinates of the serving cell, often represented by antenna locations or the cell coverage area's centroid. Enhanced Cell ID (E-CID) improves upon CID's accuracy by incorporating additional reference data such as RSS levels, which assist in distance estimations, and Round-Trip Time (RTT) values. In advanced LTE networks, E-CID may also utilize AOA data, though its effectiveness is mitigated in dense urban environments due to multipath propagation challenges. E-CID's significance extends to its role as a fallback positioning method in scenarios where GNSS signals are unavailable, highlighting its critical application in emergency call location services within 4G networks and the LTE Positioning Protocol (LPP) [63-64].

Authors in [65] discussed E-CID+RTT positioning accuracy by implementing a forced soft handover algorithm, which increases the accuracy of position estimation for users within soft handover regions, improving overall accuracy and network performance without negative impacts due to the algorithm's reduced complexity.

In the study [66], the authors propose a method that estimates the direction of user equipment more accurately for E-CID positioning than conventional sector-based positioning methods.

2.5.2.2 Distance Measurements

Received Signal Strength (RSS)

The RSS technique in cellular positioning relies on the power levels received by a sensor from a transmitting source. This method presumes that the received power diminishes following an exponential decay model, dependent on the transmitted power, path loss constant, and distance between the source and sensor. Unlike systems requiring synchronization for TOA, TDOA, or TSOA measurements, RSS offers simplicity by eliminating the need for synchronization. Distance estimations from RSS measurements allow for source localization similar to TOA, requiring a minimum of three receivers for accurate positioning. This approach provides a cost-effective solution for positioning, leveraging existing cellular infrastructure without additional synchronization hardware [24] [67].

In [68], the cooperative RSS-based positioning algorithm leverages the concept of mobile-to-mobile communications, a promising feature in next-generation cellular networks, to improve location accuracy. By utilizing additional RSS data from short-range communications between MSs, the algorithm significantly enhances the precision of traditional RSS-based positioning methods. This improvement is demonstrated through simulations, which show that incorporating data from these cooperative interactions between MSs allows for a more accurate determination of a mobile station’s position within the network.

Furthermore in [69], the authors introduce a new WLAN positioning approach that utilizes RSS collected at both access points and mobile devices. The approach is algorithm-independent and has been shown to improve the accuracy of location estimation by 12.84% to 38.23% on average compared to previous works. Moreover in [70], the authors analyzed RSS-based mobile terminal positioning in GSM networks, proposing statistical estimators that improve positioning accuracy by mitigating distance estimation errors and improving service quality, especially in multipath environments. Then in [71], the researchers introduced a novel approach to model RSS measurements in cellular networks for user positioning, comparing the performance of synthetic and real-life scenarios using a fingerprinting-based K-nearest neighbour algorithm. This study highlights the potential of RSS in enhancing the accuracy of cellular positioning systems. Also, the authors in [72] introduce a novel differential RSS positioning algorithm tailored for Radio Frequency Identification (RFID) technology, primarily aimed at tracking construction equipment. Unlike traditional positioning methods that directly correlate RSS with distance, their approach is based on a linear regression between the angle and differential RSS, significantly reducing the impact of RFID tag heterogeneity and directional discrepancies between tags and readers.

Time Advance (TA)

The TA technique in cellular positioning leverages time offset data between MS and BS to refine positioning accuracy. Primarily used to synchronize transmission times and prevent signal collision, TA also facilitates distance estimation by measuring the time it takes for signals to travel between the MS and BS. This method enhances the basic Cell-ID positioning by providing additional range estimates, thus reducing positional errors. However, its application is limited to active calls, requiring handoffs across BS for continuous range determination, which highlights its dependency on ongoing network interactions for accurate location estimation [73-74].

In [75], the authors propose a new positioning system architecture for 4G and 5G technology that utilizes the timing advance parameter to generate continuous position estimates. This architecture aims to reduce data overhead and improve positioning accuracy, demonstrating the potential to meet federal emergency services standards.

The authors in [76], propose a significant shift in how TA calculations are approached, by integrating satellite positioning systems to calculate the distance more accurately between mobile phones and base stations. This innovative method not only aims to enhance the precision of cellular positioning but also explores the broader implications and adaptability of this technology in both current and future cellular communication systems.

Time of Arrival (TOA)

The TOA methodology is predicated on the duration a radio signal requires to travel from a BS to a MS. This duration, coupled with the known speed of signal transmission, forms the basis for calculating the distance between these entities. Essential to this calculation is the velocity of signal propagation, which facilitates the direct computation of the spatial distance based on the signal's time of flight. TOA's utility extends across multiple wireless communication technologies, such as UWB and Wi-Fi, showcasing its adaptability and precision in pinpointing locations within cellular networks. Figure 6 represents a TOA measurement-based positioning system [64][77].

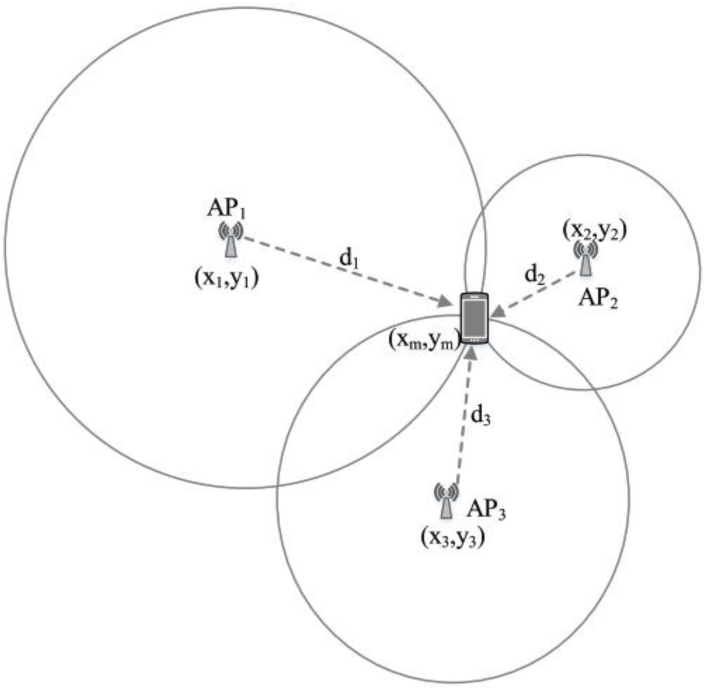

Figure 6 Positioning based on TOA measurement. [77]

In the operational framework of TOA for positioning, the distance between ith AP and a tag device is quantified by the formula $d_i = (t_i - t_0) \times c$, where d_i is the distance sought, t_0 and t_i are the times of signal transmission and reception, respectively, and c represents the speed of light. This formula is crucial for implementing the trilateration algorithm, which relies on meticulous time synchronization between transmitting and receiving units to accurately deduce the user's position. [77]

In [78], the study introduces a subspace-based algorithm for mobile positioning using TOA measurements. It generalizes the mobile localization method based on multidimensional similarity analysis and includes computer simulations to compare the estimator performance with the Cramer-Rao lower-bound.

In the paper [79], the authors present an improved TOA estimation algorithm designed for cellular signals in multipath fading channels. The algorithm combines a super-resolution approach with a multipath estimating delay lock loop to enhance the accuracy of TOA estimation under multipath fading conditions. Simulation results demonstrate the effectiveness of the proposed algorithm compared to existing methods.

Time Difference of Arrival (TDOA)

The TDOA method emerges as an alternative to the TOA technique in the domain of cellular positioning, addressing some of the latter’s limitations. Unlike TOA, which necessitates the maintenance of accurately synchronized clocks across all stations to measure the distance based on signal travel time, TDOA operates on a different principle. This technique relies on the comparative analysis of the signal’s arrival times at various base stations, eliminating the need for precise clock synchronization among the participating stations. TDOA’s unique approach hinges on identifying the temporal disparities in the reception of a specific data marker or epoch transmitted from the target, thereby sidestepping the complexities associated with the direct time of flight measurements and synchronized timing. Figure 7 illustrates the positioning technique based on TDOA measurements [24] [80].

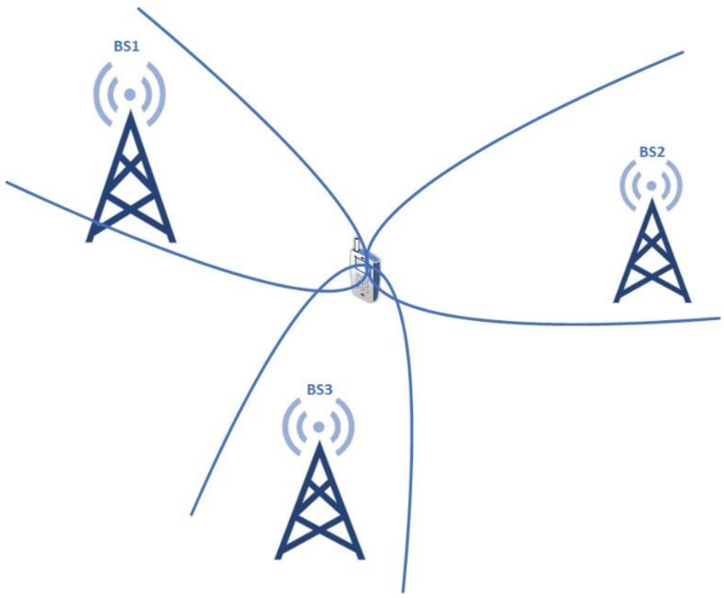

Figure 7 TDOA positioning. At least three BS are required for two-dimensional localization.

TDOA's efficacy in cellular positioning is attributed to its ability to accurately determine location by calculating the time differences observed in signal reception across multiple base stations. This method does not require the transmission's start time to be communicated from the initiator to the receiver, simplifying the location estimation process. By focusing on the relative timing of signal reception rather than the absolute timing of signal dispatch and arrival, TDOA significantly reduces the infrastructural demands on the positioning system. This characteristic not only mitigates the disadvantages associated with the TOA technique, such as the necessity for stringent time synchronization, but also enhances the applicability of TDOA in various scenarios where maintaining synchronized clocks is impractical or challenging [24].

Authors in [81], Introduce a TDOA positioning algorithm within a factor graphs framework for wireless cellular networks. This approach addresses the nonlinear estimation problem inherent in mobile station localization, showing that factor graph based TDOA positioning can achieve very accurate estimates with moderate computational complexity.

The researchers in [82], analyze a TDOA-based positioning technique using ultrasound transmissions received by wireless nodes. The study identifies and characterizes potential inaccuracies due to lack of synchronization and presents an algorithm to correct such inaccuracies, demonstrating the feasibility of ultrasound based TDOA measurements for range and position estimation.

In [83], the authors present an improved TOA estimation algorithm for cellular signals in multipath fading channels, demonstrating its effectiveness through simulation results and showing its potential for enhancing the accuracy of TDOA-based positioning.

Observed Time Difference of Arrival (OTDOA)

The OTDOA methodology, a distinguished positioning technique within the LTE framework, capitalizes on the temporal discrepancies observed in downlink (DL) reference signals emanating from multiple sources. The essence of OTDOA lies in its ability to compute the RSTD, which signifies the temporal disparity between a pair of cellular stations – specifically, a reference station and another station under measurement. This calculation hinges on identifying the minimal temporal interval separating two subframes, each originating from the respective cells. The precision of this method is contingent upon acquiring timing data from at least three strategically positioned base stations, which must be sufficiently dispersed to ensure a robust geometric configuration. This configuration is critical to guarantee that the hyperbolic paths, defined by pairs of cells based on equal Reference Signal Time Difference (RSTD) values, do not intersect more than once, thereby facilitating a unique solution for the UE’s coordinates [24] [64].

In [84], the study evaluates the OTDOA positioning method using real measured channel data in an urban LTE scenario, finding that the measured channel allows for positioning accuracy that fulfills FCC requirements with a safe margin. Moreover in [85], authors propose an iterative method for the detection of the first channel tap in an estimated channel impulse response to improve TOA estimation for OTDOA positioning, also analyzing the impact of RSTD quantization resolution on positioning accuracy, and in another study [86], the authors present an improved TOA estimation algorithm for cellular signals in multipath fading channels, which is crucial for the accuracy of OTDOA positioning. The algorithm uses a super-resolution approach and a multipath estimating delay lock loop to enhance TOA estimation accuracy.

2.5.2.3 Directional Measurements

Angle of Arrival (AOA)

The application of directional antennas in cellular positioning introduces a nuanced approach to locating targets through triangulation, a geometric method that leverages the known coordinates of fixed terminals relative to a reference point. This technique circumvents the need for time synchronization and is indifferent to the modulation type or protocol of the transmitted signals, offering a versatile solution for determining the direction of a target. The process involves at least two fixed stations equipped with directional antennas, which ascertain the target's location by measuring the angles of arrival of the signals. These angles, denoted as $\theta 1$ and $\theta 2$, are referenced from a northward direction and are instrumental in computing the position of a mobile transmitting target. The precision of this location estimation is predominantly influenced by the directivity of the antennas, highlighting the importance of antenna design in the efficacy of triangulation for position determination. Figure 8 depicts a mobile transmitter labelled T and two stationary bases, F1 and F2, each equipped with directional antennas. F1 and F2 coordinates are known, and the arrival angles of the signal, $\theta 1$, and $\theta 2$, measured in a clockwise direction from north, are determined [51].

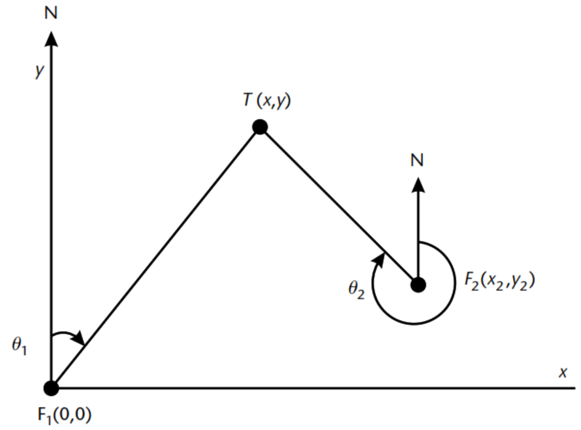

Figure 8 AOA position measurement configuration. [51]

The triangulation method, while innovative in leveraging directional antennas for pinpointing target locations, encounters notable limitations. Chief among these is the dependency on the directivity of the antennas, which dictates the precision of the location estimation. High directivity necessitates the use of larger antennas, imposing constraints on deployment due to increased spatial requirements. Moreover, the method’s reliance on electronically steered antennas for automated direction finding introduces additional complexity and potential cost implications. This reliance not only complicates the system’s architecture but also limits its scalability and practical application in constrained environments, highlighting a significant trade-off between precision and feasibility in the use of directional antennas for location triangulation [87-88].

In [89], researchers proposed a non-iterative closed-form solution for AOA-based positioning, offering detailed statistical analysis and comparison with classical techniques. Furthermore, in [90], the authors focus on enhancing the AOA positioning technique by introducing an algorithm optimized for hardware implementation. This innovation is significant as it reduces the computational complexity traditionally associated with AOA methods, making it more feasible for real-world applications, particularly in systems where computational resources are limited. Their approach, which relies on simple shift and add operations, presents a practical solution that could be easily integrated into existing wireless communication systems, thereby improving the efficiency and accuracy of location estimation in these networks. In another research [91], the authors introduce a novel approach to AOA localization specifically tailored for LTE cellular systems. They exploit the relationship between the transmitter antenna's orientation and the indices of various multiple-input and multiple-output (MIMO) precoders to establish a method for determining user position. Moreover in [92], the authors develop and validate a comprehensive AOA system, integral to enhancing mobile wireless communication for precise positioning. The system's validation includes extensive MATLAB 38 simulations and practical experiments, ensuring its reliability and effectiveness in real-world scenarios, thus showcasing its potential for broader application in mobile positioning technologies.

