Localization in 6G: A Journey along existing Wireless Communication Technologies

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***Abstract*—In this study, the authors examine the technical challenges associated with wireless localization algorithms in indoor environments. The paper presents an in-depth analysis of various wireless communication technologies, meticulously summarizing their salient features and their implications within the broader scope of research. The outcomes of this study contribute significant technical insights into the capabilities and limitations of Joint Communications and Sensing (JCAS) technology. These insights are pivotal for advancing seamless data exchange and achieving comprehensive connectivity in the realm of 6G wireless communication networks, particularly those that integrate localization functionalities. The detailed findings of this research are poised to inform and influence subsequent technical research and developmental strategies in this specialized field.**

***Index Terms*—Indoor localization, JCAS, wireless technologies**

I. Introduction

In a world where precise localization of objects and individuals is becoming increasingly crucial, the sixth generation of mobile communication, 6G, opens up revolutionary possibilities. Known for its high speed, large capacity, and ultra-low latency, 6G is not just an evolution in connectivity but a gateway to advanced localization methods. The integration of 6G into modern communication networks promises to fundamentally change our approach to data and our spatial relationship with the environment.

At the forefront of this development is the concept of *Joint Communication and Sensing (JCAS)*. JCAS represents a significant innovation by merging the functionalities of communication and sensing into a unified technology. This integration goes beyond traditional communication paradigms, offering unique opportunities for precise localization and environmental understanding. In particular, the localization functions within JCAS, supported by 6G technology, open new horizons for applications such as object tracking, environmental monitoring, and indoor localization ([1]).

The challenge lies in efficiently integrating advanced localization techniques into 6G communication networks. This requires innovative developments in waveforms, signal processing algorithms, and network architectures specifically optimized for supporting localization functions. Moreover, the accuracy and reliability of localization data are crucial, necessitating the use of advanced sensing techniques and high-precision sensors.

In conclusion, JCAS, empowered by the capabilities of 6G, presents a forward-looking concept that could revolutionize the way we use mobile communication networks and localization technologies. While there are many challenges to overcome, an accelerated development of new technologies and applications is expected in the coming years, opening up new opportunities for innovation and growth in the fields of mobile communication and localization ([1]).

The subsequent sections will delve deeper into these developments. Section II addresses localization in general, while Section III examines various wireless technologies that already support localization features, including their current state of research regarding indoor localization. Section IV discusses the realm of JCAS and the idea, how far approaches of existing wireless communication technologies could be adopted by 6G. Based on this, Section V provides an overview of the open challenges concerning 6G. Finally, Section VI summarizes the key aspects at the end of this paper.

II. Localization

The aim of achieving precise indoor localization remains a vibrant area of research, distinctively challenging when contrasted with the outdoor scenario. While outdoor localization has largely been mastered through the *Global Positioning System (GPS)*, achieving similar levels of accuracy indoors presents a unique set of challenges. Notably, indoor environments often lack GPS signal availability, and the accuracy of GPS-based algorithms typically diminishes indoors often to a level of only a few meters' precision ([2]).

Indoor localization algorithms, particularly those based on wireless technologies, encounter physical phenomena like signal reflections and multi-path propagation. These phenomena can significantly distort the measurements of various parameters which are pivotal in determining an object's location within an indoor setting. This situation necessitates the development of innovative algorithms designed to reduce localization errors.

Addressing these challenges, this section will focus on wireless technology-based localization methods suitable for indoor settings. It will also introduce advanced algorithms designed to minimize positional errors, specifically targeting the unique inaccuracies prevalent in indoor localization.

