Journal of Ubiquitous Systems & Pervasive Networks
Volume 18, No. 1 (2023) pp. 31-38

5G-enhanced Positioning Accuracy in Smart City

Salam Traboulsi [a*], Dieter Uckelmann [a]

[a] *Stuttgart University of Applied Sciences, D-70174 Stuttgart, Germany*

Abstract

The new 5G mobile network promises to enhance existing services or include new ones to address key challenges presented by smart city stakeholders (citizens, municipalities, politics, industries, architects, etc.) to improve system implementations. These challenges cover various smart city fields such as transportation, environmental monitoring, healthcare, industrial automation, smart grid, etc. Thus, the main objective of 5G functionalities is to provide solutions to the various identified needs, which are defined as constraints and requirements. Therefore, three categories of 5G-based use cases have been defined: Enhanced Mobile Broadband (eMBB), Massive Machine Type Communications (mMTC), and Ultra-reliable and Low Latency Communications (uRLLC). Each group involves a set of use cases and characterized by specific technical features that address the corresponding needs. However, accurate and real-time positioning information is a vital requirement common to all three categories, but the degree of performance varies across scenarios and descriptions. Therefore, this work presents a summary of existing positioning technologies crossed with wireless technologies and smart city use cases to highlight the potential that will add accurate and real-time positioning to 5G capabilities. 5G promises decimeter accuracy in some critical use cases.

Keywords: *5G, Positioning methods, Smart city*

1. Introduction

The new 5G mobile communication standards are defined under the Third Generation Partnership Project (3GPP). The development of 5G is currently continuing to be standardized in form of phases [1], it includes new technical types of features, which effectively offer fast, reliable, dynamic, and everywhere available mobile network services. In addition, it appears to enhance the mobile data potential of previous generations (e.g., 4G, LTE/LTE-Advanced) [2, 3].

Many proposed use cases defined by various stakeholders highlight the need for their existence in our society with varying requirements and capabilities [4–6]. The NGMN white papers [7] describe 5G as a multifaceted system capable of supporting many combinations of throughput, latency, reliability, and availability, simultaneously under different constraints in different use cases, where Internet of Things (IoT) and mobile internet based use cases and their challenges become the main driver of the technology evolution [4, 8–10]. As a result, the 5G system sponsors a considerable number of use cases, which address the challenges of everything and everyone (cities, industries, digital lifestyle, transportation, environmental protection, education, and more). In this context, several use cases share similar descriptions and requirements. Therefore, it was useful to group them into clusters that share similar description and requirements. For example, the ITU-R [11] classified these use cases into three categories, with each category supporting many of the use cases specified by IMT-2020 [12–14] and the NGMN [7], and identified by their key performance indicators (KPIs). The three categories are as follows:

- eMBB is the first phase of 5G systems, which is also considered as an enhancement of services from previous generations of communication [15]. It offers high bandwidth and data rates for services such as ultra-high video streams (Gb in a second) and as well as the application of virtual reality or augmented reality (smart work, 3D video 4K/8k). eMBB addresses the challenges of the digital lifestyle, promoting various intelligent interactions across the world [12].

*Corresponding author. Tel.: +49 711 8926 2583
Fax: +49 711 8926 2553; E-mail: salam.traboulsi@hft-stuttgart.de

DOI: 10.5383/JUSPN.18.01.005

- mMTC stands for high density and communications between various and massive numbers of connected objects. It supports applications that require the distribution of massive devices. Therefore, this category can handle the exponential increase of connections (up to one million per square kilometer). The data rate to be transmitted by communication is generally low, and the transfer speed is not very restrictive. However, reducing power consumption and optimizing communication between terminals are the main challenges here. In addition, 5G systems must be able to support computational and analytical power throughout the network infrastructure. Sharing location information between devices is also a key parameter to improve system implementations, such as energy consumption. Typical domain in this category are smart services in city, such as smart home, smart building, and smart navigation in an indoor environment where the main objectives are the ability to optimize public resources and improve services to network users [16].
- uRLLC corresponds to applications requiring sensitive real-time communication, low latency, and high reliability; where communication failure or loss is not accepted. Therefore, the interaction of positioning information between massive IoT devices is also critical, requiring 100% reliability of device positioning, millisecond latency, and high consistency. Key applications in this category include smart manufacturing, security and emergency services, telesurgery (remote medical surgery), smart transportation, distribution automation in smart grid, etc.