2.5.2.4 Survey Information

Fingerprinting

The fingerprinting technique in cellular positioning is predicated on the notion of mapping distinct physical characteristics, known as fingerprints or signatures, to specific geographical points within a designated area. These unique identifiers derive from the inherent spatial variation of the environmental attributes, enhancing the system's ability to distinguish between different locales and thereby increasing the granularity of location determination. The effectiveness of this method is paradoxically linked to the environmental factors that typically hinder non-survey-based approaches, such as multipath fading encountered in RF systems. However, these same factors advantageously contribute to the efficacy of survey-based fingerprinting methods, illustrating a distinctive interplay between environmental properties and technological application [64] [93].

Fingerprinting methodologies are primarily differentiated by the nature of the physical properties they record. Among these, RSS, channel impulse response (CIR) in the time domain (or its frequency domain counterpart, the channel transfer function (CTF)), and the frequency channel coherence function (FCF) are prevalent in the realm of RF properties utilized for positioning. RSS stands out due to its widespread adoption in commercial wireless systems, attributed to its resilience in N-LOS conditions, straightforward data architecture, and minimal computational demands. Despite its ubiquity, facilitated by integration into common wireless frameworks such as IEEE 802.11, RSS fingerprinting faces challenges such as reduced distinctiveness in environments with limited access points, leading to poorer location accuracy. Conversely, while CIR, CTF, and FCF signatures offer more unique localization cues, they necessitate advanced, costlier hardware for data acquisition and entail greater storage needs, posing substantial challenges for implementation, especially in extensive indoor settings. Additionally, the complex nature of these data formats demands more sophisticated pattern-matching algorithms, further escalating computational requirements [64] [93].

The authors in [94] presented the adaptive enhanced Cell-ID (AECID) fingerprinting localization method, which improved the accuracy of cell-ID-based positioning by clustering high-precision position measurements. This method represented a robust fingerprinting approach, enhancing traditional cell-ID positioning accuracy. Furthermore, in [95], the authors proposed a Signal-Aware Fingerprinting-Based Positioning technique in cellular networks, demonstrating higher positioning accuracy and efficiency than traditional methods. They implemented this in the Android platform for GSM networks and analyzed accuracy through experiments. Moreover in [96], the authors proposed a 3D fingerprinting positioning method based on cellular networks, enhancing efficiency and accuracy by employing cell matching degrees and introducing a new searching window. This scheme was found to perform better than traditional methods such as maximum likelihood and weighted K nearest neighbours ‘method. In another study [97], the author outlined an approach using decision tree ensembles for cellular fingerprint-based positioning. This machine learning approach was evaluated against traditional fingerprint comparison functions, showing consistently better estimations for outdoor positioning.

2.5.2.5 Hybrid Techniques

In cellular networks, hybrid methodologies amalgamate multiple distinct strategies to enhance positioning precision beyond the capabilities of singular techniques. Typically, these approaches synergize signal-based methodologies, such as TOA and AOA, with additional techniques such as cell identification, fingerprinting, or artificial intelligence algorithms, thereby ensuring robust and accurate results even in environments that pose significant challenges. The authors in [98] investigated the use of enhanced versions of TOA and AOA techniques, which, when combined, optimize location positioning estimations in mobile cellular networks. The study demonstrates that accuracy improves significantly with the hybrid approach, especially when considering the Line-of-Sight (LOS)/ Non-Line-of-Sight (nLOS) propagation effects.

Also, in [99], the authors delved into enhancing positioning accuracy in heterogeneous networks under scenarios where signal transmission faces obstacles, commonly known as critical hearability environments. Their method combines data from TOA, AOA, and RSS using a two-level unscented Kalman Filter, optimized further by genetic algorithms. This hybrid approach not only leverages the strengths of each positioning technique but also mitigates its weaknesses, particularly in urban or indoor areas where traditional methods may falter due to signal obstructions or multipath effects, showcasing a significant improvement in location accuracy and reliability.

In [100], the authors explored the role of TOA and AOA in hybrid positioning algorithms and analyzed the influence of weight parameters on accuracy, demonstrating the effectiveness of combining these signal characteristics.

In another study [101], the authors address the common challenges faced in cellular network-based positioning, particularly issues arising from multipath and N-LOS signal propagation, which traditionally degrade the accuracy of positioning algorithms. Their proposed TOA/AOA hybrid algorithm leverages the strengths of both Time of Arrival and Angle of Arrival measurements, applying a Bayesian approach to mitigate the adverse effects of these signal distortions. By 41ultisens measurement errors as a mixture Gaussian model, the method not only refines the estimation of the user's location but also dynamically adjusts for channel biases, leading to a notable improvement in positioning precision compared to conventional methods. This enhancement is particularly valuable in urban environments, where multipath and N-LOS conditions are prevalent.

Furthermore, authors in [102] developed a hybrid indoor positioning algorithm that integrates the strengths of cellular and Wi-Fi network signals to overcome the limitations of individual systems in complex indoor environments. The innovative use of principal component analysis (PCA) during the offline phase helps in effectively reducing the dimensionality of the fingerprinting data, thereby streamlining the database, and improving the efficiency of the positioning process. Moreover, by applying an adaptive genetic algorithm to optimize the back-propagation (BP) neural network during the online positioning phase, the algorithm enhances the precision of location estimation. This dual-phase approach not only refines the accuracy of indoor positioning but also ensures that the system adapts dynamically to changes in the environment, significantly improving the reliability of location services in scenarios where traditional methods might fail due to signal obstruction or interference.

2.6 Barycentric Interpolation in Positioning

2.6.1 Introduction

Barycentric interpolation is a mathematical technique utilized for estimating unknown values within a specific domain by leveraging the known values at a discrete set of points. This method is deeply rooted in the concept of BCS, which offer a means to express the position of any point within a simplex (e.g., a triangle in two dimensions, a tetrahedron in three dimensions) as a weighted average of the simplex's vertices. The weights, or barycentric coordinates, are calculated based on the geometric properties of the point in relation to the vertices of the simplex, ensuring that they sum up to one and maintain a non-negative status [103].

The elegance of BCS lies in its geometric intuitiveness and computational efficiency, especially when interpolating within the convex hull formed by the known points. This method is especially prevalent in fields such as computational geometry, computer graphics, machine learning and Data science, geographical information systems (GIS), and numerical analysis where it is essential to interpolate values across irregularly spaced data points. By assigning weights to the vertices of a simplex based on the relative position of the interpolation point, BCS allows for a seamless calculation of interpolated values without the need for solving linear systems or employing iterative methods [103-104].

The formulation of BCS involves determining the barycentric coordinates of the interpolation point concerning the simplex formed by the known data points. These coordinates effectively serve as weights in a linear combination of the values at the vertices, yielding the interpolated value. This process is underpinned by mathematical principles that ensure the conservation of vital properties such as continuity and differentiability within the interpolation domain, making BCS a robust and versatile tool for a wide array of applications [103-104].

2.6.2 Theoretical Framework

In the study of BCS, a significant technique for value estimation within the convex hull of a simplex, the representation of a point P within a 2D triangle defined by vertices A, B, and C is of particular interest [104]. As shown in Figure 7, Any point P inside (or on the boundaries of) this triangle can be expressed as a weighted sum of these vertices:

$$P = \lambda_A A + \lambda_B B + \lambda_C C \tag{1}$$

λ_A, λ_B ,and λ_C are the barycentric coordinates of P, satisfying the conditions:

$$\lambda_A + \lambda_B + \lambda_C = 1 \quad and \quad \lambda_A, \lambda_B, \lambda_C \geq 0 \tag{2}$$

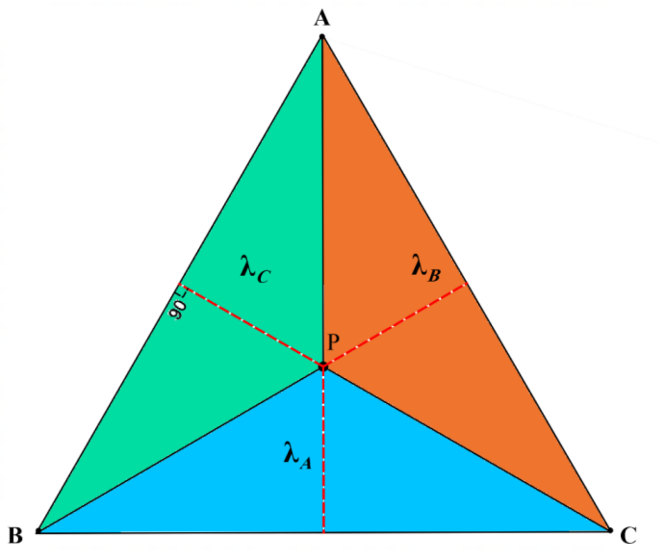

Figure 7. Each barycentric coordinates within the ABC triangle.

The weights (λ) in barycentric interpolation are essentially measures of how much each vertex (or point) influences the interpolated value at the point P. These weights depend on the geometric position of P relative to the vertices of the simplex. In the 2D triangle, the weights can be calculated using areas. For example, the weight λ_A corresponding to vertex A can be determined by the area of the triangle formed by P, B, and C, normalized by the area of the triangle ABC. Similarly, weights λ_B and λ_C are calculated using the areas of triangles PAC and PAB, respectively [104-105].

In general, the formula for calculating the barycentric weights in a triangle can be derived from the areas of sub triangles or using determinants in linear algebra for higher dimensions [104] [105]. For a triangle, with the coordinates of vertices *A* (x_A, y_A), *B* (x_B, y_B), and *C* (x_C, y_C), and a point *P* (*x*, *y*), the weights can be calculated as follows:

Step 1: Calculating the total area of the triangle ABC using determinant formula.

$$Area_{ABC} = \frac{1}{2}|x_A(y_B - y_C) + x_B(y_C - y_A) + x_C(y_A - y_B)| \quad (3)$$

Step 2: Calculating the area of the sub triangle *PBC*, *PCA*, and *PAB* similarly, and then normalize these areas to find λ_A, λ_B , and λ_C.

$$\lambda_A = \frac{Area_{PBC}}{Area_{ABC}}\ ,\ \lambda_B = \frac{Area_{PCA}}{Area_{ABC}}\ ,\ \lambda_C = \frac{Area_{PAB}}{Area_{ABC}} \quad (4)$$

2.6.3 Functional Evaluation

The extensive application of BCS across various disciplines highlights its effectiveness and versatility. This segment aims to explore some studies on the utilization of BCS within diverse domains, with a special focus on wireless positioning. It seeks to present an evaluative review of how this method enhances computational precision and operational efficiency in various domains.

In [106] author discusses how the BCS, motivated by the Mean Value Theorem for harmonic functions, offer a generalization that simplifies and improves methods for parameterization and morphing. This makes BCS versatile for various geometric and computational applications.

Researchers in [107] highlighted the role of BCS in interpolating scalar or vector data from the boundary of a domain to its interior, demonstrating their application in computer graphics and geometry processing. The ability to interpolate without a closed-form expression underlines their adaptability and utility.

In another study [108], authors leveraged BCS in the Turkish Permanent GPS Network, enhancing geospatial measurement precision and demonstrating robustness against geometrical distortions common in Cartesian systems. By adopting BCS, the study effectively handled affine transformations, which are crucial for accurately mapping the earth’s surface onto a flat plane, thereby improving both the accuracy and reliability of geodetic network analyses. This approach represents a significant step forward in the field of geodesy, demonstrating how mathematical concepts resembling BCS can be applied to solve complex real-world problems in geographical information systems (GIS) and navigation.

In the research [109], BCS play a pivotal role in enabling a distributed approach to sensor network localization. By utilizing BCS, the algorithm efficiently calculates the positions of sensor nodes relative to anchor nodes, even when these sensor nodes fall outside the traditional convex hull formed by the anchors. This method fundamentally departs from many conventional localization techniques that rely on sensors being within a predefined geometric boundary. The utilization of BCS thus allows for a more versatile and adaptable framework for determining sensor locations across a wide array of network geometries, significantly enhancing the scalability and application of localization processes in diverse sensor network deployments.

3 Methodology

3.1 Introduction

In this thesis, a novel algorithm based on the Barycentric interpolation (BCS) method is proposed to determine the active user equipment (UE) coordinates within a two-dimensional latitude/longitude grid using available 2G cellular towers' information around the UE's location. In this proposed work, the BCS algorithm which is used for positioning and evaluating mobile-based method depends on received signal strength (RSS) measurements along with the 2G antennas' geographical positions.

In this research, it is assumed that the UE does not have access to an internet connection, GPS, cell antenna configuration, or network infrastructure information. The offline cell towers' information database file is the only data available for UE's position estimation.

This algorithm uses measurements and datasets obtained from the on-site 2G cellular networks' scanning process and cell towers' offline database file data of the OpenCelliD.org website to estimate the coordinates of the UE at each pre-pinned data point on the map.

The geographical coordinates of the UE were acquired simultaneously at each data point using both GPS and the BCS algorithm. This study leverages the geographic coordinate obtained by GPS as reference coordinates to evaluate and validate the BCS algorithm estimation accuracy for each data point by measuring the distance between two coordinates from each other.

3.2 Data Collection

3.2.1 Cellular Towers' Information Database

The geographical position of cellular towers plays a key role in cell positioning. There are two ways to obtain this information, accessing the cellular network infrastructure information of operators or using the information of open databases of cell towers online/offline. Mobile operators usually do not allow unauthorized individuals or communities to access their infrastructure information. Therefore, this study utilized one of the world's largest open databases of cellular towers, OpenCellid.org, in an offline form and in a CSV file format.

OpenCelliD operates as a communal initiative where volunteers share GPS positions of cellular towers along with their specific location area identities (LAI) and the Cell ID parameter. The project boasts over 49,000 participants who collectively contribute around a million new data points daily to the OpenCelliD database. As recorded on August 21, 2017, this database houses over 35.5 million unique cellular IDs and 2.1 billion distinct measurements. The data, which is an incorporating of cellular locations, is freely published under the Creative Commons Attribution-Share Alike 4.0 International License. This promotes the free use and redistribution of the information [111]. This work uses the last updated offline database file of the OpenCellid website related to Finland which contains cellular towers' positions in two-dimensional coordinates latitude and longitude and other cell antennas' parameters such as location area identity (LAI) and CID.

3.2.2 Cellular Network Scanning Hardware

Cellular devices scan cellular networks to ensure seamless service connectivity. This scanning is crucial as it enables devices to locate the nearest cell towers, thus maintaining optimal communication quality and network stability. Several key parameters are returned to the mobile device during each scanning process, such as CID, LAI, and RSS level [126-127]. These are essential in this study to find the cellular antennas' geographical coordinates from the offline database as well as the UE's position estimation process by the BCS algorithm. This work leveraged an Arduino MKR GSM 1400 board for the data scanning, normalization, and storing process.

The Arduino MKR GSM 1400 is a development board designed for global mobile communication and uses the functionality of the GPRS/GSM network. This module operates using Arduino C/C++, a variant of C++ simplified for ease of use in embedded programming. This programming environment allows interaction with the hardware components of the board and implements functionality for various applications. In Arduino programming, a "sketch" is the term used for a program written using the Arduino IDE, and in this study, the program of the 2G cellular networks scanning process is called the cell scanning sketch [128-129].

One significant limitation of the MKR GSM 1400 is its reliance on 2G networks; it does not support newer generation networks such as 4G or 5G, which is considered a constraint in this study. Another limitation of this board is its processing capabilities and lack of stability, which make it difficult to implement some functions [128] [130]. The specifications of the module are shown in Table 1, and Table 2 display the tech specs of the Dipole antenna connected to the board.

Table 1. Arduino MKR GSM 1400 board Specification [128].

Components	Description
Microcontroller	SAMD21 Cortex-M0+ 32bit low power ARM MCU
Network Module	u-Blox SARAU201, supporting GSM bands 850/900/1800/1900 MHz
Input Voltage	5V (supplied via the USB or Vin pin)
Digital I/O Pins	8, with 12 PWM and UART
Analog Input Pins	7 (ADC 8/10/12 bit)
Analog Output Pins	1 (DAC)

Connectivity	GPRS/GSM and 2G EDGE data networks.
Interfaces	I2C, SPI, UART
Flash Memory	256 KB
SRAM	32 KB

Table 2. The Dipole Antenna technical characteristics [131].

