Localization in Cellular and Heterogeneous Networks for 5G and Beyond: A Review

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Abstract

Localization in modern and future wireless networks has been established as an important field of research work due to the requirements of location-based applications and services with variety of accuracy requirements. These are driven by the strong heterogeneity in terms of processing power, size and range of the nodes in beyond Fifth Generation (5G) telecommunications. Thus, localization methods in cellular and heterogeneous networks (Het-Nets) diversify in their application scenario (terrestrial and based on aerial platforms) and bands (licensed and unlicensed). They are categorized, according to the methodology used to perform the positioning, into three groups – fingerprinting (learning-based location estimation), trilateration and triangulation (distance or angular based), and hybrid (combining two geometric features of the received signals) methods. For each category, a summary of the methods' design features and achieved accuracy is presented in tabular

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form. On the basis of the review, directions for future research are outlined, that will facilitate the further advancements in the design and application of localization methods for wireless communications.

Keywords: 5G, cellular networks, fingerprinting, Het-Net, localization, positioning, triangulation, trilateration, wireless networks.

1 Introduction

As research efforts for beyond 5G telecommunications intensify to fulfill the envisioned requirements and concepts of the Sixth Generation or 6G [1, 2], new challenges for user connectivity continue to emerge. This is caused by the variety of new applications and the inter-connected terrestrial, underwater, air and space networks that provide them. Together with the traditional problems of resource management and reliable wireless access, precise localization (or positioning) for mobile users, has received considerable attention in literature [3, 4]. Positioning methods aim to estimate the location of a user equipment (UE) in real time, as it is moved at various speeds on the ground (by pedestrians in both inside and outside of buildings, or driven by vehicles) and in the air. Their importance is significant for not only navigation or emergency applications but also communication-specific functionalities (such as radio environment mapping, user association with the wireless network infrastructure, remote control etc). Therefore, this kind of methods require high accuracy (in the span of meters or less, depending on the application and network scenario) and low computational complexity (for energy efficiency and real-time processing), which are often contradictory characteristics. The localization of a target is performed by measuring the signals of the anchor nodes (used as reference, their position being known) at a receiving node (which may also be the target itself). Furthermore, positioning considered in two dimensions (2D) may not be viable, which for contemporary and future networks, such as those including unmanned aerial vehicles (UAVs) and Internet of Things (IoT) devices, establishes the need for three dimensional (3D) localization. It should be noted that the localization problem may be defined as not only from the network's point of view but also from that of the mobile UEs/UAVs/IoTs. In other words, the task may not only be to localize the UEs themselves but to use them to locate other moving targets. The metric that is most commonly used to determine the positioning accuracy is the round mean square error (RMSE). It represents the square root of the distance between the actual position of the target (known in an experimental setting), and the estimated one. In other words, it defines the method's accuracy, which is why the terms are used interchangeably in this work. Additionally, the method's reliability is often assessed through the Cramer-Rao lower bound (CRLB). It determines the theoretical optimal accuracy for a particular scenario, which is the objective of the proposed solution.

The importance of localization is emphasized even more by the recent visions for its integration with communication itself [4]. Motivated by these observations, the present review describes the advancements in the most prominent types of localization methods with their particular design characteristics and accuracy (in the 90th percentile, i.e. that achieved in at least 90% of the simulation instances) summarized in tabular form for each type. In addition, particular directions to facilitate future research, are outlined. For each method, it is noted, whether localization is performed by the network (N) or the mobile terminal (MT). Cellular and heterogeneous networks (Het-Nets), operating in both licensed or in industrial, scientific and medical (ISM) bands, are considered as system models in this paper due to their prominence in the literature. Most of the positioning methods are applied in terrestrial scenarios where the users are walking on foot, or in a vehicle. There is, nevertheless, an increasing emphasis on UAV-based localization, which is also accounted for. The methods are divided in three categories, in which most research efforts relevant to cellular and Het-Nets, are focused. The rest of this paper is organized in the following way. A review of fingerprinting, trilateration and triangulation, and hybrid methods, is presented in Sections 2, 3, and 4, respectively. The directions for further research and conclusions are given in Section 5.

