# 5G Localization and Context-Awareness

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**Abstract** The fifth generation (5G) wireless ecosystem will be essential for a myriad of new applications based on accurate location awareness and other contextual information. Such wireless ecosystem will be enabled by advanced 5G wireless technologies integrated with existing technologies for the Internet-of-things (IoT) and the global navigation satellite system (GNSS). First, we will explore the main 5G use cases and key performance indicators (KPIs) presented by the third generation partnership project (3GPP) where accurate positioning is required. Second, the main technologies will be described. Then, foundations and signal processing techniques for accurate localization will be presented. Finally, some context-aware applications beyond localization are discussed.

## 1 Localization Use Cases and KPIs

### 1.1 Use Cases

The 3GPP categorizes the main localization use cases based on verticals, briefly summarized in the following.

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### 1.1.1 Regulatory and Mission Critical

- Accurate localization within an *emergency call* service refers to the geolocation of an user when contacting a public safety answering point (PSAP) through a short dial emergency telephone number (e.g., E-911);
- Accurate localization of a *first responder* who is injured or incapacitated during mission critical operations has long been a goal of public safety. A mission critical service enables a first responder to stay in contact with other first responders as well as dispatch and command/control during normal and critical operations;
- The *alerting service of nearby emergency responders* refers to the alert of all qualified individuals within close vicinity of the victim via their phones with a request to provide urgent care in case of a medical emergency; The purpose of this use case is to improve the localization of the emergency responders closest to the victim, in order to safeguard the quickest availability of care;
- The localization service of *emergency equipment outside hospitals* refers to the localization of life-saving medical equipment, such as automated external defibrillators (AEDs), deployed throughout public and private spaces in case of need. This use case is about knowing where the equipment actually is, rather than where it is supposed to be.

### 1.1.2 Location-Based Services

- The *bike sharing* service allows a rider to rent a bike via a mobile app and drop it off anywhere for the next user. The accurate locations of shared bikes that are available is required by the riders to find the nearest bike;
- The localization of users is a key service for *augmented reality* together with the estimation of motion. Moreover, the access to databases of contextual information and geo-localized information systems (GIS) need to be provided with low latency;
- The *wearable devices* such as smart watches can replace mobile terminals to provide the customer with basic services such as tracking, activity monitoring, and emergency messages. However, they require higher power durability in order to replace smart terminals in applications that depend on accurate localization;
- Localization for *advertisement push* refers to the advertisement the relies on data analysis of human activity location. For the advertisement to be effective, it needs to be closely related to the user profile and location in a period of time;
- The location-based *flow management* refers to the use of location data of people in public spaces or any transportation hub (airports, metro or rail station, etc.) facing large passenger flows to elaborate statistics on passengers as well as to optimise their organisation and signalling to passenger.

### 1.1.3 Industry and eHealth

- The localization of *persons and medical equipment in hospitals* in real time on the site of the hospitals (indoor and outdoor, even in the presence of large green areas and several buildings) is important, for example, to notify the medical staff if patients reach a non-authorised area and to locate caregivers and medical equipment (e.g. crash cart), especially in emergency situations;
- The localization of *patients outside hospitals* refers to patients who manage to leave the hospital without authorisation and ambulatory patients with a potentially critical condition (e.g. cardiac, diabetes, high-risk pregnancy);
- For a smarter and more efficient *waste collection and management*, location data is essential for finding optimal routes for collection vehicles and for locating bins where sensors detected fires or other anomalies.

### 1.1.4 Transport (Road, Railway, Maritime, and Aerials)

- Localization for *traffic monitoring, management, and control* refers to vehicles and their location in a map of the infrastructure (roads, lanes). The vehicles position information needs to be managed over multiple road segments and long distance. This use case addresses a more dynamic implementation, complementing sensor and videos with position-related data determined using the 5G system;
- *Road-user charging (RUC)* defines generic services monitoring vehicle positions (and/or motion) with the aim of levying a charge or a tax based on the way the road infrastructure is used.
- The tracking of *asset and freights* has a key role to optimize the overall transportation efficiency, and to improve end-to-end traceability. Freight tracking enables more accurate scheduling of all involved operations, while asset tracker should fulfil very long lifetime (up to 15 years) and position-related data need to be secured and protected against tampering.
- The accurate positioning of *unmanned aerial vehicle (UAV)* is important to support their missions and operations. Each UAV needs to be geo-localized with high accuracy (absolute position information) to contextualize data collected in the monitored area (e.g. images of the environment that is flown over).

In specific applications, the network operator can be asked to provide a customized localization service with different performance for different users. Therefore, the *support of multiple different localization services* can be considered as a use case itself. This can be obtained by relying on multiple technologies for example, 3GPP technologies and non-3GPP technologies. Different localization methods support different levels of accuracy capabilities as described in Sec. 2. So, it is suggested to support negotiation of localization capabilities considering user, application, or network operator's demands.

## 1.2 Key Performance Indicators and Key Attributes

The 3GPP introduces several location-based KPIs for 5G applications. The KPIs are defined based on an absolute or a relative position estimation, which can be further specialized into an horizontal position (referring to the position in a 2D reference or horizontal plane) and into a vertical position (referring to the position on the vertical axis or altitude) [1]. In some applications, the *availability* of position estimates is an additional attribute that describes the percentage of time when a positioning system is able to provide the required position data within the performance targets or requirements.

