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A Look at the Recent Wireless Positioning Techniques with a Focus on Algorithms for Moving Receivers

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***Abstract*—Employment of ground-based positioning systems has been consistently growing over the past decades due to the growing number of applications that require location information where the conventional satellite-based systems have limitations. Such systems have been successfully adopted in the context of wireless emergency services, tactical military operations and various other applications offering location-based services. In current and previous generation of cellular systems, i.e., 3G, 4G, and LTE, the base stations (BSs), which have known locations, have been assumed to be stationary and fixed. However, with the possibility of having mobile relays in 5G networks, there is a demand for novel algorithms that address the challenges that did not exist in previous generations of localization systems. This work includes a review of various fundamental techniques, current trends, and state-of-the-art systems and algorithms employed in wireless position estimation using moving receivers. Subsequently, performance criteria comparisons are given for the aforementioned techniques and systems. Moreover, a discussion addressing potential research directions when dealing with moving receivers, e.g., receivers movement pattern for efficient and accurate localization, non-line-of-sight problem, sensor fusion, and cooperative localization, is briefly given.**

***Index Terms*—AOA, Gaussian mixture, geolocation, FDOA, Kalman filter, particle filter, TDOA, TOA.**

I. INTRODUCTION

In global navigation satellite systems (GNSS), the receiver, which might be near or on the ground, receives measurements from some satellites, and then estimates its position if enough line of sight (LOS) satellites are available. One of the most popular systems is the global positioning system (GPS), which is operated by the US government, initially used for military applications, and over two decades by civilians. The GPS system has several disadvantages: (i) the battery life of GPS devices is high, making it unsuitable for several low-power devices, (ii) the performance of GPS systems is degraded in indoor places or dense urban areas where the GPS signal is week or unavailable. Due to such limitations, it becomes necessary for several applications to rely on a ground-based network to find the position of radio-frequency (RF) devices more accurately, denoted as network-based localization or wireless geolocation systems.

In order to find the location of an RF device, different measurements can be used: received signal strength (RSS), time of arrival (TOA), time difference of arrival (TDOA), frequency difference of arrival (FDOA), and angle of arrival (AOA) are the most popular types of measurements. In [1, 2] and the references therein, the different position estimation methods and techniques can be found.

Different wireless networks can benefit from location information, such as cellular networks [3] and wireless sensor networks [4]. Due to expanding demand and applications of wireless geolocation such as: location-based services (LBSs) [5], wireless emergency services [6], intelligent transportation systems, and military applications [7], wireless geolocation has received considerable attention over the past two decades. This continuous growth and reliance on wireless geolocation will make the fifth-generation (5G) networks the first generation to benefit from location information that is sufficiently precise to be leveraged in its design and optimization at the various network layers [8].

Cellular location technologies, which are designed to estimate the position of a mobile station (MS) or user equipment (UE), have received much of attention over the past few decades. The quality of service (QoS) of positioning accuracy of such systems has been driven by the requirements on subscriber safety service (i.e., E-911 and E-211 [9–11]) and the continuously growing interest in location-based services (LBSs) applications, that will be described in more details below:

- Emergency positioning requirements: Due to the order by U.S. Federal Communication Commission (FCC) [9], cellular network operators are required to locate and provide the position of wireless terminals with 1 meter of accuracy by 2020. This requirement might be satisfied for rural areas for UEs equipped with GPS, however, in urban canyons and indoor areas where a GPS signal is week, the GPS has limitations [1, 12]. By relying on a ground-based wireless network, such as cellular network, the limitation of GPS can be overcome, however, the accuracy may not be guaranteed in none-line-of-sight (NLOS) scenarios, which is usually unavoidable in indoor areas and urban canyons.

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- LBSs: The growing number of LBSs dictates that current and future cellular systems, such as LTE systems and beyond, need to respond efficiently to service-dependent positioning in unprecedented manner. Due to various wireless environments that could be complex and harsh, the node that carries-out the positioning process needs to be capable of selecting the appropriate combination of positioning methods to achieve the desired positioning QoS.

Therefore, enhanced accuracy position estimation algorithms under various circumstances and environments are becoming a necessity [13]. Some LBSs requiring certain level of QoS that could not be met with traditional approaches may require that future positioning technologies deploy new and more sophisticated methods. For instance, it may become feasible to process photos and additional data at positioning servers to provide precise positioning accuracy previously unattainable at a given setting whether outdoor or indoor. It is envisioned that assisted GPS (A-GPS) [1, 3, 14, 15] will still remain the conspicuous technology in the current and future releases of cellular-based systems as in LTE systems [16, 17] among the many alternative positioning technologies.

From our previous discussions, it is evident that the current interests to use localization approaches for RF emitters is continuously expanding. In response to demands imposed by newly developed applications, dynamic mobile platforms are employed as receivers [4, 18, 19]. To address such specialized systems and advanced complex algorithms, we start by providing a brief introduction of most popular position-related parameters involved in wireless geolocation in conjugation with localization methods and error mitigation techniques. Then, we conduct a focused exploration of positioning systems and algorithms that are available to mobile receivers architectures (base stations). Unlike previous studies and surveys, our literature survey presents and focuses on some recent advances and current research articles on positioning systems for wireless systems deploying moving receivers platforms. Various current state-of-the-art techniques that utilize the different positioning parameters and algorithms that were investigated in the literature are explored. In such systems, the main challenge is in the ad-hoc nature of the network where one or more receivers are not fixed like in conventional wireless networks.

The rest of the paper is organized as follows: in Section II, we classify different localization techniques and mainly discuss range-free and range-based classifications. In Section III, different localization systems that have been used and are still useful will be described. Localization and tracking algorithms with moving receivers are reviewed in Section IV, and the comparison and challenges facing such systems are given in Section V. Finally, conclusions and future works are given in Section VI.

II. Classification of RF Localization Techniques

Localization techniques can be classified in several different ways [20] as will be described briefly below.

A. Centralized or distributed

Based on the computation handling, localization can be divided into centralized or distributed techniques. In centralized techniques all the measurements and information are collected at a fusion center and then the locations of the targets are estimated. Some popular centralized techniques have been proposed in [21–23]. However, in distributed approaches, the position of the targets can be locally estimated either at the target itself [24, 25], or at the closest BSs or anchors [26]. The distributed approaches have several advantages over centralized techniques due to being scalable and tolerant against node failure, however, they are generally sub-optimal in accuracy and require exchange of information iteratively until convergence.

B. Non-cooperative or cooperative

In non-cooperative techniques, each target only exchanges information with the anchors or BSs. However, in cooperative networks, the targets obtain measurements from their neighboring targets and exchange information with one another. In this way, the localization performance can be improved and the targets that are far from fixed reference nodes and have other targets in their neighborhood can be localized more accurately [27].

C. Deterministic or probabilistic

Based on utilization of the probability density function (PDF) information, we can also classify different localization techniques. In deterministic approaches the information about the probability distribution (e.g., noise distribution) is not employed directly and the estimation is done by techniques such as least squares. The probabilistic approaches, on the other hand, take advantage of prior knowledge of statistical distributions of the measurements if they are available. For instance, particle filter is a probabilistic approach where the probability distribution information has direct impact on its performance [28]. Another class of probabilistic approaches are belief propagation (BP) approaches which are techniques to simplify the joint probability distribution of a network using factorization on a graphical model [25]. In general, if knowledge about the distribution is available, probabilistic techniques perform better than deterministic ones and are preferred.

D. Range-free or range-based:

If in determining the location of an RF device, the measurements are employed to somehow relate the position of the device to some metric such as distance, and then the position is estimated, these techniques are referred to as range-based techniques. However, in range-free techniques, the measurements are not converted to range and instead the location is estimated by some other metrics. In the sequel, we describe these two main categories.

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1) Range-free techniques: The range-free techniques can be divided into two main categories:

Fingerprinting: In fingerprint-based localization systems, a database of fingerprints should be incorporated a priori. There are various fingerprint-based localization techniques proposed in the literature [29]. Localization performance of each fingerprinting type varies in their metrics such as accuracy, latency, etc. in addition to their implementation. The goal of position estimation in mapping techniques (fingerprinting) is to identify a relationship, relaying on a set of training data, for the purpose of estimating the position of a desired node [2]. Fingerprinting schemes have became feasible and a viable approach due to present trends in increasing storage capacities of current mobile terminals and other electronic devices [29]. The method entails two-steps: training phase and positioning phases. In the training phase, the RSS measurements (fingerprints) from all the available APs at some locations are collected and a database is formed. In the positioning phase, the RF device compares the received RSS powers from the available APS and compares them with the RSS of the corresponding APs collected at the database. In positioning phase, different data mining and machine learning approaches such as k-nearest neighbour (K-NN) algorithm [30] or a neural network [31] can be used. Proper selection of important features (fingerprints) and construction of the database will influence the performance of these methods. Very accurate position estimation with multipath and NLOS propagation in addition to challenging environments is a prominent advantage of fingerprinting techniques [31–33]. This is because they pose a form of natural robustness when employed in unfavorable scenarios of propagation. However, the main drawback of these techniques is that the training database could grow very large to have sufficient resemblance of the operational environment to produce accurate positioning fix. Moreover, the database linked to a certain scenario and environment must be updated as often as changes in the environment occur that could alter the channel characteristics significantly from the characteristics used while constructing the RSS database [34].