According to many important studies, such as in [3, 17–20], achieving these KPIs requires challenges in terms of data rate (eMBB), people and device density (mMTC), network stability, consistency, low latency and high reliability (uRLLC), as well as many others ubiquitous service. Real-time availability and accuracy positioning of information at the base station (BS) level remains the key factor for implementing and enhancing various new services. Therefore, 5G offers technologies like massive multiple-input multiple-output (Massive MIMO), millimeter wave (mmWave), ultra-dense networks, Network slicing, non-terrestrial network (NTN), and device-to-device (D2D) communications to meet the KPIs challenges and improve positioning performance [1, 21]. However, while our presented work is part of the 5G-based smart city project, this paper aims to show the role of 5G positioning technologies to improve smart city implementations.

Thus, this paper is organized as follows: the next section, Section 2, presents a summary of existing positioning methods, it also shows the intersection between positioning methods and wireless technologies to meet the requirements of use cases. Then Section 3 presents the critical role of the positioning performance for the potential implementation of 5G use cases, where it is a comparison between the performance of positioning services of different technologies in terms of latency and real-time accuracy. Section 4 presents an analysis and discussion based on the literature study. Before concluding in Section 6, some technical challenges are presented in Section 5, highlighting the role that positioning methods will play in 5G implementations.

2. Summary of Positioning Methods

The principal goal of the location information is to obtain knowledge on the position of connected nodes, and more efficiently, the position of a specific node, which is provided by means of an estimation method, known as positioning [22]. Such a system consists of two different devices, namely, anchors and targets. Anchors refer to any fixed node whose position is already determined, such as a BS in a cellular network, an access point in a network, or a specific node whose location is identified by the Global Positioning System (called GPS). On the other hand, a target can be any UE, such as tags, cell phones, laptops, or any other module whose positioning parameter is unknown and needs to be evaluated using a positioning algorithm. The positioning evaluation is effectively measured by the average of the wireless distance, angle, or power profile. In this context, the positioning method must be identified based on the use case requirements, as well as the low latency of the information that we need. For instance, in some use cases related to emergency and healthcare, industrial automation, indoor positioning, personal tracking, and many other critical services, real-time and accurate positioning measurements are recommended with very low errors [23, 24]. However, to estimate the positioning of the target, a positioning algorithm will be used. Thus, a target communicates and obtains information only from the anchors, so in an indoor environment, each device must be connected to known BSs to perform a range of positioning methods. However, there are three categories of positioning methods: distance-based methods, Angle-based methods, and fingerprinting-based methods [21, 23, 25–28].

- Fingerprinting methods are based on power profile evaluations of the Channel Impulse Response (CIR). In practice, they are performed in two phases: the training phase and the localization phase. In the training phase, fingerprints are collected to estimate locations at known positions. During the localization phase, the positioning measurements are performed in real time by searching for the best estimation with an optimized error. In these methods, the accuracy depends on the reliability of the training set results. Therefore, several methods are proposed in the literature to improve this positioning estimation, such as statistical learning [29], non-parametric kernel regression [30, 31], and many others [22].
- Angle-based methods, e.g., angle-of-arrival (AOA), are based on the triangulation theory to estimate the UE position.
- Distance-based methods are the most famous methods for their ease of implementation and high real-time accuracy. These categories include range-based methods, e.g., Time-of-Arrival (TOA) and Received Signal Strength (RSS), and range-difference-based methods, e.g., Time-Difference-of-Arrival (TDOA). The first is a direct measurement of the distance between nodes (ranging). The second is a differential measure (or range-difference) of distances between two nodes. Thus, with the use case design, TOA and RSS can be designed where positioning can be measured, and the TDOA where it can be estimated.

The performance of positioning measurements depends not only on the method used but also on the type of wireless technologies that play an important role, whether it is Long-Term Evolution (LTE), Ultra-Wideband (UWB), Bluetooth Low Energy (BLE), Radio-Frequency Identification (RFID), Wireless

Local Area Network (WLAN), etc. These technologies offer different technical properties as well as different advantage and disadvantage [24]. The technical properties, predefined use cases scenarios, and type of information play an important role in improving the performance of the positioning system information, in addition to the methodology that can be employed, whether the methodology is cooperative or non-cooperative [22]. The non-cooperative approach means that the target can communicate and exchange information only from/to anchors, and the cooperative means that all nodes communicate with each other, there is not a fixed node. Therefore, the latter guarantee high accuracy with low latency, and can be adopted by critical use cases. Both non-cooperative and cooperative methodologies could be implemented in the positioning system. The advantage of the non-cooperative approach is the centralized data sources, but the problem is the scalability of the computation and the need to add additional resources. On the other hand, the cooperative approach is more reliable for distributed environment, but can be critical for fake exchange which costed time. Therefore, the choice depends on the goal of the use case and required performance [22].