Frequency Band (MHz)	700-750	824-960	1710-1990	2110-2170	2500-2700
Gain (dBi)	>-5	>-1	>0.4	>-1	>-1
Total radiation efficiency (dB)	>-5	>-3	>-2.5	>-3	>-3
S11 (dB)	<-5	<-4.2	<-10	<-7	<-10
Polarization	Linear	Linear	Linear	Linear	Linear
Parameter					
Dimension			130x16x5		
Operating temperature			-40/85 °C		
Pattern			Omnidirectional		

3.2.3 Datasets

Data Collection Points

In the initial phase of the data collection, 12 data points were pinpointed on the Google Maps based on several conditions, including the density of 2G cellular networks, terrain features, and the presence of urban structures. The data collection area was designated in the center of Helsinki, within a radius of one kilometre from the Kamppi shopping mall which is represented by Figure 8.

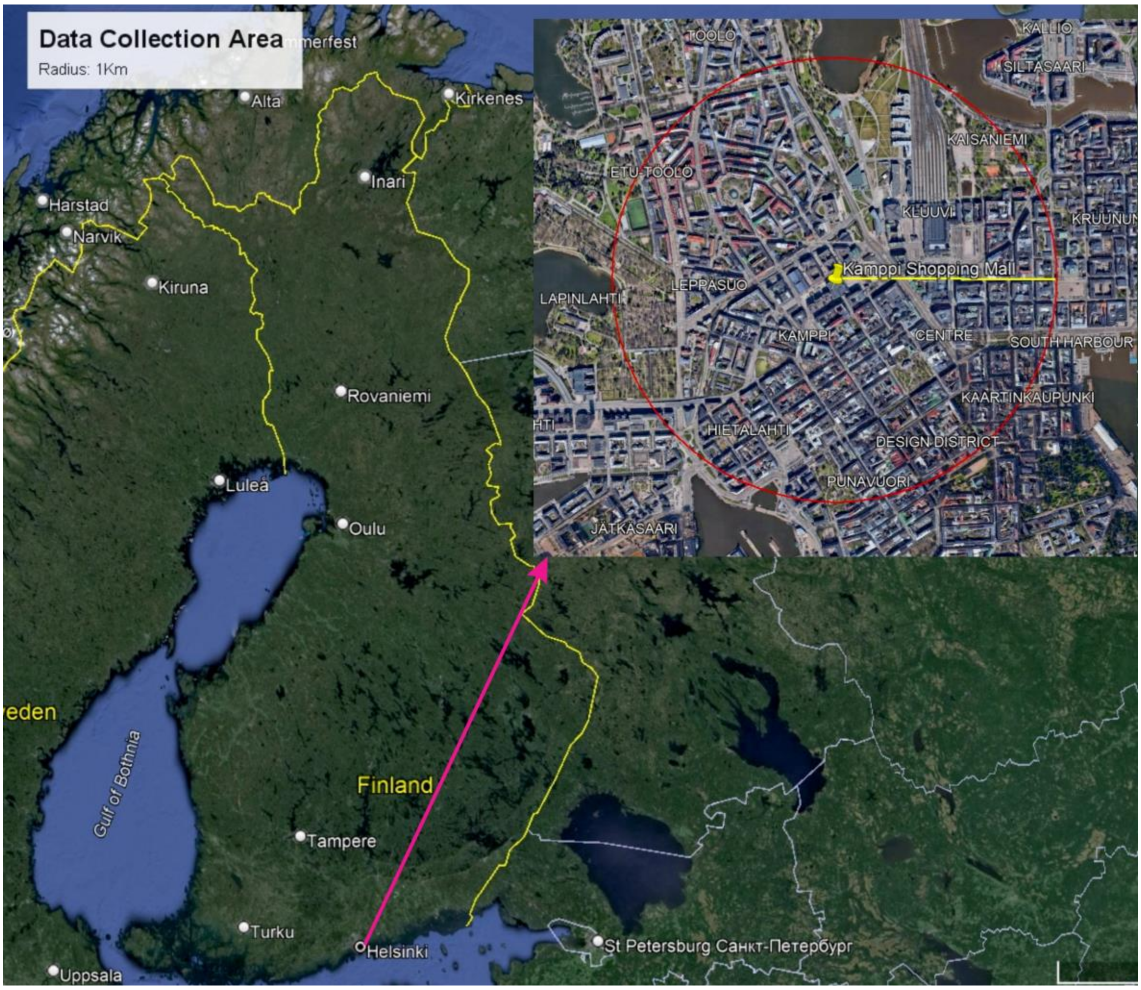

Figure 8. Data collection area on Google map.

In Finland, there are three major mobile network operators Elisa, DNA, and Telia that offer comprehensive coverage across the country, including technologies ranging from 2G to the more recent 5G and LTE-M networks [132]. The distribution of 2G cell antennas operated by all network providers within the designated study area is shown in Figure 9, these data are collected from the live cell towers map of the OpenCelliD.org website [133]. Additionally, the locations of data collection points are illustrated in Figure 10.

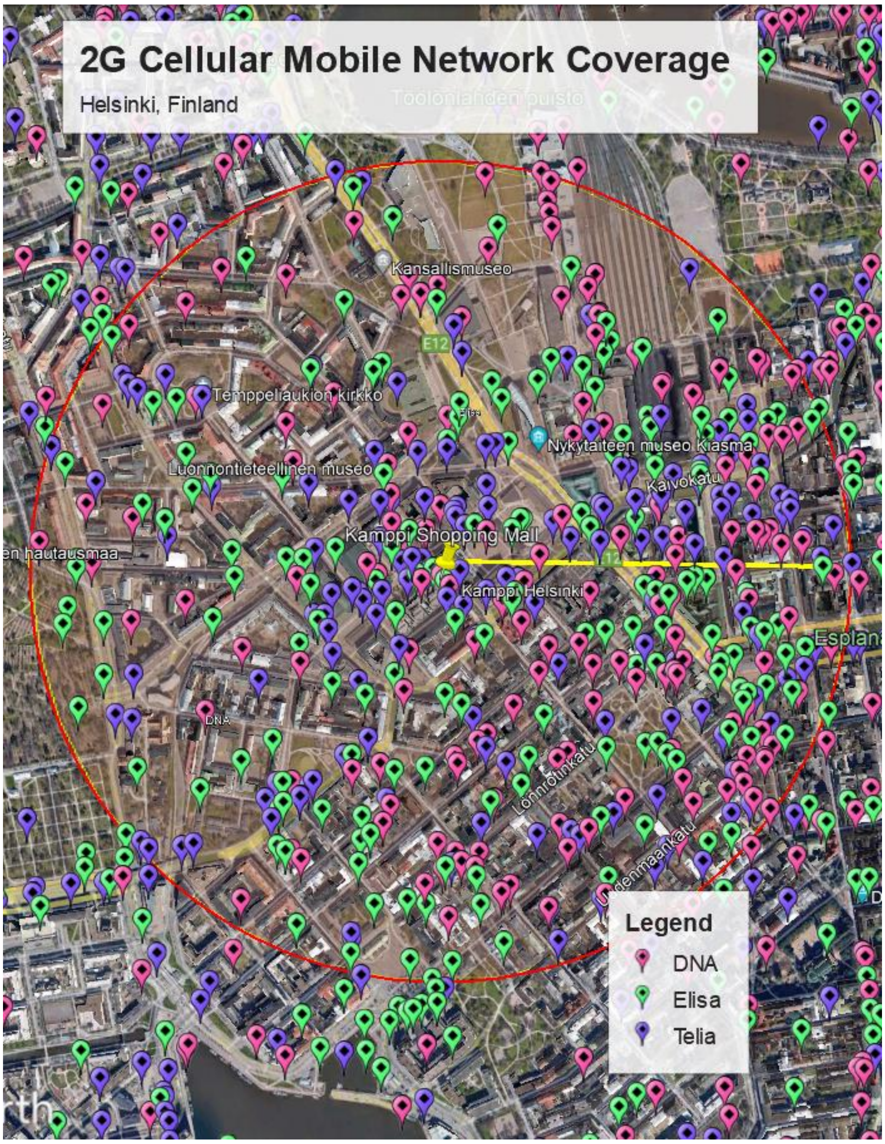

Figure 9. 2G cell antennas distribution in the study area

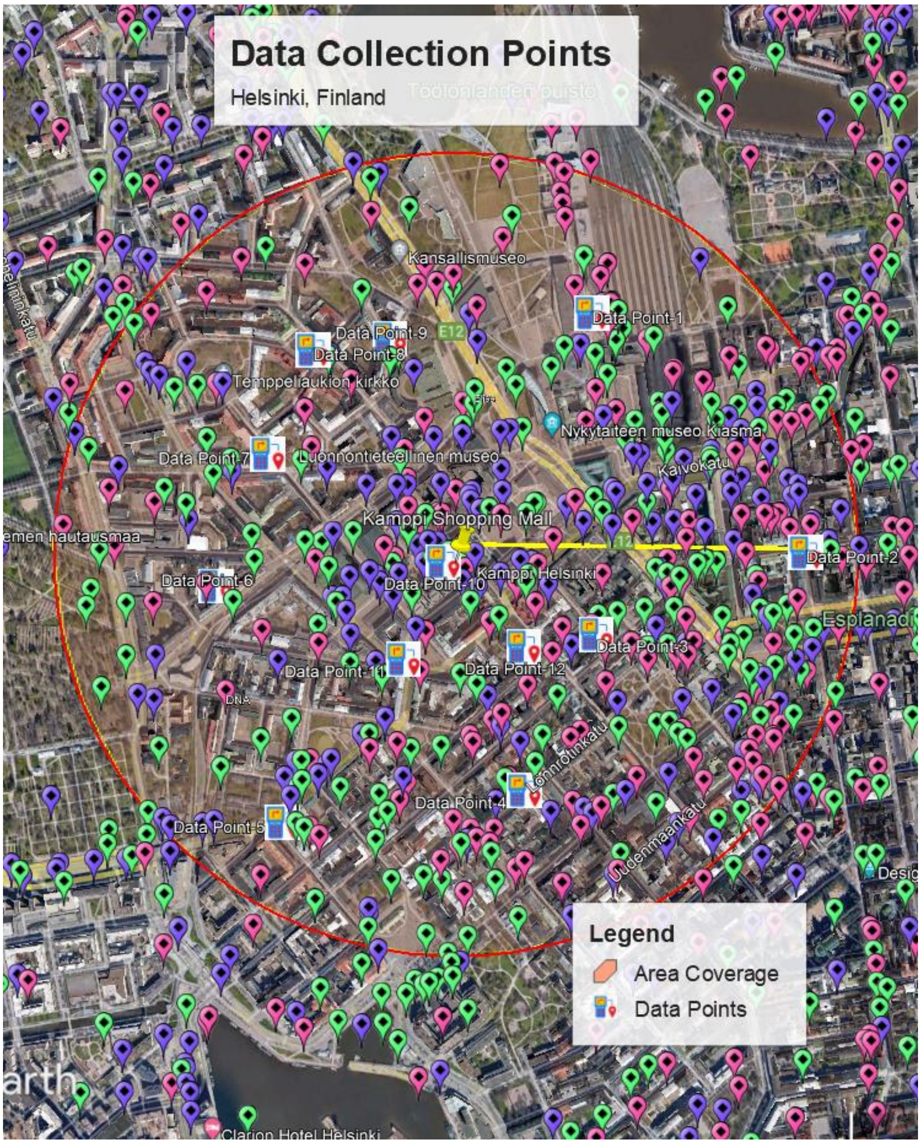

Figure 10. Data points in the study area

SCN Sketch

This study aims to develop and evaluate an outdoor positioning algorithm using the Barycentric interpolation method. Hence this algorithm leverages two data resources:

- The database of 2G cellular antennas' information of network operators in the study area including the geographic coordinates and other parameters.

- The obtained dataset from 2G cellular antennas near each data point by scanning process, including RSS level measurements and parameters such as LAI and CID.

The location area identity (LAI) is a unique identifier that consists of three parameters: MCC, MNC and LAC. By combining the LAI's parameters, it is possible to determine a cell antenna's location from a broad to a more defined area. When they are used in conjunction with other parameters such as the Cell ID and the received signal strength (RSS), can significantly enhance the accuracy and reliability of location-based services. All 2G measurements and parameters used in this study are detailed in Table 3.

Table 3. Details on 2G cellular antenna measurements, and parameters.

<table>
<tr><th colspan="2">Measurements / Parameters</th><th>Description</th></tr>
<tr><td rowspan="3">LAI</td><td>MCC</td><td>The mobile country code (MCC) is a three-digit number that uniquely identifies a specific country or geographical region where the mobile network operator is located. For instance, this code for Finland is 244.</td></tr>
<tr><td>MNC</td><td>The Mobile Network Code (MNC), which usually comprises two or three digits, specifies a particular mobile network within a country (identified by the MCC). The MNC is essential for distinguishing between different operators within the same geographical region, especially in countries with multiple carriers.</td></tr>
<tr><td>LAC</td><td>The location area code (LAC) is a parameter used within a mobile network (defined by an MCC and MNC) to specify a smaller region known as a location area. This area encompasses multiple cell towers. Mobile devices perform a location update for various reasons, such as when they move into a new LAC, ensuring that the network knows their approximate location without needing to pinpoint their exact position continually.</td></tr>
<tr><td colspan="2">CID</td><td>The Cell ID (sometimes abbreviated as CID or CI) is assigned to any cell antenna within a mobile network as a unique identifier. This identifier allows the network and the connected devices to distinguish one cell from another within the same location area (specified by the LAC).</td></tr>
<tr><td colspan="2">RSS</td><td>The received signal strength level or RSS is a measurement that indicates the power level being received by the antenna of a mobile device from a specific cell tower. The RSS is typically expressed in dBm and is used by the device to determine the strength of the signal it is receiving. Contrary to what might be expected, this indicator is inversely proportional to the distance: the higher the RSS value (which is a less negative dBm number), the closer the mobile device is to the cellular antenna. Conversely, a lower RSS value (more negative) indicates a greater distance between the device and the antenna.</td></tr>
</table>

In the Arduino MKR GSM 1400 board, the RxLev standard is employed to measure and report the RSS level. By presenting RSS values as positive integers, the module simplifies the interpretation and comparison of signal strengths across different 2G cellular antennas.

The RxLev standard functions by converting the signal strength from cellular antennas, typically measured in negative dBm (decibel-milliwatts), into a positive integer scale. This conversion simplifies the process of signal interpretation, making it easier to process and compare signal strength values. For example, a scale might map a very weak signal of -110 dBm to a value of 0 and a strong signal of -47 dBm to a value of 63, with each step in between scaled accordingly. This standardized scale allows mobile devices and network equipment to assess and manage cellular network conditions more efficiently, aiding in tasks such as cell selection and handover decisions based on signal strength [112].

For obtaining 2G cellular antennas' information near each data point such as MCC, MNC, LAC, CID, and RSS level, a scanning and normalization program was developed using Arduino C++ language which in this study called SCN sketch. In this proposed work, an Arduino MKR GSM 1400 board was programmed by the SCN sketch. When the sketch is run on the Arduino board starts performing three major functions, nearby cellular antennas' data scanning, data normalization, and data storing respectively. Appendix 1 displays source code of the SCN sketch and Appendix 2 represents the SCN algorithm sketch.

In the data scanning process, the network module of the Arduino responds by returning measurements and parameters of cell antennas in a string data format. This format includes the following elements: MCC, MNC, LAC, CI, BSIC, arfcn, RxLev. The values of all elements are in decimal format, except for LAC and CI, which are in hexadecimal. Therefore, the second function, data normalization, begins by converting LAC and CI from hexadecimal to decimal format. It also removes the BSIC and arfcn elements from the string data of each dataset, as these elements are not within the scope of this study.

#

This process was performed at all 12 pre-determined data points on the map acquiring 4 samples per data point, resulting in a total of 48 records stored in 12 TXT format files separately. Simultaneously, the GPS coordinates of the data points were recorded by a cell phone and incorporated into all 12 stored files proportionally using Notepad++ software.

