Location Awareness in Beyond 5G Networks

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Location awareness is essential for enabling contextual services and for improving network management in 5G and B5G networks. The authors provide an overview of the expanding opportunities offered by location awareness in wireless networks, discuss SI-based approaches for improved location awareness, and present case studies in conformance with the 3GPP standardization by ETSI.

Abstract

Location awareness is essential for enabling contextual services and for improving network management in 5th generation (5G) and beyond 5G (B5G) networks. This article provides an overview of the expanding opportunities offered by location awareness in wireless networks, discusses soft information (SI)-based approaches for improved location awareness, and presents case studies in conformance with the 3rd Generation Partnership Project (3GPP) standardization by the European Telecommunications Standards Institute (ETSI). Results show that SI-based approaches can provide a new level of location awareness in 5G and B5G networks.

Introduction

Location awareness is vital for fifth generation (5G) and beyond 5G (B5G) networks [1, 2]. On one hand, location awareness enables numerous location-based services (LBSs) including autonomy, asset tracking, smart environments, and the Internet of Things.[1] On the other hand, location awareness permits more efficient utilization of wireless resources via techniques including pencil beamforming and network slicing [3, 4]. Therefore, it is important to determine positional information of network nodes (including devices, objects, people, and vehicles), referred to as Localization of Things (LoT). The positional information of network nodes is inherently encapsulated in soft information (SI) [5], which is related to various types of positional features (e.g., distance, angle, and proximity) extracted from measurements and of contextual data (e.g., dynamic model, digital map, and user profile) corresponding to the environment. It is therefore essential to develop localization techniques that are capable of accounting for all the SI present in a B5G ecosystem. Indeed, accurate location awareness depends on the ability to extract and exploit SI, both of which can be challenging in complex wireless environments.

The demand for accurate location awareness has grown rapidly [6]. Classical localization approaches typically rely on single-value estimates (SVEs), such as distance and direction estimates, and on knowledge associated with the SVE uncertainty (when available) to serve as inputs for a position inference algorithm. Localization accuracy obtained by such methods depends heavily on the quality of the SVEs, which deteriorates in complex wireless environments. In particular, the performance of conventional techniques degrades in wireless environments due to biases in SVEs caused by non-line-of-sight (NLoS) conditions and multipath propagation. This challenges both the reliability of LBSs and the efficiency of network management.

To improve location awareness, the SI-based approach has recently been proposed [5]. This approach probabilistically accounts for the relation between any position-related measurement and a positional feature. It enables full exploitation of the positional information inherent in different types of measurements (namely, multimodal LoT) together with contextual data. Multimodal LoT requires efficient fusion algorithms for measurements and data gathered from heterogeneous sensors, management strategies for networks consisting of nodes with stringent resource limitations, and communication strategies that can cope with the dimensionality of the SI. In order to improve the localization accuracy and reduce the communication overhead in 5G and B5G networks, it is vital to develop efficient learning methods that capture the essential positional information while reducing the dimensionality of SI.

Pivotal questions related to location awareness in B5G networks are:

- What level of performance gain do SI-based methods provide compared to classical methods in different scenarios?
- How are models learned for describing SI from different measurements in wireless networks?
- How do we fuse heterogeneous measurements and contextual data for location awareness in the B5G ecosystem?

The answers to these questions provide insights into achieving new levels of location awareness in B5G networks for enabling LBSs and improving network management. The goal of this article is to present SI-based approaches for multimodal LoT in 5G and B5G networks, as well as to quantify their performance improvement compared to conventional approaches. We advocate the exploitation of SI to achieve a new level of accuracy and efficiency for location awareness in B5G networks.

This article introduces SI-based approaches for location awareness in B5G networks and demonstrates that SI is more capable than SVEs of providing accurate location awareness. In particular, the article:

- Presents methodologies for achieving location awareness in 5G and B5G networks, particularly describing SI-based approaches for LoT
- Discusses model learning and information fusion for SI-based localization in standardized European Telecommunications Standards Institute (ETSI) 3rd Generation Partnership Project (3GPP) scenarios

[1] The IEEE Communications Society's Best Readings covering location awareness can be found at https://www.comsoc.org/publications/best-readings/network-localization-and-navigation.

