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Localization Techniques Overview Towards 6G Communication

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Abstract: Worldwide Researchers and scientist have started the investigation of the sixth generation (6G) while the fifth generation (5G) cellular system is being deployed. Under this main investigation the main aim of 6G is to provide intelligent and ubiquitous wireless connectivity with Terabits per second (Tbps) data rates. Accurate location information of the mobile devices is very much useful to accomplish these aims with the improvements of various parameters of wireless communication. The development in communication technology often creates new opportunities to improve the localization efficiency as demonstrated by the expected centimetre-level localization accuracy in 6G. While there are comprehensive literatures separately on wireless localization or communications, the 6G study is still in its inception. This article is therefore intended to provide an overview of localization techniques towards 6G wireless networks. Finally, some interesting future localization technique research directions are highlighted.

Keywords: Wireless localization, integrated localization and communication, cellular networks, 6G

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I. INTRODUCTION

Although the worldwide fifth generation (5G) cellular infrastructure is being deployed, researchers have begun researching mobile communication networks of the sixth generation (6G). Although 6G's critical specifications and main use scenarios are still to be established, it is believed that 6G should be able to provide Terabits per second (Tbps) data rate and sub-millisecond (sub-ms) latency over three-dimensional (3D) network coverage with intelligent and limitless wireless connectivity. Acquiring accurate location information from mobile terminals is becoming extremely useful to accomplish such objectives, not only for location-based services, but also to enhance the efficiency of wireless communication in various ways, such as channel estimation, beam alignment, medium access control, routing, and optimization of the network. The improvement, on the other hand, communication technologies also offer fresh

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opportunities to significantly improve the efficiency of localization, as demonstrated by the planned localization precision at the centimetre level in 6G MIMO (multiple-input multiple-output) and millimetre wave (mmWave) ultra-massive technology. In this respect, the Integrated Localization and Communication (ILAC), an integrated research is important to unlock the full potential of wireless networks for integrated localization and communication and for dual purposes, best use of network infrastructure and radio resources. Although there are substantial literatures separately on wireless localization or communications, ILAC research is still in its inception.

Wireless localization has been included as a mandatory feature in the standardisation and implementation of cellular networks beginning from the second generation (2G), with continuous improvement of localization accuracy over each generation, e.g., from hundreds of metres of precision in each generation. Localization for the coming fifth generation (5G) of mobile networks, due to its basic support for different location-based services, it is considered one of the key components and the location accuracy requirement is up to the sub-meter level [1]. For future cellular networks, the availability of accurate real-time location information for mobile terminals is expected to play an increasingly important role. Although the implementation of 5G networks is underway, the sixth investigation has already begun by researchers around the world. (6G) mobile connectivity generation targeting the 2030 network with different visions proposed [2]–[6]. For example, it was expected that "ubiquitous wireless Intelligence" should be achieved by 6G, to provide users anywhere in the world with smart context-aware services through wireless connectivity. This results in the acquisition of the right real-time location. User knowledge is becoming more important than ever before, with 6G localization accuracy at the possible centimetre stage [4]. In cluttered environments, however most current localization services provided by global navigation satellite systems (GNSS), wireless local area networks (WLAN) or cellular networks can achieve meter-level localization precision at best. The centimeter-level localization accuracy requirements of many emerging applications are difficult to meet with such coarse localization services. For example, the following three promising 5G and beyond network usage scenarios, namely, intelligent interactive networks, smart city, and automatic factory, all highlight the crucial role of precise localization in future network design.

Intelligent interactive networks: It is assumed that the ultimate aim of communication networks is to facilitate intelligent people-to-people connections across the globe. people-to-machine, and machine-to-machine-to-machine. An exceptional growth of the new Internet of Things (IoT) services such as multisensory extended reality (XR) covering Augmented/mixed/virtual (AR/MR/VR) fact [7], brain computer interfaces (BCI) [3], as well as tele-presence and tele-control services [4], brings excellent opportunities to realize the goal of interaction with everything. For such new applications to be introduced, it is important to achieve the high efficiency of localization.