The Table 1 groups various positioning methods associated with specific wireless technologies and use cases, and the corresponding methodology (cooperative or non-cooperative) [20, 32–36]. Based on the use case scenarios, the table shows that for the same positioning methods, either a centralized or distributed trilateration technique can be used [22]. For example, for TOA and RSS positioning methods (distance-based methods) and with UWB technologies, the environmental monitoring scenarios allow the cooperative positioning, since the sensors are connected in a mixed network, and the sensors communicate with each other. In contrast, indoor navigation, also with UWB technology, requires a centralized or non-cooperative methodology where each device receives/sends information from a fixed node. Furthermore, this table shows that we can use the same positioning methods for the same use cases but with LTE devices, where the target is connected only to known BSs in such radio technology. This table also shows the advantage of using UWB. It offers high availability and real-time positioning accuracy, so it is ideal to be adopted in industrial environment to improve service performance[24].

It is worth mentioning that Obeidat et al. [37] also present the advantages and disadvantages of each of the positioning methods studied, and make comparisons between them in [38]. For example, they show that AOA and TOA suffer from multipath, but RSS, which is very easy to deploy, does not. This study concludes that the choice of the appropriate positioning method depends on many factors, e.g., cost, resources availability, type of environment (indoor, outdoor, etc.), critical requirements, adopted network infrastructure, and the level of accuracy also required [1, 16, 18, 21, 39]. Thus, the following section shows what the new 5G mobile network will add to optimize the real-time positioning accuracy performance.

3. Positioning Technologies in 5G

As described before, the real-time accurate positioning of UEs in a wireless network is becoming increasingly important for critical use cases such as healthcare, environmental monitoring, navigation, and devices/vehicles communication [23]. Therefore, recently, positioning-based technologies in cellular networks have received increased support to improve the performance of positioning methods (e.g., E911). In this way, the positioning services have been integrated into the 3GPP use cases requirements [40]. Thus, the second release (Release 16) [41] of the 5G mobile network includes several features to support and enhance the positioning requirements of its predecessors (LTE). The main features of 5G that enable more accurate positioning are the millimeter-wave communication (mmWave) frequency bands that adopt directional beamforming, with which AOA positioning methods enable accurate angle estimation, especially in dense indoor multipath environment [21, 42]. The 3GPP is continuously working on positioning accuracy in the current release, Release 17 [43], to achieve, in theory, a performance accuracy of 1 meter. Then, 3GPP promises, in the future, high accuracy up to a few decimeters in Release 18. Thus, depending on the releases of the 5G standard, the promise of low latency and accurate positioning can only be expected from Release 17 onwards. However, today, the features of 5G are in the development phase, especially with regard to improved positioning accuracy. Therefore, Table 2 [44] presents the latency and the positioning accuracy in the different technologies. As shown in this table, the best results in latency and positioning accuracy are obtained with 5G technology and at the end of Release 18.

4. Discussion

Based on various studies, this section shows the improvement of positioning methods to improve accuracy performance.

As mentioned above, 5G Networks rely on mmWave technology to provide high frequency and bandwidth. The mmWave enables improved multipath resolution, as well as distance-based measurement accuracy [45, 46]. Abu-Shaban et al. [47] investigated the mmWave positioning limit under multipath channel conditions and reported the limit of the uplink and downlink positioning errors. While the correlation between some antennas [1, 48, 49], the uplink is more sensitive to the terminal direction, which reduces the interference of TOA measurement by other multipath signals. Lemic et al. [50] specify that only direct radiation is considered. In [51, 52], the authors proposed a data-driven deep neural network (DNN) approach to determine node positioning using a lower frequency spectrum.

As the need for 5G increases, the large-scale MIMO-based research has improved angle-based methods by enhancing the multiple signal classification algorithm (MUSIC) [53] and providing the signal of parameters estimation by the mean of rotational invariance techniques (ESPRIT) algorithm [21, 54–58]. On the one hand, research on massive MIMO technology has significantly improved the angular resolution [49], but in multi-path scenarios, it is still difficult to distinguish the line-of-sight (LOS) path and locate the user. In response to this problem, the authors of [46, 56, 59] proposed to directly measure the positioning distance. Guerra et al. [60] analyzed the maximum positioning performance that can be achieved using massive MIMO and mmWave beamforming methods in the single BS condition. The results in this study show the correlation between the beamforming observations, thus, this is provided by changing the number of antennas in terms of multipath reduction and positioning precision. Moreover, the combination of technologies (e.g., femtocells, mmWave, massive MIMO, etc.) could reduce

Table 1. Positioning methods intersected with wireless technologies and dedicated use cases.