3.3 The BCS Algorithm

This section details the development of the BCS algorithm using Excel and Power Query tools, focusing on the methodological application and subsequent validation of accuracy in estimating the UE coordinates. The validation is performed through a comparative analysis between coordinates derived from the BCS algorithm and those obtained via GPS, employing the Haversine formula to quantify discrepancies based on distance.

The Microsoft Excel version 2021 was selected for its widespread availability and robust data manipulation capabilities, particularly through Power Query tool, which allows for efficient data cleaning, transformation, and merging. The use of M language within this environment facilitated precise control over data operations, crucial for creating unique identifiers (UIDs) for querying and data integration purposes.

In this study, the algorithm assumes ideal signal conditions for the estimation of UE's coordinates, as access to detailed 2G network infrastructure information and configurations of cellular antennas was not available. Consequently, factors that typically affect RSS levels, such as environmental obstructions, multipath interference, and channel effects, are not accounted for. This simplification focuses on an ideal scenario to isolate and evaluate the algorithm's performance without external noise factors.

The BCS algorithm file consists of three power query tables, two excel tables, and two excel charts as shown in Table 4.

Table 4. The components of the BCS algorithm file.

Name	Type	Column Headers\ Description
CellDB	Power Query Table	**UID:** Unique identifier of each Cellular 2G antenna. **Longitude:** Longitude of each Cellular 2G antenna. **Latitude:** Latitude of each Cellular 2G antenna.
DataSet	Power Query Table	**dpNum:** The sample number of each data point. **UID:** Unique identifier of each Cellular 2G antenna. **RxLev:** The RSS level of each Cellular 2G antenna. **GPS.Long:** The acquired longitude of each data point by GPS. **GPS.Lat:** The acquired latitude of each data point by GPS. **CellDB.Longitude:** Longitude for each data point retrieved from the CellDB query table. **CellDB.Latitude:** Latitude for each data point retrieved from the CellDB query table. **RSS*Long:** The multiplication product of the longitude and the RSS value of each cellular antenna per each data point. **RSS*Lat:** The multiplication product of the latitude and the RSS value of each cellular antenna per each data point. **D_GPS2Cell:** Positional discrepancies between GPS and each cell antenna based on distance by the Haversine formula.
Report	Power Query Table	**dpNum:** The sample number of each data point. **Sum of DataSet.RxLev:** The sum of the retrieved RxLev values from the DataSet table based on the sample number. **Sum of DataSet.RSS*Long:** The sum of the retrieved “RSS*Long” values from the DataSet table based on the sample number. **Sum of DataSet.RSS*Lat:** The sum of the retrieved “RSS*Lat” values from the DataSet table based on the sample number. **BCS.Long:** The acquired longitude of each data point by the BCS formula. **BCS.Lat:** The acquired latitude of each data point by the BCS formula.
Result / Filtered Result	Excel Table	**DP#:** The data point number **Sample Number:** The sample number of each data point. **ScannedCells:** The number of scanned cellular 2G antenna based on the sample number.

		GPS.Longitude: The longitude obtained from each data point by GPS retrieved from the DataSet table. **GPS.Latitude:** The latitude obtained from each data point by GPS retrieved from the DataSet table. **BCS.Longitude:** The acquired longitude of each data point by the BCS formula retrieved from the Report table. **BCS.Latitude:** The acquired latitude of each data point by the BCS formula retrieved from the Report table. **GPS-BCS.Dist:** Positional discrepancies between GPS coordinates and the BCS based on distance in meters by the Haversine formula. **GPS-FurthestCell.Dist:** Positional discrepancies between GPS and the furthest scanned cellular 2G antenna based on distance in meters by the Haversine formula. **Relative Error of the Distance (%):** The product of dividing “GPS-BCS Dist” by “GPS-Furthest Cell Dist multiplied by 2” based on the percentage.
Graph 1	Scatter	The correlation between the number of cellular 2G antennas scanned by the module and the relative error rate of the distance based on each data point

The development of the BCS algorithm starts with normalizing data by removing unnecessary parameters. This step ensures that only relevant data is used in the subsequent calculations. Using the cleaned data, the algorithm calculates theUE's estimated position through a weighted centroid of the known cellular antennas' coordinates. This calculation's weights are derived from each cellular antenna's RSS level.

The following algorithm sketches and source codes detail each step in the data preprocessing, coordinates estimation, and accuracy evaluation phases of the BCS algorithm, providing a structured guide for its application in practical scenarios.

The BCS algorithm sketch, simplified and structured to outline the main steps is shown in Appendix 3.

In the BCS algorithm, the position of the UE is calculated using the following formulas:

$$Latitude_{UE} = \frac{\sum_{i=0}^{n} RSS_i \, Lat_i}{\sum_{i=0}^{n} RSS_i} \tag{5}$$

$$Longitude_{UE} = \frac{\sum_{i=0}^{n} RSS_i \, Long_i}{\sum_{i=0}^{n} RSS_i} \tag{6}$$

Where:

- RSS_i is the received signal strength from the i^{th} antenna.
- Lat_i and Lon_i are the geographical coordinates of the i^{th} antenna.
- n represents the number of antennas considered in the calculation.

The formula effectively assigns a greater influence to antennas with stronger signal strengths, assuming that a stronger signal correlates with closer proximity. Each antenna's latitude and longitude are weighted by its RSS, and the sum of these weighted coordinates is normalized by the total RSS to compute the UE's estimated position.

The weights for the calculation are derived from the RSS values, where the total weight W is the sum of all RSS values:

$$W = \sum_{i=0}^{n} RSS_i \tag{7}$$

The weighted average for latitude, and Longitude, then, are given by:

$$Latitude_{UE} = \frac{1}{W} \sum_{i=0}^{n} RSS_i \times Lat_i \tag{8}$$

$$Longitude_{UE} = \frac{1}{W}\sum_{i=0}^{n} RSS_i \times Long_i \tag{9}$$

In the Result table, the Haversine formula is employed to calculate the accuracy of the BCS algorithm by measuring the distances between coordinates estimated by the algorithm and those obtained via GPS. Similarly, the Report Power Query table applies this formula to assess the positional discrepancies between GPS coordinates and the most distant 2G cellular antenna based on distance. These calculations are essential for determining the relative error in distance in the final analysis.

The Haversine formula calculates the great-circle distance between two points on the surface of a sphere given their longitudes and latitudes.

The formula is given by:

$$\begin{aligned} \Delta lat &= lat_2 - lat_1 \\ \Delta long &= long_2 - long_1 \end{aligned} \tag{8}$$

$$\alpha = (\sin(\frac{\Delta lat}{2}))^2 + \cos(lat_1) * \cos(lat_2) * (\sin(\frac{\Delta long}{2}))^2 \tag{9}$$

$$c = 2 * \alpha \tan 2 (\sqrt{\alpha} - \sqrt{1-\alpha}) \tag{10}$$

$$distance = R * c \tag{11}$$

Where:

- $lat_1, long_1$ are the latitude and longitude of the first point (from GPS).
- $lat_2, long_2$ are the latitude and longitude of the second point (from the BCS algorithm or the furthest cellular 2G antenna).
- r is the radius of the Earth (approximately 6,371 kilometers).

In the last column of the result table, the relative error of the distance is calculated. This metric provides significant insights into the performance and reliability of the BCS algorithm by comparing the positional discrepancies in a standardized manner.

The relative error of distance, as given by the formula:

$$R_e = \frac{d_i}{d_j * 2} \times 100\% \tag{12}$$

Where:

- d_i is the distance between the GPS coordinates and the coordinates estimated by the BCS algorithm for each data point.

- d_j is the distance between the GPS coordinates and the coordinates of the furthest cellular antenna for each data point.

This formula normalizes the error by the distance to the furthest antenna, providing a percentage that indicates how much error the BCS algorithm produces concerning a baseline measure of spatial extent.

The M code source of the CellDB, DataSet, and Report tables are presented in Appendix 4, 5, and 6 respectively. These listings provide a detailed, step-by-step breakdown of the transformations and operations performed on each table in Power Query.

4 Results

In this study, the hypothesis was that the BCS algorithm could estimate the UE's position using nearby 2G cellular antennas, without relying on cellular network infrastructure information, internet connection, or cellular antenna configuration. The accuracy of this estimation was evaluated by the relative error of the distance as a metric in the FilteredResult table, as shown in Table 5 for each data point. The column headers of this table are described in Table 4 as the FilteredResult table.

Table 5. The accuracy evaluation of the BCS positioning algorithm based on the Relative Error of the distance ratio per data point.

DP#	Sample Number	Scanned Cells (#)	GPS.Long	GPS.Lat	BCS.Long	BCS.Lat	GPS-BCS Dist (m)	GPS-Furthest Cell Dist (m)	Relative Error of the Distance %
1	1.3	14	24.9389	60.1734	24.9385	60.1740	62.6456	1199.4852	2.61%
2	2.2	4	24.9457	60.1688	24.9437	60.1739	583.7228	2012.2270	14.50%
3	3.2	4	24.9379	60.1677	24.9300	60.1668	447.6078	1190.3417	18.80%
4	4.2	4	24.9347	60.1651	24.9288	60.1663	352.1608	1012.9403	17.38%
5	5.4	12	24.9260	60.1650	24.9218	60.1662	268.0525	1345.5678	9.96%
6	6.2	6	24.9245	60.1693	24.9254	60.1705	144.5509	1741.3772	4.15%
7	7.3	12	24.9268	60.1716	24.9311	60.1734	315.9286	1807.2339	8.74%
8	8.2	15	24.9288	60.1733	24.9354	60.1772	562.6651	1841.6135	15.28%
9	9.1	17	24.9316	60.1734	24.9360	60.1751	307.0485	1815.1293	8.46%
10	10.4	11	24.9327	60.1693	24.9325	60.1705	133.1769	1149.0393	5.80%
11	11.4	8	24.9309	60.1677	24.9295	60.1672	90.0851	732.8646	6.15%
12	12.3	5	24.9352	60.1677	24.9310	60.1682	241.9808	581.2613	20.82%

In the table, the samples with the minimum relative error ratio of the distance corresponding to each data point were retrieved from the Result table. This metric expresses the ratio of the distance between the location of the UE obtained by GPS as a reference and the BCS positioning algorithm to the distance between the location of the UE obtained by GPS and the farthest scanned cell antenna for each data point based on percentage.

Analysis of Table 5 reveals that the BCS positioning algorithm's positional discrepancies from GPS coordinates range from 62.64 meters (2.61% relative error) to a maximum of 563.72 meters (20.82% relative error) across the 12 data points. On average, the BCS positioning algorithm exhibits a relative distance error of 11.05% and a positional difference of 292.46 meters compared to GPS coordinates.

The data analysis in Table 5 reveals a relative correlation between the number of 2G cellular antennas scanned by the module and the corresponding relative error rate of the distance for each data point. Consequently, a scatter graph was plotted to visually depict this correlation, as shown in Figure 8.

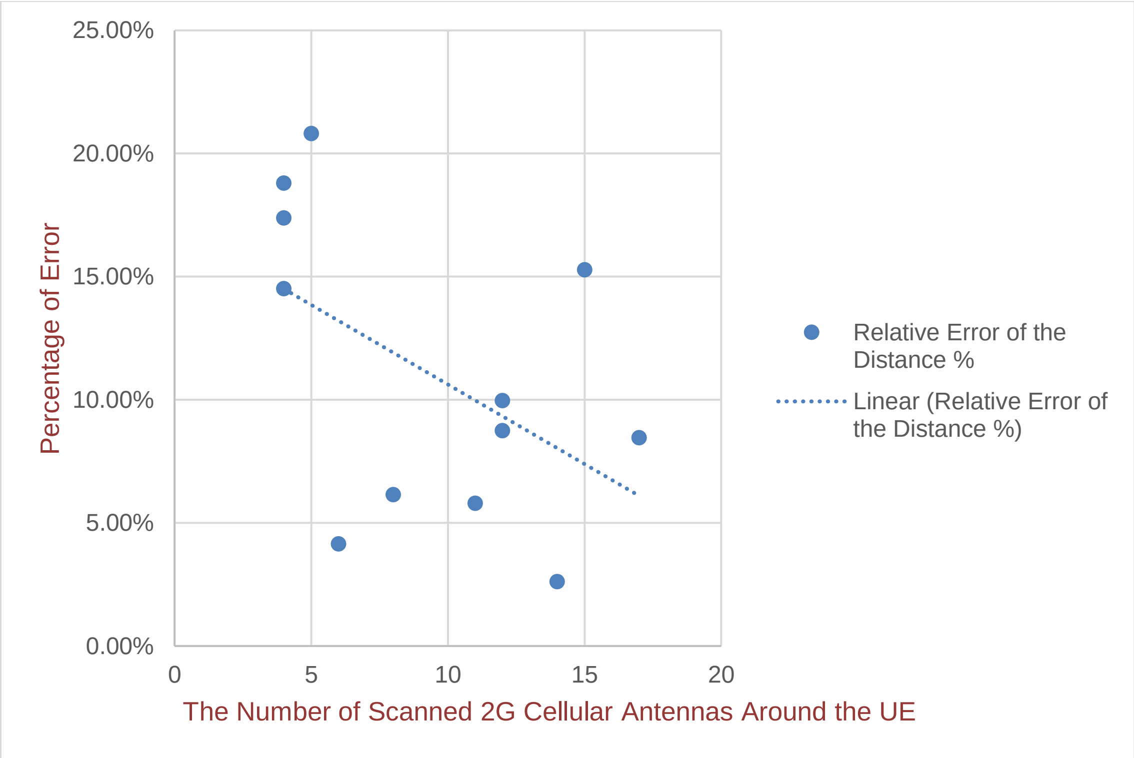

Figure 11. The graph of the correlation between the number of cellular 2G antennas scanned by the module and the relative error rate of the distance based on each data point.

Each point on the graph represents a specific data point, where the x-coordinate displays the number of scanned 2G cellular antennas, and the y-coordinate denotes the relative error of the distance.

Considering the potential inaccuracies in the geographical coordinates of cellular 2G antennas retrieved from an open database of cell towers, the scatter graph provides insights into the performance of the BCS positioning algorithm under real-world conditions. Despite these inaccuracies, a general trend of decreasing relative error is observed as the number of scanned cells increases. This trend suggests that scanning more 2G cellular antennas leads to improved accuracy in estimating the user’s position using the BCS positioning algorithm.

However, the scatter graph indicates variability in the relative error among data points with the same number of scanned cells. This variability can be attributed to factors such as fluctuations in received signal strength, environmental conditions in urban areas, and inaccuracies in the geographical coordinates of cell antennas. Overall, while the scatter plot demonstrates the potential of the BCS positioning algorithm for accurate position estimation, it also highlights the challenges associated with relying on geographical coordinates from external databases.

5 Discussion

5.1 Implications of Findings

The findings of this study offer valuable insights into applying the Barycentric interpolation method for estimating the position of user equipment (UE) using neighbouring 2G cellular network data. These insights are pivotal for both academic research and practical applications across various sectors. The main implications of this study are outlined in the following points:

- The successful application of the BCS algorithm, as demonstrated in this study, shows its potential for outdoor positioning with the mobile-based positioning approach in urban areas where GNSS signals are often obstructed. By utilizing existing cellular network-land-based infrastructures, the BCS approach offers a cost-effective and readily deployable alternative to conventional GNSS systems, which could transform location-based IoT technologies, urban navigation systems, and emergency response strategies.

- By showcasing the effectiveness of BCS in real-world scenarios, this research may influence industry standards related to cellular network-based positioning systems. It can provide a basis for standardizing methods and practices for implementing positioning systems that use cellular signals, thereby enhancing interoperability and consistency across devices and networks.

- The findings suggest that regulatory frameworks could be developed to support the use of cellular-based positioning systems such as the BCS algorithm. This would ensure that such technologies are leveraged to improve public services such as emergency response systems, where location data in any circumstances is crucial.

5.2 Limitations of the Study

This study, while illustrating the potential of the Barycentric interpolation method for UE positioning, acknowledges several limitations:

- The precision of cellular antennas' coordinates sourced from the OpenCellID.org database plays a crucial role in the performance of the BCS algorithm. Inaccurate geographic data can lead to significant errors in estimating the UE's coordinates. This study highlights the impact of data accuracy on positioning algorithms and underscores the need for reliable data sources. Enhancing the database's accuracy or integrating multiple data sources could potentially improve the reliability and accuracy of geographical position estimations in future implementations of the BCS algorithm.