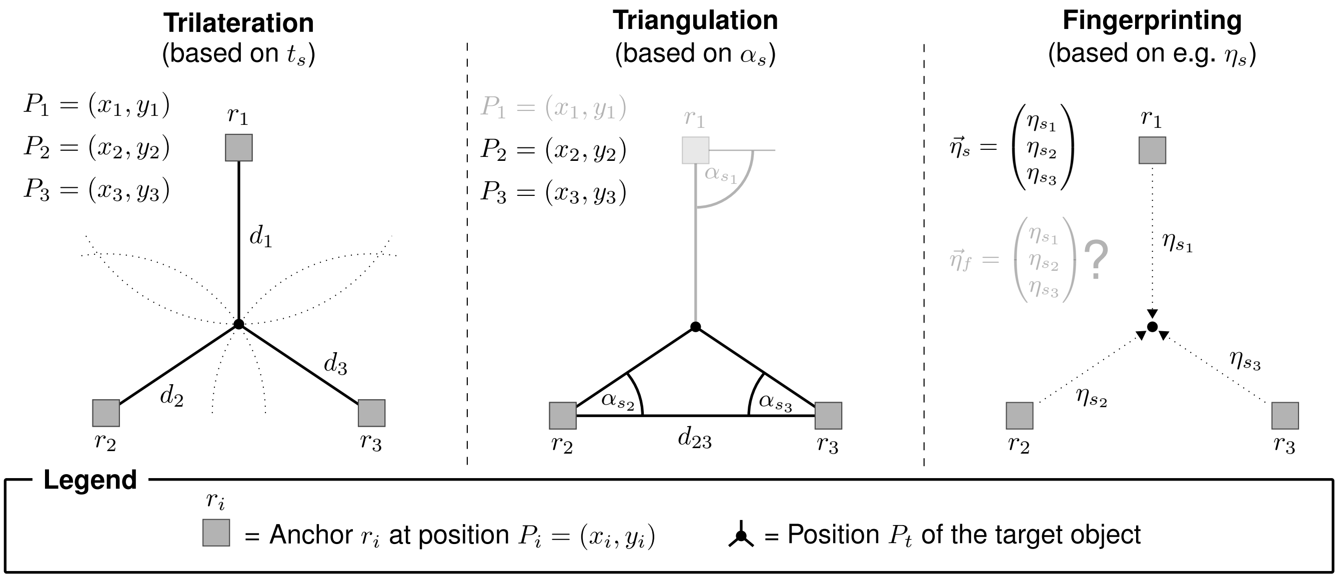

Figure 1. Localization algorithms to calculate the target position P_t in $\mathbb{R}^2$ (acc. [3], [4])

A. Localization algorithms for wireless technologies

To accurately localize a target object using wireless technologies, the physical properties of their signals are utilized. Specifically, the following physical parameters can be measured:

- the time t_s of transmitting data from the sender side to the receiver side,
- the angle α_s of an incoming signal,
- the received signal strength η_s.

Depending on these physical parameters, different algorithms exist which allow to determine the current position P_t of a target object. These algorithms are summarized in Figure 1.

As shown in this figure, *trilateration* can be used, if at least three reference points r_i, which are called *anchors*, are available. In addition to that, the distances d_i to these anchors and their positions P_i have to be known. For calculation of the distance d_i, the time t_{s_i} and the speed of signal propagation v_s or the signal strength η_s have to be determined ([4]). Regarding the time t_s, several methods to measure this parameter exist. For instance, Obeidat et al. cite the *time of arrival (ToA)* and the *time difference of arrival (TDoA)* in [3]. Only the former is shown in Figure 1.

Another approach is to calculate P_t by using angular information. The Figure 1 shows that *triangulation* can be used, if at least two anchors r_j and r_k are available. In addition, their angles α_{s_j} and α_{s_k}, respectively, as well as the distance d_{jk} between the corresponding anchors have to be known. In this regard, the terms *direction of arrival (DoA)* and *angle of arrival (AoA)* are often used in literature ([3], [4]).

The *fingerprinting* algorithm, which is also illustrated in Figure 1, can be compared with a pattern matching approach ([3], [4]). The basic idea of this method is to compare the measured parameters, e.g. the *received signal strengths (RSS)* $\vec{\eta}_s$ of all surrounding anchors with all available data sets in a database. It should be noted that these data sets are recorded at different positions P_j before such a fingerprinting algorithm is executed. The position P_t of the target is set to the position P_j of the data set $\vec{\eta}_f$, which is most *similar* to the measured parameters $\vec{\eta}_s$. Similarity is calculated by using different distance metrics, e.g. *Euclidean* or *Manhattan distance* that are described in [5].

Besides wireless technologies, further algorithms, e.g. *proximity* and *dead reckoning* exist. These algorithms are not shown in Figure 1 but are still mentioned in [3] and [6].