Wireless Technology	Positioning Methods	Approach	Use Cases
LTE	TDOA	Non-cooperative	Navigation, health care, tracking, industrial automation
	TOA, RSS	Non-cooperative	Entertainment, indoor navigation, emergency services
	AOA	Non-cooperative	Radar, Indoor Tag positioning
UWB	TDOA	Non-cooperative	Navigation, health care, Personal tracking, industrial automation
	TOA, RSS	Cooperative	environmental monitoring, industrial monitoring, healthcare, logistics
	TOA, RSS	Non-cooperative	Entertainment, indoor navigation, emergency services
	AOA	Cooperative	Robot navigation
	AOA	Non-cooperative	Radar, indoor tag positioning
	Fingerprinting	Non-cooperative	Health care, positioning, retail, industrial monitoring
BLE	RSS	Non-cooperative	Personal tracking, storage database
	AOA	Non-cooperative	Radar, indoor tag positioning
WLAN	RSS	Non-cooperative	Personal tracking, storage database
	Fingerprinting	Non-cooperative	Healthcare, positioning, retail, industrial monitoring
RFID	RSS	Non-cooperative	Personal tracking, storage database

the issue of bottlenecks in a large infrastructure of indoor positioning systems [60].

The RSS-based method measures the strength of the received signal representing the distance between the user and the access point, it is one of the cheapest and easiest methods to implement, and it does not require any modification of existing systems [16, 61]. Many studies, such as [45, 59, 62–66], have adopted mmWave propagation, where the accuracy of RSS-based positioning depends on the measurement of the direct signal in an area [48].

Some researchers aim to combine two or more positioning methods to improve the positioning accuracy, and since the 5G systems support the implementation of various positioning methods. For example, [20, 59] proposed the hybrid positioning technique of ToA, AoA, RSS, and fingerprinting on the positioning accuracy when the number of BSs is less than three.

With the emergence of 5G, some studies [67, 68], have improved the fingerprint-based positioning methods, where the fingerprint matching is based on the statistical estimation of the target signal and the fingerprint library. The maximum estimation is used to determine the position through the statistics of the training set. Real-time experiments have been performed with LTE signals in indoor environments. These experiments enhance the real-time positioning measurements to provide accurate results everywhere. Many related fingerprint-based studies rely on the various probabilistic models to reflect the signal strength distribution of the reference position, such as Gaussian process [69], Bayesian network [70], conditional random fields [71], and more. However, the only drawback, which 5G IoT devices, is the compression rate of the fingerprint library. Therefore, the database of fingerprint is still a key challenge in such a positioning method.

5. Technical Challenges

Toward our project, there will be a huge use of distributed IoT devices in the 5G system, where the positioning information of the devices can provide the necessary support to optimize the data transmission. Compared to a dense network, many access points need to be deployed to improve positioning accuracy. Cooperative 5G positioning of devices in the IoT uses positioning information between terminals as a data source to improve positioning accuracy. Safavi et al. [72] proposed a distributed cooperative

Table 2. Performance of positioning services of 5G and other Technologies in term of accuracy and latency.

Technologies	latency (s)	positioning accuracy (m)
5G Release 16	5 ms	< 3 m
5G Release 17	<5 ms	1 m
5G Release 18	< 5ms	0.01 m
LTE	5ms	25 m
UWB	10 ms	0.01-2 m
BLE	10-20 ms	2-5 m
Wlan	10 ms	1- 5 m
RFID	< 1ms	1 m

linear iterative method to estimate the position of IoT devices. This solution is also suitable for dynamic scenarios, in which the positions of the UEs change. The drawback is the accumulated error from the positioning measurements. In this context, studies [17, 49] have suggested the conventional minimum mean square error (MMSE) method, removing unreasonable estimates to optimize errors of positioning problems. Bueher et al. [73] presented the status of cooperative positioning in 5G systems and IoT applications in terms of theoretical limitations, algorithm, and practical challenges, and relied on range-based as well as range-angle-based techniques.

Nowadays, 5G-based positioning research promises many improved results, but so far, everything is still in the theoretical phase and faces several challenges:

1. The eMBB functions offer the enabled use cases with high data rates over a wide coverage area, the positioning accuracy is very important to achieve the aforementioned goal, so some technical challenges need to be discussed:
    - The positioning of different devices is necessary to support the enhancement of the quality of service and data transmission, as well as the enhancement of energy consumption by improving the performance of the computational resource allocation [48];
    - In addition, interaction and implementation of more than one positioning method in a density and dynamic environment could improve the low latency, reliability, and validity of positioning results.
2. The functions of uRLLC provide real-time and reliable communication between devices. Thus, based on the positioning methods, the real-time integration of the location of different devices can ensure the reduction of errors during communication.
3. The functions of mMTC support the concept of power consumption and connection management of a large number of devices [1, 74]. In such scenarios, positioning technologies are needed to accurately locate cooperative devices to improve power consumption.