2 Fingerprinting Based Methods

Arguably the most notable type of localization methods in recent years, are in this category. This is primarily due to the proliferation of learning on deep neural networks (NNs) in modern wireless communications. These methods are based on the preliminary (or offline) construction of a dataset that describes the environment using parameters (such as power, statistical features, etc.) extracted from the reference radio signals at the receiver. Then, supervised learning algorithms use the database to learn these characteristics (also known as fingerprints), so online measurements can be performed with minimal processing complexity. Thus, the challenge of even complex indoor propagation conditions may be reliably surmounted.

For this purpose, however, fingerprinting methods require a large dataset with complex pre-processing.

2.1 Fingerprinting for Cellular Networks

To reduce the volume of the fingerprinting dataset and computational complexity for localization in Long Term Evolution (LTE) for the Fourth Generation (4G), the authors in [5] consider several statistical features of the received signal reference power (RSRP) and the channel state indicator (CSI), rather than using the CSI measurements themselves. Real-world measurements in indoor and outdoor conditions are gathered, which are processed by the k-Nearest Neighbor (KNN), achieving fast convergence in both cases. Extended simulations for indoor positioning in [6] show that the accuracy is improved with increasing the bandwidth, while it does not significantly degrade as the number of reference measurement points decreases. An alternative method in [7] proposes the use of images of the received signal strength indicator (RSSI) and other similar parameters, to construct the fingerprinting dataset, which is based on real-world LTE measurements. The images in the dataset are preliminary rotated and resized to normalize the data. Then, they are first used to train a coarse localization method consisting of a deep residual network (DRN). The output of this step is then processed by a multi-layer perceptron, which tunes the DRN's parameters through transfer learning. The proposed solution achieves near 95% positioning accuracy for 30×30 m area. Another deep-learning based fingerprinting solution for commercial LTE networks is developed in [8]. An SDR-based CSI collection and feature extraction method is employed. First, the SDR measures the CSI at different reference points, the features of which are afterwards extracted through a deep NN. They are used to construct the fingerprinting dataset for preliminary training. During the inference stage, the NN automatically determines the positioning by the new CSI measurements. Experimental results demonstrated error of under 1 m for indoor and of less than 50 m for outdoor scenarios, respectively. A surface correlation preprocessing of the LTE fingerprinting dataset is proposed in [9]. The measured RSS in time domain is converted to a spatial pattern by estimating the walking distance between the UE and the pedestrian dead reckoning (PDR) point. Then, these measurements are correlated to the spatial RSS pattern of a pedestrian's movement trajectory. In this way, the localization errors caused by multipath fading and noise in an urban area are reduced. The majority of the estimated accuracy levels are below 15 m in an open space, whereas in the much more challenging dense urbanization scenario, they are around 50 m but decrease significantly with distance. Low-cost, high-accuracy solution for commercial LTE localization is developed in [10]. The dataset derived from GNSS measurements is processed via a Gaussian mixture model (GMM) unsupervised learning algorithm to differentiate between indoor and outdoor positions. If the UE is detected to be in an indoor location (i.e. non-GNSS measurements), a Bayesian classifier identifies the specific building. The experiments in a real-world LTE network with over 100 BSs show identification accuracy of 90% and an indoor localization error of below 100 m. The authors in [11] propose a fingerprinting method that maps the measurement parameters (fading, received signal reference power, delay spread) to the geographical location. These are extracted from the LTE control channel signals, and are then processed by a NN that yields the UE positions. The solution is tested in both indoor and outdoor conditions, with achieving less than 20 m and 300 m, respectively in each of them. Indoor 2D localization for LTE via fingerprinting is proposed in [12]. The fingerprinting dataset stores the spatial pattern of the RSS measurements that represents the UEs' movements. To improve its accuracy, the pattern is filtered by a feature matching algorithm. Additionally, the authors employ correlation pattern analysis to enhance the convergence speed. About 95% of the RMSE measurements have values less than 10 m. To account for indoor propagation environment in LTE, the authors in [13] employ the measurements of the physical uplink control channels, physical uplink shared channel, and CSI at the BS. They are used to construct a dataset from a number of sensors at particular locations. This data is used to train NN models that are implemented in a real-world testbed using SDRs and the OpenAirInterface software platform. A positioning solution for two indoor 5G scenarios is proposed in [14]. The RSS measurements are first processed by a Kalman filter with a spherical kernel, after which, a fingerprinting dataset is built using the universal Kriging algorithm. The online UE location estimation is performed by the KNN algorithm. Up to 20% improvement over other methods is reported. Improved localization for UE in 5G urban scenarios, using beamformed RSS measurements fused with GNSS data, is proposed in [15]. Both of these measurements are processed via separate NN, the output of which is fused to increase their accuracy. A 2D signal coverage map of the measurement area is constructed, and the positioning accuracy is assessed for different values of the error's standard deviation. The combined results outperform the RSS-only accuracy by nearly 50%, while the error increases with the error's deviation.