Hop count: Other categories of range-free techniques is when instead of using RF measurements, each sensor counts the number of hops that it is located from each anchor through a routing protocol. Then the closest anchor will be used as a reference for the position of the sensor. For instance if the sensor is three hops away from an anchor, it can approximately locate itself to be in a circle with radius $3R$ with the aforementioned anchor in the center and R being the sensing range of the nodes. For a more detailed overview of hop-count techniques the readers are referred to [35].

While these techniques do not require the infrastructure for ranging, due to the rough approximations made in estimating the position, these techniques are not applicable for applications that require accurate location estimates.

2) Range-based techniques: In range-based techniques several different types of measurements can be employed so that the position can be estimated, as described below.

Received Signal Strength (RSS): The RSS is one of the most widespread types of measurements, firstly used in [36]. The RSS of a signal traveling between two transceivers is a signal

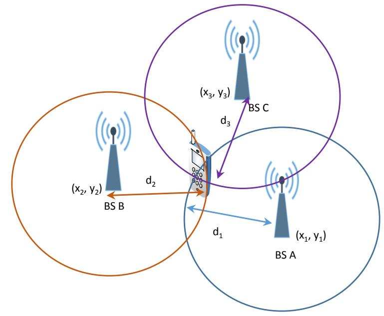

Fig. 1. Location by ranges such as RSS or TOA measurements

parameter that contains information related to the distance between them. This RSS can be used in conjugation with a suitable attenuation model and shadowing effect to estimate distance [37]. The shadowing effect is commonly modeled as a zero mean Gaussian random variable with a variance of σ^2 in the logarithmic scale. Therefore, the received power $P(d)$ in dB can be expressed as:

$$P(d) = P_0 - 10n\log_{10}(d/d_0) + \gamma, \tag{1}$$

where n is the path loss exponent that takes on values between 1 and 5, P_0 is the received power in dB at a short reference distance d_0, and $\gamma \sim \mathcal{N}(0, \sigma^2)$. Note that this model can be used in both line-of-sight (LOS) and non-line-of-sight (NLOS) scenarios with an appropriate choice of channel parameters. However, it is very difficult to find a suitable choice of parameters in multipath and NLOS environments and therefore RSS measurements cannot be converted to range accurately.

An RSS estimate at a receiver (base station/sensor) determines the position of a transmitter (a mobile station/target) on a circle in the error-free case. Fig. 1 shows the intersection of range circles formed by three base stations and a mobile terminal, which is referred to as *trilateration*. For estimation of a target in a 2-D space using trilateration, a minimum of three receivers is needed. In the presence of measurement noise, the circles will not intersect at a single point and a LS solution is obtained instead. However, the trilateraiton does not yield the ML solution and furthermore, its performance is not robust in the presence of outliers or NLOS errors.

The Time-of-Arrival (TOA): The TOA allows us to deduce the range directly. It requires an accurate synchronization between the mobile station (target) and the base stations (sensor) [38]. The receive time, τ_i with reference to the transmit time of a signal is known, then it can be used to calculate a distance as $d_i = c\tau_i$, where c is the speed of light. The larger the bandwidth of the signal is, the better the estimation performance for such parameters will be [39]. The correlation method is conventionally used to calculate the TOA with a matched filter (MF) to the known transmitted signal. Measurement of TOA, τ_i, on the i^{th} base station implies that both transmitter and receiver are tightly synchronized,

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which is not the case in mobile networks. Furthermore, a time-stamp has to be included in the signal, which is why TOA measurement is used in an active localization scenario. If synchronization can not be maintained, then the Round Trip Time (RTT) protocol can be used, in which the receiver should send back another TOA signal to the transmitter and by averaging the two TOA signals, most of the clock error terms will be canceled and the range can be estimated accurately. Similar to the RSS-based techniques, the position of the mobile is the intersection of circles whose radii are equal to d_i as depicted in Fig. 1 in the error-free case. In practice where there is measurement error, the measurements are linearized and the position is estimated by solving a system of linear equations. While the trilateration works well in LOS scenarios, in the presence of NLOS measurements, the TOA measurements become positively biased which can drastically degrade the performance of trilateraion or other techniques used assuming zero-mean measurement errors. In NLOS scenarios, more advanced techniques need to be used, [40–43]. A summary of techniques used in cellular systems for TOA-based localization in NLOS is also given in [44].

The Time-Difference-of-Arrival (TDOA): If the target can not be synchronized with the receivers and RTT cannot be obtained, then the received timing signals at the receivers are subtracted from the signal of one of the receivers selected to be the reference (usually home BS). Let the measured time of flight at the i-th receiver be τ_i. If we select the BS with index $i = 1$ as the reference, then the TDOA measurement will be $\Delta\tau_i = \tau_i - \tau_1$, where the clock error terms will disappear. Similar to TOA, this also requires synchronization among receivers, however, the TDOA technique is less restrictive as it does not require accurate synchronization between the transmitter and the receivers. The position of the target outlines a hyperbola, with foci at the two anchors or BSs. The target lies at the intersections of hyperbolas, as shown in Fig. 2. In case of error, the measurements can be linearized in a similar way to trilateration, called hyperbolic localization. However, a minimum of four receivers are required in 2-D space such that the location can be estimated therefore TDOA-based techniques have a drawback in this respect compared to TOA-based techniques. As in TOA, the larger the bandwidth the better the estimation performance for such parameters. As compared to TOA-based techniques, TDOA-based ones have not received attention in NLOS scenarios and seem to be degraded in performance in NLOS scenarios. There are only a few works in the literature which have mitigated the NLOS effect for TDOA or other techniques [45]. In general, the TDOA-based techniques are less suitable for NLOS situations as compared to TOA-based techniques.

Frequency-Difference-of-Arrival (FDOA): Analogous to TDOA methods, in FDOA measurements or in frequency-of-arrival (FOA), we rely on the fact that when the emitter is moving, the motion creates a frequency shift proportional to the signal frequency and radial velocity [46, 47]. The Doppler characteristics, which are the basis to determine the location coordinates of a source [48], are obtained as a result of measuring the instantaneous frequency of a received signal [49]. FDOA eliminates the need to know the transmitted

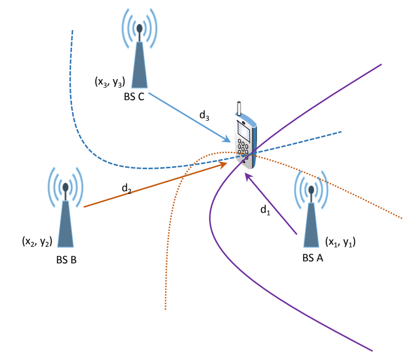

Fig. 2. Hyperbolas of the TDOA method with three base station receivers.

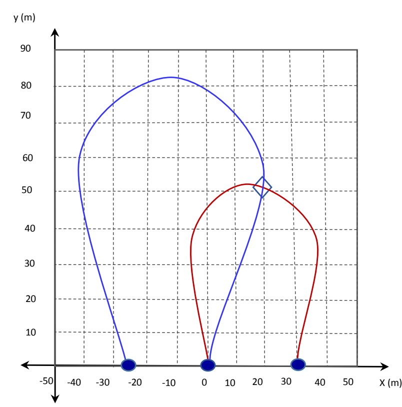

Fig. 3. Differential Doppler target positioning with curves of constant differential Doppler shift [51]

frequency [50]. Fig. 3 demonstrates positioning of a stationary target by three sensors all moving at a velocity of 100m/s along the x-axis relying on FDOA from [51]. The FDOA receiver is difficult to implement, and very costly, especially when the signal is already at a very low power level [52]. At the receiver, the ability to measure frequency with more accuracy than the smallest expected frequency shift, is a requirement. Also, similar to TDOA, all receiver nodes must be synchronized to correlate measurements.

The Angle-of-Arrival (AOA): The AOA is the arrival angle of the signal observed at a receiver, which was emitted by the target [53]. A line of bearing (LOB) can be drawn for each AOA (emitter to receiver), and the intersection of at least two LOB will provide the possible position estimation for the unknown target (emitter) in 2-D space [54]. This technique is known as triangulation as shown in Fig. 4. Geolocation using AOA requires a minimum of two receivers, while in TOA techniques three range measurements are required for a two-dimensional position estimate. However, AOA-based systems require relatively large and complex smart antenna arrays and complex periodic calibration. For a more detailed survey on AOA estimation see in [55].