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PSL	A/R	Accuracy		Availability	Latency	Environment and velocity	
		H	V			Positioning service area	Enhanced positioning service area
1	A	10 m	3 m	95%	1 s	Indoor (30 km/h); outdoor (rural and urban; 250 km/h)	Indoor (30 km/h)
2	A	3 m	3 m	99%	1 s	Outdoor (rural and urban; trains 500 km/h; others 250 km/h)	Outdoor (dense urban, 60 km/h; roads, 250 km/h; railways, 500 km/h); indoor (30 km/h)
3	A	1 m	2 m	99%	1 s	Outdoor (rural and urban; trains 500 km/h; others 250 km/h)	Outdoor (dense urban, 60 km/h; roads, 250 km/h; railways, 500 km/h); indoor (30 km/h)
4	A	1 m	2 m	99.9%	15 ms	NA	Indoor (30 km/h)
5	A	0.3 m	2 m	99%	1 s	Outdoor (rural 250 km/h)	Outdoor (dense urban, 60 km/h; roads and railways, 250 km/h); indoor (30 km/h)
6	A	0.3 m	2 m	99.9%	10 ms	NA	Outdoor (dense urban, 60 km/h); indoor (30 km/h)
7	R	0.2 m	0.2 m	99%	1 s	Indoor and outdoor (rural, urban, dense urban) 30 km/h; the relative positioning is between UEs or other positioning nodes within 10 m distance from each other	

TABLE 1. Service level requirements, also referred to as PSLs (first column), for 5G localization according to 3GPP TS 22.261 [1]. Such requirements are given in terms of absolute (A) position of a UE or of relative (R) position between two UEs or between one UE and another 5G network node; and in terms of horizontal (H) and vertical (V) accuracy. The table also reports the service availability and latency associated with each level. Requirements are specified for a general positioning service area or an enhanced positioning service area for different maximum speeds.

- Quantifies the performance gain of SI-based methods via case studies for different scenarios in conformity to ETSI 3GPP standardization technical reports [7]

The remaining sections are organized as follows. The following section presents location awareness in 5G and B5G networks. We then describe SI-based LoT, and provide results in 3GPP settings. Lastly, we offer final remarks.

Location Awareness in B5G Networks

Localization Requirements

The standardization for LBSs in 5G and B5G networks is based on various use case scenarios and network operating conditions. The service level requirements for the use cases are specified in terms of key performance indicators (KPIs) that are related to the localization of user equipments (UEs). The main KPIs defined by 3GPP are horizontal and vertical accuracy, availability, and latency. Other important KPIs are related to the power consumption and energy needed for localization, and the scalability with the number of user equipments (UEs).

The 3GPP specification [1] describes seven positioning service levels (PSLs) as summarized in Table 1. Notice that most of the foreseen services require high accuracy (horizontal and vertical precision below 1 m over 99 percent of instantiations) and, some of them, low latency (location updates every few tens of milliseconds) even in complex wireless environments. These requirements can be fulfilled by exploiting multimodal network capabilities, where both radio access technology (RAT)-dependent and RAT-independent measurements are jointly used for inferring UE positional states.

Localization Measurements

The 3GPP standard has specified, since earlier releases, the signals dedicated to localization or those that can be exploited for localization, including the positioning reference signal (PRS) in downlink and the sounding reference signal (SRS) in uplink. Related measurements that carry positional information are the down-link and up-link time-difference-of-arrival (TDoA), the angle-of-arrival (AoA), and the angle-of-departure (AoD). Other types of measurements related to UE positional states can also be considered, particularly in private networks. Therefore, examples of measurements for location awareness include inter-node measurements, commonly obtained by radio measurement units; and intra-node measurements, commonly obtained by inertial measurement units. The environmental information associated with a UE can also be used as prior information to improve the localization accuracy. Examples of environmental information include digital maps, dynamic models, and UE profiles. The accuracy of location awareness is strongly affected by the quality of measurements and by the knowledge of the environment. Figure 1 illustrates an example of position estimation with accurate and inaccurate measurements for LBSs and shows how network management can exploit higher localization accuracy, specifically for pencil beamforming [3].