Smart City: The term "smart city" defines the concept in which a city significantly enhances the quality of life (QoL) for the people in it by optimising its operations and functions to sense, detect, evaluate and act by integrating the core components that operate the city using the available infrastructures. A smart city has the potential to evaluate various social needs effectively and to manage and leverage public resources, such as power, water, transportation and healthcare, in a reasonable way, in order to provide better public services [8]. Many different things are involved in a genuinely smart city. However a city can only be fragmentarily smart in 5 G, meaning that the major components such as services (i.e. power, water, waste and waste) healthcare and control and transport networks are individually intelligent, so on). For a truly smart community, 6G would take a holistic approach in an integrated way.

Automatic Factory: The development of connected robotics and autonomous systems (CRAS), such as autonomous robotics, drone delivery systems, etc., encourages the advancement of automated factories. For industry growth, the massive integration of robots into automation and warehouse transportation is essential. The evolving notion of industry X.0 seeks to boost industry 4.0 through social, interactive, analytics and cloud exploitation (SMAC). It is a prerequisite for the precise localization of different IoT devices to allow effective cooperation between them. Different from other demands, cooperative localization between massive IoT devices is of vital importance for the automated factory, requiring the massive devices to create end-to-end (E2E) communication links with highly accurate, low latency, and highly reliable location information.

***Table I**: The Localization requirements of various application of 5G/6G Networks*

	Applications	Requirements
Intelligent Interactive Networks	Tele-presentation and Tele-control	• High reliability • Centimeter-level accuracy (i-e 1-10cm) • Calibration between two different localization systems
	Multisensory XR	• Low latency (less than 20 ms) • Centimeter-level accuracy
	WBCI	• Centimeter-level accuracy • Low latency • High requirement on cooperative localization among IoT devices
Smart City	Smart Transportation	• Wide coverage • High mobility tracking • Cooperative localization in V2X • Submeter-level localization
	Smart Indoor Services	• NLoS based localization • Encryption classification and protection
Automatic Factory	CRAS	• Low Latency • High Reliability • Atleast submeter-level accuracy

Table I summarises the key localization criteria of multiple applications in 5G/6G networks, It is observed that achieving highly-accurate, low-latency, and highly-reliable localization will play an important role in future wireless networks.

II. WIRELESS LOCALIZATION BASICS:

The purpose of a wireless localization framework is to estimate the targeting object's position based on a collection propagated wireless reference signals between the reference nodes and the object of targeting. The functions of localization can be used deploy on the basis of either the existing wireless communication systems such as WLAN and cellular networks, or dedicated infrastructures, such as GNSSS. The targeting entity is often referred to as the agent node or mobile user with its unknown location, and the reference nodes with known locations are often referred to as anchor nodes (ANs) or landmarks[9]. A wireless localization system usually consists of two wireless localization essential components: a set of ANs and a location estimation unit that can be deployed either on the agent node itself or on a remote site. Localization techniques typically require two steps. In the first step, either the ANs or the agent node are transmitted to unique reference signals which are calculated by the other end of the connection in order to obtain some Information relating to the spot, such as received signal intensity (RSS), arrival time (TOA), arrival time difference (TDOA), or the received signal angle of arrival (AOA). Such measurements are gathered in the second stage at the unit of location estimation to estimate the agent's location node. It is possible to categorise localization systems from different perspectives, such as based on algorithms for position estimation [10] or localization infrastructure [11]. One popular classification is to consider where the calculation of the location is carried out[12], on the basis of which we have self-localization or remote systems for localization.

II-A1. Self- Localization: In self-localization, On the agent node, which receives reference signals transmitted from several ANs, a position estimation device is deployed. The node of the agent has the ability to perform acceptable signal measurements, on the basis of which it estimates its own position. There are some Self-localization schemes benefits. First because nearly all position-relevant operations are performed locally at the agent node, the location speed depends primarily on the agent node's computational capacity. Therefore, these systems are easier for performance enhancement by procedural or computational updating or the measurement units of the node of the agent, without having to alter infrastructure for the network. Second, the inherent mechanism for user privacy security is self-localization systems, because the agent node only passively receives signals transmitted from ANs, with little chance of location information leakage from the user hand [13]. Self-localization systems, however have high hardware requirements on the agent node, such as elevated caching and computational capability, to perform signal calculation and position estimation tasks on their own.