2.2 Fingerprinting for Het-Nets in ISM Bands

The authors of [16] apply deep learning with CSI as input for indoor localization with Wi-Fi in a real-world experiment. Localization of multiple positions is performed by a single AP via offline training from the obtained normalized measurements dataset. In the online phase, the CSI variance and training data are used to compute the posterior probability for each location. The proposed solution is rigid in NLOS conditions and is up to 20% more efficient than other contemporary methods. This study is extended in [17] by a method that utilizes CSI, averaged RSS and AOA measurements for the fingerprinting dataset. It is based on Wi-Fi in the 5 GHz ISM band, and implemented in a real-world testbed. During the offline phase, the RSS and AOA are obtained and used to form the training dataset. Then, a probabilistic model for location estimation based on the dataset combines the posteriori probabilities of the measured CSI of all targets. Up to 20% improvement in accuracy, compared to [16] is reported. An analogical solution for Wi-Fi based indoor positioning, is studied in [18]. To decrease the RSS measurements' variance, a modification that accounts for the distance between the anchor and the agent, is proposed. The number k of nearest neighbors is adapted to account for the distance difference. Additionally, the measurement database is used to determine which APs provide the best positioning accuracy, so they may be used during the online phase. The estimation error increases linearly with the standard deviation of the noise, whereas it is not considerably influenced by the path loss exponent. The authors in [19] propose an alternative solution that employs Bluetooth Low Energy (BLE) for indoor localization. It emphasizes on the method for offline fingerprinting dataset construction via an automated robotic system, with the obtained measurements being made available in an online repository. A graph-based algorithm that optimizes the robot's positioning so as to obtain more precise measurements (on the basis of previous ones), are employed. Once the dataset is constructed, new measurements are fitted via several regression and NN models. 2D signal coverage maps of the evaluated indoor area are presented, and the positioning models are assessed. Their performance does not differ significantly, however, the NN yields slightly better results.

3 Trilateration and Triangulation Based Methods

These methods are traditionally the most prominent as they rely on the geometric relationships between the anchors and the target, to estimate the

Table 1 Summary of fingerprinting-based methods

Reference	Measurement Data	Communication Technology	Accuracy [m]	Notes
[5, 6]	CSI, RSRP	LTE	<5	N, KNN processing
[7]	RSSI, RSRP, RSRQ	LTE	<60	N, DRN processing
[8]	CSI	LTE	<1 (indoor) <50 (outdoor)	N, NN
[9]	RSS, PDR movement trajectory	LTE	<20	N
[10]	GNSS	LTE	<100	N, GMM, Bayesian classifier
[11]	Fading, RSRP, delay spread	LTE	<20 (indoor) <300 (outdoor)	N, NN
[12]	Spatial pattern of the RSS	LTE	<10	N, feature-matching algorithm
[14]	RSS	5G	<3	N, Kalman filtering, KNN estimation
[15]	RSS, GNSS	5G	<2	N, NN
[16]	CSI	Wi-Fi	<2	N, NN
[17]	CSI, RSS, Angle-of-arrival	Wi-Fi (5 GHz ISM band)	<2	N, probabilistic estimation
[18]	RSS	Wi-Fi	<2	N, KNN
[19]	RSS	BLE	<2	N, regression and NN processing

latter's position. This can done by either determining the distance (trilateration) through the propagation conditions, or the angular features derived by reference signals. A disadvantage of these methods is their lack of agility in complex propagation conditions and lack of line-of-sight (LOS).