Beyond 5G Technologies

A new paradigm that is foreseen to play a key role in B5G networks is the integrated sensing and communication, that is, the exploitation of the same signal for both sensing the environment and communicating information (e.g., radar and communication for autonomous vehicles). This calls for research on waveform design, interference mitigation, spectrum sharing, time sharing, and hardware reuse between sensing, localization, and communication. Joint sensing and communication can also be used in a passive radar setting for the detection and localization of device-free targets. This setting leverages both base stations and access points as illuminators of opportunity, without deploying any dedicated wireless source, relying on any target device, and incurring additional costs. The signals propagate in the monitored environment and are reflected by both background objects (clutter) and target objects [8]. Sensing and localization in this case can be performed by a network of receivers (specific sensors or UEs) that are deployed in a desig-

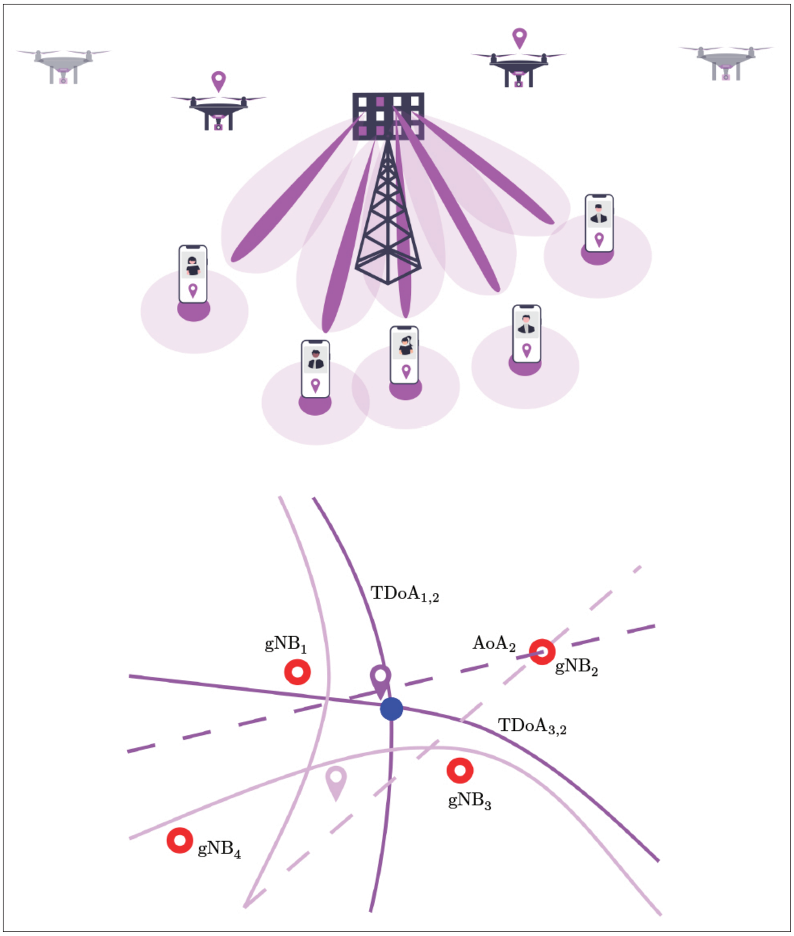

FIGURE 1. Example of accurate positional information exploited for network management; a next generation NodeB (gNB), employing pencil beams based on estimated UE position, communicates with five users. The lower/higher uncertainty in the estimated UE position is depicted using dark/light purple ellipses. Two beamwidths are considered, where a smaller/larger beamwidth (dark/light purple beams) is used in case of lower/higher uncertainty. Positional information can also be used to guide mobile gNB nodes exemplified by drones. In the bottom part of the figure, an example is shown for estimated UE position with lower/higher uncertainty (dark/light purple) obtained with two TDoA measurements and one AoA measurement in the presence of four gNBs (empty red circles) and a single UE (blue circle).

nated area to receive the signals emitted by base stations or by other sources of opportunity and reflected by the passive targets.

Recently, research efforts have been devoted to resiliency and robustness of localization systems in harsh electromagnetic environments affected by severe impairments such as multipath and non-line-of-sight (NLoS) conditions. In such environments, the use of intelligent surfaces (ISs) promises to mitigate these impairments by controlling the electromagnetic environment [9]. Therefore, ISs can be employed to create desirable wireless propagation conditions that improve the performance of localization systems in B5G networks. In addition, the use of THz bands is envisioned as a key wireless technology to satisfy the demand for extremely high throughput and can be utilized for localization in environments such as those of B5G for Industry 4.0 [10].