- The assumption of ideal signal conditions in this study does not account for real-world challenges such as urban structures and multipath effects, which can significantly influence signal reception and degrade the accuracy of position estimation. This limitation stems from a lack of access to mobile network infrastructure information and cellular antenna configuration, which are crucial for accurately calculating environmental effects on signals. Addressing these factors could enhance the robustness and reliability of the positioning algorithm, particularly in urban environments where such influences are prevalent.

- The research assumes a static environment, meaning it doesn't consider the dynamic changes that could significantly influence signal propagation, such as varying weather conditions, urban development, or changes in physical obstacles such as construction. This static model may not fully reflect real-world conditions where such factors can affect signal strength and the reliability of data used for positioning.

- The study’s reliance on the Arduino MKR GSM 1400, which only supports 2G networks, introduces a significant constraint on the technological scope of this research. While 2G networks are broadly available, their gradual phase-out globally in favour of more advanced 4G and 5G networks restricts the utility and future applicability of the developed algorithm. Moreover, newer network generations offer higher data throughput and more detailed network parameters, which could significantly enhance the accuracy of positioning algorithms such as the BCS. This technological limitation not only narrows the research's current relevance but also poses challenges for adapting the findings to newer technologies that provide richer data and improved precision in user equipment positioning.

- Utilizing the Rx level (RxLev) standard rather than the dBm unit represents a notable limitation in this study. The RxLev, being a coded representation of dBm, does not leverage the exponential-logarithmic relationship between signal strength (measured in dBm) and distance. This relationship could potentially offer richer insights into the proximity of cell antennas relative to the user's location, allowing for more accurate distance approximations and refined position estimations. Incorporating dBm units directly could enhance the algorithm's capability to infer distances based on signal strength, thus improving the overall precision of the BCS algorithm in urban environments where signal propagation can vary significantly due to obstacles and building density.

5.3 Recommendations for Future Research

While the findings of this study offer promising insights into the use of the BCS algorithm for cellular mobile-based positioning, they also highlight several areas where further research could provide deeper understanding and improvements. The following recommendations are proposed for future research:

- Future studies could focus on optimizing the BCS algorithm to enhance its efficiency and accuracy. This could involve refining the mathematical model to better account for variables such as multi-path effects, signal reflection, and diffraction which are prevalent in urban environments.

- Applying machine learning algorithms to the BCS could potentially improve the estimation accuracy of the system. Future research could explore various machine learning models that could predict the positional error based on historical data and environmental factors, thus dynamically adjusting the algorithm’s parameters for enhanced accuracy.

- Further studies are needed to understand the impact of environmental changes on the performance of both outdoor and indoor positioning algorithms. This includes changes in urban infrastructure, such as the construction of new buildings or the alteration of existing structures, which could affect signal propagation.

- To validate the robustness and versatility of the BCS algorithm, it is recommended that future research include a broader dataset encompassing different geographic locations, network types, and urban densities. This would provide a more comprehensive understanding of the algorithm’s performance across diverse environments.

- Future research could also consider the regulatory and ethical implications of the widespread adoption of cellular-based positioning systems. This includes issues related to privacy, data security, and user consent, particularly in applications involving personal location tracking which was not the scope of this study.

By addressing these recommendations, future research can significantly advance the field of cellular mobile-based positioning and contribute to the development of more accurate, reliable, and efficient location-based services.

6 Conclusion

This thesis explored the application of the Barycentric Interpolation (BCS) method for outdoor cellular positioning with the mobile-based approach, demonstrating its potential as a viable alternative to traditional GNSS systems, especially in urban environments where GNSS may falter due to jamming, signal attenuation, and multipath propagation effects.

The research confirmed that employing the BCS, which leverages received signal strength and the geometric disposition of cellular antennas, offers a feasible solution for positioning without relying on satellite signals, internet connection, cellular network infrastructure information, or cellular antenna configuration. Through extensive data collection, development of the algorithm, and thorough field testing within the Helsinki city center, this study was able to quantify the performance of the BCS method. The algorithm achieved an average accuracy of approximately 292.46 meters for user equipment's position estimation across twelve data points, with an average relative error of 11.05%. These metrics underline the method's capability within the tested urban context and provide a benchmark for further research and development.

While enhancing accuracy was not a direct objective of this research, the findings provide crucial data points on the operational efficacy of BCS in real-world settings. This foundational work paves the way for future investigations to refine the algorithm and explore its integration with emerging cellular technologies and IoT devices, potentially improving positioning accuracy and reliability.

References

1. Loren Edward De. Loran-Inertial Navigation Systems for Long-Range Use. Cambridge: J Navig. 1965;18(3):319-29. Available from: https://doi.org/10.1017/S0373463300019214
DOI: 10.1017/S0373463300019214

2. Jacqueline Ho. LORAN hyperbolic grid lines [image on Internet]. New York: Mini-circuits; 2021. Available from: https://blog.minicircuits.com/radio-history-the-birth-death-and-resurrection-of-loran/

3. Sherman La, Benjamin Pe. Enhanced Long-Range Navigation (eLORAN). Stanford University GPS Lab. 2007. Available from: https://gps.stanford.edu/research/early-gpspnt-research/enhanced-long-range-navigation-eloran

4. Blanchard W. The Genesis of the Decca Navigator System. Cambridge: J Navig. 2015;68(2):219–37. Available from: https://www.cambridge.org/core/journals/journal-of-navigation/article/genesis-of-the-decca-navigator-system/1D1639DFD97C2EAC30AAAEA2A8704D47
DOI: 10.1017/S0373463314000666

5. Getting IA. Perspective/navigation-the global positioning system. IEEE Spectr. 1993 Dec 30(12):36-8. Available from: https://ieeexplore.ieee.org/document/272176
DOI: 10.1109/6.272176

6. Chu HC, Jan RH. Cell-based positioning method for wireless networks. InNinth International Conference on Parallel and Distributed Systems, 2002. Proceedings. IEEE. 2002 Dec 17 (pp. 375-380). Available from: https://ieeexplore.ieee.org/document/1183427
DOI: 10.1109/ICPADS.2002.1183427

7. Campos RS. Evolution of positioning techniques in cellular networks, from 2G to 4G. Wirel Commun Mob Comput. 2017 Jan 12. Available from: https://www.hindawi.com/journals/wcmc/2017/2315036/
DOI: 10.1155/2017/2315036

8. Zandbergen PA. Accuracy of iPhone locations: A comparison of assisted GPS, WiFi and cellular positioning. Transactions in GIS. 2009 Jun; 13:5-25. Available from: https://onlinelibrary.wiley.com/doi/10.1111/j.1467-9671.2009.01152.x
DOI: 10.1111/j.1467-9671.2009. 01152.x

9. Fischler B, Griffin D, Lubeck T, Wapman KH, Vu M. Device-agnostic Wi-Fi fingerprint positioning for consumer applications. In2015 IEEE 26th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC) 2015 Aug 30 (pp. 2187-2192). IEEE. Available from: https://ieeexplore.ieee.org/document/7343660
DOI: 10.1109/PIMRC.2015.7343660

10. Alarifi A, Al-Salman A, Alsaleh M, Alnafessah A, Al-Hadhrami S, Al-Ammar MA, Al-Khalifa HS. Ultra-wideband indoor positioning technologies: Analysis and recent advances. Sensors. 2016 May 16;16(5):707. Available from: https://www.mdpi.com/1424-8220/16/5/707
DOI: 10.3390/s16050707

11. Brena RF, García-Vázquez JP, Galván-Tejada CE, Muñoz-Rodriguez D, Vargas-Rosales C, Fangmeyer J. Evolution of indoor positioning technologies: A survey. Journal of Sensors. 2017 Mar 29;2017. Available from: https://www.hindawi.com/journals/js/2017/2630413/
DOI: 10.1155/2017/2630413

12. Elsanhoury M, Koljonen J, Välisuo P, Elmusrati M, Kuusniemi H. Survey on recent advances in integrated GNSSs towards seamless navigation using multi-sensor fusion technology. In Proceedings of the 34th International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS+ 2021) 2021 Sep 24 (pp. 2754-2765). Available from: https://www.ion.org/publications/abstract.cfm?articleID=17961
DOI: 10.33012/2021.17961

13. Jeong SG, Do QV, Hwang HJ, Hasegawa M, Sekiya H, Hwang WJ. Hybrid quantum convolutional neural networks for UWB signal classification. IEEE Access. 2023 Oct 9. Available from: https://ieeexplore.ieee.org/abstract/document/10274707
DOI: 10.1109/ACCESS.2023.3323019

14. Urgelles H, Picazo-Martínez P, Monserrat JF. Application of quantum computing to accurate positioning in 6g indoor scenarios. In ICC 2022-IEEE International Conference on Communications 2022 May 16 (pp. 643-647). IEEE. Available from: https://ieeexplore.ieee.org/abstract/document/9838523
DOI: 10.1109/ICC45855.2022.9838523

15. Karimi H. An analysis of satellite visibility and single point positioning with GPS, GLONASS, Galileo, and BeiDou-2/3. Applied Geomatics. 2021 Dec;13(4):781-91. Available from: https://link.springer.com/article/10.1007/s12518-021-00391-2
DOI: 10.1007/s12518-021-00391-2

16. Waadt A, Bruck GH, Jung P. An overview of positioning systems and technologies. In2009 2nd International Symposium on Applied Sciences in Biomedical and Communication Technologies. IEEE; 2009 Nov 24 (pp. 1-5). Available from: https://ieeexplore.ieee.org/abstract/document/5373694 DOI: 10.1109/ISABEL.2009.5373694

17. Hegarty CJ, Chatre E. Evolution of the global navigation satellite system (gnss). IEEE. 2008 Dec;96(12):1902-17. Available from: https://ieeexplore.ieee.org/abstract/document/4745647 DOI: 10.1109/JPROC.2008.2006090

18. Groves PD. Principles of GNSS, inertial, and multisensor integrated navigation systems, [Book review]. IEEE Aerospace and Electronic Systems Magazine. 2015 Feb;30(2):26-7. Available from: https://ieeexplore.ieee.org/abstract/document/7063664 DOI: 10.1109/MAES.2014.14110

19. Elliott D.K, Christopher HE. Understanding GPS/GNSS: principles and applications. Artech house; 2017 May 31. Available from: https://www.navtechgps.com/understanding_gpsgnss_principles_and_applications-3rd_edition/

20. Choy S, Bisnath S, Rizos C. Uncovering common misconceptions in GNSS Precise Point Positioning and its future prospect. GPS solutions. 2017 Jan; 21:13-22. Available from: https://link.springer.com/article/10.1007/s10291-016-0545-x DOI: 10.1007/s10291-016-0545-x

21. Chew WK, Zakaria MA. Outdoor localisation for navigation tracking using differential global positioning system estimation (DGPS): positioning errors analysis. Mekatronika. 2019 Jul 15;1(2):103-14. Available from: https://journal.ump.edu.my/mekatronika/article/view/4994 DOI: 10.15282/mekatronika.v1i2.4994

22. Calian GNSS. Precise Point Positioning (PPP) System Architecture [image on Internet]. Ontario: Calian Wireless Inc. Available from: https://www.tallysman.com/gnss-positioning-techniques/

23. Manito J, Sanguino J. Performance Evaluation of GPS Auto-Surveying Techniques. Sensors. 2021 Nov 6;21(21):7374. Available from: https://www.mdpi.com/1424-8220/21/21/7374 DOI: 10.3390/s21217374

24. Zekavat R, Buehrer RM. Handbook of position location: Theory, practice and advances. Wiley-IEEE Press; 2019. Available from: https://ieeexplore.ieee.org/book/8633728

25. Janssen T, Weyn M, Berkvens R. A primer on real-world RSS-based outdoor NB-IoT localization. In2020 International Conference on Localization and GNSS (ICL-GNSS) 2020 Jun 2 (pp. 1-6). IEEE. Available from: https://ieeexplore.ieee.org/abstract/document/9115578 DOI: 10.1109/ICL-GNSS49876.2020.9115578

26. Song Q, Guo S, Liu X, Yang Y. CSI amplitude fingerprinting-based NB-IoT indoor localization. IEEE. 2017 Jul 03;5(3):1494-504. Available from: https://ieeexplore.ieee.org/abstract/document/7962759 DOI: 10.1109/ICCW.2017.7962759

27. Lin X, Bergman J, Gunnarsson F, Liberg O, Razavi SM, Razaghi HS, Rydn H, Sui Y. Positioning for the internet of things: A 3GPP perspective. IEEE Communications Magazine. 2017 Sep 11;55(12):179-85. Available from: https://ieeexplore.ieee.org/abstract/document/8030544 DOI: 10.1109/MCOM.2017.1700269

28. Ratasuk R, Mangalvedhe N, Bhatoolaul D, Ghosh A. LTE-M evolution towards 5G massive MTC. In2017 IEEE Globecom Workshops (GC Wkshps) 2017 Dec 4 (pp. 1-6). IEEE. Available from: https://ieeexplore.ieee.org/abstract/document/8269112 DOI: 10.1109/GLOCOMW.2017.8269112

29. Mogyorósi F, Revisnyei P, Pašić A, Papp Z, Törös I, Varga P, Pašić A. Positioning in 5g and 6g networks—a survey. Sensors. 2022 Jun 23;22(13):4757. Available from: https://www.mdpi.com/1424-8220/22/13/4757 DOI: 10.3390/s22134757

30. Khan SZ, Mohsin M, Iqbal W. On GPS spoofing of aerial platforms: a review of threats, challenges, methodologies, and future research directions. PeerJ Computer Science. 2021 May 6;7: e507. Available from: https://peerj.com/articles/cs-507/ DOI: 10.7717/peerj-cs.507

31. De Angelis G, Baruffa G, Cacopardi S. GNSS/cellular hybrid positioning system for mobile users in urban scenarios. IEEE Transactions on Intelligent Transportation Systems. 2012 Sep 19;14(1):313-21. Available from: https://ieeexplore.ieee.org/document/6307871 DOI: 10.1109/TITS.2012.2215855

32. Mortier J, Pagès G, Vilà-Valls J. Robust TOA-based UAS navigation under model mismatch in GNSS-denied harsh environments. Remote Sensing. 2020 Sep 10;12(18):2928. Available from: https://www.mdpi.com/2072-4292/12/18/2928 DOI: 10.3390/rs12182928

33. Abugabal M, Fahmy Y, Tawfik H. NOVEL position estimation using differential timing information for asynchronous LTE/NR networks. International Journal of Computer Networks & Communications (IJCNC). 2021;13(4):39-52. Available from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3907744

34. Rustamov RB, Hashimov AM, editors. Multifunctional Operation and Application of GPS. BoD–Books on Demand; 2018 May 30. Available from: https://www.intechopen.com/books/6540
DOI: 10.5772/intechopen.71221

35. Trimble Autonomy. Trimble Maxwell 7 Technolo–y - Advanced Multipath Mitigation with Everest Plus. California: Trimble Intech; 2022 Feb 9. Available from: https://autonomy.trimble.com/en/resources/technical-papers/advanced-multipath-mitigation-trimble-technical-publication

36. Morrison A, Sokolova N, Solberg A, Gerrard N, Rødningsby A, Hauglin H. Jammertest 2022: Jamming and Spoofing Lessons Learned. Engineering Proceedings. 2023 Oct 29;54(1):22. Available from: https://www.mdpi.com/2673-4591/54/1/22
DOI: 10.3390/ENC2023-15445

37. Riskintelligence. Maritime navigation under threat: GNSS spoofing raises security concerns. Denmark: Risk Intelligence; 2023 Oct 9. Available from: https://www.riskintelligence.eu/analyst-briefings/maritime-navigation-under-threat

38. Morrison A, Sokolova N, Solberg A, Gerrard N, Rødningsby A, Hauglin H, Rødningen T, Dahlø T. Jammertest 2022: Jamming and Spoofing Lessons Learned. Engineering Proceedings. 2023 Oct 29;54(1):22. Available from: https://ieeexplore.ieee.org/document/7444136
DOI: 10.1109/JPROC.2016.2525938