3.1 Angle-of-Arrival (AOA) Based Methods

Wi-Fi based AOA localization in a real-time indoor deployment is investigated in [20]. Two APs as anchor nodes achieve a median error of less than 3 m, with most of the measurements being under 2 m. However, LOS is required to obtain such accuracy. The authors of [21] consider the estimation of the distance to a UAV. A sub-optimal solution for less computationally-intensive processing of the UAV's positional parameters, taken from an a priori known Gaussian probability density function (PDF). Their filtering is done via the AoA measurements obtained by eight terrestrial WSN nodes. The solution achieves an RMSE of about 10 m, with rare spikes of up to several times higher error. A two-step location estimation method based on LS is proposed in [22]. The error variance of the first step is used to define weights for each anchor node, which refine the LS estimation during the second phase. The task is considered in 3D space (LOS conditions) in which up to 11 BLE anchors locate one mobile UE through the elevation and azimuth angles. The weights for the second step are a function of the RSS measurements. The RMSE declines exponentially with the increase of the number of anchors.

3.2 Received Signal Strength (RSS) Based Methods

Positioning based on the RSRP in LTE is investigated in [23]. The method estimates the distance between the anchor BS and the UE by using the BS azimuth and beamwidth as well as the RSRP. For simulations are performed with real measurement data, most of the achieved error values are less than 200 m. As an alternative, the authors in [24] propose frequency shift of the positioning reference signal (PRS) so as it may be spread to all subcarriers. Thus, the distance is determined by the auto-correlation function of the spread PRS at the UE, as measurement noise in the form of high side peaks is reduced. Simulations of the proposed solution for 21 BSs and 105 UEs exhibit localization error smaller than 500 m. Localization of a target node with unknown transmit power by at least 4 sensors, is considered in [25]. Through Taylor expansion of the position and RSS measurements at the anchor nodes, an unbiased LS estimator is developed. Simulations show linear increase of the RMSE with the measurement noise variance. A 5G BS-based localization for urban mobile users employing the Syncrhonization Signal-Received Signal Reference Power (SS-RSRP) parameter is studied in [26]. The distance between two users is obtained using the estimated SS-RSRP, the frontal distances between each of them and the BS, and the angle they create. It has been found that the distance estimation reliability increases almost linearly with the SNR. The authors in [27] investigate a 3D self-positioning for a UAV via multiple BSs under LOS conditions. An initial location estimation using the ML method from the BS measurements along the UAV's trajectory, is afterward refined by combining the UAV positions estimated by different BSs. Results show that the average distance estimation error increases linearly with the noise measurement variance, and declines in the same manner, with the increase in the path loss exponent. The CRLB is derived for the particular scenario, and the results follow it closely. A positioning algorithm accounting for antenna directivity is considered in [28]. The position and orientation of the agents are estimated jointly through a message passing on a factor graph. The proposed model uses an input that combines the RSS, antenna pattern, and measurement noise (that follows a Gaussian distribution). A real-world recorded data is used for the simulations, which show that the estimation accuracy does not shift significantly with the measurement noise variance. Increasing the cell-ID trajectory estimation accuracy for UEs in moving vehicles (such as trains, buses, etc.), is the goal of [29]. Through a modified longest common subsequence method, the obtained cell-ID measurements are refined by comparing them to those of the BSs that serve the (a priori known) routes followed by the public service vehicles. The method is tested using a real-world dataset consisting of measurements of RSS-based parameters, GNSS positioning data and cell-IDs. Through a heuristic global optimization, the anchors (BSs) with most accurate measurements are discovered in about 90% of the time. The mean error increases linearly with the measurement sampling interval.