In [1], three KPIs are defined for the *accuracy* of parameter estimation: (1) *position accuracy* describes the closeness of the estimated position of the user equipment (UE) (either of an absolute position or of a relative position) to its true position; (2) *speed accuracy* describes the closeness of the estimated magnitude of the UE's velocity to the true magnitude; (3) *bearing accuracy* describes the closeness of the measured bearing of the UE to its true bearing. For a moving UE, the bearing is a measure of the velocity's direction and this KPI can be combined with speed accuracy into the velocity's accuracy.

Other three KPI are related to the *timing* of parameter estimation availability: (1) *latency* describes time elapsed between the event that triggers the determination of the position-related data and their availability at the positioning system interface; (2) *time to first fix (TFF)* describes the time elapsed between the event triggering for the first time the determination of the position-related data and their availability at the positioning system interface; (3) *update rate* is the rate at which the position-related data is generated by the localization system. It is the inverse of the time elapsed between two successive position-related data.

Moreover, two KPIs are related to the *energy consumption* for localization: (1) *power consumption* indicates the electrical power (usually in mW) used by the localization system to produce the position-related data.; (2) *energy per fix* indicates the electrical energy (usually in mJ per fix) used by the localization system to produce the position-related data. It represents the integrated power consumption of the positioning system over the required processing interval, and it considers both the processing energy and the energy used during the idle state between two successive productions of position-related data. This KPI can advantageously replace the power consumption when the positioning system is not active continuously (e.g. device tracking).

Finally, the *system scalability* defines the amount of devices for which the positioning system can determine the position-related data in a given time unit, and/or for a specific update rate.

Table I summarizes the localization KPIs requirements for positioning use cases organized per verticals.

| Use Cases | Potential Requirements | | | | |
|---|---|---|---|---|---|
| | Environment of Use | Position Accuracy | Avail. | Update interval; TTFF; Latency | Other KPI |
| Emergency Call | 5G positioning service area - outdoor/indoor | 50m hor.; 3m ver. | 95% | TTFF: 30s; L: 60s | reliability/ confidence |
| First Responders | Outdoor | 1m hor.; 0.3m ver. | 98% | TTFF: 10s; L: 5s | MCX confidence; |
| | Indoor | 1m hor.; 2m ver. | 95% | TTFF: 10s; L: 1s | event-triggered report |
| Alerting Nearby Emergency Responders | 5G positioning service area - outdoor/indoor | 50m hor.; 3m ver. (floor) | 99% | TTFF: 10s | privacy, scalability, cross operator |
| Emergency Equipment Outside Hospitals | 5G positioning service area - outddot/indoor | 10m hor.; 3m ver. (floor) | 95% | TTFF: 10s | extended sleep periods |
| Bike sharing | 5G positioning service area - outdoor | 2 m hor. | 90% | TTFF: 10s; L: 1s | |
| | Enhanced positioning area - outdoor | 0.2m hor. | 99% | TTFF: 10s; L: 1s | |
| Augmented Reality | 5G positioning service area - outdoor | 1-3m hor.; 0.1-3m ver.; vel. 2m/s 10deg. | 80% | UI: 0.1-1s;TTFF: 10s; L: 1s | low energy |
| Wearables | 5G positioning service area - outdoor/indoor | 2 m hor.; 1-3 m ver. | 90% | UI:30s-300s; TTFF: 10s | power saving mode |
| | 5G positioning service area - outdoor/indoor | 2 m hor.; 1-3 m ver. | 99% | UI: 1s-30s; TTFF: 10s; L:1s | normal mode |
| Advertisement Push | 5G positioning service area - outdoor/indoor | 3m hor.; 3m ver. | 90% | L: 60s | |
| Flow Management | Enhanced positioning area - outdoor/indoor | 10m hor. | 80% | TTFF: 10s; L: 10s | |
| Person and Medical Equipment Location in Hospital | Enhanced positioning area - outdoor/indoor | 3m hor.; 2m ver. | 99% | L: 60s | |
| Patient Location (outside hospital) | 5G positioning service area - outdoor/indoor | 10m hor.; 3m ver. (floor) | 99% | | |
| Trolley | Enhanced positioning area - outdoor/indoor | 0.5m hor./ 1-3m ver. | 99% | L: 0 ms | |
| Waste Management | 5G positioning service area - outdoor | 3m hor. | 99% | UI: 2h-1 day; L: 60s | very low energy (15 years) |
| Traffic Monitoring & Control | 5G positioning service area - outdoor | 1-3m hor.; 2.5m ver. | 95% | UI:0.1s; TTFF: 10s; L: 30ms | antispoofing; antitampering |
| Road User Charging | 5G positioning service area - outdoor; Enhanced positioning area - tunnels | < 1m (across track); 3m (along track) vel. 2m/s | 99% | UI: 1s; TTFF: 10s | antispoofing; antitampering |
| Asset Tracking and Management | 5G positioning service area - outdoor | 10-30m hor.; vel. 5m/s | 99% | UI: 300s-1day | 20 mJ/fix (average); antispoofing; antitampering; |
| | Enhanced positioning area - outdoor | 1m hor. | 99% | TTFF: 1s; L: 1s | out of coverage |
| UAV (Data Analysis) | 5G positioning service area - outdoor | 0.1m hor.; 0.1m ver. | 99% | TTFF: 10s | low energy; anti spoofing; antitampering |
| UAV (Rem. Contr.) | 5G positioning service area - outdoor | 0.5m hor.; 0.3m ver. | 99% | L: 150ms | antispoofing; |
| | Enhanced positioning area - outdoor | 0.5m hor.; 0.1m ver. | 99.9% | L: 150ms | antitampering |
| Support Multiple Location Services | 5G positioning service area - outdoor | 2m hor. | 90% | TTFF: 10s; L: 1s | management of different KPI and positioning services |
| | Enhanced positioning area - indoor | 0.1m hor. | 99% | TTFF: 10s; L: 1s | |
| Support Location Method Negotiation | 5G positioning service area - outdoor/indoor | | | | support and negotiation of positioning methods (inc. hybrid) |