B. Error minimization algorithms

The algorithms shown in Figure 1 represent ideal cases. More precisely, it was assumed that the positioning error ε_t is zero for each algorithm. In the reality, measurements are subject to uncertainty. Consequently, deviations from the real position P_t may occur, which result in a positioning error ε_t.

In regard to indoor localization, various algorithms have been developed that can reduce the positioning error ε_t. *Sensor fusion* is often considered in recent literature that combines different sources of sensor data to improve the quality of results. Consequently, in context with localization purposes, using sensor fusion enables the minimization of the positioning error ε_t.

For instance, Marković et al. describe in [2] a localization system, which is used for tracking of an *unmanned aerial vehicle (UAV)* in an indoor environment, where GPS signals are not available. More precisely, the authors use four different devices to record sensor data, which are fused to improve the positioning accuracy. In this way, they combine the acceleration a and angular velocity ω of an *inertial measurement unit (IMU)* with the calculated position P_t, which is determined by an *Ultra Wideband (UWB)* system, environment information that are provided by a *LiDAR*, and visual information of a camera.

To combine the whole sensor data, in [2], Marković et al. use an extended version of a *Kalman filter* to improve the positioning accuracy of their UAV. In 1960, Kálmán introduced the original algorithm in [7] to estimate the state s_j of a system at time t_j based on its current state s_{j-1} at time t_{j-1}, its underlying physical model and the recorded measurement of sensor data in consideration of uncertainty. In regard to localization, the state of a system could correspond to the position P_t of a target. Simply put, the algorithm of the Kalman filter can be divided into two phases:

1) Prediction of the new state $s_{j|j-1}$ by using the mathematical correlations of the underlying physical model and the current state s_{j-1},
2) Combination of the predicted state $s_{j|j-1}$ and the measured state z_j, which is determined by the recorded measurement, to estimate the new state s_j of the system.

Due to high complexity, the mathematical background of the Kalman filter is not described in detail. For further reading, reference [7] is recommended.

There are other algorithms called *particle filters* that are also able to combine different types of sensor data to improve the accuracy of positioning. According to Nurminen et al. in [8], a particle filter based on a *Monte Carlo algorithm*. Therefore, a certain number of random states $\vec{s}_{j-1}$ of a system, which are called *particles*, are generated first. After that, by applying measured sensor data, which correspond to the state z_{j-1}, to all previously generated states $\vec{s}_{j-1}$, the latter are transitioned to their following state $\vec{s}_{j|j-1}$. Finally, by comparison of the predicted state $\vec{s}_{j|j-1}$ with the measured state z_j based on the measured sensor data, all predicted states $\vec{s}_{j|j-1}$ that do not match z_j are deleted ([8]).

By repeating the previously described steps of a particle filter, after finite time steps, the diversity of generated states $\vec{s}$ will be increasingly reduced. Consequently, in context with localization, the current position P_t of a target can be determined after several iterations.

III. Wireless Communication Technologies with Localization Support

In the realm of indoor localization, a variety of wireless technologies are employed, each characterized by distinct physical properties that influence the accuracy of localization algorithms. Consequently, this section will discuss four different wireless technologies and their current research status in relation to indoor localization.

A. IEEE 802.11 Wireless Local Area Networks

Since its inception in the 1990s, WLAN, or Wi-Fi, has become a staple in providing wireless data connections in homes, businesses, and public hotspots. With the widespread adoption of over nine billion Wi-Fi devices globally, primarily for video streaming and emerging uses in VR, AR, gaming, and cloud computing, the demand for higher data rates and lower latency is ever-growing ([9]).

To address these demands, the IEEE 802.11 standards committee is set to release the *IEEE 802.11be - Extremely High Throughput (EHT)* standard, also known as Wi-Fi 7, succeeding the *IEEE 802.11ax* (Wi-Fi 6). This new standard aims to deliver significantly higher throughput rates and lower latency. It targets a maximum throughput of at least 30 Gbps and will operate over a carrier frequency range of 1 to 7.250 GHz. According to [9], the considered IEEE standard will maintain backward compatibility with older IEEE 802.11 devices across the 2.4, 5, and 6 GHz bands.