39. Wesson KD, Gross JN, Humphreys TE, Evans BL. GNSS signal authentication via power and distortion monitoring. IEEE Transactions on Aerospace and Electronic Systems. 2017 Oct 25;54(2):739-54. Available from: https://ieeexplore.ieee.org/document/8082785
DOI: 10.1109/TAES.2017.2765258

40. Lee DK, Nedelkov F, Akos DM. Assessment of android network positioning as an alternative source of navigation for drone operations. Drones. 2022 Jan 23;6(2):35. Available from: https://www.mdpi.com/2504-446X/6/2/35
DOI: 10.3390/drones6020035

41. Brendan CO. Map Shows NATO Territory Losing GPS Amid Russia Electronic Warfare Drill. New York: Newsweek; 2024 Jan 18. Available from: https://www.newsweek.com/russia-poland-kaliningrad-gps-jammer-1861842

42. Michael JO. Spoofing in the Black Sea: What really happened. Ohio: North Coast Media ATTN; 2017 Oct 11. Available from: https://www.gpsworld.com/spoofing-in-the-black-sea-what-really-happened/

43. Guy BU. Thousands of GNSS jamming and spoofing incidents reported in 2020. Virginia: The Resilient Navigation and Timing Foundation; 2020 Dec 24. Available from: https://rntfnd.org/2020/12/24/thousands-of-gnss-jamming-and-spoofing-incidents-reported-in-2020-guy-buesnel

44. Steindl E, Dunkel W, Hornbostel A, Hättich C, Remi P. The impact of interference caused by GPS Repeaters on GNSS receivers and services. In European Navigation Conference 2013. Available from: https://www.researchgate.net/publication/312158775_The_impact_of_interference_caused_by_GPS_Repeaters_on_GNSS_receivers_and_services

45. Roi MI. Two years since the Tesla GPS hack. Ohio: North Coast Media ATTN; 2021 Aug 30. Available from: https://www.gpsworld.com/two-years-since-the-tesla-gps-hack/

46. Inside GNSS. Spoofing Incident Report: An Illustration of Cascading Security Failure. New Jersey: Inside GNSS Media & Research LLC; 2017 Oct 9. Available from: https://insidegnss.com/spoofing-incident-report-an-illustration-of-cascading-security-failure/

47. Bill GE. Electronic GPS ‘spoofing’ behind civilian jet navigation failures over Iraq. New York: The Washington Times; 2023 Sep 28. Available from: https://www.washingtontimes.com/news/2023/sep/28/electronic-gps-spoofing-behind-civilian-jet-naviga/

48. Bjorn BE. AIS Ship Tracking Data Shows False Vessel Tracks Circling Above Point Reyes, Near San Francisco. West Virginia: SkyTruth; 2020 May 26. Available from: https://skytruth.org/2020/05/ais-ship-tracking-data-shows-false-vessel-tracks-circling-above-point-reyes-near-san-francisco/

49. Clare SE. Getting lost near the Kremlin? Russia could be 'GPS spoofing. Atlanta: CNN Sans; 2016 Dec 2. Available from: https://money.cnn.com/2016/12/02/technology/kremlin-gps-signals/

50. John KE. Iran–U.S. RQ-170 incident has defense industry saying 'never again' to unmanned vehicle hacking. London: Endeavor Business Media; 2016 May 3. Available from: https://www.militaryaerospace.com/computers/article/16715072/iranus-rq170-incident-has-defense-industry-saying-never-again-to-unmanned-vehicle-hacking

51. Jacqueline Ho. LORAN hyperbolic grid lines [image on Internet]. New York: Mini-circuits; 2021. Available from: https://blog.minicircuits.com/radio-history-the-birth-death-and-resurrection-of-loran/

52. Bensky A. Wireless positioning technologies and applications. Artech House; 2016 Mar 1. Available from: https://us.artechhouse.com/Wireless-Positioning-Technologies-and-Applications-Second-Edition-P1794.aspx

53. Jeong M, Lee B. Comparison between path-loss prediction models for wireless telecommunication system design. In IEEE Antennas and Propagation Society International Symposium. 2001 Digest. Held in conjunction with: USNC/URSI National Radio Science Meeting (Cat. No. 01CH37229) 2001 Jul 8 (Vol. 2, pp. 186-189). IEEE. Available from: https://ieeexplore.ieee.org/document/959661
DOI: 10.1109/APS.2001.959661

54. Mohamed I. Path-loss estimation for wireless cellular networks using Okumura/Hata model. Science Journal of Circuits, Systems and Signal Processing. 2018;7(1):20-7. Available from: https://ieeexplore.ieee.org/document/959661
DOI: 10.1109/APS.2001.959661

55. Karttunen A, Valkama M, Talvitie J. Positioning based on noise-limited censored path loss data. In2020 International Conference on Localization and GNSS (ICL-GNSS) 2020 Jun 2 (pp. 1-6). IEEE. Available from: https://ieeexplore.ieee.org/document/9115572
DOI: 10.1109/ICL-GNSS49876.2020.9115572

56. Wen JH, Han DY. Performance analysis of cellular mobile communications under multipath interference. Wireless Personal Communications. 2000 Jan;12:27-53. Available from: https://link.springer.com/article/10.1023/A:1008843816055
DOI: 10.1023/A:1008843816055

57. Jiang T, Chen D, Ni C, Qu D. OQAM/FBMC for future wireless communications: Principles, technologies and applications. Academic Press; 2017 Sep 13. Available from: https://doi.org/10.1016/C2016-0-05186-0

58. Ge L, Han S, Rizos C. Multipath mitigation of continuous GPS measurements using an adaptive filter. GPS solutions. 2000 Oct;4:19-30. Available from: https://link.springer.com/article/10.1007/PL00012838 DOI: 10.1007/PL00012838

59. Shamaei K, Kassas ZM. LTE receiver design and multipath analysis for navigation in urban environments. Navigation. 2018 Dec;65(4):655-75. Available from: https://onlinelibrary.wiley.com/doi/10.1002/navi.272 DOI: 10.1002/navi.272

60. Karl H, Willig A. Protocols and architectures for wireless sensor networks. John Wiley & Sons; 2007 Oct 8. DOI: 10.1002/0470095121

61. Sarkar TK, Ji Z, Kim K, Medouri A, Salazar-Palma M. A survey of various propagation models for mobile communication. IEEE Antennas and propagation Magazine. 2003 Jun;45(3):51-82. Available from: https://ieeexplore.ieee.org/document/1232163 DOI: 10.1109/MAP.2003.1232163

62. Liu H, Darabi H, Banerjee P, Liu J. Survey of wireless indoor positioning techniques and systems. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews). 2007 Oct 22;37(6):1067-80. Available from: https://ieeexplore.ieee.org/abstract/document/4343996 DOI: 10.1109/TSMCC.2007.905750

63. Gustafsson F, Gunnarsson F. Mobile positioning using wireless networks: possibilities and fundamental limitations based on available wireless network measurements. IEEE Signal processing magazine. 2005 Jun 27;22(4):41-53. Available from: https://ieeexplore.ieee.org/document/1458284 DOI: 10.1109/MSP.2005.1458284

64. Campos RS. Evolution of positioning techniques in cellular networks, from 2G to 4G. Wireless Communications and Mobile Computing. 2017 Jan 12;2017. Available from: https://www.hindawi.com/journals/wcmc/2017/2315036/ DOI: 10.1155/2017/2315036

65. Gentile C, Alsindi N, Raulefs R, Teolis C. Geolocation techniques: principles and applications. Springer Science & Business Media; 2012 Nov 11. Available from: https://link.springer.com/book/10.1007/978-1-4614-1836-8 DOI: 10.1155/2017/2315036

66. Borkowski J, Niemela J, Lempiainen J. Enhanced performance of Cell ID+ RTT by implementing forced soft handover algorithm. InIEEE 60th Vehicular Technology Conference, 2004. VTC2004-Fall. 2004 2004 Sep 26 (Vol. 5, pp. 3545-3549). IEEE. Available from: https://ieeexplore.ieee.org/document/1404724 DOI: 10.1109/VETECF.2004.1404724

67. Shen J, Oda Y. Direction estimation for cellular enhanced cell-ID positioning using multiple sector observations. In2010 International Conference on Indoor Positioning and Indoor Navigation 2010 Sep 15 (pp. 1-6). IEEE. Available from: https://ieeexplore.ieee.org/document/5647833 DOI: 10.1109/IPIN.2010.5647833

68. Zhu J, Durgin GD. Indoor/outdoor location of cellular handsets based on received signal strength. In2005 IEEE 61st Vehicular Technology Conference 2005 May 30 (Vol. 1, pp. 92-96). IEEE. Available from: https://ieeexplore.ieee.org/document/1543256 DOI: 10.1109/VETECS.2005.1543256

69. Saadat R, Shafiei A, Tadaion A. Cooperative mobile positioning based on received signal strength. IEICE transactions on communications. 2009 May 1;92(5):1912-5. Available from: https://www.jstage.jst.go.jp/article/transcom/E92.B/5/E92.B_5_1912/_article DOI: 10.1587/transcom.E92.B.1912

70. Yeung WM, Ng JK. Wireless LAN positioning based on received signal strength from mobile device and access points. In13th IEEE International Conference on Embedded and Real-Time Computing Systems and Applications (RTCSA 2007) 2007 Aug 21 (pp. 131-137). IEEE. Available from: https://ieeexplore.ieee.org/document/4296845 DOI: 10.1109/RTCSA.2007.73

71. Markoulidakis JG. Received signal strength based mobile terminal positioning error analysis and optimization. Computer Communications. 2010 Jun 15;33(10):1227-34. Available from: https://www.sciencedirect.com/science/article/abs/pii/S0140366410001179?via%3Dihub DOI: 10.1016/j.comcom.2010.03.008

72. Talvitie J, Lohan ES. Modeling received signal strength measurements for cellular network based positioning. In2013 International Conference on Localization and GNSS (ICL-GNSS) 2013 Jun 25 (pp. 1-6). IEEE. Available from: https://ieeexplore.ieee.org/document/6577278 DOI: 10.1109/ICL-GNSS.2013.6577278

73. Talvitie J, Lohan ES. Modeling received signal strength measurements for cellular network-based positioning. In2013 International Conference on Localization and GNSS (ICL-GNSS) 2013 Jun 25 (pp. 1-6). IEEE. Available from: https://www.sciencedirect.com/science/article/abs/pii/S1474034619302083?via%3Dihub DOI: 10.1016/j.aei.2019.100960

74. Soliman SS, Wheatley CE. Geolocation technologies and applications for third generation wireless. Wireless Communications and Mobile Computing. 2002 May;2(3):229-51. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1002/wcm.55 DOI: 10.1002/wcm.55

75. Samarah KG. Mobile Positioning Technique Based on Timing Advance and Microcell Zone Concept for GSM Systems. Available from: https://www.praiseworthyprize.org/jsm/index.php?journal=irecap&page=article&op=view&path[]=18938 DOI: 10.15866/irecap.v6i4.9161

76. Roth JD, Tummala M, McEachen JC. Efficient system geolocation architecture in next-generation cellular networks. IEEE Systems Journal. 2017 May 18;12(4):3414-25. Available from: https://ieeexplore.ieee.org/document/7931547 DOI: 10.1109/JSYST.2017.2701903

77. Lokhvitskiy MS, Shorin OA, Shorin AO. Implementation of the Invention" Method of Cellular Systems": Time advance calculation. In2019 Systems of Signals Generating and Processing in the Field of on Board Communications 2019 Mar 20 (pp. 1-4). IEEE. Available from: https://ieeexplore.ieee.org/document/8706788 DOI: 10.1109/SOSG.2019.8706788

78. Subedi S, Pyun JY. A survey of smartphone-based indoor positioning system using RF-based wireless technologies. Sensors. 2020 Dec 17;20(24):7230. Available from: https://www.mdpi.com/1424-8220/20/24/7230 DOI: 10.3390/s20247230

79. So HC, Chan FK. A generalized subspace approach for mobile positioning with time-of-arrival measurements. IEEE transactions on Signal Processing. 2007 Sep 24;55(10):5103-7. Available from: https://ieeexplore.ieee.org/document/4305461
DOI: 10.1109/TSP.2003.896092

80. Wang P, Morton YJ. Improved time-of-arrival estimation algorithm for cellular signals in multipath fading channels. In2020 IEEE/ION Position, Location and Navigation Symposium (PLANS) 2020 Apr 20 (pp. 1358-1364). IEEE. Available from: https://ieeexplore.ieee.org/document/9110178
DOI: 10.1109/PLANS46316.2020.9110178

81. Mensing C, Plass S. Positioning algorithms for cellular networks using TDOA. In2006 IEEE International Conference on Acoustics Speech and Signal Processing Proceedings 2006 May 14 (Vol. 4, pp. IV-IV). IEEE. Available from: https://ieeexplore.ieee.org/document/1661018
DOI: 10.1109/ICASSP.2006.1661018

82. Mensing C, Plass S. Positioning based on factor graphs. EURASIP Journal on Advances in Signal Processing. 2007 Dec;2007:1-1. Available from: https://asp-eurasipjournals.springeropen.com/articles/10.1155/2007/41348
DOI: 10.1155/2007/41348

83. De Angelis A, Moschitta A, Comuniello A. TDoA based positioning using ultrasound signals and wireless nodes. In2017 IEEE International Instrumentation and Measurement Technology Conference (I2MTC) 2017 May 22 (pp. 1-6). IEEE. Available from: https://ieeexplore.ieee.org/document/7969873
DOI: 10.1109/I2MTC.2017.7969873

84. Wang P, Morton YJ. Improved time-of-arrival estimation algorithm for cellular signals in multipath fading channels. In2020 IEEE/ION Position, Location and Navigation Symposium (PLANS) 2020 Apr 20 (pp. 1358-1364). IEEE. Available from: https://ieeexplore.ieee.org/document/9110178
DOI: 10.1109/PLANS46316.2020.9110178

85. Medbo J, Siomina I, Kangas A, Furuskog J. Propagation channel impact on LTE positioning accuracy: A study based on real measurements of observed time difference of arrival. In2009 IEEE [2]0th International Symposium on Personal, Indoor and Mobile Radio Communications 2009 Sep 13 (pp. 2213-2217). IEEE. Available from: https://ieeexplore.ieee.org/document/5450144
DOI: 10.1109/PIMRC.2009.5450144

86. Ryden H, Zaidi AA, Razavi SM, Gunnarsson F, Siomina I. Enhanced time of arrival estimation and quantization for positioning in LTE networks. In2016 IEEE 27th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC) 2016 Sep 4 (pp. 1-6). IEEE. Available from: https://ieeexplore.ieee.org/document/7794634
DOI: 10.1109/PIMRC.2016.7794634

87. Wang P, Morton YJ. Improved time-of-arrival estimation algorithm for cellular signals in multipath fading channels. In 2020 IEEE/ION Position, Location and Navigation Symposium (PLANS) 2020 Apr 20 (pp. 1358-1364). IEEE. Available from: https://ieeexplore.ieee.org/document/9110178
DOI: 10.1109/PLANS46316.2020.9110178

88. Hansen RC. Fundamental limitations in antennas. Proceedings of the IEEE. 1981 Feb;69(2):170-82. Available from: https://ieeexplore.ieee.org/document/1456218
DOI: 10.1109/PROC.1981.11950

89. Malhotra N, Krasniewski M, Yang C, Bagchi S, Chappell W. Location estimation in ad hoc networks with directional antennas. In 25th IEEE International Conference on Distributed Computing Systems (ICDCS'05) 2005 Jun 6 (pp. 633-642). IEEE. Available from: https://ieeexplore.ieee.org/document/1437124
DOI: 10.1109/ICDCS.2005.47

90. Pages-Zamora A, Vidal J, Brooks DH. Closed-form solution for positioning based on angle of arrival measurements. InThe 13th IEEE international symposium on personal, indoor and mobile radio communications 2002 Sep 18 (Vol. 4, pp. 1522-1526). IEEE. Available from: https://ieeexplore.ieee.org/document/1045433
DOI: 10.1109/PIMRC.2002.1045433