3.3 Time-of-Arrival (TOA) Based Methods

The authors in [30] estimate the CIR threshold iteratively to obtain the TOA. This threshold is determined at each iteration by the strongest measurement for the CIR. The autocorrelation statistics of the LTE positioning reference signal refine the choice of threshold. The majority of the measured error values are less than 50 m. Estimating TOA in the frequency domain by the rotational invariance technique for LTE is proposed in [31]. The channel frequency response is first processed using singular value decomposition that allows for the channel length to be estimated. Then, the rotational invariance matrix is formed and its eigenvalues provide the delay and phase information. Finally, the TOA is estimated from the smallest delay. Simulations show that the RMSE decreases as the SNR is increasing. The drawback of this algorithm is the very significant computational complexity that makes it impractical for real-time deployment. The authors in [32] propose a probabilistic TOA model to learn and negate the influence of environmental distortions in indoor LTE scenarios. The Bayesian generative model describes the quantization, clock and noise-based errors, and estimates the TOA by an expectation propagation method. Using measurements from a real-world LTE network, the proposed solution exhibits accuracy from 70 m to less than 10 m. Appropriating LTE signals for navigating UAVs is evaluated through an SDR-based implementation in [33]. The proposed solution needs only one reference BS, while considering the positions of multiple other BSs. The obtained cell-specific reference signal (CRS) measurements are refined by an extended Kalman filter that compensates for the lack of clock synchronization between the receiver and the anchors. RMSE of less than 6 m with 6 anchor BSs, is achieved. The authors in [34] propose TOA estimation through the narrowband-IoT (NB-IoT) narrowband positioning reference signal (NPRS). It relies heavily on the adequate noise estimation, which is done via inverse Fast Fourier Transform (FFT) of the NPRS. Error of less than 100 m at low SNR (-14.5 dB) is achieved. Increasing the FFT size reduces the error but that comes with higher computational complexity.

3.4 Time-Difference-of-Arrival (TDOA) Based Methods

An asynchronous TDOA for reduced computational complexity in indoor scenarios, is proposed in [35]. Measurements from only the target and reference nodes are used, without the need for synchronization from the anchor nodes. These are fused via an interpolation method and an LS estimator obtains the TDOA between the target and anchor nodes. Experiments conducted with IEEE 802.15.4 transceivers show quick convergence of the RMSE and constant number of messages with the increasing the number of nodes. A narrowband IoT (NB-IoT) localization based on successive interference cancellation (SIC) with adaptive TDOA threshold for urban scenarios is proposed in [36]. The TDOA detection threshold is determined, through cross-correlation, on the basis of the noise statistics and the SIC measurements (reference signals) of each BS, to account for the NLOS conditions. The proposed solution achieves up to 10% improvement in accuracy.

TDOA target localization by 3 sensors through channel impulse response (CIR) measurements in real-time outdoor experiments is implemented in [37]. A preliminary obtained dataset is used to refine the location estimates via statistical analysis, without a priori knowledge of the propagation parameters of other scenarios. In LOS, the localization error decreases linearly with the increase in SNR, whereas it changes only slightly in the NLOS conditions. An alternative solution [38] is derived on the basis of the standard localization information provided by the long-range low-power wide-area network (LoRaWAN) technology. The authors implement four practical Raspberry PI based fusion centers that perform the localization. The measurements are processed via the LS method which yields up to 30% accuracy improvement. Extensive investigation of TDOA estimation for UE localization in different mobility and channel models including LOS/NLOS, is done in [39]. The TDOA measurements are processed by a particle filter to determine the channel state in order to model the likelihood functions. It is used to adapt the filter's coefficients, and thus, account for the fast changing environment. The results are close to the derived CRLB for the evaluated conditions with achieving accuracy of less than 50 m for 5 BS anchors. A centralized cooperative localization based on uplink TDOA (also referred to as UTDOA) in LTE, is investigated by the authors of [40]. The measurements are sent not only from the UEs to the BSs but also exchanged between the UEs (round trip time is considered to account for the lack of synchronization). Through ML estimation, the UEs' positions are estimated, achieving error of less than 100 m is achieved in 80% of the RMSE measurements. The authors in [41] consider UTDOA positioning, coverage control and quality of service for drone-based BSs for cellular communications. UTDOA is obtained from the sounding reference signals (SRS) provided by the UEs to the aerial BSs. Then, the estimated positions are used for optimal BS deployment and configuration via a mixed integer non-linear problem (MINLP). Accuracy of 30 m or less can be achieved for about 100 users.