Hybrid Measurements: A combination of the measurement techniques introduced so far can be combined together to

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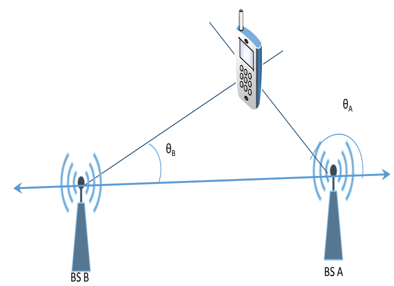

Fig. 4. Angle of arrival

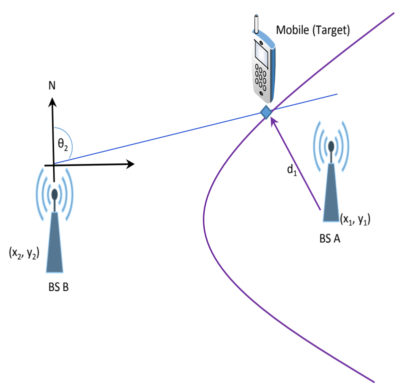

Fig. 5. A hybrid AOA-TDOA geolocation scheme

obtain more accurate estimate of the target's position. The selected schemes to be combined together in order to determine the position of the target will depend on the type of application, available infrastructure, and the localization environment. Demonstrations of such combinations for various positioning applications can be found in several works. For instance, different hybrid schemes have been proposed such as AOA/RSS [56], RSS/TOA [57], TDOA/RSS [58], and TDOA/AOA [59]. Other combinations also exist for improved precision in certain applications, e.g., a hybrid of TDOA, angle-of-departure, and Doppler shift is found in [60, 61], while an hybrid of AOA, gain-ratio-of-arrival, and TDOA is presented in [62], and a hybrid AOA/TDOA geolocation approach is depicted in Fig. 5.

A comparison of different types of measurements used for localization is summarized in Table I.

III. Overview of Different Systems Used for Localization

We will provide a brief presentation on some of the current RF geolocation technologies and systems such as wireless local area network (WLAN) [63], radio frequency identification (RFID) [64, 65], wireless sensor network (WSN) [66, 67] with ZigBee [68–70], Bluetooth technology [71–73], bluetooth low energy (BLE) [74], ultra-wide band (UWB), and the cellular system. A considerable amount of research has been focused on improving the accuracy [75] and enhanced performance of such indoor positing systems. Most network-based positioning systems use geometric positioning techniques with similar basic functional principles to the methods described earlier, in addition to various signal processing algorithms [76–78] used for calculating target's position from measured signal parameters representing the geometric relationships to sensor nodes. The methods include typical measured positioning parameters: TOA [79, 80], TDOA [81, 82], AOA [64, 83], but using RSS [84–86] is an attractive approach for indoor positioning since it can take advantage of existing wireless infrastructures and thus presents tremendous cost savings where all current standard indoor radio technologies report RSS measurements, and therefore can share the same algorithms across various platforms [1, 87].

A. *Wireless Local Area Network (WLAN)*

WLAN positioning has attracted considerable research to improve the positioning accuracy mainly due to its cost effectiveness and availability [88, 89]. That is because the WLAN technology is very mature, popular, and has been deployed in various public and private areas such as hospitals, train stations, airports, and universities just to name a few. Also, as was mentioned, WLAN-based positioning systems can reuse the already installed WLAN infrastructures in indoor environments [90], which reduces the cost [35]. Examples of some of the well-know WLAN positioning systems include: RADAR [91], Ekahau [92, 93], COMPASS [94], Pazl [95], HiMLoc [96], EDIPS [97], WaP [98]. However, because of complex indoor environments, the accuracy of indoor location estimations based on the signal strength of WLAN signals is of several meters [35], and is affected by various elements in indoor environments. The influence of these elements, which may include human body, mobile terminals and electronic devices, building materials, doors, and such, has been studied and discussed in the literature [94, 99]. Due to the dynamic changes in the environment, the database needs to be updated after several weeks or months, which makes WiFi fingerprinting difficult to maintain over time.

Most of recent research efforts concentrate on establishing more accurate functional mappings relating the RSS and the physical position for improved WLAN positioning accuracy [84, 90, 100, 101]. To this end, special considerations of the deployment of APs have been discussed and optimization methods were suggested [63, 102]. Others suggested the use of compressive sensing theory to reduce fingerprint collection in conjugation with RSS from WLAN APs for indoor localization [103–105] relaying on the sparse nature of location finding through sparse signal recovery for more accurate indoor positioning. The idea of Gaussian process has also been deployed in some works to reconstruct the RSS map in [106].

Recently, other metrics of WiFi system such as channel state information (CSI) has been employed instead of RSS for getting more diverse features at each location [107, 108]. The CSI has better stability and less variation compared to RSS and can be considered as a more reliable metric

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TABLE I
COMPARISON OF DIFFERENT MEASUREMENT METHODS FOR SOURCE LOCALIZATION [1].

Method	Signal Measurement	Advantages	Disadvantages
RSS	Signal power	Simple and inexpensive. Time synchronization is not required.	An accurate propagation model is needed for reliable distance estimation. MT mobility and channel variation may yield large errors Low localization accuracy Suffers from NLOS and shadowing
TOA	Time	Accuracy is high	Time synchronization across source and all receivers is needed. LOS is assumed.
TDOA	Time-difference	Accuracy is high. No time synchronization at source is required. Independent of the source transmission	LOS is assumed. Accurate time synchronization between receivers is needed and much higher complexity due to TDOA optimization based geolocation
FDOA	Frequency-difference	Prior knowledge of the carrier frequency is not required. Explicit ability to use mobile receivers	the emitter or one of the receivers is moving difficult to implement, very costly, LOS is assumed.
AOA	Angle	Only at least two receivers are required. Time synchronization is not required.	Require expensive antenna arrays. LOS is assumed.

for fingerprinting. Using the CSI measurements for all the subcarriers and antennas at each location instead of only a single RSS measurement, can provide more useful information as a signature, and thus fingerprints can be distinguished more accurately. The fingerprinting techniques using CSI is promising for research and will likely be employed in commercial localization systems in the future.

B. Radio Frequency Identification (RFID)

The RFID is a technology for storing and retrieving data through electromagnetic transmission to an RF compatible integrated circuit [109–111]. RFID has been recognized as a promising technology in enabling indoor positioning systems [112]. RFID positioning systems are deployed for a wide range of applications in complicated indoor environments such as offices, hospitals, factories, warehouses, and libraries just to name a few [113, 114]. As a wireless technology, RFID provides flexible and low-cost advanced automatic identification of individuals or devices [110, 115] via RFID tags. An RFID system consists of three principal parts: RFID tags, readers and miniature antennas between the tags and the readers.

RFID position estimation is accomplished through electromagnetic communication between the RFID readers and the corresponding RFID tags [116, 117]. With passive RFID, which is usually small and inexpensive, a tracked tag is a receiver. These technologies rely primarily on using the readily available RSS information for positioning. Hence, the range is limited to approximately $1-2$ m for these passive tags. When coupled with the relative cost of compatible readers, they constitute drawbacks of theses RFID systems [64, 118, 119].

C. Bluetooth

Bluetooth is a specification for wireless personal area networks (PANs) as was standardized in the IEEE 802.15.1 standard. It is a short-range wireless communications technology with an approximate range of 100m for class 1 devices. It enables low-cost and low-bandwidth communication for the purpose of connecting electronic devices such as mobile phones, headsets, tablets, portable computers, printers, etc. In addition, several Bluetooth devices can be connected to form Piconets [120]. Bluetooth has evolved through several versions since it was first conceived to enhance speeds and features.

In Bluetooth-based positioning systems [120–122], various Bluetooth clusters are formed as infrastructures for positioning [123, 124]. Examples of such systems are: BluePos [125], BlueCat [126], BLIP [73, 127], PBIL [128], Topaz [129]. The position of a Bluetooth mobile device is located by the effort of other mobile terminals in the same cluster [130]. Bluetooth positioning technology locates object by measuring the signal strength [72, 131] in conjunction with localization techniques such as fingerprinting [132] and signal processing algorithms (e.g., Bayesian filtering, or neural networks, etc.) [133, 134].

One of the example Bluetooth positioning technologies that use tags in indoor environments is Topaz [129]. The Topaz positioning solution is suitable for tracking humans and assets. It is made-up of three types of elements: positioning server(s), wireless access points, and wireless tags [111]. The system consists of software and hardware parts for local positioning of Bluetooth tags or any device equipped with Bluetooth technology [35]. The system provides room-wise accuracy, or a 2 m spatial accuracy, with more than 95% reliability. The positioning delay is 15-30s. In this system, 32 IR and Bluetooth APs are typically associated with one Bluetooth server, which is responsible for various functionality and managing APs [35]. Bluetooth servers, location servers and location clients are connected with LAN. Tens of objects can be tracked at the same time. In general, in complex and varying indoor environments, Bluetooth positioning systems suffer from similar drawbacks as of other RF positioning techniques [35, 89].

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D. Bluetooth Low Energy

The most current version of Bluetooth technology, i.e., version 4.0, a.k.a Bluetooth low energy (BLE) [135] has several interesting properties that has made big companies such as Apple Inc, focus on this technology for improving the location accuracy of the devices. Unlike the ordinary Bluetooth technology in which the devices need to be paired, in BLE, such a requirement is not needed and the BLE devices can be employed in broadcast mode only. It also seems that BLE is a promising technology in the Internet of Things (IoT) implementations [136–138]. Localization using BLE is based on RSS measurements. Therefore, the RSS measurements can either be converted to range and then the range-based techniques can be employed, or can be used in conjugation with fingerprinting techniques. The first approach has a low accuracy, which is similar to other technologies due to the difficulty in relating the range to RSS accurately. However, in LOS and with a close proximity to BLE beacons, a few meters of accuracy can be obtained. The second approach might be of interest in some applications, but the advantages of BLE over WiFi for fingerprinting has not been studied in the literature extensively, and hence it is not clear which one is a better candidate.