II-A2. Remote Localization: In remote localization, The reference signals are sent to ANs from the node of the agent. The ANs will send their respective signal measurements to a remote central station upon receipt of the reference signals, where the position calculation is carried out. The key advantage of remote localization systems over the equivalents of self-localization is that the agent node is less demanding, as nearly all time-consuming and complex computing operations are conducted at the remote central station, such as cellular base stations (BSs) or computer centre. Thus for resource-limited applications, such as IoT devices and wireless sensor nodes, remote localization is particularly attractive. Moreover, remote localization systems can maintain locations for all agent nodes in the region of interest, which can be used for different purposes, such as location-aware communication, unlike self-localization systems where location information is only accessed by the agent node itself [14]. However because all location information of agent nodes is stored in a remote server, privacy and protection of information is a critical problem in remote localization.

II-B. Wireless Localization Techniques:

Localization methods can usually be divided into two localization techniques. Main categories: direct localization and localization in two-steps. The received signals are specifically for direct localization [15]–[17] used for estimating the position of the node of the agent, while for two-step localization, the data related to the location, such as firstly, RSS, TOA, TDOA and AOA are derived from the received signals on the basis of it the agent's position is estimated. The direct localization can achieve better output in theory than two-steps localization. However, two-step localization methods are typically used in functional systems, in terms of the complexity and implementation constraints.

The two-step localization methods can be further divided into geometric-based, which depends on the various concepts of Analysis of scenes (also known as fingerprinting), and proximity approaches.

II-B1. Geometric-Based Localization: To locate the agent node, geometric-based localization technologies leverage the geometric properties of triangles. Usually, approaches based on geometry have two variations: Trilateration and Triangulation.

Trilateration specifies the location of the node of the agent with distance-related signal measurements from different ANs, so it's called ranging as well. Triangulation, on the other hand usually tests the AOAs of the received signals propagated between the ANs and the node of the agent and locates the node of the agent at the intersection of angle direction lines. With the assistance of directional antennas or antenna arrays deployed on the agent node or the ANs, the AOAs can be measured. Two ANs are sufficient for triangulation to find the agent node in a 2D space, unlike trilateration that requires at least three ANs [18], [19].

II-B2. Scene Analysis/ Fingerprinting-Based Localization: Due to increasing number of sensors on intelligent devices has resulted in a rapid progression of wireless localization. The new method has been proposed based on scene analysis or fingerprints. In order to obtain unique geotagged signatures, i.e. fingerprints, this method first manipulate the data obtained by the sensors, such as cameras, accelerometers, or specific WiFi access points (APs), and then define the location of the agent node by comparing the online signal measurements against the pre-recorded geotagged fingerprints. [18], [20]. The fundamental idea of localization based on signal fingerprints is to estimate by matching the position of the mobile devices the fingerprint of the received signal against a previously registered database with established information on signal-location. The fingerprint technique involves two main phases: the populating phase of the signal fingerprint (also known as the training or offline phase) and the matching phase of the signal fingerprint (also known as online phase). The training phase generated a signal map by exploring the signal fingerprint at each reference position within the area of interest. The position of the mobile device is estimated during the matching process by comparing the signal fingerprint produced by one device to the pre-defined signal map. Fig.1 summarizes the workflow of a signal fingerprint-based localization phases. A summary of fingerprint-based localization techniques are given in table II.