3.5 Observed Time-Difference-of-Arrival (OTDOA) Based Methods

An expectation-maximization based SIC (EM-SIC) algorithm that compensates for frequency offset and fading in NB-IoT localization is developed in [42]. It is composed of two stages for detecting TOA, on the basis of which, the OTDOA is obtained. In the first stage, an initial TOA is estimated for each anchor BS through the EM-SIC algorithm. Then, the TOA is refined by a low-pass filter that interpolates the correlated measurements. At least three anchors are required for localization. Accuracy of less than 50 m (in AWGN), and less than 500 m (in fading). In the study [43], the influence of reference signal time difference (RSTD) measurements' frequency on the localization error, is investigated. An adaptive method for acquiring measurements, based on the SNR at the UEs in multipath fading conditions, is considered. The measurement noise is then negated through an extended Kalman filter. It has been found that the anchor BSs' coverage also influences the accuracy, and

Table 2 Summary of trilateration/triangulation based methods

Reference	Measurement Data	Communication Technology	Accuracy [m]	Notes
[20]	AOA	Wi-Fi	<3	MT
[21]	AOA	WSN	<10	N, UAV localization
[22]	AOA, RSS	BLE	<3	N
[23]	RSRP, BS azimuth and beamwidth	LTE	<200	N
[24]	PRS	LTE	<500	N, autocorrelation analysis of the PRS
[25]	RSS	WSN	<10	N, LS estimator
[26]	SS-RSRP	5G	<100	N
[27]	RSS	5G	<250	MT, positioning for UAVs
[28]	RSS, antenna pattern, measurement noise	WSN	<1	N
[30]	RSS, Cell-ID, GNSS	LTE	<1000	N, moving vehicles scenario
[31]	CIR, TOA	LTE	<50	N, autocorrelation analysis of the PRS
[32]	TOA	LTE	<60	N, Kalman filtering
[31]	TOA	LTE	<70	N
[33]	CRS	LTE	<6	N, UAV localization, extended Kalman filter, real-world implementation
[34]	NPRS	NB-IoT	<100	N, inverse FFT of the NPRS
[35]	TDOA	IEEE 802.15.4	<0.25	N, asynchronous localization, real-time experiments

(*Continued*)

Table 2 Continued

Reference	Measurement Data	Communication Technology	Accuracy [m]	Notes
[36]	TDOA	NB-IoT	<60	N, cross-correlation between the noise and reference signal
[37]	CIR	WSN	<4	N, real-time experiment
[38]	TDOA	LoRaWAN	<30	N, real-world implementation
[39]	TDOA	LTE	<50	N, particle filtering
[42]	TOA, OTDOA	NB-IoT	<500	N, low-pass filtering
[43]	RSTD, NPRS	NB-IoT	<300	N, extended Kalman filtering
[44]	RSRP, TOA, RSTD, OTDOA	LTE	<30	N
[45]	RSTD	NB-IoT	<40	N, NN
[40]	UTDOA	LTE	<100	N/MT
[41]	SRS	LTE	<30	N/MT, UAV-based positioning

thus, the UEs uses the measurements from only unique sites if there are multiple anchors available. Accuracy between 40 and 300 m is achieved, depending on the fading model. The authors in [44] formulate the OTDOA estimation problem in LTE as a hyperbolic equation. First, the TOA is measured by the UEs from the neighboring BSs' downlink received signal reference power. The OTDOA is then estimated using at least three BS, while the TOA is filtered out from the measurement, and the RSTD from two of the BS is considered. The intersection of the two hyperbolic equations corresponding to these measurements, estimates the UEs' location. The achieved accuracy is determined primarily by the considered channel conditions, with fading and multipath propagation severely deteriorating it. OTDOA-based positioning for NB-IoT is investigated in [45]. The RSTD measurements are processed via a neural network, and thus localization error of less than 40 m is observed for the majority of the cases even in the NLOS scenario. An alternative method presented in [46], employs multiple linear regression to predict the influence of weather conditions (temperature, humidity, etc.) on the OTDOA accuracy. On the basis of a large dataset of measurements, the impact of each factor on the localization error for each individual UE, can be inferred. The relevant environmental conditions are simulated using the NS-3 software, and their influence is determined numerically.