**Fig. 1** Potential requirements per use case highlighted by the 3GPP Rel. 16

## 2 Technologies for Cellular Network Localization

In principle, any signal propagating in a wireless environment intrinsically conveys position-dependent information that can be exploited for localization. Such a position-dependent information can be extracted from measurements of signal metrics such as received signal strength (RSS), time-of-arrival (TOA), angle-of-arrival (AOA), phase, or combinations of them, depending on the radio technology. One or multiple receivers compute signal measurements with respect to one or multiple reference transmitters, and then infer the position by means of a localization algorithm.

In cellular networks, the reference transmitters can be navigation satellites, cellular base stations (BSs), and, for cooperative localization, other mobile users. Satellite navigation has been considered the main technology for localization so far, due to its global coverage and high accuracy [2]. Cellular-based localization is used as a complementary solution, when there is a lack of satellite visibility due to the blockage of the satellite signals, which is typically the case in urban and indoor environments. The positioning methods can be classified into two main categories depending on the entity that computes the position: (1) *mobile-based*: the (mobile) device itself calculates its location by using signal measurements from terrestrial or/and satellite transmitters. The assistance data from the network can be exploited to perform the signal measurements and infer the position; (2) *network-based*: the network location server infers the position of the mobile device, by means of signal measurements performed by the network with respect to the mobile device, or signal measurements performed and sent by the mobile device to the network.

Classical signal processing techniques for cellular networks include

- *Trilateration:* the position estimate is obtained by intersecting geometric forms, e.g. circles or hyperbolas, created by distance or angle measurements between the terminal and the reference transmitters or receivers. Several types of measurements can be used, such as time of arrival (ToA), time difference of arrival (TDoA), direction or angle of arrival (DoA or AoA), and received signal strength (RSS).
- *Proximity:* the known transmitter position is assigned to be the position of the terminal. An example is the *cell-ID* method, where the position provided is the one of the serving base station.
- *Fingerprinting:* the algorithm is based on finding the best match for a certain signal measurement, such as RSS, time delay or channel delay spread, from a database of fingerprints. Each fingerprint is associated with a specific location.

A combination of the previous localization algorithms can be implemented to improve the overall performance, or to support an algorithm that cannot be computed stand-alone given the lack of signal measurements. More advanced techniques based on soft information rather than in single value estimates are described in [3]

The choice of the technology and the type of measurements affect the complexity of the localization process and the KPIs.

## 2.1 Localization in 1G - 4.5G Cellular Networks

### 2.1.1 1G - 3G Cellular Networks

Positioning of UEs exploiting the pervasive diffusion of existing cellular networks, hence without the necessity to deploy ad hoc and expensive wireless infrastructures, has been discussed since the introduction of the first generation (1G) for vehicles location (a comprehnsive survey can be found in [2]). In fact, at that time, UEs were not equipped with global positioning system (GPS) receivers or, if any, they were costly. In subsequent years, one of the main driving application was emergency positioning (e.g., E-911 in U.S.) which became a mandatory requirement of the U.S. Federal communications commission (FCC). In this context, cellular networks operators are responsible for positioning UEs with an accuracy of 100 m and 300 m in 67% and 90% of all positioning attempts, respectively.

Unfortunately, 1G-3G cellular standards were initially designed and optimized having in mind data and voice communication services but not positioning. Nevertheless, due to the increasingly demand of location-based servicess (LBSs), in 2008 the specifications of positioning methods to be supported in global system for mobile communications (GSM), also known as 2G, and universal mobile telecommunications system (UMTS), also known as 3G, were included in the 3GPP standardization process [4] through the definition of some classes of location services and the introduction of some approaches designed to provide position information using the available signals structures. They can be classified in *UE-based positioning*, where the measurements and position computation are done by the mobile terminal, and *Network-based positioning*, where the measurements and position computation are carried out at network level.