Soft Information for Location Awareness

Localization aims to determine the positional states of network nodes. At a given time, the positional state of a node includes its position (absolute or relative coordinates) and other mobility-related quantities (e.g., velocity, acceleration, and orientation). Localization methods infer the positional states of the nodes based on inter-node and intra-node measurements, and on contextual data.

Location awareness is the knowledge of probabilistic information on UEs' possible positional states. Such information is described by the conditional posterior of the positional state, which can serve to infer the positional state of each UE and enable applications where probabilistic information of the positional state is sufficient. The location awareness for the UEs at different time instants can be obtained based on inter-node measurements with respect to both base stations and neighboring UEs (cooperation with other UEs via side links), intra-node measurements, and contextual data. Most location-aware services, including those relying on 5G and B5G networks, require inference of sequences of positional states. The joint posterior distribution of positional states can be determined via a *prediction step* (using a dynamic model) followed by an *update step* (using an observation model and a new measurement) .

Location awareness can be obtained from SI, which is composed of soft feature information (SFI) and soft context information (SCI) [5]. In particular, SI can be determined from a joint distribution function of positional features, measurements, and contextual data. This joint distribution is obtained from a *generative model* tailored to wireless environments, including those described by technical specifications for 5G networks. The SI-based approach provides a statistical characterization of the relation between position-related measurement and a positional feature. Therefore, even measurements affected by severe multipath or NLoS conditions can be used by SI-based localization since SI relies on probabilistic models that have already accounted for such situations.

In cases where positional states follow a linear evolution and both SFI and SCI are Gaussian functions, the inference can be performed in a closed form as in Kalman filters [11]. Otherwise, its implementation employs approximations that account for a trade-off between complexity and accuracy [12]. Compared to existing works that rely on predefined measurement models, such as those in the field of multi-sensor multi-target tracking [13], SI-based approaches do not require specific measurement models. This can be especially useful if the measurement models for the wireless environment are not available or if the data volume of the measurements prohibits the direct use of likelihood functions.

Distributed Implementation

In 5G and B5G networks, it is important to infer positional states in a distributed manner. In non-cooperative scenarios, each UE can determine its own position, resulting in a distributed implementation. However, it is known that spatiotemporal cooperation can significantly improve localization accuracy. Unfortunately, a distributed implementation of cooperative methods is hindered by information coupling, that is, the UE positional state inferences are highly interrelated. Therefore, the optimal implementation of cooperative approaches requires a centralized implementation to determine the joint posterior distribution of all UEs.

Distributed techniques for cooperative localization in B5G networks are expected to rely on the approximation of marginal distributions. Such approximations can be obtained from graphs that describe the network connectivity after disregarding cycles. Hence, each node keeps track of its own positional estimate and uncertainty, and individual estimates and uncertainties are updated by means of message passing among different processing nodes.

Learning Soft Information

In complex 5G and B5G wireless environments, finding an accurate generative model for the SI is challenging, and it is preferable to learn it via machine learning techniques using measurements, positional features, and contextual data. The SI can be determined by a two-phase algorithm summarized here.

Offline (Training) Phase: Learn a generative model using trial data such as heterogeneous measurements, ground truth features, and contextual data.

Online (Operation) Phase: Determine the SI using the generative model from the training phase together with the new measurement and/or contextual data.

Learning a generative model in the training phase from trial data is particularly difficult when measurement vectors have high dimensionality (e.g., samples of received waveforms). In such cases, dimensionality reduction techniques are essential for efficiently learning the SFI. The SI-based approach is general and can be used with different types of measurements in the B5G ecosystem. The specific method used for reduction of the dimensionality and for learning the generative model depends on the technology used. Different techniques for learning SFI based on unsupervised machine learning have been discussed in [5].

Data Fusion in Heterogenous Networks

The development of 5G and B5G networks leverages an ecosystem composed of heterogeneous technologies. Therefore, it is essential to exploit diverse types of measurements. The SI-based approach naturally and efficiently fuses heterogeneous measurements from multimodal sensors. Fusion of such measurements can be implemented by multiplying SFIs corresponding to different measurements, as long as the random measurement data are conditionally independent given the positional states.