4 Hybrid Methods

Hybrid methods have traditionally represented a combination of a Global Navigation Satellite Systems (GNSS) and some of the other types of methods. Recently, however, methods that fuse two kinds of trilateration or triangulation methods have gained prominence. Their purpose is to improve the performance of standard geometric-based localization methods in challenging propagation conditions and for tracking fast moving targets in real time.

4.1 Hybrid Time-Difference-of-Arrival/ Frequency-Difference-of-Arrival (TDOA/FDOA) Based Methods

Hybrid TDOA/FDOA localization for moving targets through an iterative ML estimator, is proposed in [47]. First, the optimization problem is solved by a semi-definite programming (SDP) method that estimates the velocity and position. These are then refined by an iterative method that adapts the velocity by weighted LS method, and the position by SDP. The RMSEs of both parameters increase linearly with the measurement noise variance, while following closely the CRLB. An alternative based on the expectation-maximization method for computational relaxation, is proposed in [48]. The TDOA and FDOA measurements are processed by a non-linear filter, after which they are estimated via a Gaussian distribution. These estimates are then refined in the maximization step. For up to 8 sensors, the proposed solution provides quick convergence and exponential decline in the RMSE with the increase of the SNR. The authors in [49] combine TDOA and FDOA measurements made by two UAVs that localize a mobile terrestrial vehicle. An unscented Kalman filter with Gaussian kernel refines the measurements. Three configurations for the UAV sensors (with specific initial states of the positioning data) are used for the evaluation. The combined TDOA and FDOA measurements achieve convergence much faster than either of them combined. The RMSE decreases exponentially with the measurement time. Further estimation accuracy for hybrid TDOA/FDOA localization is investigated in [50]. A rough localization is performed via two-stage weighted LS, which is afterwards refined via a bi-iterative method. The received signal delay and frequency of the reference anchor node are used as an input of the weighted LS method that defines the localization optimization problem. It is solved via the Gauss-Newton bi-iterative method. The RMSEs of position and velocity increases linearly with the measurement noise variance. They also converge quickly and achieve their minimum at azimuth angle of around 60°. An alternative method for 3D localization, that does not require a priori knowledge of the measurement noise for 5 sensors, is proposed in [51]. The expressions for the velocity and position estimators are solved by the weighted LS method via SDP, without needing the variances of the FDOA and TDOA measurement noises. Simulations show that the RMSE rises in a linear fashion, with the increase in variance, even when it substantially high. A Low Earth Orbit (LEO) based 2D localization, impeded by interference from UAV communications is considered in [52]. The authors propose a Gauss-Hermite Kalman filter to refine the geolocation measurements. The solution achieves fast convergence, and significant performance improvement in comparison to employing TDOA or FDOA individually and separately.

4.2 Hybrid Angle-of-Arrival/Received Signal Strength (AOA/RSS) Based Methods

The authors in [53] study a hybrid AOA/RSS indoor localization in 3D for up to 11 sensors. The weighted LS estimation of the measurement noise variance, AOA and RSS are performed via a first-order Taylor approximation of the error covariance matrix and the anchor nodes' weights. The RMSE declines exponentially with the number of sensors, but remains relatively constant with the increase of the elevation, azimuth and received power noise variances. An alternative solution that considers a low number of anchor nodes and achieves improved computational efficiency is proposed in [54]. Using the azimuth, elevation and RSS (assuming to be Gaussian distributed) of all sensors, a LS optimization problem is solved through second-order cone programming. A relatively small RMSE, close to the CRLB, is reached for as little as 3 sensors. It declines exponentially as they increase in number.