Wi-Fi also finds innovative use in indoor localization as a form of radar. This technique, known as *Wi-Fi sensing* or *passive Wi-Fi radar*, exploits changes in wireless signals that are caused by human movement. As individuals move, they impact the Wi-Fi signal in terms of frequency shift, propagation paths, and signal attenuation. Analyzing these deviations enables the location of a person to be determined. This method offers key advantages such as non-intrusive operation, preservation of privacy, and widespread availability in indoor settings ([10]).

B. Bluetooth

Bluetooth, standardized under *IEEE 802.15.1*, is a widely-used wireless technology designed for short-range device connectivity. Operating on radio frequencies between 2.402 GHz and 2.480 GHz, akin to Wi-Fi, Bluetooth is known for its cost-effectiveness, low power usage, secure communication, and user-friendly solutions.

The advent of *Bluetooth Low Energy (BLE)* has further enhanced this technology. BLE boasts of high power efficiency, with a coverage range of 70 to 100 meters and a data rate of up to 2 Mbps. However, it's important to note that Bluetooth, including BLE, is not ideally suited for large-scale localization tasks. BLE has found application in localized scenarios such as airports, train stations, and shopping centers, using neural networks trained on the received signal strength η_s for indoor positioning in these environments ([3], [11]).

As highlighted by Toasa et al. in [12], Bluetooth 5.1 introduces a *directional finding* feature, particularly beneficial for location services in *Internet of Things (IoT)* scenarios. This feature employs techniques like AoA and *angle of departure (AoD)* to ascertain the angular position of transmitted signals, significantly enhancing indoor positioning accuracy and offering substantial advantages for IoT applications. Further advancements in Bluetooth-based indoor positioning involve various techniques. These include localization fingerprinting methods using RSS in conjunction with multi-path interference and power control, as well as approaches utilizing multiple antennas and trilateration or adaptive machine learning frameworks for AoA estimation, as discussed in [13] and [14].

C. Ultra Wideband

Ultra Wideband (UWB) technology stands out from other wireless technologies due to its low-energy consumption and robustness against multi-path propagation. UWB is predominantly utilized for localization, offering centimeter-level accuracy, rather than communication. Its distinguishing features include a large bandwidth of at least 500 MHz and specific functionalities detailed by Obeidat et al. in [3].

In terms of recent advancements, Mayer et al. describe in [15] a self-sustaining UWB-based indoor localization system designed for mobile sensor nodes. This system can pinpoint the location of a node within a 200 m^2 area in *non-line-of-sight (NLOS)* conditions. The system employs small, solar-powered tags, ideal for long-term operation without the need for battery recharging. An event-driven algorithm further enhances energy efficiency, and the system achieves a maximum localization error of less than 40 cm in two-dimensional space.

In [16], Huang et al. explore the challenges posed by multi-path propagation in NLOS scenarios for UWB-based systems. They developed an algorithm that enhances positioning accuracy by integrating data from an inertial measurement unit with UWB sensor data, effectively reducing measurement errors caused by multi-path effects. This sensor fusion approach has shown to increase positioning accuracy in NLOS scenarios, although it is noted that in *line-of-sight (LOS)* conditions, this method may be less accurate than using UWB alone.

Cerro et al. investigate UWB in terms of indoor localization in a more theoretical manner. More precisely, in [17], the authors present a design tool for optimizing the placement and the minimum number of anchors in a two-dimensional space. This tool considers various parameters, such as the localization algorithm used, the maximum number of available anchors, uncertainty models of devices, and desired positioning accuracy. It is designed to predict the most effective setup for enhancing the accuracy of indoor localization algorithms.

D. Cellular Networks

Cellular networks, as detailed by Tanenbaum et al. in [18], originated in the early twentieth century, primarily serving military and maritime communication needs. Today, these networks are integral to daily life, facilitating communication between modern mobile devices like smartphones.

The evolution of mobile communication has been marked by significant milestones. The first and second generations were primarily focused on transmitting analog and digital voice, respectively. However, it was in the 1990s that a major shift occurred with the standardization of mobile communication by the *3rd Generation Partnership Project (3GPP)*, starting with the third generation (3G). This standardization enabled the transmission of both digital voice and data ([4], [18]). Presently, 3GPP is in the process of standardizing the fifth (5G) and sixth (6G) generations of mobile communication. These newer generations promise substantially higher data transmission rates and lower latency compared to the fourth generation (4G). Additionally, 5G and 6G are increasingly focusing on enhancing localization capabilities ([4]). Thus, the following sections will delve into these two advanced mobile communication standards, exploring their implications and developments in the context of localization.