The conditional independence of the observations adequately represents the behavior of actual measurements obtained by sensors that are spatially scattered or by sensors belonging to different technologies. Examples of multimodal measurements are those associated with different types of amplitude-, time-, and angle-related features [14].

Case Study: 3GPP Standardized Scenarios

This section presents results on localization accuracy, in terms of the empirical cumulative distribution function (ECDF) of the horizontal localization error, based on the ETSI 3GPP standard. In particular, the performance obtained with the SI-based approach is compared to that reported in the 3GPP Technical Report (TR) [7]. The position root mean square error (RMSE) is also presented for different generative models of the SI and cardinalities of the trial data.

Two 5G standardized scenarios are considered, namely urban microcell (UMi) and indoor open office (IOO). The UMi scenario exhibits a lower probability of LoS links and a higher delay spread, while the IOO scenario is characterized by higher probability of LoS links and lower delay spread. In both cases, we account for the spatial consistency of the wireless channel. For the UMi scenario, a 550 m × 550 m area is considered with 19 sites; each site includes three gNBs, each covering an angular sector of 120° and emitting at a power level of 43 dBm. For the IOO scenario, a 120 m × 50 m area is considered with 12 single-sector gNBs emitting at a power level of 24 dBm. For both scenarios, the UEs are randomly deployed within the monitored area, and the noise figure at the receiver side is 5 dB. Figure 2 shows LoS maps and gNBs spatial displacement for the UMi (top) and IOO (bottom) standardized scenarios. In particular, the figure shows instantiations of UE positions in which a UE would be in LoS with zero (white), one (light purple), two (salmon), and at least three (dark purple) gNBs.

TDoA measurements obtained from the PRS are considered with two combinations of bandwidth and carrier frequency: 50 MHz bandwidth at 2 GHz, namely Type I simulation setting; and 100 MHz bandwidth at 4 GHz, namely Type II simulation setting. According to [7], the gNBs are synchronized. The channel instantiations are generated using the QuaDRiGa channel simulator, which supports 3GPP standardized channel models and accounts for spatially correlated large- and small-scale fading [15].

The generative model for SI is based on Fisher-Wald settings, considering a Gaussian mixture model (GMM) with three mixtures. The UE location is inferred by maximizing a GMM. The offline and online phases employ a 10-fold cross-validation technique for each of the standardized settings. In particular, 1000 instantiations of large- and small-scale fading are generated, and for each instantiation, 10 UEs are randomly deployed within the monitored area, and position inference is performed. At each iteration of the cross-validation procedure, the TDoA-related measurements and positional feature obtained from 900 instantiations of the 10 UEs are used to train the generative model, while 100 instantiations of the 10 UEs are used for position inference. In the online phase, the maximum of the GMM is obtained via an exhaustive search. A coarse position estimate is first obtained by searching over the entire area with a grid of 5 meters per step. A fine position estimate is then obtained by searching over a 30 m × 30 m area centered on the coarse estimate with a grid of 0.5 meters per step.

Figure 3 shows the ECDF of the horizontal localization error for both UMi and IOO scenarios with Type I and Type II settings. Markers represent the results obtained by current techniques reported in 3GPP TR [7], while lines represent the results obtained by the SI-based approach. It can be observed that the SI-based approach provides significant performance improvements compared to the results obtained by current techniques described in the 3GPP TR for all percentiles, scenarios, and settings. In particular, at the 90th percentile, the SI-based approach improves the localization accuracy by about 2.5 m for the UMi

The SI-based approach is general and can be used with different types of measurements. In complex 5G and B5G wireless environments, finding an accurate generative model for the SI is challenging, and it is preferable to learn it via machine learning techniques using measurements, positional features, and contextual data.