Table 3 Summary of hybrid methods

Reference	Measurement Data	Communication Technology	Accuracy [m] or [dB]	Notes
[47]	TDOA/FDOA	WSN	<25 dB	N, weighted LS estimation
[48]	TDOA/FDOA	WSN	<25 dB	N, non-linear filtering
[49]	TDOA/FDOA	WSN	<7 dB/km	N/MT, UAV-based positioning, Kalman filtering
[50]	TDOA/FDOA	WSN	<200 m	N, weighted LS estimation
[51]	TDOA/FDOA	WSN	<30 dB	N, weighted LS estimation
[52]	TDOA/FDOA	WSN	<4000 m	N, Gauss-Hermite Kalman filtering
[53]	RSS/AOA	WSN	<3 m	N, weighted LS estimation
[54]	RSS/AOA	WSN	<5 m	N, LS estimation

5 Conclusions and Further Directions

This paper presents a review of the three most prominent types of localization methods in modern cellular and Het-Nets, namely such based on fingerprinting, trilateration and triangulation, and combination of the latter in a hybrid manner. For each of these categories, a summary of the methods' design features and achieved accuracy is given. On the basis of the review, the following directions for future research can be outlined:

- Recently, the integration of localization and communication has been envisioned to lead to a convergence between the latter and sensing (the process of acquiring data about physical processes via sensors and radio signals) [55, 56]. In this way, the audio-visual and user input data obtained by the network's intelligent nodes can supplement the signal processing to improve the quality of user experience, data caching, resource allocation, user association, communication quality, etc. Due to the prominence of machine learning-based algorithms for these functionalities, it is expected that fingerprinting localization will continue to be even more relevant. Its main challenges are to obtain a sufficiently descriptive dataset that allows for efficient offline training, as well as data processing that is of low complexity.

- Legacy UEs will likely benefit from combined GNSS and triangulation/trilateration/fingerprinting localization for fast moving outdoor as well as indoor scenarios [10, 15, 29]. In addition, contemporary methods that use standard 4G/5G positioning signals to achieve higher performance, thus reducing the processing load and relaxing the energy requirements and design complexity [11, 23, 26]. Real-world implementations of such methods have also shown that they are practical in their accuracy.
- Localization for aerial nodes has been, and will continue to be, an important topic in the field due to the prominence of UAV-based communications in wireless networks research [57]. A variety of methods (such as AOA, hybrid, RSS and TOA based) have been employed for this scenario [21, 27, 49, 52]. The most important consideration for these methods is reducing the effect of noise and signal attenuation on the measurement accuracy in real time to account for the aerial nodes' movement in 3D. This obstacle is most often surmounted through different forms of the fast-converging Kalman filtering of the measured parameters.
- Another notable trend in localization research, is its application for IoT nodes [34, 36, 42, 45]. Such methods are susceptible to imprecise noise estimation and NLOS conditions, and usually utilize OTDOA, TDOA and TOA measurements. The advances for this application scenario include Kalman filtering and neural network-based processing.
- Apart from the very prominent Kalman filters, graph signal processing may also be a viable tool for filtering of the measurement noise. It has been utilized successfully for this purpose in the case of climate parameter measurements in [58]. Such methods, however, require the description of the experimental setup and its parameters as a graph, so that this novel multi-domain filtering may be applied.

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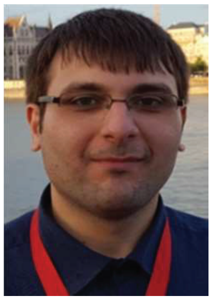
Biographies



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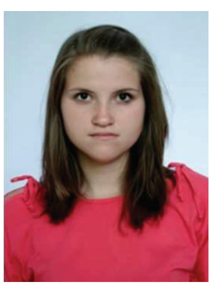

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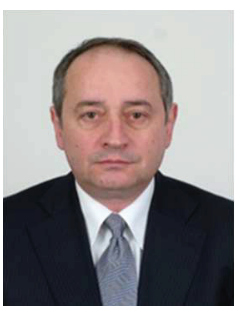

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