E. Ultra-wide Band (UWB)

Another technology that has received considerable attention for accurate ranging is the Ultra-wide Band Sensors (UWB) technology. The unlicensed use of UWB in the frequency range of 3.1-10.6GHz is authorized by FCC. With UWB signaling, accurate TOA measurements can be obtained due to the fine timing resolution of UWB pulses. The larger the bandwidth, the more accurate the measured range in LOS scenarios. The UWB signals can penetrate the objects and walls and are useful also in NLOS scenarios, although in such scenarios the range measurements become positively biased. The UWB ranging is well suited for short-range applications and thus it is useful for indoors, while for outdoors it has certain limitations.

F. Wireless Sensor Network (WSN)

The WSNs have attracted much attention in recent years due to their potential use in many applications including some that can have vital impact such as surveillance and combat operations [139]. Sensor nodes can be exposed to a physical or environmental condition to sense sound, pressure, temperature, light, etc., and generate proportional outputs [35, 67]. WSN-based positioning is considered a cost effective and low power technology for locating individuals and objects because of the decreasing prices, power, and the sizes of various types of sensors [140, 141]. Positioning methods using sensor networks were described in [85, 142–144], [145–148], where techniques based on TOA, AOA, and RSS measurements are discussed. However, compared to other wireless electronic devices, small and low-cost sensors of WSN have the drawbacks of limited processing power and battery capacity when they are in indoor positioning set-ups [149]. This imposes more restriction on the types of sensors that can be used.

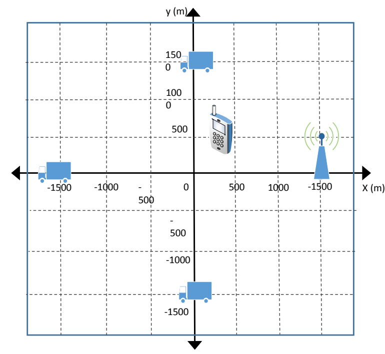

Fig. 6. Scheme of cellular localization system.

G. Cellular Networks

Previous generations of cellular systems, as well as current 4G systems such as LTE, have adopted standardized positioning schemes [150], including observed time difference of arrival (OTDOA) [1, 151, 152], AoA [1, 153–155], fingerprinting [156–158], cell identity (CID) [1, 159] and enhanced cell ID (E-CID) [1, 16, 17, 160]. The methods may be classified as UE-based, UE-assisted, or network-based, according to where the measurements are performed and final location is estimated [1]. A scheme of a cellular network is illustrated in Fig. 6.

1) Cell Identity (CID): CID is the process of using the knowledge of the network of the mobile device, within the controlling cell site and relaying the sector information [161]. CID operates in GSM, GPRS, UMTS and LTE networks. The accuracy of this method depends on the cell size; for instance, given that the GSM cell diameter can be between 2km to 20km, the accuracy can be poor [161].

Given the cell ID of the serving cell, the UE position is associated with the cell coverage area, which can be described, for instance, by a pre-stored polygon [1]. The polygon format is one of the standardized positioning reporting formats in 3GPP [1, 159], where a polygon is defined as a list of 315 corners with each corner represented by latitude and longitude encoded in the WGS84 system [1, 159]. The cell boundary is modelled by the set of non-intersecting polygon segments connecting all the corners. The UE is assumed to be within the polygon with a certain confidence. This is the fastest positioning method since no measurements are needed [1].

2) Enhanced CID (E-CID): E-CID methods employ four sources of information for position estimation [1]: the CID of the serving cell and its corresponding geographical description, the timing advance (TA) of the serving cell, the corresponding signal measurements of up to 32 cells in LTE, and AOA measurements.

CID and TA: One common E-CID method combines the geographical cell description (eNodeB position), and the distance between the eNodeB and the UE which is obtained from a time measurement. Round-trip time (RTT) positioning in the WCDMA system is a demonstration of this technique [162, 163]. The granularity of the TA is of the order of 1 km in GSM, while in LTE, the granularity is of the order of 10 m.

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A radial accuracy of at least as good as that of RTT positioning in WCDMA is expected since typically the bandwidth of LTE is larger than that of WCMDA [162, 164].

Signal Strength: Distance measures can also be derived from signal strengths measured in the UE and combined with cell polygons as done for CID and TA. Unfortunately, a direct measurement of the distance from the RSS cannot be reliable, since the value of the RSS mainly depends on the path-loss model that has been considered. Besides, RSS measurements depend on the channel characteristics and become inaccurate when shadow fading affects the signal propagation of hand-held UEs [165]. Therefore, RSS-based positioning algorithms are sensitive to channel parameters estimation [161]. The use of advanced pattern matching techniques and advanced signal processing is known to improve accuracy [1, 156]

AOA: An AOA-based positioning technique involves measuring angles of the mobile station seen by reference base station [166]. The AOA measurement standard for LTE is defined as the estimated angle of a UE with respect to a reference direction. AOA can improve accuracy, as compared to the CID and TA method, by defining the angle. If the range and angle measurements are available at a receiver, then a unique position can be estimated using hybrid techniques [1]. The traditional method for measuring AOA is by using an antenna array, but in LTE, it is also possible to utilize the precoder matrix indices (PMIs) reported by the UE [1, 153]. Each precoder index defines the corresponding antenna beam that is being used. Hence, the reported PMI points to the direction of the position of the UE [1].

3) Fingerprinting: Fingerprinting denotes a set of positioning methods that exploit detailed radio maps for positioning [1]. A fingerprint-based localization system is comprised of two main modules: fingerprint sensing module and fingerprint matching module [29]. For instance, in LTE systems, the UE measures the radio properties it experiences and sends them to the the evolved serving mobile location center (E-SMLC), which controls the coordination and scheduling of the resources required to locate the mobile device. The E-SMLC then searches for a best match between its stored geographical map of radio properties and the measured radio properties sent by the UE. The best match determines the position of the UE. Fingerprinting positioning has been studied relatively little for cellular applications [167], although fielded cellular fingerprinting systems exist [168, 169]. The LTE positioning standard has taken into account fingerprinting positioning and yields for signaling of CIDs, signal strengths, TA, and AOA along with OTDOA [170] and A-GPS/A-GNSS measurements [171] between the UE, the eNodeB and the E-SMLC [1, 172].

RF Fingerprinting: The most common technique for fingerprinting is *RF fingerprinting* or *RF pattern matching* [173, 174]. In LTE, it would exploit UE measurements of received signal strength [175–177], from a number of eNodeBs. The geographical RF maps can be created by advanced radio signal strength prediction software [178, 179], using very detailed information of the 3-D geographical topology [180] together with accurate information of the cell plan, tower locations, tower heights, antenna directions, antenna tilting, antenna patterns, and transmission power [1, 181]. To obtain a desired accuracy, it may be needed to complement utilized prediction software with surveying [182]. Alternatively, relying entirely on surveying is possible. However, this approach is considered to be of highest cost for typical sized cellular networks. The resolution of the geographical grid of the RF map will impose a bound on the positioning accuracy [1]. Other unaccounted for effects can add 10 dB of uncertainty which will affect positioning technology deploying RSS measurements. Time measurements may be less sensitive [10]. Averaging or using relative signal strength in addition to signal processing techniques relying on aspects of the signal strength can alleviate these effects [1, 156].

AECID: Adaptive enhanced cell ID (AECID) is another way to enhance fingerprinting positioning performance [160, 183] by extending the number of radio properties that are used [1]. For instance, in LTE, at least CIDs, TA [184], and AOA are suitable in addition to RSSs [1, 157]. Unfortunately, the geographical radio map then becomes much more difficult to generate [177, 180]. Moreover, using multiple radio properties requires analysis in-terms of estimated position accuracy [160] and to associate a confidence value. The AECID positioning method [1, 160] addresses the above problems [172]. It fuses geographical cell descriptions (corresponding to CIDs), received signal strengths, and TA, and can be extended to include AOA information. The method replaces the radio property prediction software and the surveying by self-learning mechanisms [1, 150, 160].

4) OTDOA: Observed time difference of arrival (OTDOA) is a downlink (DL) positioning method that exploits time difference measurements conducted on DL reference signals received from multiple locations [1, 151, 152].

When OTDOA operates in UMTS networks, the OTDOA location server estimates the position of a mobile device by referencing signal reception time at the UE from a minimum of three Node B stations [161]. The mobiles position is at the intersection of at least two hyperbolas defined by the OTDOAs of the UMTS frames from multiple Node B stations.