6. Conclusions

The new 5G mobile network promises to effectively digitize our entire physical world and meet the requirements of smart city stakeholders (citizens, municipalities, politics, industries, architects, etc.)[75]. For this reason, 5G has grouped the different use cases into three types of categories, which are: eMBB, mMTC, and uRLLC [21]. Each category involves a set of use cases sharing similar descriptions and needs [21].

In our work, our main challenge is to improve the potential for positioning accuracy in smart city platforms. However, this goal is strongly linked to the progress on 5G standards, these standards are the basis for all related work. It is also important to mention here that any technical specification normally requires important time before it can be implemented and used in a practical way (we mean here the know-how related documents). Therefore, we have limited the work in this paper to a summary of the literature on positioning technologies; a discussion of on the study of feasible positioning technologies based on 5G communication technologies; followed by the presentation of some technical challenges to present the current state of the positioning system, and its potential benefit of integration into 5G systems. 5G Release 18 promises to improve the positioning performance of 5G, especially for IoT-based use cases.

Our future work will focus on identifying the use cases that will be implemented in our smart city project, as well as improving the methodologies for accurate real-time positioning. The design of the defined use cases will be performed taking into account the requirements of the project partners (municipalities). Then, a proof of concept will be conducted to effectively evaluate the implementations and to initialize new topics for future research.

Acknowledgments

This work has been funded by the Federal Ministry of Education and Research (BMBF), Germany under the funding code 13FH9I02IA, within the research project FH-Impuls 2016: iCity-Intelligente Stadt. Nevertheless, overall responsibility for the content of this publication lies solely with the first author.

References

[1] Robin Chataut and Robert Akl. Massive MIMO systems for 5G and beyond networks—overview, recent trends, challenges, and future research direction. *Sensors*, 20(10): 2753, 2020.

[2] Series M. Minimum requirements related to technical performance for IMT-2020 radio interface (s). *Report*, pages 2410–0, 2017.

[3] Julius Burghardt, Lukas Höhn, and Dieter Uckelmann. Die potenziale von 5G für die intralogistik der zukunft. *Industrie 4.0 Management*, 38(3):57–60, 2022.

[4] Dajie Jiang and Guangyi Liu. An overview of 5G requirements. *5G Mobile Communications*, pages 3–26, 2017.

[5] Deliverable D1.1. Scenarios, requirements and KPIs for 5G mobile and wireless system, METIS. Technical report, 2013.

[6] Jose F. Monserrat, Genevieve Mange, Volker Braun, Hugo Tullberg, Gerd Zimmermann, and Ömer Bulakci. METIS research advances towards the 5G mobile and wireless system definition. *EURASIP Journal on Wireless Communications and Networking*, 2015(1):1–16, 2015.

[7] NGMN Alliances. 5G white paper. *Next generation mobile networks, white paper*, 1, 2015.

[8] Salam Traboulsi. Overview of 5G-oriented positioning technology in smart cities. *Procedia Computer Science*, 201:368–374, 2022.

[9] Karim Haricha, Azeddine Khiat, Yassine Issaoui, Ayoub Bahnasse, and Hassan Ouajji. Towards smart manufacturing: Implementation and benefits. *J. Ubiquitous Syst. Pervasive Networks*, 15(02):25–31, 2021.

[10] Nassima Tadrist, Olivier Debauche, Saïd Mahmoudi, and Adriano Guttadauria. Towards low-cost iot and lpwan-based flood forecast and monitoring system. *International Journal of Ubiquitous Systems and Pervasive Networks*, 17 (1), 2022.

[11] ITU. Work plan, timeline, process, and deliverables for the future development of IMT. *ITU-R WP5D*, 2015.

[12] Series M. IMT vision–framework and overall objectives of the future development of IMT for 2020 and beyond. *Recommendation ITU*, 2083, 2015.

[13] 3GPP. Service requirements for next generation new services and markets. 2016.

[14] 3GPP TR 38.913. Study on scenarios and requirements for next generation access technologies, ver. 14.3.0. Technical report, 2017.

[15] Valerio Frascolla, Federico Miatton, Gia Khanh Tran, Koji Takinami, Antonio De Domenico, Emilio Calvanese Strinati, Konstantin Koslowski, Thomas Haustein, Kei Sakaguchi, Sergio Barbarossa, et al. 5G-MiEdge: Design, standardization and deployment of 5G phase II technologies: MEC and mmWaves joint development for tokyo 2020 olympic games. In *2017 IEEE Conference on Standards for Communications and Networking (CSCN)*, pages 54–59. IEEE, 2017.

[16] Faheem Zafari, Athanasios Gkelias, and Kin K. Leung. A survey of indoor localization systems and technologies. *IEEE Communications Surveys Tutorials*, 21(3):2568–2599, 2019.