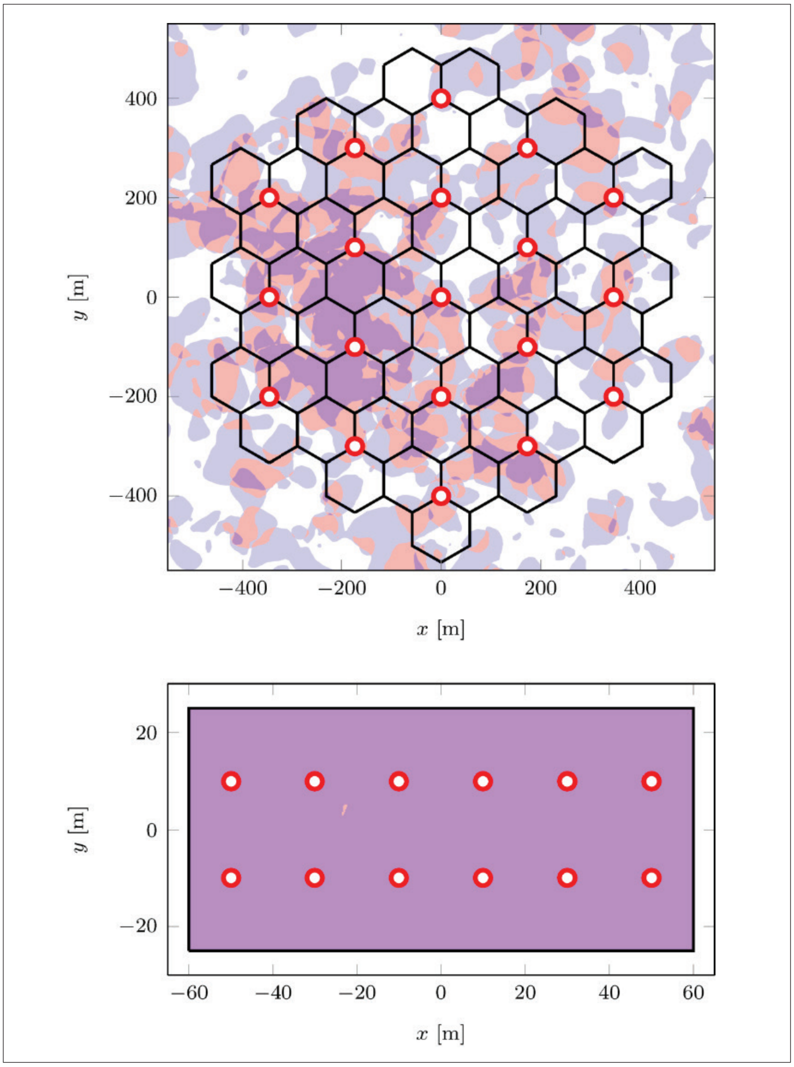

FIGURE 2. Example of LoS map for ETSI 3GPP urban microcell (top) and indoor open office (bottom) scenarios where red circles represent the gNBs. White, light purple, salmon, and dark purple areas correspond to positions with no gNBs, one gNB, two gNBs, and at least three gNBs in LoS, respectively.

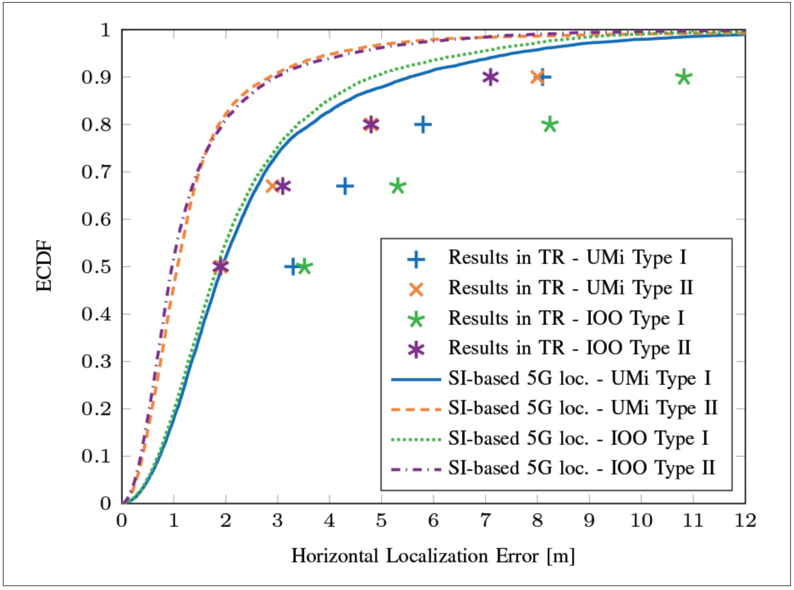

FIGURE 3. ECDF of the horizontal localization error for ETSI 3GPP UMi and IOO scenarios using PRS with 50 and 100 MHz bandwidths at 2 GHz and 4 GHz center frequencies, respectively. The performance of SI-based localization is compared to that reported in the 3GPP TR [7].