In LTE, an OTDOA measurement, reference signal time difference (RSTD), is defined as the relative timing difference between two cells, the reference and a measured cell. It is calculated as the smallest time difference between two subframes received from the different cells [1]. Geographically separated BSs that have proper geometry are used to obtain at least three timing measurements to solve for two coordinates of the UE. No two branches of the distinct hyperbolas intersect twice so that a unique solution can be found which defines a good geometry for this purpose. A larger number of measurements, typically at least six to seven, is desirable in practice [1]. The position calculation is based on the multilateration approach by which an intersection of hyperbolas is found. A hyperbola for a pair of cells corresponds to a set of points with the same RSTD for the two cells. The advantage of OTDOA is that synchronization between the eNodeBs and the UE is not required. Similar to techniques applied for solving TDOA equations [185], many approaches exist for solving the system of equations of OTDOA, where most of them involve linearization of nonlinear least squares problems. Alternatively, with the common Taylor series-based approach,

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the UE coordinates are found iteratively starting from an initial UE position estimate.

5) E-OTD: Enhanced Observed Time Difference (E-OTD) technology has been deployed by Cambridge Position Systems [161]. E-OTD operates only on GSM and GPRS networks [10]. The cell phone sends a signal to the surrounding cell emitters, and the nearest one sends back a signal. The time taken between sending and receiving the wave is analyzed by an external server, which calculates the cell phone position in the network [161, 186]. This method includes new technology in the handset to assist in locating the mobile in a network. Mobile units in an EOTD system are set up to support positioning in a network where BSs are asynchronous. Theoretically, it takes about 5 seconds to locate a mobile unit using the E-OTD technique and the accuracy is about 30-50m. Real-world tests have yielded less accurate measurements of about 50-125 meters [161].

6) U-TDOA: In uplink time difference of arrival (U-TDOA), the position calculation principle is the same as that in OTDOA [187], however, the major conceptual difference between the two is that OTDOA requires multiple transmit points, while U-TDOA utilizes multiple receive points at different locations [1]. To facilitate performing of U-TDOA timing measurements, sounding reference signals (SRSs) [188] have been selected for U-TDOA measurements [1]. For U-TDOA positioning, periodically transmitted SRSs are scheduled in a non-dynamic way to allow a sufficiently long time for the measurements. The main disadvantage with U-TDOA, as compared to OTDOA, is a hearability problem due to the power control of the UE transmissions [1]. UEs close to their own BS transmit at a low power level to avoid creation of unnecessarily high levels of interference – this is denoted as the near-far problem. The consequence is that such signals may not be strong enough to reach the required UL signal strength for U-TDOA measurements at neighbor sites.

At the end of this section, we chose to highlight main expected performance characteristics of the different positioning methods in LTE as the current state-of-the-art cellular systems, which is expected to be the prevailing standard for the next decade. We adapted from reference [1] Table II and Table III that conducts side-by-side comparisons of the available standardized positioning methods in LTE systems.

IV. Localization and Tracking Algorithms with Moving Receivers

In this part, we review a collection of algorithms from the technical literature that deal with wireless networks deploying mobile receivers and use different measurements such as RSS, AOA, TOA, TDOA, FDOA, and their combination. This is departing from the traditional assumption of fixed infrastructure (BSs, Sensors, etc.) in the wireless networks. It is assumed that receivers are free to move in an arbitrary (but known) fashion. Thus, the wireless network topology may change rapidly. There exist a number of implementations of various levels of complexity and required number of receivers (sensors or BSs) to enable tracking of target(s) (or MT(s)). They range from one single mobile receiver (e.g., measurement from the closest neighboring BS), to a few, or even tens in a single configuration. This offered ”proposed” flexibility in the positioning with mobile receivers can eliminate the need to sample with many receivers (e.g., six fixed BSs or more as in previous GSM cellular systems).

A. Algorithms based on RSS

In [189–191] the authors presented an algorithm that provides geolocation and velocity estimation for a variant of a traditional cellular ”GSM” network in which base stations and users (MTs) are both mobile. They proposed using Robust Extended Kalman Filter (REKF) equations, that were derived from the system state estimation and the corresponding Riccati differential equation to utilize the RSSI’s to obtain an estimate of the MTs current location and velocity. The analysis demonstrates that the proposed algorithm can successfully track the mobile users with less system complexity, as it requires measurements from only one or two closest mobile BSs.

In addition, the technique is robust against system uncertainties caused by the inherent deterministic nature of the mobility model. Through simulations, they demonstrate the accuracy of their prediction algorithm and the simplicity of its implementation. In a 70 minutes simulations, the 15x40km suburban service area with a mobile-user in a three car coverage area was set-up. The network is assumed to have location and acceleration information of the mobile BSs via GPS, as shown in Fig. 7. The mobile user does not have access to location and acceleration information. The closest (1 or 2) car(s) is/are measuring the forward-link signal in the GSM system and track(s) the MTs location and predicts the velocity. Fig. 8 shows the attained location accuracy in the two scenarios: when using a single car (mobile BS), and two cars. Considering the distance between the MT and the mobile BSs, the error in position estimation is from a few meters to about 500 meters in a properly configured system.

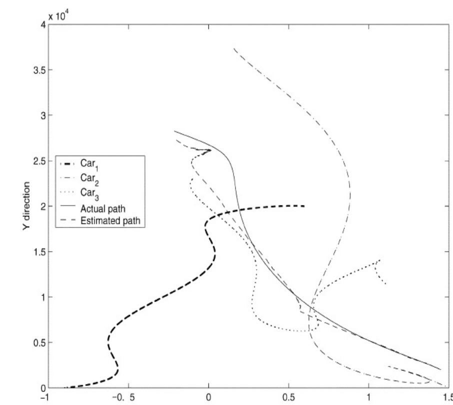

Fig. 7. Trajectories of the cars and the mobile user with dual base station measurements [189].

In [192] a network of small unmanned aerial vehicles (SUAVs) for localization of RF emitters has been designed. Because of better incidence angles near the target than large dedicated manned surveillance platforms, an unmanned aerial vehicle (UAV) is preferred. To provide local mean distance

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TABLE II
TYPICAL CHARACTERISTICS OF DIFFERENT POSITIONING METHODS IN LTE [1]

Positioning Method	Earliest LTE Release/Optional	Environment Limitations	UE Impact	Site Impact	Site Impact
CID	All/no	No	No	No	Small
E-CID	Rel-9/yes	No/medium	Small	Small/large	Medium
RF Fingerprinting	Rel-9/yes	Rural	Small	Small	Large
AECID	Rel-9/yes	No	Small	Small	Medium
OTDOA	Rel-9/yes	Rural	Medium	Medium	Medium
U-TDOA	Rel-11/yes	Rural	Small	Large	Large

TABLE III
TYPICAL ACCURACY OF DIFFERENT POSITIONING METHODS AVAILABLE IN LTE , SUBJECT TO RESTRICTIONS OF TABLE II [1]

Positioning Method	Availability	Response Time (in RAN)	Horizontal Result Uncertainty	Vertical Result Uncertainty
CID	100 %	Very low	High, $\alpha = 1$	n.a.
E-CID	Very high	Low	Medium, $\alpha < 1$	n.a.
RF Fingerprinting	High	Low/medium	Low/Medium, $\alpha < 1$	Medium
AECID	High	Low	Low/Medium, $\alpha < 1$	Medium
OTDOA	High	Medium	$< 100m$	Medium
U-TDOA	High	Medium	$< 100m$	Medium

[1] Proportional to the cell range, with a proportionality constant α.

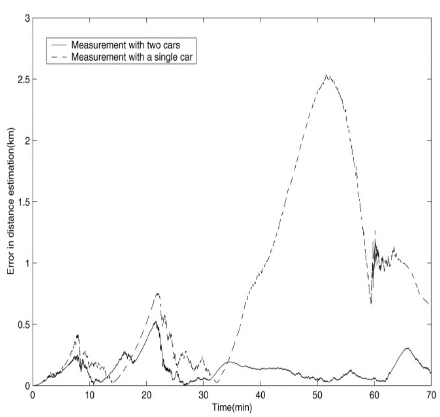

Fig. 8. Error in location estimation for single and dual car measurements [189].

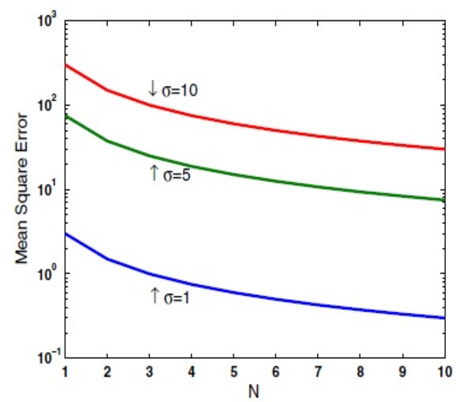

Fig. 9. Upper bound of geolocation area mean square error for a three UAV network (where σ^2 is the variance of log-normal shadowing) [192].

estimation based on RSSI, a set of N electronic surveillance (ES) sensors is utilised by each small UAV. Based on UAV triangulation, a fusion center will estimate the location of the target. This method employs the RSS positioning parameter and relies on an empirical path-loss and log-normal shadowing model to offer an effective solution. The performance degradation between UAVs and fusion center is also accounted for through the effect of modulation order and wireless fading channel. The analysis of the geolocation error is shown in Fig. 9 based on the proposed system. It is indicated that robust performance is achieved for high frequency RF emitters.