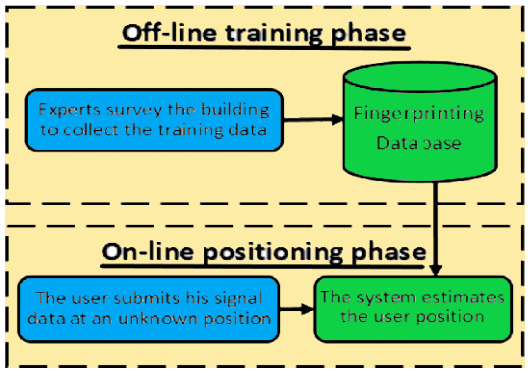

Figure1. Phases of Fingerpring localization

Table II: *Summary of Fingerprint-Based Localization Techniques*

Fingerprint Type	Fingerprint Matching	Fingerprint Population
VISUAL FINGERPRINT	• Content Based Image Retrieval(CBIR) • Coarse Localization Techniques • Nearest-Neighbor Search (NNS)	Crowdsourcing-based Fingerprint populating Techniques
MOTION FINGERPRINT	Digital Map Matching Techniques	Digital Map Construction Techniques
SIGNAL FINGERPRINT	• Received signal strength ordering • Euclidean Distance based Matching Algorithm	• Grid-Based War Driving Techniques • Signal Subspace Interpolation Method • Crowdsourcing-based Fingerprint populating Techniques

II-B3. Proximity-Based Localization: The concept of localization based on proximity is that the location of the locality is the node of the agent is calculated according to proximity limits [21]–[23]. The mathematical model behind such proximity methods is close to that of fingerprinting-based localization deterministic approaches. However unlike fingerprinting techniques, the estimation of the proximity position depends on the positions of the real ANs, so the precision of the localization depends on the density of ANs, which can only be enhanced by increasing the number of ANs. In general, the proximity approach is easier to implement than other methods of localization. This method can however, only provide a very rough localization service, so it is typically used in systems with low position accuracy requirements. Cell-ID (CID)[24], RFID [11] and bluetooth-based localization systems [10] are representative applications for this process, which are also location-based systems used in mobile and IoT networks. Another proximity-based localization use case is to decrease the search size fingerprint-based localization before matching the pattern of fingerprints is carried out. A summary of the aforesaid localization above approaches are given in Table III, which compares their approaches and differences between measurement models and their benefits.

***Table III**: Summary of different Techniques of Localizations*

Model	Location Information	Benefits
Geometric-Based	RSS	LoS and Time synchronization is not required
	AOA	• Time synchronization is not required • Two ANs are sufficient for 2D localization
	TOA	High accuracy for LoS
	TDOA	• High accuracy for LoS • Time synchronization and Time stamp is not needed
Scene Analysis	Fingerprints	• High Accuracy • Robust to clutter environment • LoS path is not required
Proximity	RSS	Simple and inexpensive and easy to implement

II-C. Location Estimator:

There are two types of localization estimators in general, namely nonlinear and linear, to solve the problems of localization. The nonlinear estimators namely, nonlinear least squares (NLS), weighted nonlinear least squares (WNLS) and maximum likelihood (ML) address the issues directly by minimising a cost function. Usually, such nonlinear estimators result in high precision of localization. However, as their cost functions are typically multi-modal, often the global solution of such systems cannot be guaranteed, and nonlinear estimators normally have high time complexity if grid or random search is involved. By comparison, linear estimators which are the linear least squares (LLS) and weighted linear least squares (WLLS), that transform nonlinear equations into a collection of linear equations, with degraded localization accuracy compared to nonlinear estimators, can easily find efficient solutions. A summary of the localization estimators nonlinear (NLS, WNLS, ML) and linear (LLS, WLLS) are given in Table IV, which compares their measurement model with their benefits.

The nonlinear solution fixes the explicitly built nonlinear equations from the measurements of TOA, TDOA, RSS, and DOA, while the linear the technique turns nonlinear equations into linear equations. The estimation efficiency of the ML and the confined WLLS methods can achieve CRLB in the presence of zero - mean Gaussian measurement errors, while the remaining estimators can only provide suboptimal localization accuracy.