[17] Mingzhe Chen, Walid Saad, and Changchuan Yin. Virtual reality over wireless networks: Quality-of-service model and learning-based resource management. *IEEE Transactions on Communications*, 66(11):5621–5635, 2018.

[18] Zhiqiang Xiao and Yong Zeng. An overview on integrated localization and communication towards 6g. *Science China Information Sciences*, 65(3):1–46, 2022.

[19] Ryan Keating, Mikko Säily, Jari Hulkkonen, and Juha Karjalainen. Overview of positioning in 5G new radio. In *2019 16th International Symposium on Wireless Communication Systems (ISWCS)*, pages 320–324. IEEE, 2019.

[20] Ali Yassine, Youssef Nasser, Mariette Awad, and Bernard Uguen. Hybrid positioning data fusion in heterogeneous networks with critical hearability. *EURASIP Journal on Wireless Communications and Networking*, 2014(1):1–16, 2014.

[21] Ying Liu, Xiufang Shi, Shibo He, and Zhiguo Shi. Prospective positioning architecture and technologies in 5G networks. *IEEE Network*, 31(6):115–121, 2017.

[22] G. Destino. Positioning in wireless networks: Noncooperative and cooperative algorithms. *University of Oulu*, 2012.

[23] Dieter Uckelmann and Johannes Wendeberg. Echtzeitortungssysteme für industrie 4.0: Potentiale und stand der technik. *H. Zsifkovits S. Altendorfer-Kaiser (Hrsg.) Management logistischer Informationsflüsse: 3. Wissenschaftlicher Industrielogistik-Dialog in Leoben (WiLD 2015)*, pages 3–12, 2015.

[24] Linn Gerwin, Julian Schneider, and Dieter Uckelmann. Potenzialanalyse eines standards für ortungssysteme zum einsatz in der produktion und logistik. *Zeitschrift für wirtschaftlichen Fabrikbetrieb*, 117(1-2):56–60, 2022.

[25] Sun Guolin, Chen Jie, Guo Wei, and K.J. Ray Liu. Signal processing techniques in network-aided positioning: a survey of state-of-the-art positioning designs. *IEEE Signal Processing Magazine*, 22(4):12–23, 2005.

[26] Guoqiang Mao, Barış Fidan, and Brian DO Anderson. Wireless sensor network localization techniques. *Computer networks*, 51(10):2529–2553, 2007.

[27] Hui Liu, Houshang Darabi, Pat Banerjee, and Jing Liu. Survey of wireless indoor positioning techniques and systems. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 37(6): 1067–1080, 2007.

[28] Dieter Uckelmann and Giovanni Romagnoli. Rf-based locating of mobile objects. In *Proceedings of the 6th International Conference on the Internet of Things*, pages 147–154. ACM DL Digital Library, 2016.

[29] Mauro Brunato and Roberto Battiti. Statistical learning theory for location fingerprinting in wireless LANs. *Computer Networks*, 47(6):825–845, 2005.

[30] Yunye Jin, Wee-Seng Soh, and Wai-Choong Wong. Indoor localization with channel impulse response based fingerprint and nonparametric regression. *IEEE Transactions on Wireless Communications*, 9(3):1120–1127, 2010.

[31] Tarek El Saltia, Nelson Shawa, Joseph Chun-Chung Cheungb, and Edward R Sykesc. New and reliable points shifting-based algorithm for indoor location services. *International Journal of Ubiquitous Systems and Pervasive Networks*, 17, 2022.

[32] Junhai Luo, Liying Fan, and Husheng Li. Indoor positioning systems based on visible light communication: State of the art. *IEEE Communications Surveys & Tutorials*, 19(4): 2871–2893, 2017.

[33] Faheem Zafari, Athanasios Gkelias, and Kin K. Leung. A survey of indoor localization systems and technologies.

IEEE Communications Surveys & Tutorials, 21(3):2568–2599, 2019.

[34] Ramon F. Brena, Juan Pablo García-Vázquez, Carlos E. Galván-Tejada, David Muñoz-Rodriguez, Cesar Vargas-Rosales, and James Fangmeyer. Evolution of indoor positioning technologies: A survey. *Journal of Sensors*, 2017, 2017.

[35] George Oguntala, Raed Abd-Alhameed, Stephen Jones, James Noras, Mohammad Patwary, and Jonathan Rodriguez. Indoor location identification technologies for real-time IoT-based applications: An inclusive survey. *Computer Science Review*, 30:55–79, 2018.

[36] Mikkel Baun Kjærgaard, Henrik Blunck, Torben Godsk, Thomas Toftkjær, Dan Lund Christensen, and Kaj Grønbæk. Indoor positioning using gps revisited. In *International conference on pervasive computing*, pages 38–56. Springer, 2010.