In [193], an RSS-based Monte Carlo (MC) localization scheme to sequentially estimate the location of mobile nodes in a WSN using the log-normal statistical model of RSS measurements, is proposed. The RSS measurement is considered as the observation model in MC method and the nodes mobility feature as the transition model. It is mentioned that this method is widely applicable because the RSS function is easy to implement on nodes, and the mathematical model for mobile nodes may have no closed forms. Their simulation results depict that localisation accuracy is better than other methods.

The techniques based on RSS have the advantage that there is no synchronization requirement between MT-BS as well as among BSs. This will make the use of RSS easy in practice. However, due to the multipath and NLOS effects, it is difficult

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to use an accurate propagation model to relate the distance to the unknown location. Therefore, RSS measurements, when employed in a range-based technique, usually have lower accuracy in indoor and multipath areas. The RSS techniques are usually preferred in fingerprinting techniques but to the knowledge of authors fingerprinting using mobile receivers has not been considered before. How to extend the fingerprinting techniques to systems with mobile BSs remains an open and interesting problem to be considered.

B. Algorithms based on TDOA

In [194, 195] a TDOA algorithm for geolocation based on delay estimation of two correlated wireless channels is proposed. The assumed set-up described a passive receiver that is on-board a small flying UAV, while the (static or mobile) transmitter is on the ground surface. It is indicated that a Rician flat fading model should be used since it was assumed that there exists a LOS between transmitter and receiver. Block phase estimation (BPE) is used for each wireless channel estimation to estimate the delay of two correlated channels. Then the two estimated channels are compared to get the time delay corresponding to the strongest path. Also, a comparison of their approach is conducted against a cross-correlation-based TDOA algorithm. The simulation results show that the TDOA algorithm performs much better (10 times) than the cross-correlation-based TDOA algorithm with a lower level of TDOA error and Root-Mean-Square-Error (RMSE). Four different groups of Rician fading channels are evaluated as shown in Fig. 10 and Fig. 11. Conclusions are drawn for the proposed TDOA algorithm and the cross-correlation-based TDOA algorithm that larger Doppler shift *fd* (500 Hz versus 200Hz) and lower Rician fading factor *K* (9dB versus 12dB) cause TDOA performance degradation.

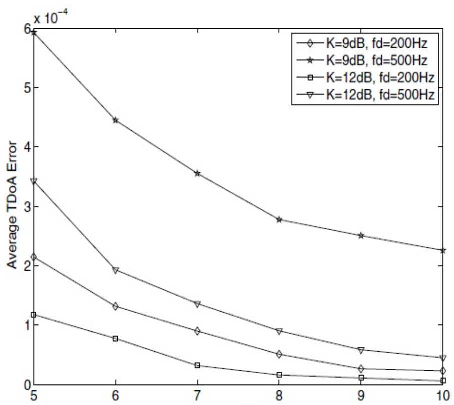

Fig. 10. The average TDOA error versus SNR for four different Rician fading channels with 1.07ms (100-symbol) time delay "*Proposed TDOA system*" [195].

In [196] the authors presented an algorithm for the geolocation and tracking of an unknown number of ground emitters using TDOA measurements in practical surveillance region scenarios. The focus is on tackling the issue of data association (i.e., deciding from which target a measurement originated). An assignment algorithm is introduced that performs the

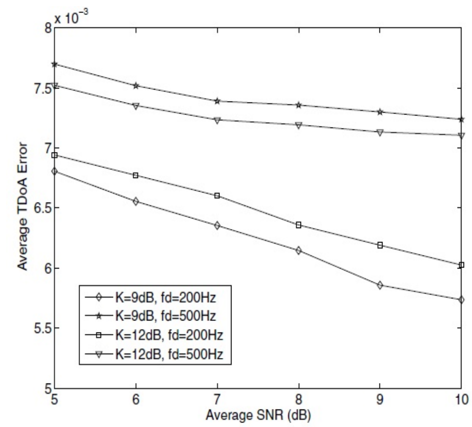

Fig. 11. The average TDOA error versus SNR for four different Rician fading channels with 1.07ms (100-symbol) time delay "*Correlation method system*" [195].

data association in one step which substantially reduces the computational cost while preserving the accuracy of tracking. The non-linear TDOA equations were set-up in the form of an optimization problem which were solved using SolvOpt (a non-linear optimization solver). The interacting multiple-model (IMM) estimator in conjunction with the unscented Kalman filter (UKF) to track the geolocated emitters is also employed. The scenarios of UAVs, used as sensor platforms, fly at a constant altitude of 6000 m. The UAVs move at a constant velocity of 100m/s, then make a 180 degrees coordinated turn with a turn rate of 2 rad/s, and proceed with constant velocity for the remaining time. It is assumed that the UAV positions are known exactly at each time step (i.e., there is no process noise in their motion model). Further, it is assumed that each UAV can cover the whole surveillance region. There are five sources: a stationary source, three constant velocity sources, and a manoeuvring source that performs a coordinated turn. Fig. 12 shows the simulated true positions and tracks of the five targets, while Fig. 13 depicts the position RMSE, averaged over 50 Monte Carlo runs with measurement noise standard deviation of 1 ns.

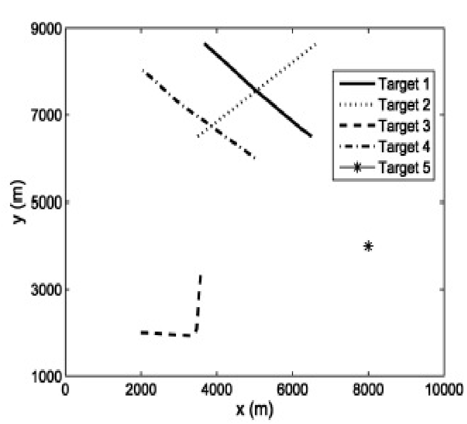

Fig. 12. Simulation of true target motion in surveillance region [196].

In [197, 198] the authors have discussed two recursive algorithms for TDOA-based source localization using mobile

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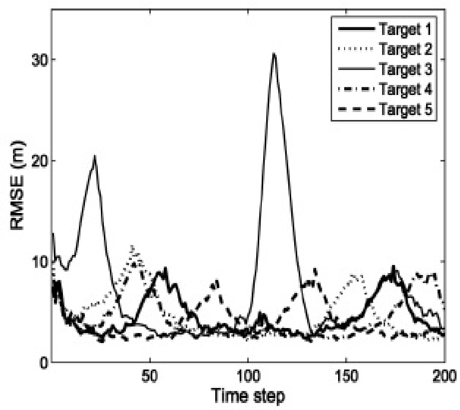

Fig. 13. Position RMSE, averaged over 50 Monte Carlo runs [196].

sensors with location uncertainty. A comparative analysis on the two recursive localization algorithms is presented. The first algorithm is called recursive localization algorithm, which uses the current estimate (using constrained weighted least squares (CWLS)) of source position to form a new measurement equation of the unknown source position. The second algorithm firstly estimates an auxiliary variable (using WLS) and then rearranges the non-linear TDOA equation into a linear measurement equation. To tackle the non-linearity of TDOA at each sampling time, each of the two localization algorithms performs reorganization to rearrange the TDOA equations. In the improved recursive localization algorithm, the principal difference is in the advance estimation of the auxiliary variable before using the TDOA equations to update the source location. However, in the recursive localization algorithm, the auxiliary variable is regarded as a completely unknown variable when updating the source location. It is shown that the second algorithm performs better than the first one as depicted in Fig. 14.

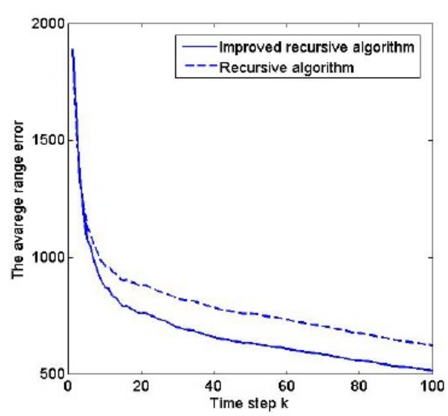

Fig. 14. Comparison of the localization accuracy of the proposed recursive localization algorithms [198].

In [199–201] the authors performed a comparative analysis of three non-linear filters for estimation of the location and velocity of a moving emitter, using TDOA measurements collected by two UAVs as they fly over the area of surveillance. The three suggested algorithms employ a Gaussian mixture (GM) representation of the posterior pdf. The comparison considers the following non-linear filters: a Gaussian mixture measurement integrated track splitting filter (GMM-ITSF), a multiple-model filter (MMF) with UKFs and an MMF with extended Kalman filters (EKFs). The CRLB of estimation errors is derived and used as the benchmark in performance analysis. While UKFB had a little better performance, the RMSE in estimation was close to the CRLB for all algorithms as shown in Fig. 15. On the other hand, GMM-ITSF had a smaller number of diverged tracks. As all algorithms presented are compatible with the real time requirements, the priorities of individual applications should determine the choice.