***Table IV**: Summary of different Localization Estimators*

Estimators	Measurement Model	Benefits
NLS	Geometric-based, Fingerprinting, Proximity	High Accuracy without error statistics
WNLS		Higher accuracy than NLS
ML		Highest accuracy as compare to others
LLS	Geometric Based	Computationally efficient without error statistics
WLLS		Higher accuracy than LLS

II-D. Key sources for techniques of error and mitigation

The efficiency of localization is fundamentally restricted by multiple biases of calculation and errors in measurement. To improve the robustness of localization systems, it is therefore important to evaluate their source of error. Here, along with their corresponding mitigation methods, we address 3 major sources of error.

II-D1. Multipath Fading: In wireless networks, multi-path fading is commonly present, which can significantly degrade the output of localization. In particular, the signals that enter the receiver from different paths are superimposed on narrowband localization systems in cluttered environments. With each other, which makes them unresolvable at the receiver. In addition, with signal propagation conditions, the multi-path effect varies, making the identification of the signal more difficult. Some diversity combination techniques are proposed to mitigate this effect, and the multi-path components are typically temporarily solvable for the ultra-wide bandwidth (UWB) systems without resorting to complex algorithms. [25], [26]. The massive number of mulitpath components, however, in harsh environments localization performance continues to degrade, particularly for geometric algorithms that need to distinguish the LoS path from the large number of NLoS paths in order to obtain the agent node location information. Recently, in order to achieve the high accuracy in localization, a new multi-path localization method is used which utilize the modern tracking algorithms or signal reflectors as virtual transmitters.

II-D2. NLoS Propagation: The detrimental effects of NLoS propagation lies in the fact that the NLoS signals obtained weaken the linkage between signal measurements and the distance of links, Since it would introduce the range estimation with a positive bias. In general, there are three approaches for dealing with the NLoS condition. The first approach is based on statistical NLoS error knowledge. The statistics of signal measurements can be obtained by assuming a scattering model of the environment, and then well-known methods, such as MAP or ML can be used to minimise the effects of NLoS errors. The limitation of such approach, however, is to obtain an accurate model that can alter with terrain and/or building construction/demolition. In order to minimise the effects of the NLoS contributions, where the weights are created from the localization geometry and the ANs layout, the second approach uses both NLoS and LoS measurements with suitable weights. While this approach is effective even in cases without LoS measurements, since NLoS errors are still present, its solution is inaccurate. The third approach is to describe and discard these measurements of NLoS, and conduct localization based on the LoS measurements. In essence, in this approach, the problem of NLoS identification is translated into a problem of statistical detection, where the conditions of NLoS and LoS are considered as two hypotheses, and the objective of the problem is to find out a metric to separate the hypotheses of NLoS and LoS.

II-D3. Systematic Errors: Systematic errors relate to errors that arise from the localization system on its own, such as inaccurate signal measurements and radio miscalibration. or instance, the ANs are in time-based localization systems equipped with the time synchronisation oscillators. Oscillators, however, often experience independent frequency drifts, resulting in drift and offset clocks, which could degrade the accuracy of localization. Systematic errors often lead to location estimators, making the value of the estimator larger than the value of the estimator real value. With regard to the targeting location, systematic errors are generally constant and can be eliminated by parameter calibration. However, certain techniques can effectively mitigate these errors. Some approaches have been proposed to tackle systemic errors, such as clock offset correction and recursive Bayesian approach [27].

II-E. LOCALIZATION INFRASTRUCTURE:

The localization systems are deployed in two simple ways. The first is developing a dedicated infrastructure for localization, it's like GNSS. In addition to connectivity facilities, the second approach is to reuse existing wireless network infrastructures with incentive signal of opportunity(SoOP), such as cellular networks, WLAN, etc., to provide wireless localization services. For the first approach, the main benefit is that by using unique reference signal and competent hardware, it can achieve high localization efficiency, while the disadvantage is the hardware cost and the restriction on application optimization. It avoids the costly and time-consuming implementation of infrastructure for the second method, but such systems typically depend on complex algorithms to enhance performance. The most popular localization infrastructures are GNSS, cellular networks, WiFi, and UWB, and a comparison on their efficiency is given in Table V.