The main methods to estimate the position in cellular networks are:

- *Cell-ID*: The position of a UE connected to a specific base station (BS), which is identified by its cell ID, is determined by the location of the BS itself (proximity). This is a very rough method of positioning which can be improved by considering the center of gravity of multiple BSs seen by the UE (up to 7 in GSM);
- *RSSI*: received signal strength indicator (RSSI) measurements can be used to infer the distance between the UE and the BS. Unfortunately, propagation effects make the correlation between RSSI and distance weak thus leading to errors in the order of 150-200 meters. RSSI measurements can be exploited for *trilateration* or in *fingerprinting* techniques, or radiofrequency pattern matching (RFPM), where RF maps can be created by an advanced radio propagation prediction software, possibly refined by surveying, and exploited through pattern matching algorithms to determine the UE position. Fingerprinting can be in principle very accurate but it requires frequent RF maps updates and it is very sensitive to changes in propagation conditions;
- *Mobile-Assisted time-of-arrival (TOA)*: In GSM a rough measurement of the signal round-trip time (timing advance (TA)) is provided in order to synchronize the UE with the BS timing of slots. When combined with Cell-ID, such mea-

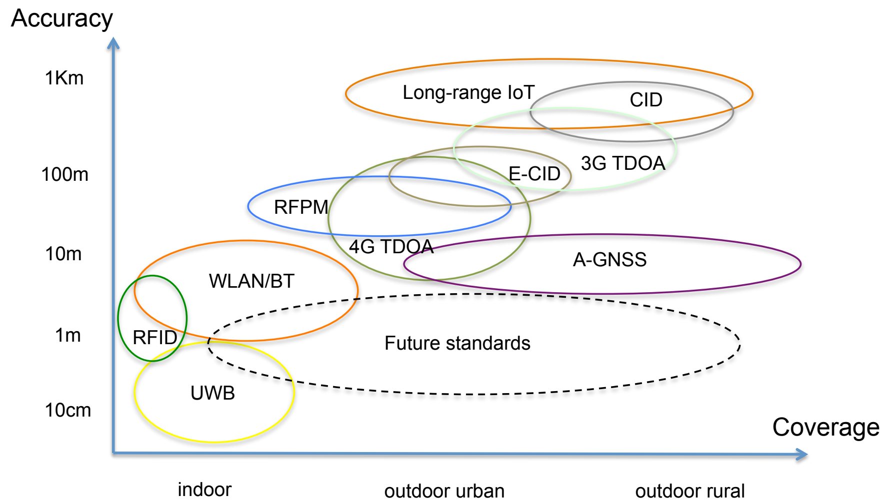


**Fig. 2** Qualitative accuracy and coverage of positioning technologies.

surements can slightly increase the positioning performance even though TA is available only during the call at the UE;

- *OTDOA*: The observed time difference-of-arrival (OTDOA) is the time-difference between the system frame numbers (SFNs) generated by two BSs as observed by the UE. These measurements, together with other information concerning the position of the involved BSs and the relative time difference (RTD) of the actual transmission of the downlink signals, is used to estimate the position of the UE. Since each OTDOA measurement related to a pair of BSs describes a line of constant TOA difference, yielding a hyperbola in two dimensions, UE position is determined by the intersection of hyperbolas of at least two pairs of BSs. Clearly, OTDOA is a UE-based positioning method which requires a specific implementation at the UE;
- *Assisted - GNSS*: Cellular network standard protocols have allocated resources to carry GNSS assistance data to GNSS-enabled mobile devices in both GSM and UMTS networks. The purpose is to assist the receiver in improving the performance in terms of startup time, sensitivity and power consumption.

A comparison of different approaches is qualitatively illustrated in Fig. 2.

### 2.1.2 4G and 4.5G Cellular Networks

The first long-term evolution (LTE) Release 8 did not provide positioning protocols. 3GPP boosted location services in LTE Release 9, delivered in December 2009 [4], with particular emphasis to emergency calls, as required by FCC E-911. Positioning methods in LTE networks can be dependent on the radio access technique (RAT),

| Positioning technology | | GPS | UMTS | LTE (R8) | LTE-A (R9) | LTE-A (R11) | LTE-A pro (R12) | LTE-A pro (R13) |
|---|---|---|---|---|---|---|---|---|
| RAT-dependent | Cell-ID | X | X | | | | | |
| | E-CID | | | X | X | X | X | X |
| | OTDOA | X | X | | X | X | X | X |
| | UTDOA | | X | | | X | X | X |
| | RFPM | | | | | | X | X |
| RAT-independent | A-GNSS | X | X | X | X | X | X | X |
| | TBS | | | | | | | X |
| | WLAN | | | | | | | X |
| | Bluetooth | | | | | | | X |
| | Barometer | | | | | | | X |

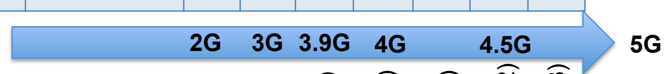


**Fig. 3** Positioning methods in cellular network standards.

that is making use of LTE signals, or independent of the RAT, that is using other signals such as GPS.