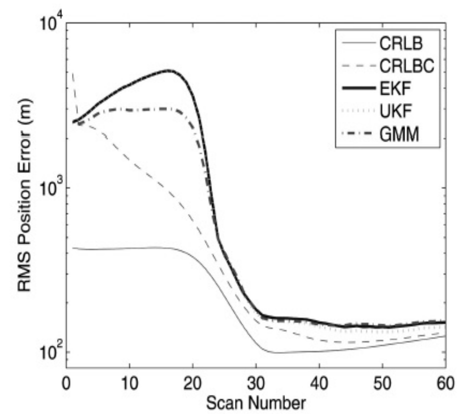

Fig. 15. RMS errors of combined estimate [199].

The TDOA-based methods are suitable for target tracking since there is no need for synchronization between target and reference nodes. The accuracy of TDOA-based techniques will be deteriorated in NLOS environments since the TDOA measurements will become biased. One way to mitigate the NLOS error is to use Kalman filters on the measured TDOAs to make the measurements smooth, as done for cellular systems in the past [202]. These techniques as well more recent ones can be extended to next generation systems with moving receivers.

C. Algorithms based on FOA

In this section, we explore location tracking systems and algorithms that utilize FOA in conjugation with various signal processing prediction and tracking filters.

In [203, 204] particle filter (PF) is used with a single moving sensor for Doppler geolocation of non-cooperative RF emitters. This proposed recursive approach based on PFs tracks the non-stationary carrier drift. It discretely represents the multi-modal state space of the emitter through time, and ultimately converges to the true emitter location. The new approach is compared to Newton optimization and extended EKF based solutions in Fig. 16. Unlike existing Doppler-based geolocation techniques, this approach does not assume that the unknown emitter's carrier frequency is stable during triangulation interval. This assumption is frequently violated considering manufacturing tolerances that allow significant carrier drift.

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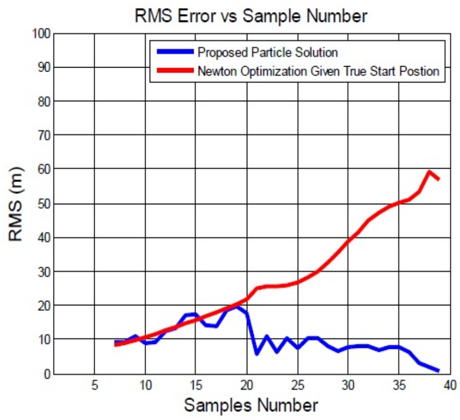

Fig. 16. RMS geolocation comparison of Gauss-Newton (GN) iterative descent (given initial state truth) with proposed particle filter solution [203].

In [205] the authors reported the performance of a recently developed PF technique to locate a stationary push-to-talk (PTT) radio using the Doppler-shifted signal as observed by a single moving ground vehicle. Because of the strong dependence of a solution on the target's unknown original carrier frequency, this is considered to be a principal difficulty for single-sensor Doppler-based localization. This uncertainty permits several potential location estimates to be mapped with the observations. Also, over short time intervals, the PTT carrier drifts substantially. This creates a dynamic, multimodal objective function and prompts the application of the PF solution. The performance of the technique was verified on real data gathered by a slow-moving (10-40 mph) ground vehicle over a relatively short 0.5 km range. The location estimation errors achieved are compared to the theoretical FOA CRLB and with the more common two sensor FDOA solution as shown in Fig. 17. These results indicate that the single sensor FOA method achieved the same performance as the two sensor FDOA solution on targets with significant carrier drift during the collection interval. The results also indicate that even at fairly slow speeds, Doppler geolocation methods can be applied and still obtain reasonable geolocation accuracy.

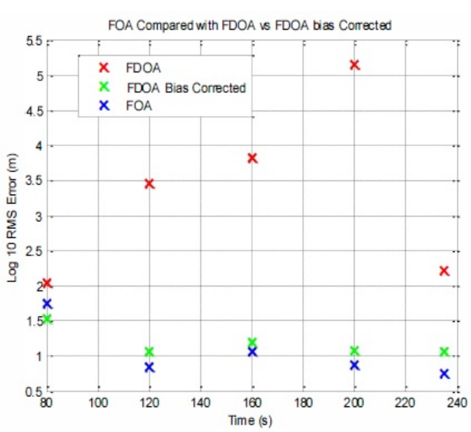

Fig. 17. Comparison of FOA Solution with FDOA Bias Corrected and FOA [205].

The FOA-based techniques like TOA-based ones require accurate synchronization and therefore it might have limitations in some applications. The performance of FOA-based can be severely degraded in the presence of NLOS and multipath, where the doppler frequency will change dramatically. Therefore, FOA-based techniques that are robust against multipath and NLOS need to be developed so they can be used in the next generation of cellular networks.

D. Algorithms based on AOA for Positioning and Tracking

The authors of [206] investigated the problem of manoeuvring target tracking using angular measurements. The target dynamics is modelled by multiple models, while the measurements are collected asynchronously from possibly multiple moving platforms. First a theoretical lower bound on the performance error is derived. The theoretical bound is conservative, being derived under the assumption that the model history is known. Then three tracking algorithms are proposed and compared to the theoretical bound. The proposed algorithms include: (i) the IMM algorithm with EKF, (ii) the IMM with UKFs and (iii) the multi-mode PF. All three filters are suboptimal but their performances show remarkable agreement with the theoretical bound. Fig. 18 illustrates the performed comparisons.

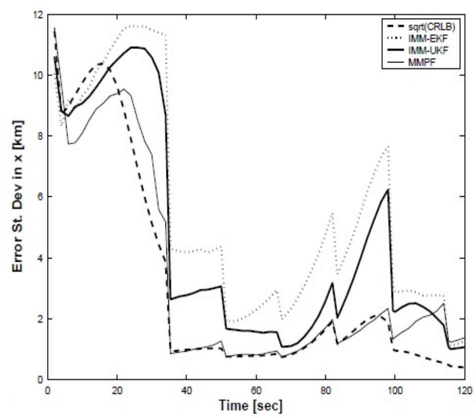

Fig. 18. Comparison of error performance of the the three algorithms against the theoretical bound [206].

In [207] a new approach for single sensor tracking using measurements with passive bearings only is proposed. A single moving sensor measures direction of target emissions at known random times. GMM presentation, together with a track splitting algorithm (GMM-ITS) filter, allow space-time integration of the target position uncertainty with a simple algorithm. The bearings-only measurements are incorporated into track as they arrive using a dynamic bank of linear KFs. The focus of [207] is on the target trajectory estimation using associated measurements. A simulation study demonstrates the benefits of this approach. Near the end of the simulation interval, the target observability criteria are satisfied, and CRB and estimation errors fall sharply. GMM-ITS and particle filter in this environment have smallest estimation errors of the filters considered, falling to within 10% of the CRB as can be seen in Fig. 19. Other presented techniques follow with increasing estimation errors.

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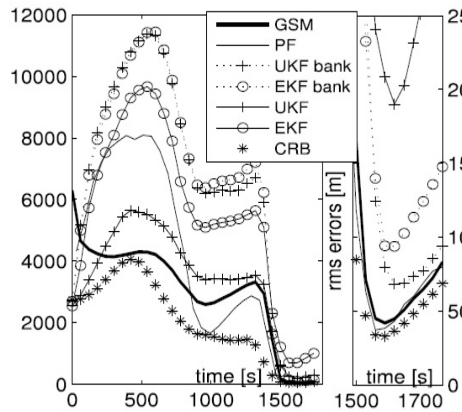

Fig. 19. Comparison of error performance against the theoretical bound [207].

In [208] an efficient target tracking technique is proposed with the help of beam steering enabled directional sensors mounted on the nodes. At every step of beam steering, the sensor node updates the location of the target to the nearest cluster head or BS. Each sensor will continuously monitor the target until it crosses the field of view (FoV) or sensing range of the passive sensor. The performance of the algorithm was studied for various mobilities using directional sensors and ensured continuous tracking of the target. Using the proposed approach, the system was able to track the target speeds up to 8 m/sec with 60 deg FoV angle, 6 m/sec with 45 deg FoV angle and 3 m/sec with 30 deg FoV angle for all the mobilities. The accuracy of the target location is dependent on the FoV of the radiation pattern. The average location error of the target is high for larger FoV angles. It was also seen that the location accuracy of the target was mainly dependent on the FoV angle and FoV sensing radius of the sensor. Fig. 20 depicts a sample random mobility tracking performance with the proposed algorithm.

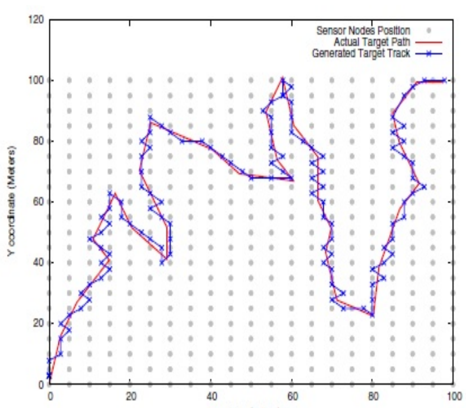

Fig. 20. Random Mobility (passive sensor); FoV angle = 60 deg; Target speed = 2 m/sec [208].