Type I setting and by about 5 m for the UMi Type II setting. Significant performance improvements can also be observed for the IOO scenario. At the 90th percentile, the SI-based approach improves localization accuracy by about 6.5 m for the IOO Type I setting and by about 4 m for the IOO Type II setting. This can be attributed to the fact that the SI-based approach better exploits the positional information inherent in the measurements via generative models learned from the wireless environment and is more robust compared to classical approaches. It can also be observed that the accuracy of the SI-based approach is not influenced by the considered scenario. This can be attributed to the fact that when the generative model is tailored to a specific scenario, the key factors determining the localization accuracy are the signal bandwidth and carrier frequency.

Figure 4 shows the position RMSE as a function of the number of mixtures used in the generative model for all scenarios and settings. It can be observed that a mixture cardinality of three and two already provides an RMSE close to the best possible one for UMi and IOO scenarios, respectively. Table 2 shows the position RMSE for different numbers of UE measurements used at each iteration of the cross-validation procedure in training the generative model for both UMi and IOO scenarios with Type I and Type II settings. It can be observed that RMSE already approaches its best possible value with 50 or 500 training measurements, depending on the considered scenario and setting. This shows that the SI-based approach can perform well even with a small number of training measurements.

The performance gain demonstrated in these results reveals that the SI-based approach is crucial for localization in 3GPP standardized scenarios. Such localization accuracy can be exploited for enabling LBSs and improving network management.

Final Remarks

This article introduces methodologies for achieving location awareness in 5G and B5G networks. A new SI-based approach is presented for accurate inference of UE positional states. Efficient methods for learning and exploiting SI are also discussed. Such techniques are crucial for location awareness, especially in scenarios where nodes have limited computation and communication capabilities. Case studies, according to 3GPP standardization technical reports, are presented in urban microcell and indoor open office wireless environments. Results show that SI-based localization significantly outperforms current techniques described in the 3GPP technical report. Furthermore, SI-based methods offer robustness to different conditions of the wireless environment, thereby paving the way to a new level of location awareness in B5G networks.

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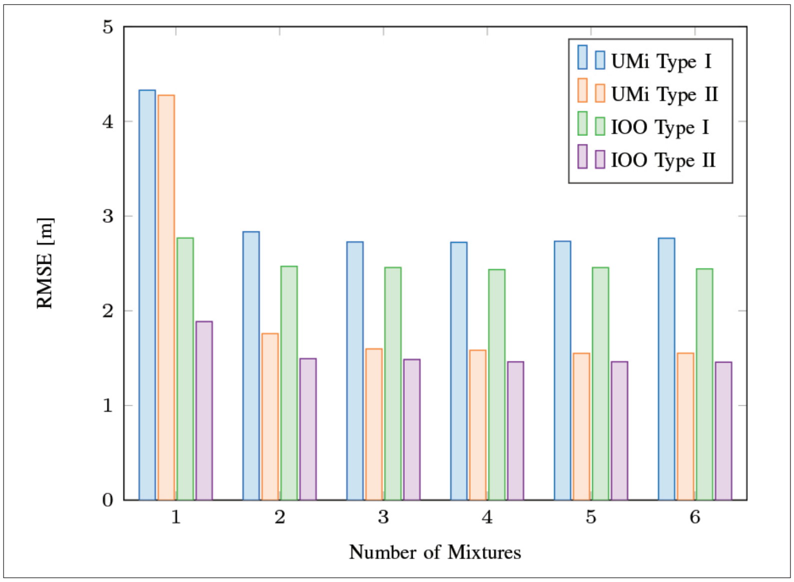

FIGURE 4. RMSE of the position estimate as a function of the number of mixtures in the GMM for ETSI 3GPP UMi and IOO scenarios using PRS with 50 and 100 MHz bandwidths at 2 GHz and 4 GHz center frequencies, respectively.

Number of UE training measurements	RMSE (m)			
	UMi Type I	UMi Type II	IOO Type I	IOO Type II
5	3.22	2.07	2.75	1.95
50	2.71	1.62	2.50	1.48
500	2.71	1.59	2.45	1.48
5000	2.72	1.61	2.46	1.48
9000	2.72	1.60	2.46	1.48

TABLE 2. Position RMSE as a function of the number of UE measurements used in each training phase.

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