As can be seen in Fig. 3, most of RAT-dependent positioning methods are similar to those used in UMTS [5]. E-CID is an improved version of Cell-ID in which cell ID information is combined with other measurements such as TA, round-trip time, and angle-of-arrival (AOA). In LTE, OTDOA uses specific downlink signals called positioning reference signals (PRSs) which are transmitted in certain positioning subframes of the orthogonal frequency-division multiple access (OFDMA) signal structure grouped into positioning occasions which occur periodically every 160, 320, 640 or 1280 ms. PRS are received by the UE so that it can perform TOA measurements (see Fig. 4). The UE measurement is known as the reference signal time difference measurement (RSTD) which represents the relative time difference between two BSs. The UE reports its RSTD measurements back to the network, specifically to the location server, which determines the position of the UE.

In LTE Release 11, the *uplink time difference-of-arrival (UTDOA)* has been introduced, thus allowing the network of BSs, also known as eNB in LTE, to collect time difference-of-arrival (TDOA) measurements of the signal transmitted by the UE and hence localize it. The UTDOA method is based on network measurements of the TOA, in at least 3 BSs, of the signal transmitted by the UE. The difference between two TOAs at two BSs defines a hyperbola and the position of the UE can be calculated

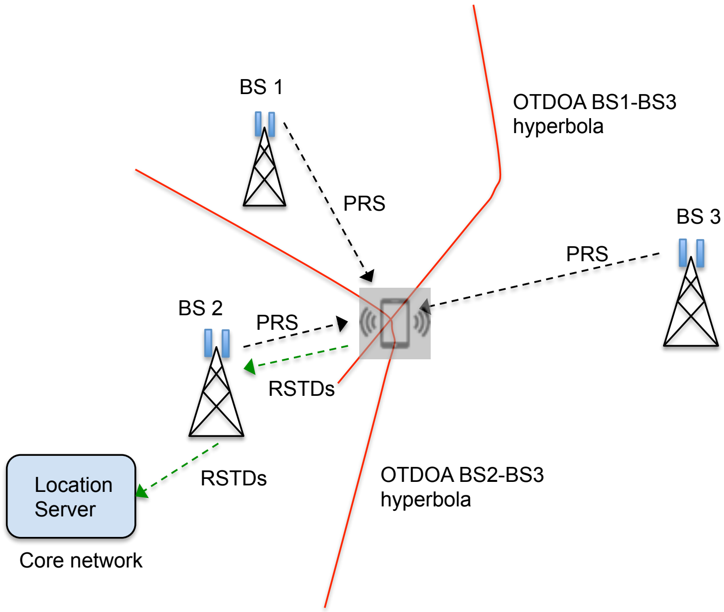


**Fig. 4** OTDOA-based positioning in LTE.

as in the OTDOA method. The main difference is that now all the processing is done by the network and no new functionalities need to be implemented in the UE.

FCC recognized that positioning requirements for indoor scenarios cannot be met by most of operators, thus new requirements were released in 2015. Specifically, a 50 m horizontal accuracy should be provided for 40, 50, 70, and 80% of emergency calls within 2, 3, 5, and 6 years respectively. For vertical performance, the operators should propose an accuracy metric within 3 years. In response, most of RAT-independent positioning methods have been specified in LTE Release 13 (LTE-Advanced pro, 4.5G) with the purpose to enhance the positioning accuracy, especially in indoor environments, as required by FCC rules. This was made possible using multiple different technologies such as wireless local area network (WLAN)/Bluetooth, barometric pressure sensors (vertical positioning), and terrestrial beacon systems (PRS beacons and metropolitan beacon systems). Also RAT-dependent methods, in particular OTDOA, have been enhanced by defining new PRS patterns and PRS bandwidth extension.

## 2.2 Localization in 5G Cellular Networks

The main difference between 5G and previous standards is that 5G KPIs requirements are no longer defined by the regulatory body for emergency calls, but they are driven

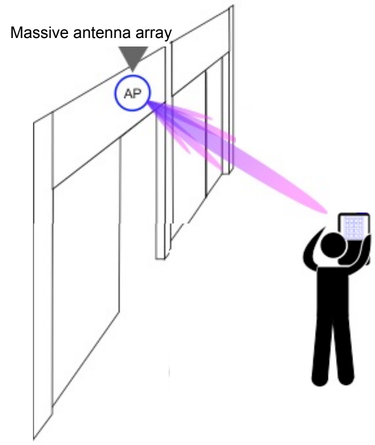


**Fig. 5** Single-anchor positioning with massive mmWave antenna arrays.

by the 5G use-cases as described in Sec. 1 and are being used in standardization [6]. The KPIs for accuracy, latency, and energy consumption are reported in Sec. 1.2. The standardization of positioning in 5G is still under discussion within dedicated task in Release 16 [1]. Localization will be based on the characteristics of the up-link and down-link signals of new radio (NR) (3GPP-technologies) but also on new technologies and network configurations, for example, GNSS (e.g. BeiDou, Galileo, GLONASS, and GPS), Terrestrial Beacon Systems (TBS), Bluetooth, WLAN, RFID, and sensors [7].