[37] Huthaifa Obeidat, Wafa Shuaieb, Omar Obeidat, and Raed Abd-Alhameed. A review of indoor localization techniques and wireless technologies. *Wireless Personal Communications*, pages 1–39, 2021.

[38] Joaquín Torres-Sospedra, Raul Montoliu, Germán M. Mendoza-Silva, Oscar Belmonte, David Rambla, and Joaquín Huerta. Providing databases for different indoor positioning technologies: Pros and cons of magnetic field and wi-fi based positioning. *Mobile Information Systems*, 2016, 2016.

[39] 5Gradar. Technical report, 2019. https://www.5gradar.com/features/millimeter-wave-the-5g-mmwave-spectrum-explained.

[40] 3GPP. Study on positioning use cases; stage 1 (release 16). Technical report, TTR 22.872, 2020 .

[41] 3GPP. Study on scenarios and requirements for next generation access technologies (release 16). Technical report, TR 38.913 V16.0.0, 2020 .

[42] Satyam Dwivedi, Ritesh Shreevastav, Florent Munier, Johannes Nygren, Iana Siomina, Yazid Lyazidi, Deep Shrestha, Gustav Lindmark, Per Ernström, Erik Stare, et al. Positioning in 5G networks. *IEEE Communications Magazine*, 59(11):38–44, 2021.

[43] 3GPP. 5G in release 17—strong radio evolution. Technical report, TS 23.501 V16.1.0, 2019 .

[44] Fabian Dietrich. Teil 5: 5G in der intralogistik. *Proceedings of the 6th International Conference on the Internet of Things*, 2022. Webinar, 5G-Anwendungen und deren Potenziale. Fraunhofer IPA.

[45] Shu Sun, Theodore S. Rappaport, Mansoor Shafi, Pan Tang, Jianhua Zhang, and Peter J. Smith. Propagation models and performance evaluation for 5G millimeter-wave bands. *IEEE Transactions on Vehicular Technology*, 67(9):8422–8439, 2018.

[46] Nil Garcia, Henk Wymeersch, Erik G. Larsson, Alexander M. Haimovich, and Martial Coulon. Direct localization for massive MIMO. *IEEE Transactions on Signal Processing*, 65(10):2475–2487, 2017.

[47] Zohair Abu-Shaban, Xiangyun Zhou, Thushara Abhayapala, Gonzalo Seco-Granados, and Henk Wymeersch. Error bounds for uplink and downlink 3D localization in 5G Millimeter-Wave systems. *IEEE Transactions on Wireless Communications*, 17(8):4939–4954, 2018.

[48] Xueyan Han, Jingjing Wang, Wei Shi, Qiuna Niu, and Lingwei Xu. Indoor precise positioning algorithm using 60GHz pulse based on compressive sensing. *Journal of Mathematics and Computer Science*, 16:256–272, 06 2016.

[49] Jincheng Lin, Xiaochuan Ma, Shefeng Yan, and Chengpeng Hao. Time-frequency multi-invariance esprit for DOA estimation. *IEEE Antennas and Wireless Propagation Letters*, 15:770–773, 2015.

[50] Filip Lemic, James Martin, Christopher Yarp, Douglas Chan, Vlado Handziski, Robert Brodersen, Gerhard Fettweis, Adam Wolisz, and John Wawrzynek. Localization as a feature of mmWave communication. In *2016 international wireless communications and mobile computing conference (IWCMC)*, pages 1033–1038. IEEE, 2016.

[51] Marcus Z. Comiter, Michael B. Crouse, and HT. Kung. A data-driven approach to localization for high frequency wireless mobile networks. In *GLOBECOM 2017-2017 IEEE Global Communications Conference*, pages 1–7. IEEE, 2017.

[52] Fuxi Wen, Henk Wymeersch, Bile Peng, Wee Peng Tay, Hing Cheung So, and Diange Yang. A survey on 5G massive MIMO localization. *Digital Signal Processing*, 94:21–28, 2019.

[53] Ralph Schmidt. Multiple emitter location and signal parameter estimation. *IEEE transactions on antennas and propagation*, 34(3):276–280, 1986.

[54] Richard Roy and Thomas Kailath. ESPRIT-estimation of signal parameters via rotational invariance techniques. *IEEE Transactions on acoustics, speech, and signal processing*, 37(7):984–995, 1989.

[55] Zhipeng Lin, Tiejun Lv., and P. Takis Mathiopoulos. 3-D indoor positioning for millimeter-wave massive MIMO systems. *IEEE Transactions on Communications*, 66(6):2472–2486, 2018.

[56] Claudio Bohorquez, G. Fraidenraich, and Luciano Mendes. Probability of detection of the angle of arrival for massive mimo arrays. *IEEE Access*, PP:1–1, 10 2018.