1) The fifth generation (5G): The fifth generation (5G) of mobile communication, as expanded by 3GPP in 2021, has incorporated localization features, a significant advancement in the field. In [19], Palamà et al. explore the potential of open-source software systems representing the software component of a *Radio Access Network (RAN)* within the 5G architecture. By integrating these systems with a *software-defined radio (SDR)*, the authors demonstrate the feasibility of constructing a 5G network using open-source software and SDRs. Additionally, this setup enables the testing of preliminary localization algorithms that based on ToA measurements.

In a similar vein, Ruan et al. discuss *Hi-Loc*, a 5G indoor localization system that also incorporates a software-defined radio, in [20]. Moreover, they introduce a novel localization algorithm that utilizes the *Channel State Information (CSI)* of 5G signals. Their research findings indicate that the Hi-Loc system can localize a target object within a few meters. Specifically, the positioning error ε_t of their system can be as low as three meters, varying based on the indoor environment.

Especially for localization approaches, 3GPP standardizes a *Localization Management Function (LMF)* for the 5G core network ([21]). Currently, this feature is not implemented by existing open source 5G core solutions like *OpenAirInterface* and *Open5GS* ([22], [23]). However, Pinto et al. have already proposed a possible implementation of the LMF in [24].

A possible signal metric, which can be used by the LMF to calculate the position of a target UE, is the *positioning reference signal (PRS)*. It was already introduced by 3GPP in 2009 to add positioning capabilities to 4G networks ([25]). To increase the positioning accuracy, 5G introduces an enhanced version of PRS for downlink (DL-PRS) and the *sounding reference signal (SRS)* for uplink (UL-SRS), which are used for the standardized UE positioning methods ([26]). Referring to this, in [27], Huang et al. propose a PRS detection algorithm, which based on the TDoA method and the DL-PRS.

In [28], Håkegård et al. also investigate open source 5G implementations regarding the coverage, throughput and latency of *5G standalone (SA) networks*. In combination with SDRs, the authors reveal the relationship between configuration and performance of such a 5G network. Additionally, they conclude that current open source 5G SA networks are not able to reach the full potential of 5G, because of limitations in available software and hardware.

2) The sixth generation (6G): The sixth generation (6G) will redefine mobile communications by 2030 and beyond. It is expected that 6G will offer extremely high data transfer rates, ultra-low latency and massive connectivity, which are essential to support a wide range of new applications. These applications range from smart environments and holographic communication to high-precision industrial manufacturing. To meet these ambitious goals, 6G will likely utilize cutting-edge technologies such as edge computing, network slicing, and massive *multiple input multiple output (MIMO)* systems. The detailed potential requirements, challenges, and evolutionary trends of 6G are thoroughly discussed in [29] and [30].

In Germany, the *Federal Ministry of Education and Research (BMBF)* has initiated a funding program for 6G research, aiming to position the country as a key player in the global development of 6G technology. Early projects under this initiative include:

- *6G-ANNA* that focuses on developing comprehensive 6G mobile network solutions.

Table I
OVERVIEW OF SELECTED COMMUNICATION-CENTRIC WIRELESS TECHNOLOGIES FOR SENSING PURPOSES (ACC. [3])

Technology	**Technique**	**Parameter**	**Reference list**
WiFi	Trilateration, Fingerprinting	ToA, TDoA, CSI, RSS	[3], [10]
Bluetooth	Trilateration, Triangulation, Fingerprinting	ToA, AoA, AoD, RSS	[3], [12], [13]
UWB	Trilateration, Triangulation, Fingerprinting	ToA, TDoA, AoA, RSS	[3], [17]
5G	Trilateration, Fingerprinting	ToA, RSS, CSI	[3], [20]

- *MassIMO* that is dedicated to creating a distributed multi-antenna system for 6G.
- *6G-TakeOff* that seeks to design an innovative 6G network architecture integrating ground stations, airborne platforms, and satellites.