The main breakthrough in 5G is due to the employment of massive multiple-input–multiple-output (MIMO) beamforming and of millimeter wave (mmWave) signals. The use of mmWave brings a two-fold advantage: large available bandwidth and the possibility to pack a large number of antenna elements even in small spaces (e.g., in a smartphone). Wideband signals offer better time resolution and robustness to multipath thus improving the performance of OTDOA/UTDOA schemes, as well as paving the way to new positioning methods such as multipath-assisted localization exploiting specular multipath components to obtain additional position information from radio signals [8]. A large number of antenna elements enables massive MIMO and very accurate beamforming (see Fig. 5). This will make possible the introduction of single-anchor approaches providing cm-level and degree-level accuracy in 6D positioning (3D position and 3D orientation) [9], thus overcoming the problem of deploying a redundant ad-hoc infrastructure which is, nowadays, a major bottleneck for the widespread adoption of indoor localization systems. In addition, device-to-device (D2D) are under consideration in Release 16 for ultra-dense networks enabling cooperative localization, for instance, in vehicle-to-everything (V2X) scenarios [10].

## 2.3 Non-3GPP Technologies for 5G Localization

The lack of service coverage of GNSSs in indoor environments has generated a rich research activity on the design of indoor localization solutions in the last two decades. Some solutions exploit acoustic, infrared, laser, inertial, and vision technologies, whereas others are based on measurements of specific features of radio signals (e.g., TOA, RSSI, etc.) [11].

In the context of radio-based positioning technologies, research efforts followed two main directions: exploitation of existing standards designed only for communication; and design of ad-hoc standards/solutions for positioning. Recently, particular emphasis has been given to technologies for IoT applications which typically use low-cost, low-complexity, and low-energy devices.

### 2.3.1 Communication-designed Technologies

Several wireless technologies and standards are currently available for WLANs, wireless sensor networks (WSNs) and IoT applications in general. Examples are Wi-Fi, radiofrequency identification (RFID), ZigBee and Bluetooth low energy (BLE). They do not offer specific positioning capabilities, but their transmitted signals can be exploited to provide different localization performance levels. While RFID and BLE, due to their limited range, are typically used with proximity methods, Wi-Fi technology has been successfully adopted in several positioning systems typically leveraging on fingerprinting methods where meter-level accuracies can be achieved in many conditions. Wi-Fi ands BLE have already been considered as complementary technologies in LTE Release 13 to enhance positioning in indoor environments, especially thanks their wide diffusion.

### 2.3.2 Ad-hoc Technologies

The most promising ad-hoc technology for high-accuracy positioning in indoor environment is ultra-wideband (UWB) [12]. This is justified by the fact that the larger is the signal bandwidth the higher will be the resolution of time measurements and hence positioning [13, 14].

According to the FCC, an UWB signal is defined as a signal that has fractional (relative) bandwidth larger than 20% or an absolute bandwidth of at least 500 MHz [15]. UWB signals are efficiently generated using impulse generators that are simple and energy efficient. After the FCC allowed the use of UWB signals in 2002 in the U.S. and the same happened in Europe in 2007 [16] and worldwide, standardization efforts took place. This effort resulted in the publication of the IEEE 802.15.4a standard in 2007 [17] as a physical layer (PHY) alternative based on UWB to the IEEE 802.15.4 standard for WSNs (the PHY of ZigBee). This standard was followed by the IEEE 802.15.4f standard published in 2012 for applications in the field of port & marine cargo, automotive, logistics, industrial and manufacturing [18] .

After an initial slow market penetration, mainly caused by the high-cost of proprietary devices and the fragmented worldwide power emission mask regulations, since 2014 the market of real time locating systems (RTLS) took off, thanks to the availability of low-cost chips compliant with the IEEE 802.15.4a standard, and its growing rate is around 40% yearly, especially in the field of logistic and Industry 4.0. Recently, UWB has been coupled with the RFID technology to detect and track battery-less tags powered via wireless links [19]. Besides active positioning, thanks to its peculiarities, the UWB technology enables also other applications like multi-static radar for non-collaborative localization [20], life signs detection systems, and through-wall and underground imaging as will be discussed in Sec. 2.3.4.

### 2.3.3 Long-range IoT Applications

Most of long-range IoT applications (e.g., smart city, asset tracking, smart metering, smart farming, and smart logistics) are low-rate applications with coverage of tens of kilometers, and require battery life lasting years (in some cases more than 10 years). Moreover, nodes have small capabilities in terms of computation and memory, which makes accurate localization challenging [21]. Currently, two proprietary solutions are emerging: LoRa and Sigfox. Both have very low throughputs from few tens of bits per second up to few hundreds of kbps. They are not designed for positioning and employ narrowband signals that make time measurements very inaccurate because of the consequent scarce temporal resolution. Despite that, recent studies showed that rough positioning accuracy in the order of hundred of meters are possible by properly processing TDOA measurements at BSs [22].

The IoT market is under consideration also by the standardization bodies. The two main standard technologies for long-range IoT solutions are IEEE 802.11 Long Range Low Power (LRLP) and the 3GPP narrowband technologies, i.e., LTE-M, LTE NB-IoT, and EC-GSM-IoT. The positioning capabilities of 3GPP narrowband technologies were investigated in LTE Release 14. The main positioning algorithms are enhanced-CID (ECID), OTDOA and UTDOA with a target accuracy of 50 m [23]. The 5G standard is expected to include dedicated protocols for positioning to enable positioning in IoT applications, even though several technical issues have still to be studied [24].