91. Salamah M, Doukhnitch E, Bayramer C. Dynamic hardware-oriented algorithm for angle of arrival positioning technique. In2007 IEEE International Conference on Signal Processing and Communications 2007 Nov 24 (pp. 201-204). IEEE. Available from: https://ieeexplore.ieee.org/document/4728290
DOI: 10.1109/ICSPC.2007.4728290

92. Kangas A, Wigren T. Angle of arrival localization in {LTE} using {MIMO} pre-coder index feedback. IEEE Communications Letters. 2013 Jul 2;17(8):1584-7. Available from: https://ieeexplore.ieee.org/document/6550878
DOI: 10.1109/LCOMM.2013.062113.130870

93. Arenas M, Podhorski A, Arrizabalaga S, Goya J, Sedano B, Mendizabal J. Implementation and validation of an Angle of Arrival (AOA) determination system. In2015 Conference on Design of Circuits and Integrated Systems (DCIS) 2015 Nov 25 (pp. 1-7). IEEE. Available from: https://ieeexplore.ieee.org/document/7388579
DOI: 10.1109/DCIS.2015.7388579

94. Conesa J, Pérez-Navarro A, Sospedra JT, Montoliu R. Geographical and fingerprinting data to create systems for indoor positioning and indoor/outdoor navigation. Elsevier: Amsterdam, The Netherlands; 2018. Available from: https://doi.org/10.1016/C2016-0-04606-5

95. Wigren T. Adaptive enhanced cell-ID fingerprinting localization by clustering of precise position measurements. IEEE Transactions on Vehicular Technology. 2007 Sep 24;56(5):3199-209. Available from: https://ieeexplore.ieee.org/document/4305545
DOI: 10.1109/TVT.2007.900400

96. Huang CM, Hsieh TH, Lin SY. A signal-aware fingerprinting-based positioning technique in cellular networks. I^{n2}011 14th International Conference on Network-Based Information Systems 2011 Sep 7 (pp. 325-332). IEEE. Available from: https://ieeexplore.ieee.org/document/6041937
DOI: 10.1109/NBiS.2011.56

97. Wang YH, Li H, Luo XL, Sun QM, Liu JN. A 3D fingerprinting positioning method based on cellular networks. International Journal of Distributed Sensor Networks. 2014 Jul 8;10(7):248981. Available from: https://journals.sagepub.com/doi/10.1155/2014/248981
DOI: 10.1155/2014/248

98. Viel A, Brunello A, Montanari A, Pittino F. An original approach to positioning with cellular fingerprints based on decision tree ensembles. Journal of Location Based Services. 2019 Jan 2;13(1):25-52. Available from: https://link.springer.com/chapter/10.1007/978-3-319-71470-7_3
DOI: 10.1007/978-3-319-71470-7_3

99. Deligiannis N, Louvros S, Kotsopoulos S. Optimizing location positioning using hybrid TOA-AOA techniques in mobile cellular networks. In3rd International ICST Conference on Mobile Multimedia Communications 2010 May 16. Available from: https://eudl.eu/doi/10.4108/icst.mobimedia2007.1906
DOI: 10.4108/ICST.MOBIMEDIA2007.1906

100. Yassine A, Nasser Y, Senior Member IEEE, Awad M, Uguen B. Hybrid positioning data fusion in heterogeneous networks with critical hearability. EURASIP Journal on Wireless Communications and Networking. 2014 Dec;2014:1-6. Available from: https://jwcn-eurasipjournals.springeropen.com/articles/10.1186/1687-1499-2014-215 DOI: 10.1186/1687-1499-2014-215

101. Wang F, Liu X. Empirical Analysis of TOA and AOA in Hybrid Location Positioning Techniques. In IOP Conference Series: Materials Science and Engineering 2018 Dec 1 (Vol. 466, No. 1, p. 012089). IOP Publishing. Available from: https://iopscience.iop.org/article/10.1088/1757-899X/466/1/012089 DOI: 10.1088/1757-899X/466/1/012089

102. Zhang Z, Kang S, Zhang X. A Bayesian Probabilistic TOA/AOA Hybrid Localization Algorithm in Multipath Environments. In2020 IEEE 3rd International Conference on Computer and Communication Engineering Technology (CCET) 2020 Aug 14 (pp. 303-307). IEEE. Available from: https://ieeexplore.ieee.org/document/9213169 DOI: 10.1109/CCET50901.2020.9213169

103. Guo T, Chai M, Xiao J, Li C. A hybrid indoor positioning algorithm for cellular and Wi-Fi networks. Arabian Journal for Science and Engineering. 2021:1-5. Available from: https://link.springer.com/article/10.1007/s13369-021-05925-9 DOI: 10.1007/s13369-021-05925-9

104. Wikipedia. 2024. Barycentric coordinate system. [Online]. [Accessed 23 Feb 2024]. Available from: https://en.wikipedia.org/wiki/Barycentric_coordinate_system

105. Ungar AA. Barycentric calculus in Euclidean and hyperbolic geometry: A comparative introduction. World Scientific; 2010 Aug 26. Available from: https://www.worldscientific.com/worldscibooks/10.1142/7740#t=aboutBook DOI: 10.1142/7740

106. Hormann K. Barycentric interpolation. In Approximation Theory XIV: San Antonio 2013 2014 (pp. 197-218). Springer International Publishing. Available from: https://link.springer.com/book/10.1007/978-3-319-06404-8 DOI: 10.1007/978-3-319-06404-8

107. Floater MS. Mean value coordinates. Computer aided geometric design. 2003 Mar 1;20(1):19-27. Available from: https://www.sciencedirect.com/science/article/abs/pii/S0167839603000025?via%3Dihub DOI: 10.1016/S0167-8396(03)00002-5

108. Weber O, Poranne R, Gotsman C. Biharmonic coordinates. In Computer Graphics Forum 2012 Dec (Vol. 31, No. 8, pp. 2409-2422). Oxford, UK: Blackwell Publishing Ltd. Available from: https://onlinelibrary.wiley.com/doi/10.1111/j.1467-8659.2012.03130.x
DOI: 10.1111/j.1467-8659.2012.03130.x

109. Ansari K, Corumluoglu O, Verma P. The triangulated affine transformation parameters and barycentric coordinates of Turkish permanent GPS network. Survey Review. 2018 Sep 3;50(362):412-5. Available from: https://www.tandfonline.com/doi/full/10.1080/00396265.2017.1297016
DOI: 10.1080/00396265.2017.1297016

110. Diao Y, Lin Z, Fu M. A barycentric coordinate based distributed localization algorithm for sensor networks. IEEE Transactions on Signal Processing. 2014 Jul 16;62(18):4760-71. Available from: https://ieeexplore.ieee.org/document/6857433
DOI: 10.1109/TSP.2014.2339797

111. Wikipedia. 2024. OpenCellID. [Online]. [Accessed 26 Feb 2024]. Available from: https://en.wikipedia.org/wiki/OpenCellID

112. 3GPP. Technical Specification Group GSM/EDGE Radio Access Network; Radio subsystem link control (Release 1999). 3GPP. 2005 Nov, TS 05.08 V8.23.0. Available from: https://portal.3gpp.org/

113. Nurmi J, Lohan ES, Wymeersch H, Seco-Granados G, Nykänen O, editors. Multi-Technology Positioning. Berlin/Heidelberg, Germany: Springer; 2017 Mar 28. DOI: 10.1007/978-3-319-50427-8

114. Chen H, Huang P, So HC, Sezaki K. Mobility-assisted position estimation in wireless sensor networks. I^{n2}008 14th IEEE International Conference on Parallel and Distributed Systems 2008 Dec 8 (pp. 607-614). IEEE. Available from: https://ieeexplore.ieee.org/document/4724371
DOI: 10.1109/ICPADS.2008.62

115. Wang L, Li Z, Yuan H, Zhao J, Zhou K. Research and implementation on BDS/GNSS real-time positioning for urban high-precision location-based services. In China Satellite Navigation Conference (CSNC) 2016 Proceedings: Volume I 2016 (pp. 277-286). Springer Singapore. Available from: https://link.springer.com/chapter/10.1007/978-981-10-0934-1_25
DOI: 10.1007/978-981-10-0934-1_25

116. Calle D, Carbonell E, Chamorro A, González A, Mezzera C, Navarro P, Rodríguez D, Rodríguez I, Tobías G. Assured Precise Point Positioning Techniques Driving the Future. In Proceedings of the 33rd International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS+ 2020) 2020 Sep 25 (pp. 549-572). Available from: https://www.ion.org/publications/abstract.cfm?articleID=17683 DOI: 10.33012/2020.17683

117. Liang T, Yang J, Zhang T. UAV aided vehicle positioning with imperfect data association. In2021 IEEE 93rd Vehicular Technology Conference (VTC2021-Spring) 2021 Apr 25 (pp. 1-6). IEEE. Available from: https://ieeexplore.ieee.org/abstract/document/9448650 DOI: 10.1109/VTC2021-Spring51267.2021.9448650

118. Novick B, Mayston D, Marcus S, Barry R, Fox G, Betts B, Pasquali S, Eisenmann K. Artificial intelligence and machine learning in asset management. Blackrock. Oct. 2019. Available from: https://www.blackrock.com/corporate/literature/whitepaper/viewpoint-artificial-intelligence-machine-learning-asset-management-october-2019.pdf

119. Lowry solutions. How GPS Tracking is Reshaping Transportation and Logistics: 8 Benefits. Michigan. Available from: https://lowrysolutions.com/blog/benefits-of-gps-tracking-reshaping-transportation-and-logistics/

120. Advanced Machine Works. Introduction to precision positioning systems: What are they and why are they crucial. Michigan. 2023 Sep Available from: https://advancedmw.com/introduction-to-precision-positioning-systems-what-are-they-and-why-are-they-crucial/

121. Chen R, Chen L. Smartphone-based indoor positioning technologies. Urban informatics. 2021:467-90. Available from: https://link.springer.com/chapter/10.1007/978-981-15-8983-6_26 DOI: 10.1007/978-981-15-8983-6_26

122. Camajori Tedeschini B, Brambilla M, Italiano L, Reggiani S, Vaccarono D, Alghisi M, Benvenuto L, Goia A, Realini E, Grec F, Nicoli M. A feasibility study of 5G positioning with current cellular network deployment. Scientific reports. 2023 Sep 15;13(1):15281. Available from: https://www.nature.com/articles/s41598-023-42426-1 DOI: 10.1038/s41598-023-42426-1

123. Yang Y, Chen M, Blankenship Y, Lee J, Ghassemlooy Z, Cheng J, Mao S. Positioning Using Wireless Networks: Applications, Recent Progress and Future Challenges. arXiv preprint arXiv:2403.11417. 2024 Mar 18. Available from: https://arxiv.org/abs/2403.11417
DOI: 10.48550/arXiv.2403.11417

124. Satyam D, Johannes N, Florent M, Fredrik G. 5G positioning: What you need to know. Stockholm: Telefonaktiebolaget LM Ericsson; 2020 Dec 18. Available from: https://www.ericsson.com/en/blog/2020/12/5g-positioning—what-you-need-to-know

125. Ramtohul A, Khedo KK. Mobile positioning techniques and systems: A comprehensive review. Mobile Information Systems. 2020 Sep 16;2020:1-8. Available from: https://doi.org/10.1155/2020/3708521
DOI: 10.1155/2020/3708521

126. Hellebrandt M, Mathar R. Location tracking of mobiles in cellular radio networks. IEEE transactions on Vehicular Technology. 1999 Sep;48(5):1558-62. Available from: https://ieeexplore.ieee.org/document/790530 DOI: 10.1109/25.790530

127. Nguyen V, Baccelli F, Thomas L, Chen C. Best signal quality in cellular networks: asymptotic properties and applications to mobility management in small cell networks. EURASIP Journal on Wireless Communications and Networking. 2010 Dec;2010:1-4. Available from: https://jwcn-eurasipjournals.springeropen.com/articles/10.1155/2010/690161
DOI: 10.1155/2010/690161

128. Arduino. MKR GSM 1400. Italy: Smart Projects. Available from: https://docs.arduino.cc/hardware/mkr-gsm-1400/#tech-specs

129. Wikipedia. 2024. Arduino. [Online]. [Accessed 15 May 2024]. Available from: https://en.wikipedia.org/wiki/Arduino

130. Kondaveeti HK, Kumaravelu NK, Vanambathina SD, Mathe SE, Vappangi S. A systematic literature review on prototyping with Arduino: Applications, challenges, advantages, and limitations. Computer Science Review. 2021 May 1;40:100364. Available from: https://www.sciencedirect.com/science/article/abs/pii/S1574013721000046?via%3Dihub
DOI: 10.1016/j.cosrev.2021.100364

131. Arduino. Dipole Pentaband Waterproof Antenna.Italy: Smart Projects. Available from: https://store.arduino.cc/products/dipole-pentaband-waterproof-antenna

132. Omnitele. Mobile networks in Finland today. Finland: Oy Omnitele; 2022 Feb 9. Available from: https://omnitele.com/news/mobile-networks-in-finland-today

133. OpenCellid. Live Cell Towers Map. India: Unwired Labs; 2022 Feb 9. Available from: https://opencellid.org/#zoom=16&lat=37.77889&lon=-122.41942

The source code of SCN sketch

```
#include <MKRGSM.h>
#include <SD.h>
#include <SPI.h>
GSM gsmAccess;
File myFile;
const int chipSelect = 4;
 void setup() {
   Serial.begin(9600);
   while (!Serial) {}
  Serial.println("Initializing Module...");
   if (!gsmAccess.begin()) {
      Serial.println("Failed to initialize the module");
      while (true);
      }
  Serial.print("Initializing SD card...");
   if (!SD.begin(chipSelect)) {
      Serial.println("initialization failed!");
      while (true);
      }
   Serial.println("initialization done.");
   myFile = SD.open("cell_data.csv", FILE_WRITE);
   if (myFile) {
      Serial.println("File opened successfully");
      } else {
      Serial.println("Error opening file");
      return;
      }
   getCellCurrent(); // Getting current 2G cell information
}

void loop() {
```

```
  // data processing if necessary
  delay(10000);
}

void getCellCurrent() {
  MODEM.send("AT+COPS=6"); // Requesting cell tower information
  String line;
  while (MODEM.waitForResponse(10000, &line) == 1) {
    if (line.startsWith("+COPS:")) {
      processCellInfo(line); // Data Normalization
    }
  }
  myFile.close();
  Serial.println("Data processing complete and file closed.");
 }
void processCellInfo(String data) {
  // Expected format: [<MCC>,<MNC>,<LAC>,<CI>,<BSIC>,<arfcn>,<RxLev>]
  int firstCommaIndex = data.indexOf(',');
  int lastCommaIndex = data.lastIndexOf(',');
  String mcc = data.substring(0, firstCommaIndex);
  String mnc = data.substring(firstCommaIndex + 1, data.indexOf(',',
firstCommaIndex +   1));
  int lacStart = data.indexOf(',', firstCommaIndex + 1) + 1;
  int lacEnd = data.indexOf(',', lacStart);
  String lacHex = data.substring(lacStart, lacEnd);
  long lac = strtol(lacHex.c_str(), NULL, 16); // Converting LAC from hex to
decimal
  int ciStart = data.indexOf(',', lacEnd + 1) + 1;
  int ciEnd = data.indexOf(',', ciStart);
  String ciHex = data.substring(ciStart, ciEnd);
  long ci = strtol(ciHex.c_str(), NULL, 16); // Converting Cell ID from hex to
decimal
  // Skipping BSIC and arfcn parameters
```

```
    int rxLevStart = data.lastIndexOf(',') + 1;
    String rxLev = data.substring(rxLevStart);
    // Constructing the new string in CSV format
    String csvLine = String(mcc + "," + mnc + "," + lac + "," + ci + "," + rxLev +
"\n");
   if (myFile) {
      myFile.print(csvLine);
      Serial.print("Writing to file: ");
      Serial.println(csvLine);
    }
  }
```

The algorithm sketch of the SCN program in pseudocode style

```
Begin

    Initialize Serial Communication

    Initialize GSM Module

        If initialization fails

            Print "Initialization Failed" and halt

    Initialize SD Card

        If initialization fails

            Print "SD Card Error" and halt

    Open/Create CSV File

        If file operation fails

            Print "File Error" and halt

    Loop forever

        Send "AT+UCELLINFO?" command

        Wait for GSM response

        If response received

            For each line in the response

                If line starts with "+COPS:"
```

```
        Extract and process data

        Convert Hex to Decimal for LAC and CI

        Remove BSIC and arfcn from data

        Format data into CSV line

        Write to SD card

    Else

        Print "Failed to retrieve cell info"

    Delay for a specified time

End
```

The BCS algorithm sketch

Begin

1. Load Data

   Load DataSet table with cellular antenna parameters from DataPoint files.