[57] AJ. Van der Veen, Michaela C. Vanderveen, and Arogyaswami Paulraj. Joint angle and delay estimation using shift-invariance techniques. *IEEE Transactions on Signal Processing*, 46(2):405–418, 1998.

[58] Ziyu Guo, Xiaodong Wang, and Wei Heng. Millimeter-wave channel estimation based on 2-D beamspace MUSIC method. *IEEE transactions on wireless communications*, 16(8):5384–5394, 2017.

[59] Ke Han, Yun Liu, Zhongliang Deng, Lu Yin, and Lingjie Shi. Direct positioning method of mixed far-field and near-field based on 5G Massive MIMO system. *IEEE Access*, PP:1–1, 03 2019.

[60] Anna Guerra, Francesco Guidi, and Davide Dardari. Single-anchor localization and orientation performance limits using massive arrays: MIMO vs. beamforming. *IEEE Transactions on Wireless Communications*, 17(8):5241–5255, 2018.

[61] Gang Wang, Hongyang Chen, Youming Li, and Ming Jin. On received-signal-strength based localization with unknown transmit power and path loss exponent. *IEEE Wireless Communications Letters*, 1(5):536–539, 2012.

[62] Theodore S. Rappaport, Yunchou Xing, George R. MacCartney, Andreas F. Molisch, Evangelos Mellios, and Jianhua Zhang. Overview of Millimeter-Wave communications for fifth-generation (5G) wireless networks—with a focus on propagation models. *IEEE Transactions on antennas and propagation*, 65(12): 6213–6230, 2017.

[63] Haiming Wang, Peize Zhang, Jing Li, and Xiaohu You. Radio propagation and wireless coverage of LSAA-based 5G millimeter-wave mobile communication systems. *China Communications*, 16:1–18, 2019.

[64] Usman Virk and Katsuyuki Haneda. Modeling human blockage at 5G Millimeter-Wave frequencies. *IEEE Transactions on Antennas and Propagation*, PP:1–1, 10 2019.

[65] OC. Nosiri, CF. Umanah, CC. Otubelu, and OO. Okechukwu. Performance analysis of millimeter-wave pathloss propagation models for 5G network in an indoor environment. *vol*, 9:32–38, 2020.

[66] Zhijian Lin, Xiaojiang Du, Hsiao-Hwa Chen, Bo Ai, Zhifeng Chen, and Dapeng Wu. Millimeter-wave propagation modeling and measurement. *arXiv preprint arXiv:1804.02027*, 2018.

[67] Chengke Liu, Zengshan Tian, Mu Zhou, and Xiaolong Yang. Gene-sequencing-based indoor localization in distributed antenna system. *IEEE Sensors Journal*, 17(18): 6019–6028, 2017. .

[68] George Oguntala, Raed Abd-Alhameed, S. Jones, James Noras, Mohammad Patwary, and Jonathan Rodriguez. Indoor location identification technologies for real-time IoT-based applications: An inclusive survey. *Computer Science Review*, 30:55–80, 11 2018.

[69] Mohamed M. Atia, Aboelmagd Noureldin, and Michael J. Korenberg. Dynamic online-calibrated radio maps for indoor positioning in wireless local area networks. *IEEE Transactions on Mobile Computing*, 12(9):1774–1787, 2012.

[70] Nayef Alsindi, Zdenek Chaloupka, Nuha AlKhanbashi, and James Aweya. An empirical evaluation of a probabilistic rf signature for WLAN location fingerprinting. *IEEE Transactions on Wireless Communications*, 13(6):3257–3268, 2014.

[71] Zhuoling Xiao, Hongkai Wen, Andrew Markham, and Niki Trigoni. Lightweight map matching for indoor localisation using conditional random fields. In *IPSN-14 proceedings of the 13th international symposium on information processing in sensor networks*, pages 131–142. IEEE, 2014.

[72] Sam Safavi, Usman A. Khan, Soummya Kar, and José MF. Moura. Distributed localization: A linear theory. *Proceedings of the IEEE*, 106(7):1204–1223, 2018.

[73] R. Michael Buehrer, Henk Wymeersch, and Reza Monir Vaghefi. Collaborative sensor network localization: Algorithms and practical issues. *Proceedings of the IEEE*, 106(6):1089–1114, 2018.

[74] LTD. HUAWEI TECHNOLOGIES CO. 5G power whitepaper. Technical report, 2019. https://www.huawei.com/minisite/5g-ultra-lean-site-2019/pdf_v1.0/5G-Power-White-Paper-en.pdf.

[75] Peter Balco, Košecká Dorota, and Peter Bajzík. Small towns and regional municipalities implement smart solutions, identified issues, and challenges. *International Journal of Ubiquitous Systems and Pervasive Networks*, 17(1), 2022.