### 2.3.4 Integration with Device-free Localization

An increasing attention is recently being devoted to the capability of detecting and tracking objects that do not take actions to help the localization infrastructure or that do not wish to be detected and localized at all. This operation is referred to *non-collaborative localization* and has often been undertaken by exploiting a network of radio sensors able to scan the area of interest through wideband radio signals to create a radio image of the objects and the environment. These systems are classified based on whether the network emits a signal designed for target detection

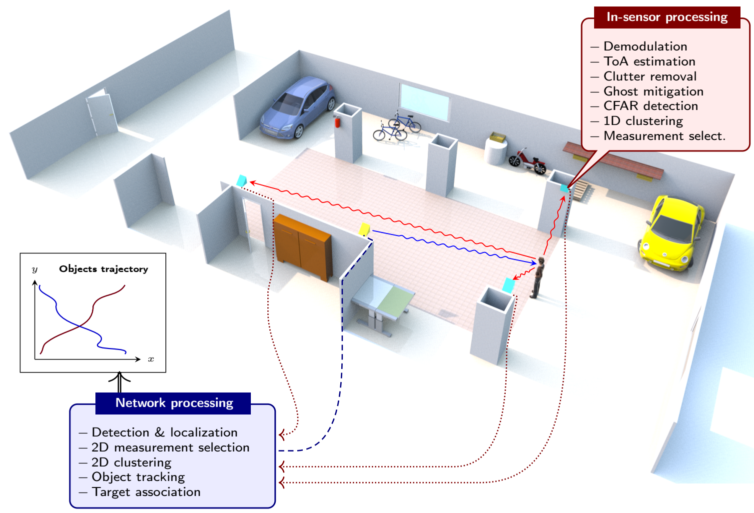


**Fig. 6** A scenario for object/people tracking through a sensor radar network. The processing steps are performed both locally on sensors and at network level.

and localization (active radar) [25], or the network exploits signals emitted by other sources of opportunity (passive radar) [26].

Accurate localization via sensor radars becomes particularly challenging in indoor environments characterized by dense multipath, clutter, signal obstructions (e.g., due to the presence of walls), and interference. In a real-world scenario measurements are usually heavily affected by such impairments, severely affecting detection reliability and localization accuracy. These operating conditions may be mitigated by the adoption of waveforms characterized by large bandwidth, e.g., UWB ones (see Sec. 2.3.2), exploiting prior knowledge of the environment, selecting reliable measurements, and using various signal processing techniques [27–30]. The UWB technology, and in particular its impulse radio version characterized by the transmission of a few nanoseconds duration pulses [31], offers an extraordinary resolution and localization precision in harsh environments, due to its ability to resolve multipath and penetrate obstacles. These features, together with the property of being light-weight, cost-effective, and characterized by low power emissions, have contributed to make UWB an ideal candidate for non-collaborative object detection in short-range radar sensor networks applications. A sketch of a scenario with the localization of objects by a radar sensor network is depicted in Figure 6.

Ubiquitous deployment of sensor radar systems integrated with existing communication infrastructure is expected to open new application scenarios, some of which have much in common with the use cases of Table 1. For example, through wall imaging, i.e., the ability to locate indoor moving targets with sensors at a standoff range outside buildings [32, 33], search and rescue of trapped victims, and people counting [34, 35] are just a few examples of promising non-collaborative localization applications.

# 3 Localization Design in 5G and Beyond

The KPI requirements in 5G scenarios can be fulfilled by exploiting different signal processing techniques and technologies, which mostly have limited resources for communication, processing, and memory. The reliability of 5G localization lies in fusing data and measurements collected from heterogeneous sensors with contextual information [36] and in designing efficient network operation strategies [37].

## 3.1 From Foundation to Operation

### 3.1.1 Fundamental Limits

To provide performance benchmarks and to guide efficient network design and operation, it is important to understand the fundamental limits of localization accuracy in 5G as well as the corresponding approaches to achieve such accuracy. For this purpose, the information inequality can be applied to determine a lower bound for the estimation errors, which is known as the Cramér-Rao lower bound (CRLB), through the inverse of the Fisher information matrix (FIM) [12].

To evaluate the localization performance in the presence of noise, CRLB-type performance bounds for the signal metrics under test, e.g., TOA, OTDOA, UTDOA, RSSI, or AOA are usually considered. Nevertheless, the properties of the signal metrics depends heavily on the method used to infer user positions, and the use of certain signal metrics may discard relevant information for localization. Thus, in deriving the fundamental limits of localization accuracy, it is desirable to fully exploit the information contained in the received waveforms rather than using specific signal metrics extracted from the waveforms [12].

Given the complexity of the scenarios considered, the analysis of fundamental limits for 5G localization should take into account also for multipath and non line-of-sight (NLOS) propagations which impact localization accuracy especially in harsh propagation environments (e.g., indoor) [38]. In addition, the case of D2D cooperation where intranode measurements are available can be analyzed by taking into account spatial cooperation (together with temporal cooperation in dynamic scenarios) by characterizing the information evolution in both spatial and temporal domains [39].