Further projects such as *6G-Health*, *6G-ICAS4Mobility* and *6G-LICRIS* are set to explore various facets of 6G technology, including medical technology, system architecture and reconfigurable surfaces, respectively ([31]).

IV. JOINT COMMUNICATION AND SENSING

Radar technology, which utilizes radio signals for the detection of presence, shape, position, and movement speed of objects, is widely used in military, aircraft, and vehicular applications. Despite its extensive use in these areas, the commercial implementation of radar-based sensing in mobile networks has remained relatively limited. The advent of broadband 5G systems and the proliferation of dense small-cell networks, however, open new possibilities for sensing applications, a potential that has begun to be explored ([1]).

Joint Communications and Sensing represents an innovative convergence of wireless communication and radar sensing into a unified system ([32]). Additionally, Zhang et al. categorize JCAS systems into three distinct types in [32]: *Radar-centric design*, *communication-centric design*, and *joint design and optimization*. The wireless technologies discussed in Section III belong to the class communication-centric design. These technologies are capable of integrating radar sensing functions within a primarily communication-focused system. In the realm of 6G, the use of communication-centric systems as proxy technologies facilitates the implementation of JCAS.

In this regard, Table I presents a concise overview of selected communication-centric wireless technologies for sensing purposes. However, there remains a degree of uncertainty regarding the extent to which insights from these proxy technologies can be effectively applied in the design and development of JCAS for 6G.

As an example for JCAS, Sun et al. propose a localization algorithm in [33] that based on the wireless communication technology BLE. More precisely, the authors utilize the metrics AoA and RSS of their Bluetooth sensors in combination with a fingerprinting method to localize a target indoors.

For JCAS development, a balanced approach that leverages the strengths of both communication and sensing technologies is required. Successful implementation of JCAS in 6G is likely to necessitate a mix of communication-centric designs and joint optimization strategies to meet the demands for high data rates, low latency, high accuracy, and efficiency.

The flexibility in choosing the design approach, whether communication-centric, radar-centric, or a joint optimization, enables tailored development of JCAS systems for specific use cases and needs. This highlights the importance of an adaptable framework that can accommodate the unique requirements of diverse applications while addressing the challenges and uncertainties inherent in merging communication and sensing functionalities.

V. OPEN CHALLENGES AND RESEARCH DIRECTIONS FOR JCAS IN 6G

Several pivotal research areas in the domain of JCAS for 6G wireless communication networks have been identified in [1]. These areas encompass a diverse range of topics, including distributed sensing, multi-band sensing, AI/ML processing, sensor fusion, channel modeling specific to JCAS, and the investigation of potential waveform candidate schemes. A notable aspect of this research is the enhancement of communication through sensing and localization. These capabilities can directly augment communications, for instance, by anticipating device blockages in scenarios demanding high reliability, and leveraging geolocation data for more effective beamforming. Liu et al. delve into the synergistic relationship between JCAS and other emerging technologies in [34]. An area of particular interest is the integration of JCAS with edge intelligence, underscoring the crucial role of AI algorithms in processing the data generated by JCAS systems. Additionally, it is anticipated that the amalgamation of JCAS with *Reconfigurable Intelligent Surfaces (RIS)* will yield significant enhancements in both sensing and communication capabilities, potentially improving coverage, accuracy, and the resolution of sensing.

VI. CONCLUSION

In summary, this paper has explored the role of JCAS as a pivotal technology in the advancement of 6G wireless communication networks, with a special emphasis on its application in wireless communication technologies aiding localization. The research has reviewed the current state of various wireless technologies, including IEEE 802.11, Bluetooth, Ultra Wideband, and cellular networks, and their relevance to indoor localization.

The study highlights the critical need to tackle the existing challenges and chart new research directions for JCAS in the context of 6G, to fully harness its capabilities and foster groundbreaking applications in mobile communication and sensing sectors. This research illuminates the vital contribution that JCAS is poised to make in the evolution of 6G wireless communication networks. It stresses the importance of ongoing research and development in this area. By addressing the challenges identified and delving into the suggested research pathways, JCAS technology is expected to transform the landscape of mobile communication networks and radio sensing technologies significantly, opening doors to novel innovations and growth opportunities.

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