II-E1. GNSS: Different GNNSs have already been developed and launched by many countries around the world, including the U.S. GPS, the Galileo by Europe, the Beidou by China, the GLONASS by Russia, as well as other regional systems such as the Japanese Quasi-Zenith Satellite System (QZSS) and the Indian Regional Navigation Satellite System (RNSS) (IRNNS). Although all these GNNSs implement various technologies at different locations, they share similar theoretical theories of the system and signal levels. OW-TOA or TDOA methods are the localization strategies behind GPS, where there is a need for at least four clearly visible satellites for the node of the agent to locate itself in terms of latitude, longitude, and elevation.

Table V: *Comparison of Localizations Infrastructure*

	Example	**Type**	**Efficiency**
GNSS	GPS	Trilateration	Global coverage; Accuracy 10-20 m
Cellular Networks	2G	Trilateration + Proximity	Local area coverage; Accuracy 50-500 m
	3G	Trilateration + Scene Analysis	Local & Global coverage; Accuracy 10-200 m
	4G	Trilateration + Angulation + Proximity	Local & Global coverage; Accuracy 10-200 m
Wi Fi	IEEE 802.11	Scene Analysis	50-100m coverage; Accuracy 1-5 m
UWB	IEEE 802.15.4a	Trilateration	Indoor area coverage; Accuracy 0.1-1 m

III. ENHANCED COORDINATION AND LOCALIZATION FOR 5G AND BEYOND

It is envisaged that future mobile communication networks will realize the Internet of everything (IoE) vision with a flexible approach not only networks for ubiquitous communication, but also networks for smooth localization and smart automatic control with high precision, high accuracy [28]. In order to accomplish this magnificent objective, high-performance localization techniques need to be built in order not only to meet the requirements of latest developments commercial and industrial services on location, but also to meet the requirements of different emerging commercial and industrial services on location. Although exact location data is useful for communications, we overview the promising vision of 6G with the development trends of localization in future integrated networks. In terms of accuracy, efficiency, coverage and latency, 5G networks allowed by higher carrier frequencies, broader bandwidth and large antenna arrays are expected to achieve better localization performance compared to 4G-LTE [29]. Massive MIMO, mmWave, UDNs, and device-to-device (D2D) communication are four basic 5G network technologies that will not only boost the performance of communication, but also technically benefit for localization [30]. The Channel sparsity is the major feature of mmWave transmission in 5G, in which the limited number of multi paths can reach the receiver due to short wave-length, which can be exploited to enhance the localization performance [31]. Therefore, to overcome the high path loss, mmWave transmission is usually combine with massive MIMO for directional beamforming, for which the accurate angular information can be extracted and utilized for localization. In [32] a detailed description of massive MIMO localization is given. 5G mmWave localization for vehicular networks overview is provided in [33]. In mmWave MIMO systems, standard localization techniques can be utilized to improve localization performance. One reliable way for supporting the ever-increasing throughput demand of diverse mobile apps is to change from the current cell-centric architecture to a device-centric architecture [34]. In standard cellular networks, since both communication domains are relatively close to each other, all communications must pass through the BSs, but D2D communication allows two devices to communicate without passing through the BSs. Multi-hop relaying [35], peer-to-peer (P2P) communication [36], machine-to-machine (M2M) communication [37], cellular offloading [38], and others are examples of related use cases. Densification of networks is a viable solution for meeting the ever-increasing needs in 6G mobile networks for higher spectrum utilization. In recent years, location aware communication has risen in popularity because it can be used in a number of different ways to improve communication performance in 5G and beyond networks, such as limiting communication overheads and delays, limiting energy consumption, and rising communication range. Based on the levels of the protocol stack, along with the physical, MAC, and network layers, [28] provided a detailed description of location-aware communication. Based on the levels of the protocol stack, along with the physical, MAC, and network layers, a detailed description of location-aware communication in 5G is provided in [14].