### 3.1.2 Network Operation Strategies

The performance of localization in 5G depends on the transmitting energy, signal bandwidth, network geometry, and the channel conditions [40, 41]. Such factors are driven by the network operation strategy, which determines the allocation of resources, the network nodes from which the measurements are taken, and the deployment of mobile nodes and base stations. Network operation plays a critical role in localization since it not only affects the energy consumption, which is a crucial KPI in 5G applications, but also determines the localization accuracy [37]. For example, range measurements between two nodes with poor channel conditions consume significant amounts of energy without improving localization accuracy [28].

Network operation strategies for efficient localization and navigation can be categorized into several functionalities, including node prioritization (i.e. prioritization strategies for allocating transmitting resources such as power, bandwidth, and time to achieve the best trade-off between resource consumption and localization accuracy), node activation (i.e. activation strategies for determining the nodes that are allowed to make inter-node measurements so that the localization accuracy of the entire network is maximized), and node deployment (deployment strategies for determining the positions of new nodes in the network so that the localization accuracy of certain existing nodes can be maximally improved) [21].

## 3.2 Advances in Signal Processing

The integration of hybrid technologies fusing measurements from different sensors such as inertial, GNSS, camera, various RATs, is a challenge for signal processing in 5G localization. In particular, new localization methods, for instance based on statistical machine learning, will be needed to achieve accurate, seamless, and robust localization.

### 3.2.1 Soft Information

Conventional localization methods rely on single value estimates (SVEs), i.e. each measurement used for localization corresponds to the estimate of a single-value metric such as e.g., TOA, OTDOA, UTDOA, RSSI, or AOA, as described in Sec. 2. Localization accuracy obtained by SVE-based methods depends heavily on the quality of such SVEs, which degrades in wireless environments, i.e. in the presence of multipath and NLOS that lead to measurement biases.

To cope with wireless propagation impairments, conventional localization approaches focus on improving the estimation of single values [42–45]. Techniques to refine the SVE have been exploited by relying on models for SVEs errors (e.g., the bias induced by NLOS conditions) [43,46]. Selecting a subset of received waveforms that contain reliable positional information can also mitigate SVE errors and it can be based on features extracted from their samples [28]. In addition, data fusion can be obtained by considering the SVE of different features as independent or by involving hybrid models that account for the relationship among different features [47–50]. To overcome the limitations of SVE, one-stage techniques have been explored that use measurements to directly obtain positions estimates from the received waveforms based on a prior model, namely direct positioning (DP) [51–56].

Recently, new localization techniques have been developed that rely on a set of possible values rather than on single distance estimate (DE), referred to as soft range information (SRI). To improve the localization performance it is essential to design localization networks that exploit soft information (SI), such as SRI or soft angle information (SAI), together with environmental information, such as contextual data including digital map, dynamic model, and users profiles [3].

The 5G and IoT scenarios offer the possibility to exploit different sensors in the environments with stringent limitations in terms of energy and power consumption. In fact, the reliability of multi-sensor IoT lies in fusing data and measurements collected from heterogeneous sensors with low computation and communication capabilities [21], and in designing efficient network operation strategies [37]. This calls for distributed implementation of SI-based localization capable of fusing information from multimodal measurements and environmental knowledge. Distributed localization algorithms require the communication of messages [57–59], which involves high dimensionality depending on the kind of SI. Therefore, it is of utmost importance to develop SI dimensionality reduction techniques for message passing.

### 3.2.2 Cooperative localization with D2D communication

D2D communication in 5G are under consideration in Release 16, in particular for ultra-dense networks enabling cooperative localization, for instance, in V2X scenarios [10]. Joint spatial and temporal cooperation of devices can yield dramatic localization performance improvement over conventional approaches since intranode measurements and mobility (dynamic) models yield new information for localization and navigation. In particular, joint spatial and temporal cooperation between devices incurs in associated costs such as additional communication and more complicated algorithms over the network: 1) the communication among nodes is required for inter-node measurements and information exchange; and 2) interdependency among the estimates of the agent positions hinders effective distributed inference algorithms. In [39], the concept of network localization and navigation (NLN) has been put forth to exploit spatiotemporal cooperation among nodes. Cooperative algorithms have been developed based on graphical models, a branch of statistics that makes inference possible over highly interrelated random variables. Despite the technological advances in the field, there are still several issues that need to be addressed to realize accurate, reliable, and efficient NLN.

### 3.3 Beyond Localization

In addition to specific use cases as flow management, traffic monitoring, advertisement push (see Sec. 1), many other applications such as crowd control and detection of emergency events are important for smart building and public protection. All these applications rely on ready-to-use analytics that can be defined based on localization data. The definition of such analytics will primarily leverage basic spatiotemporal features such as crowd size and people flow. To this aim, both individual and crowd-centric approaches can be adopted: (i) *individual-centric* approaches associate the measured data to single targets/terminals, and run knowledge discovery separately on each of them; (ii) *crowd-centric* approaches associate the measured data directly to a group of users, and run a crowd-level analysis, resulting in lower dimensionality and complexity [35]. Therefore new methods based on a crowd-centric approach will be conceived to provide ready-to-use analytics in 5G scenarios and fulfil the requirements in terms of latency and energy consumption.

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