   Load CellDB table with cellular antenna coordinates from the offline Database file.

   Load Report table with a single column containing DataPoint numbers from a CSV file.

2. Prepare Data

   Merge columns in DataSet and CellDB to create UID columns for linking.

   Rename the single column of the Report table to "dpNum" to identify sample number.

   Convert the "dpNum" column to numeric type in the Report table.

   Perform data cleaning by removing rows with errors or null values in all tables.

   For each entry in DataSet:

   Multiply RSS level(RxLev) by the corresponding latitude (CellDB.Latitude) and longitude (CellDB.Longitude):

   $$\mathrm{RSS.Lat}_i = (\mathrm{RSS}_i \times \mathrm{latitude}_i)$$

   $$\mathrm{RSS.Long}_i = (\mathrm{RSS}_i \times \mathrm{longitude}_i)$$

   Store results in new columns 'RSS*Lat' and 'RSS*Long'.

3. Merge Data

Merge CellDB into DataSet based on UID to get corresponding latitude and longitude.

Filter and clean merged data to ensure all entries are valid.

Merge the DataSet table into the Report table based on "dpNum" to aggregate RSS*Long, RSS*Lat, and RxLev from the DataSet for each data point.

4. Calculate the BCS Coordinates

For each entry in Report:

Aggregate RSS*Long, RSS*Lat, and RxLev from the DataSet for each data

Point based on sample number(dpNum).

```
AggregatedData = AggregateColumns(MergedData, "DataSet",
        [("RxLev", Sum, "Sum of DataSet.RxLev"),
         ("RSS*Long", Sum, "Sum of DataSet.RSS*Long"),
         ("RSS*Lat", Sum, "Sum of DataSet.RSS*Lat")])
```

Ensure aggregated sums are of numeric type

```
ConvertColumnTypes(AggregatedData,
        [("Sum of DataSet.RSS*Lat", Number),
         ("Sum of DataSet.RSS*Long", Number),
```

("Sum of DataSet.RxLev", Number)])

Calculate longitude (BCS.Long) using the barycentric formula

AddCustomColumn(AggregatedData, "BCS.Long",

Each [#"Sum of DataSet.RSS*Long"] / [Sum of DataSet.RxLev])

Calculate latitude (BCS.Lat) using the barycentric formula

AddCustomColumn(AggregatedData, "BCS.Lat",

Each [#"Sum of DataSet.RSS*Lat"] / [Sum of DataSet.RxLev])

5. Calculate distances

For each entry in DataSet:

Use Haversine formula to calculate distances:

Calculate distances between GPS coordinates and the cellular

antenna based on sample number.

//Function detailed in the Listing 4

(M code sorce of the DataSet table)

Store results in a new column 'D_GPS2Cell'.

6. Output Results

For each entry in Result table:

Count scanned cellular 2G antennas from the DataSet table based on sample number(dpNum):

ScannedCells = COUNTIF(DataSet[dpNum],dpNum)

Retrieve the GPS longitude and latitude from the DataSet table based on

sample number(dpNum):

GPS.Longitude =
XLOOKUP(dpNum,DataSet[dpNum],DataSet[GPS.Long])

GPS.Latitude = XLOOKUP(dpNum,DataSet[dpNum],DataSet[GPS.Lat])

Retrieve the BCS longitude and latitude from the Report table based on

sample number(dpNum):

BCS.Longitude = 'Report'!BCS.lot

BCS.Latitude = 'Report'!BCS.lat

Use Haversine formula to calculate distances:
Calculate distances between GPS coordinates and the BCS coorinates.

GPS-BCS.Dist = (6371*2*ASIN(SQRT(SIN((RADIANS(BCS.Latitude-GPS.Latitude))/2)^2+COS(RADIANS(BCS.Latitude))*COS(RADIANS(GPS.Latit-ude))*SIN((RADIANS(GPS.Longitude-BCS.Longitude))/2)^2)))*1000

Retrieve the furthest cellular 2G antenna compared to the GPS

coordinates in each sample dataset from the DataSet table.

GPS-FurthestCell.Dist =

MAXIFS(DataSet[D_GPS2Cell],DataSet[dpNum], Sample Number)

Calculate relative error of the distance based on each sample number.

RelativeError.Distance = GPS-BCS.Dist/(GPS-FurthestCell.Dist*2)

7. Output FilteredResult

Retrieve the sample with the minimum Relative Error of the distance corresponding to the data point from the Result table and record it in the FilteredResult table.

Sample Number = XLOOKUP(MINIFS(Result[RelativeError.Distance],Result[DP],DP#),Result[RelativeError.Distance],Result[SampleNumber])

Scanned Cells(#) = XLOOKUP(MINIFS(Result[RelativeError.Distance],Result[DP],DP#),Result[RelativeError.Distance],Result[ScannedCells])

GPS.Long = XLOOKUP(MINIFS(Result[RelativeError.Distance],Result[DP],DP#),Result[RelativeError.Distance],Result[GPS.Longitude])

GPS.Lat = XLOOKUP(MINIFS(Result[RelativeError.Distance],Result[DP],DP#),Result[RelativeError.Distance],Result[GPS.Latitude])

BCS.Long = XLOOKUP(MINIFS(Result[RelativeError.Distance]
,Result[DP],DP#),Result[RelativeError.Distance],Result
[BCS.Longitude])

BCS.Lat = XLOOKUP(MINIFS(Result[RelativeError.Distance]
,Result[DP],DP#),Result[RelativeError.Distance],Result
[BCS.Latitude])

GPS-BCS Dist (m) = XLOOKUP(MINIFS(Result[RelativeError.Distance]
,Result[DP],DP#),Result[RelativeError.Distance],Result
[GPS-BCS.Dist])

GPS-Furthest Cell Dist (m) = XLOOKUP(MINIFS(Result[RelativeError.
Distance],Result[DP],DP#),Result[RelativeError.Distance],Result
[GPS-FurthestCell.Dist])

Relative Error of the Distance % = MINIFS(Result[RelativeError
.Distance],Result[DP],DP#)

End Algorithm

The M code source of the CellDB power query table

```
let
    Source = Csv.Document(File.Contents("C:\...
..\..\Data\OpenCelliD\Final_Data\CellDB.csv"),[Delimiter=",", Columns=14,
Encoding=1252, QuoteStyle=QuoteStyle.None]),
    #"Promoted Headers" = Table.PromoteHeaders(Source,
[PromoteAllScalars=true]),
    #"Changed Type" = Table.TransformColumnTypes(#"Promoted
Headers",{{"Radio", type text}, {"MCC", Int64.Type}, {"MNC", Int64.Type},
{"LAC/TAC/NID", Int64.Type}, {"CID", Int64.Type}, {"", Int64.Type}, {"Longitude",
type number}, {"Latitude", type number}, {"Range", Int64.Type}, {"Samples",
Int64.Type}, {"Changeable", Int64.Type}, {"Created", Int64.Type}, {"Updated",
Int64.Type}, {"AV Signal", Int64.Type}}),
    #"Renamed Columns" = Table.RenameColumns(#"Changed
Type",{{"LAC/TAC/NID", "LAC"}}),
    #"Removed Columns" = Table.RemoveColumns(#"Renamed
Columns",{"Radio", "", "Range", "Created", "Updated", "AV Signal",
"Changeable"}),
    #"Merged Columns" =
Table.CombineColumns(Table.TransformColumnTypes(#"Removed Columns",
{{"MCC", type text}, {"MNC", type text}, {"LAC", type text}, {"CID", type text}},
"en-US"),{"MCC", "MNC", "LAC", "CID"},Combiner.CombineTextByDelimiter("",
QuoteStyle.None),"UID"),
    #"Removed Columns1" = Table.RemoveColumns(#"Merged
Columns",{"Samples"})
in
    #"Removed Columns1"
```

The M code source of the DataSet power query table

```
let
    Source = Folder.Files("C:\..\..\Data\OpenCelliD\Final_Data\DataSet"),
    #"Filtered Hidden Files1" = Table.SelectRows(Source, each
[Attributes]?[Hidden]? <> true),
    #"Invoke Custom Function1" = Table.AddColumn(#"Filtered Hidden Files1",
"Transform File", each #"Transform File"([Content])),
    #"Renamed Columns1" = Table.RenameColumns(#"Invoke Custom
Function1", {"Name", "Source.Name"}),
    #"Removed Other Columns1" = Table.SelectColumns(#"Renamed
Columns1", {"Source.Name", "Transform File"}),
    #"Expanded Table Column1" = Table.ExpandTableColumn(#"Removed
Other Columns1", "Transform File", Table.ColumnNames(#"Transform
File"(#"Sample File"))),
    #"Changed Type" = Table.TransformColumnTypes(#"Expanded Table
Column1",{{"Source.Name", type text}, {"Column1", type number}, {"Column2",
type number}, {"Column3", type number}, {"Column4", Int64.Type}, {"Column5",
Int64.Type}, {"Column6", type text}, {"Column7", type text}, {"Column8", type
text}, {"Column9", Int64.Type}, {"Column10", Int64.Type}}),
    #"Reordered Columns" = Table.ReorderColumns(#"Changed
Type",{"Source.Name", "Column1", "Column4", "Column5", "Column6",
"Column7", "Column8", "Column9", "Column10", "Column2", "Column3"}),
    #"Renamed Columns" = Table.RenameColumns(#"Reordered
Columns",{{"Column2", "LongGPS"}, {"Column3", "LatGPS"}, {"Column10",
"RxLev"}, {"Column1", "dpNum"}, {"Column4", "MCC"}, {"Column5", "MNC"},
{"Column6", "LAC"}, {"Column7", "CID"}}),
    #"Removed Columns" = Table.RemoveColumns(#"Renamed
Columns",{"Column8", "Column9"}),
    #"Added Custom" = Table.AddColumn(#"Removed Columns", "LAC_", each
Expression.Evaluate("0x" & [LAC])),
    #"Added Custom1" = Table.AddColumn(#"Added Custom", "CID_", each
Expression.Evaluate("0x" & [CID])),
```

```
    #"Reordered Columns1" = Table.ReorderColumns(#"Added Custom1",{"Source.Name", "dpNum", "MCC", "MNC", "LAC", "CID", "LAC_", "CID_", "RxLev", "LongGPS", "LatGPS"}),
    #"Removed Columns1" = Table.RemoveColumns(#"Reordered Columns1",{"LAC", "CID"}),
    #"Renamed Columns2" = Table.RenameColumns(#"Removed Columns1",{{"LAC_", "LAC"}, {"CID_", "CID"}}),
    #"Merged Columns" = Table.CombineColumns(Table.TransformColumnTypes(#"Renamed Columns2", {{"MCC", type text}, {"MNC", type text}, {"LAC", type text}, {"CID", type text}}, "en-US"),{"MCC", "MNC", "LAC", "CID"},Combiner.CombineTextByDelimiter("", QuoteStyle.None),"UID"),
    #"Removed Errors" = Table.RemoveRowsWithErrors(#"Merged Columns", {"LatGPS"}),
    #"Removed Blank Rows" = Table.SelectRows(#"Removed Errors", each not List.IsEmpty(List.RemoveMatchingItems(Record.FieldValues(_), {"", null}))),
    #"Removed Blank Rows1" = Table.SelectRows(#"Removed Blank Rows", each not List.IsEmpty(List.RemoveMatchingItems(Record.FieldValues(_), {"", null}))),
    #"Removed Errors1" = Table.RemoveRowsWithErrors(#"Removed Blank Rows1", {"UID"}),
    #"Merged Queries" = Table.NestedJoin(#"Removed Errors1", {"UID"}, CellDB, {"UID"}, "CellDB", JoinKind.LeftOuter),
    #"Expanded CellDB" = Table.ExpandTableColumn(#"Merged Queries", "CellDB", {"Longitude", "Latitude"}, {"CellDB.Longitude", "CellDB.Latitude"}),
    #"Filtered Rows" = Table.SelectRows(#"Expanded CellDB", each true),
    #"Renamed Columns3" = Table.RenameColumns(#"Filtered Rows",{{"LongGPS", "GPS.Long"}, {"LatGPS", "GPS.Lat"}}),
    #"Added Custom2" = Table.AddColumn(#"Renamed Columns3", "RSS*Long", each [RxLev]*[CellDB.Longitude]),
    #"Added Custom3" = Table.AddColumn(#"Added Custom2", "RSS*Lat", each [RxLev]*[CellDB.Latitude]),
    #"Added Custom4" = Table.AddColumn(#"Added Custom3", "D_GPS2Cell",
```

```
each let
    R = 6371, // Earth radius in kilometers
    ToRadians = (angle) => angle * (2 * 3.14159265358979323846) / 360,
    dlat = ToRadians([CellDB.Latitude] - [GPS.Lat]),
    dlon = ToRadians([CellDB.Longitude] - [GPS.Long]),
    a = Number.Power(Number.Sin(dlat / 2), 2) +
Number.Cos(ToRadians([GPS.Lat])) *
Number.Cos(ToRadians([CellDB.Latitude])) * Number.Power(Number.Sin(dlon /
2), 2),
    c = 2 * Number.Atan2(Number.Sqrt(a), Number.Sqrt(1 - a)),
    distance = (R * c)*1000
in
    distance),
    #"Filtered Rows1" = Table.SelectRows(#"Added Custom4", each
([CellDB.Longitude] <> null)),
    #"Changed Type1" = Table.TransformColumnTypes(#"Filtered
Rows1",{{"D_GPS2Cell", type number}, {"RSS*Lat", type number},
{"RSS*Long", type number}}),
    #"Removed Columns2" = Table.RemoveColumns(#"Changed
Type1",{"Source.Name"})
in
```

The M code source of the Report power query table

```
let
    Source = Table.FromColumns({Lines.FromBinary(File.Contents("C:\..
..\..\Data\OpenCelliD\Final_Data\Report.txt"), null, null, 1252)}),
    #"Renamed Columns" = Table.RenameColumns(Source,{{"Column1",
"dpNum"}}),
    #"Changed Type" = Table.TransformColumnTypes(#"Renamed
Columns",{{"dpNum", type number}}),
    #"Merged Queries" = Table.NestedJoin(#"Changed Type", {"dpNum"},
DataSet, {"dpNum"}, "DataSet", JoinKind.LeftOuter),
    #"Aggregated DataSet" = Table.AggregateTableColumn(#"Merged Queries",
"DataSet", {{"RxLev", List.Sum, "Sum of DataSet.RxLev"}, {"RSS*Long",
List.Sum, "Sum of DataSet.RSS*Long"}, {"RSS*Lat", List.Sum, "Sum of
DataSet.RSS*Lat"}}),
    #"Changed Type1" = Table.TransformColumnTypes(#"Aggregated
DataSet",{{"Sum of DataSet.RSS*Lat", type number}, {"Sum of
DataSet.RSS*Long", type number}, {"Sum of DataSet.RxLev", type number}}),
    #"Added Custom" = Table.AddColumn(#"Changed Type1", "BCS.Long", each
[#"Sum of DataSet.RSS*Long"]/[Sum of DataSet.RxLev]),
    #"Added Custom1" = Table.AddColumn(#"Added Custom", "BCS.Lat", each
[#"Sum of DataSet.RSS*Lat"]/[Sum of DataSet.RxLev])
in
    #"Added Custom1"
```