Future wireless networks are likely to be extremely heterogeneous and dense, with multiple types of access points (APs) such as WiFi, Bluetooth, and light fidelity (LiFi) coexisting in tiny locations, causing in reduced resource management [39]. Unmanned aerial vehicles (UAVs) have been appraised as a powerful and effective tool to enhance wireless networks from the ground to the air space due to their high mobility and on-demand deployment capacity [40]. For example, in [41], a UAV-assisted ground vehicle localization method was proposed, in which each UAV measures the RTOF of signals between the ground BSs and the UAV, then broadcasts the measurements to the ground vehicles for localization, achieving decimeter-level relative position error between vehicles and meter-level absolute position accuracy. Another method for achieving pervasive wireless communication in 3D space is 3D beamforming, which likewise requires precise UAV positioning. Another method for achieving pervasive wireless communication in cellular networks is 3D beamforming, which generally requires precise UAV positioning [42]. BS antennas are often downtilted to prevent inter-cell interference in today's cellular networks, which are built for terrestrial broadband communication [43]. One of the aims for 6G is to integrate terrestrial networks (particularly cellular networks) with aerial networks to enable pervasive wireless connectivity in 3D space [4].

IV. FUTURE WORK AND CHALLENGIES

Future 6G wireless networks are expected to be AI-enabled, heterogeneous, and multi-tier networks that include space backbone networks (SBNs), space access networks (SANs), aerial backbone networks (ABNs), aerial mobile networks (AMNs), and terrestrial networks (TNs) [44], [45]. The satellite networks are anticipated to play a key role in 6G networks due to its vast coverage, particularly in remote and offshore areas. While multiple satellite systems orbit around the earth are isolated and established distinct autonomous systems (ASs) that perform unique services such as communications, navigation, remote sensing, and so on, real-time information exchange among multiple ASs is challenging [45].

On-demand UAVs with great mobility can be installed fast and easily in aerial networks, forming dynamic adaptable AMNs to provide temporary communication services for multiple missions such as emergency communication, UAV-aided reporting, and information gathering. Due to the limitations of UAVs in terms of data storage and endurance, ABNs made up of floating HAPs like airships are required to provide reliable wireless coverage for large areas, where airships with computing and caching capabilities can act as data centre and gateways, routing data to SANs and TNs. Because the locations of HAPs may be identified by GNSS or terrestrial BSs with dedicated antennas to send reference signals, they can operate as aerial ANs to find flying UAVs for localization. Furthermore, because UAVs with high mobility can offer short-distance LoS linkages to ground devices, they can be utilized as interim ANs to improve the ground device's localization performance[46]. To enhance communication and localization performance in the TNs, mmWave, massive MIMO, and UDNs technologies can be integrated. Additionally, device-centric networks will flourish as a potential trend in cell-free mobile communications, which will entail highly precise cooperative localisation among devices for resource distribution. Future networks, on the other hand, will be more heterogeneous, merging many radio access standards such as 2G/3G/LTE/5G, WiFi, and the Terahertz (THz) and visible light frequency bands. As a result, to enable perfect wireless connectivity for mobile devices, integrated resource allocation systems and protocols must employ several frequencies. For improved performance, the system must choose the proper localization algorithms and reference signals based on the surrounding radio environments of the mobile devices.

Finally, AI-assisted cloud technique is a highly prospective wireless network trend that may be classified into two categories: RAN cloud and CN cloud. Signal restoration is aided by the distributed AI units located at the RAN's edges, which is useful for data decoding and signal measurements, which improves communication and localization performance, respectively. The centralized AI units in the CN cloud can be utilized to build 3D REMs, which can be used to help with localization method decision and proactive RRM for communications. As part of the 6G vision, AI-enabled networks are intended to optimize and manage resources autonomously in order to dynamically sustain UE communication performance based on its precise real-time location. However, many challenges remain to be resolved in order to realize the above objectives.

A. Integrated Localization And Communication (ILAC) Essential Quality Analysis and Design

The ability to achieve ultra-high spectral efficiency is crucial for future networks, particularly for IoT different applications that demand significant wireless connectivity to provide secure transmission and accurate localization services for massive IoT devices. A uniform spectrum can be utilized by localization and communication, or partitioned into two orthogonal sections for them, to obtain ultra-high signal quality for ILAC. Furthermore, in the case of shared spectrum, the signal waveform can be developed jointly for localization and communication at the same time, or two distinct waveforms can be designed independently. As a result, a serious challenge is the theoretical characterization of ILAC's fundamental performance and how to design waveforms with ultra-high spectral efficiency. On the other side, although both localization and communication benefit from wide signal bandwidth, a major challenge for orthogonal spectrum utilisation is how to properly split the spectrum to maximize the trade-off between localization and communication according to varied QoS requirements.

B. Multi-Tier ILAC Systems with Improved Signal Processing

Mobile stations in multiple levels of networks can interact in different frequency bands with various links in multi-tier networks. In this instance, how to continuously and reliably manage wireless networks is a vital issue for localization and communication. Merging of several frequency bands and adaptive resource management is a potential alternative for reconfiguring and maintaining wireless connections, and strong signal processing is a key aspect for cross-layer data transfer. Because the channel estimate units can be reused for location information extraction, the localization and communication systems can share some hardware, and communication signal processing methods can be employed for location-related information measurements as well. As a result, two fundamental challenges are how to effectively co-design hardware architecture and signal processing technology.

C. Multidisciplinary Communication Networks

Future networks will be more heterogeneous than previous networks, operating on multiple frequency bands and according to different standards. When mobile stations move quickly and are exposed to diverse wireless surroundings, a fundamental concern is how to shift protocols instantly from one to another while maintaining localization and communication performance. Because each network layer uses multiple protocols for multiple network architectures, an obvious approach is to convert the protocols at gateways to connect diverse networks. The integrated protocol design that supports cross-layer, cross-module, and cross-node data transmission is significant since such a sequence of protocol translations is economical. Furthermore, network protocol design, particularly at the physical and MAC layers, must anticipate not only transmission parameters but also localization factors.

D. 3D REMs and Proactive RRM in challenging system

The preemptive RRM is advantageous for communication in terms of cell selection, channel prediction, beam alignment, and other aspects, but it will necessitate high-accuracy REMs. Presently, works on REMs modeling are focussed on 2D models aimed at TNs in outdoor settings. As networks expand into 3D space, 3D REMs modeling in cluttered environments such as indoors and cities becomes more important and difficult, requiring more highly accurate localization in multi-path and NLoS situations. Although some successful multi-path and NLoS mitigation strategies have been developed in the literature, they are often highly sophisticated and only suitable for remote localization systems, instead of self-localization systems where UEs must perform the processing and evaluation. However, while some studies focus exclusively on localization in NLoS conditions, by modeling signal reflectors as virtual ANs, they are confined to first-order reflections for analysis simplicity, yet higher-order reflections emerge in dense multi-path systems. In order to achieve more precise and low-cost localization, more research into localization algorithms for multi-path settings is still required.

E. Artificial Intelligence for ILAC

Machine learning (ML), or artificial intelligence (AI), is one of the most key techniques for bringing intelligence to wireless networks with challenging radio circumstances. It is used to obtain network complexities and establish user-centric intelligent networks, which can autonomously organize resources, functions, and network control to maintain high performance based on the real-time location of mobile users, owing to its ability to handle appropriate pattern recognition from complicated raw data. ML can be applied to ILAC in a variety of ways, including waveform design, signal modulation/coding, resource allocation, balancing the performance trade-off among localization and communication, and creating 3D REMs to improve ILAC performance.

V. CONCLUSION

In this paper, we've covered the fundamentals of wireless localization before moving into the future of network design with ILAC for 6G networks. We presented 5G promising applications scenarios with their benefits. In localization techniques, we discussed models with their benefits also Localization estimators and Localization infrastructures. We also discussed the key sources for techniques of error and mitigation. Furthermore, we discussed the enhanced coordination and localization for 5G and beyond. Finally, some relevant enabling technologies and promising future research topics are discussed.

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