In [209] a method is proposed for tracking a manoeuvring target by employing multiple asynchronous sensors with uncertain position. Asynchronous target position triangulation is achieved. GMM presentation, together with a track splitting algorithm allow space/time integration of the target position uncertainty with a simple algorithm. Gaussian mixture measurement presentation incorporates sensor position uncertainty, as well as the spatial uncertainty brought by bearings only measurement. Each sensor detects the target emissions independently, and the measurements are incorporated into track as they arrive. Measurements by arbitrary number of sensors can be incorporated, provided that the triangulation observability criterion is satisfied. The approach is verified by a single target, two moving sensors, two-dimensional surveillance simulation experiment.

The salient advantage of AOA measurements is that like RSS measurements, there is no requirement for synchronization. Furthermore, the number of AOA measurements required to localize a target is less than the number of RSS, TOA, or TDOA measurements. However, the AOA measurements can be severely degraded in NLOS environments, in which case these measurements are often useless and discarded. Therefore, there might be limitations of available LOS AOA measurements, making it impossible to find the location of target. Therefore, AOA measurements are usually combined with other sets of measurements, e.g., TOA, or TDOA.

E. Algorithms based on TOA/RSS

The authors in [210] considered the problem of exploiting sensor mobility information in the process of sensor localization under two range measurement models, namely the TOA model and the RSS model, is studied. For each model, first the maximum likelihood (ML) location estimator for the case of error-free velocity measurements is derived. As the corresponding optimization problems are non-convex, they resort to semi-definite relaxation (SDR) techniques to find approximate solutions to each problem using semi-definite programming (SDP). Then, they extend their results to the cases where the velocity measurements are subject to measurement errors. Their simulation results show that exploiting the mobility information in the localization process can significantly improve the performance of the sensor localization using TOA and RSS measurements as shown in Fig. 21 and Fig. 22, respectively. Moreover, mobility-aided localization has the potential to address some of typical positioning problems, such as sensitivity to the ranging measurement errors and the requirement on the number of the anchors needed to uniquely localize the sensor nodes.

As mentioned earlier, RSS methods will perform poorly in multipath and NLOS areas. However, accurate TOA measurements can be obtained using high resolution wideband systems in LOS systems. The ultra-wide-band (UWB) which is allowed by FCC to operates in the unlicensed 3.1-10.6GHz band is a great technology for ranging. In the presence of NLOS the TOA measurements become positively biased, however, unlike other types of measurements, TOA measurements are more suitable in NLOS situations since the problem can be mitigated using several geometric and optimization techniques. For a survey of TOA-based NLOS identification and mitigation techniques see in [44]. In order to obtain TOA measurements, either the target and reference nodes have to be precisely synchronized, or two-way ranging (TWR) techniques can be used to remove the clock errors from the measurements.

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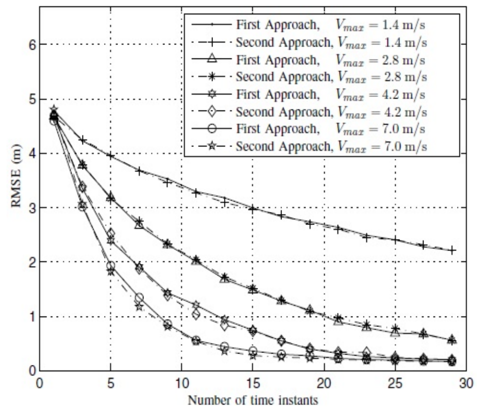

Fig. 21. The RMSE of location estimates versus number of time instants for the TOA-based model with noise-free velocity measurements [210].

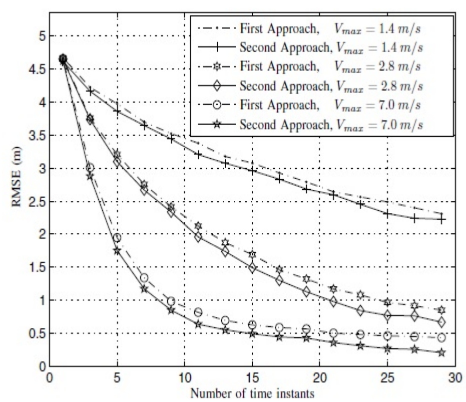

Fig. 22. The RMSE of location estimates versus number of time instants for the RSS-based model with noise-free velocity measurements [210].

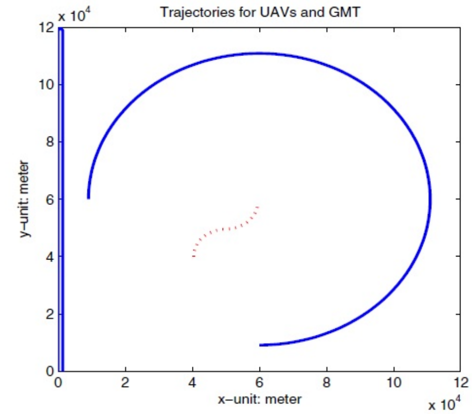

Fig. 23. Trajectories of two UAV and GMT [211].

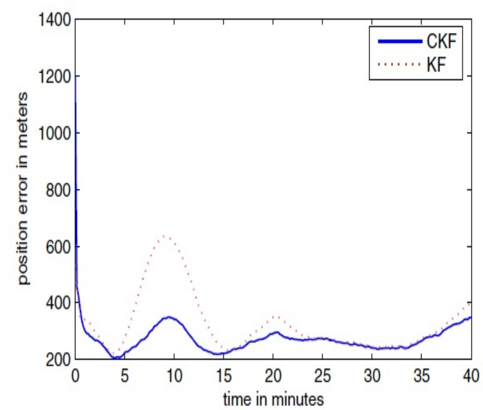

Fig. 24. RMS error for location estimate [211].

F. Algorithms based on TDOA/AOA

In [211] the problem of localization and tracking of ground moving targets (GMTs) based on measurements of TDOA and direction of arrival (DOA) is considered. The associated measurement noises are assumed to be independent and identically distributed (i.i.d.). By utilising the pseudo-measurement model that imposes a quadratic constraint on the state vector associated with the GMT dynamics from the existing literature, the problem of the constrained linear MMSE estimation is formulated. It is suggested to replace the hard constraint by its expectation because of the the randomization of the state vector for the GMT process. A solution to a similar quadratically constrained MMSE estimation problem is first derived by the authors. The constrained KF (CKF) is then developed for those estimation problems involving quadratic constraints, applicable to localization and tracking of GMTs based on TDOA and DOA measurements. Moreover, the CKF permits a recursive solution which is simple, with complexity comparable to that of the conventional KF. A simulation example is used to illustrate their proposed CKF in localization and tracking of GMTs as depicted in Fig. 23 and Fig. 24.

The AOA measurements, when combined with TDOA measurements can form a reliable system for asynchronous localization with low number of required LOS BSs. In the presence of NLOS measurements the AOA measurements can be discarded and NLOS mitigation can be applied on TDOA measurements [202].

G. Algorithms based on TDOA/FDOA

In [212, 213], an algebraic solution for the estimation of the position and velocity of a moving source using the TDOAs and FDOAs of a signal received at a number of receivers, is proposed. The method does not require initial guesses, and obtains a location estimate by solving several WLS problems. Contrary to the conventional linear iterative methods, it does not require initialization and local convergence problem. The estimated accuracy of the source position and velocity is shown to achieve the CRLB for Gaussian TDOA and FDOA noise at moderate noise level before the thresholding effect occurs. Simulations of the location geometry of the target and receivers depicted in Fig. 25 examine the algorithm's performance and compare it with the Taylor-series iterative method as shown in Fig. 26.

In [214], the authors performed analysis and developed a solution for locating a moving emitter via TDOA and FDOA measurements in the presence of random errors in the receiver locations. Error in the receivers' locations greatly affects the accuracy of a source location estimate. The CRLB is derived

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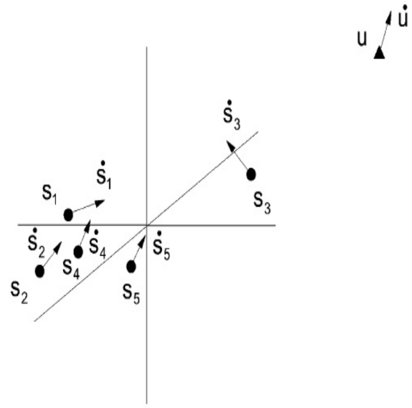

Fig. 25. Location geometry of sensors (receivers) and target in the simulation [212].

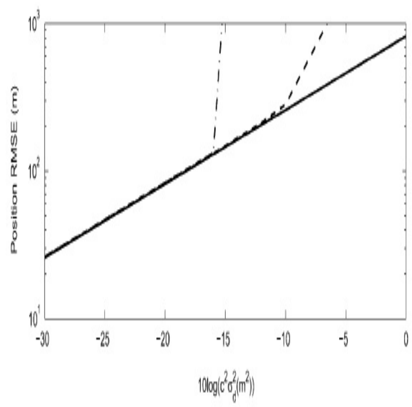

Fig. 26. Comparison of RMSE of the proposed method (Dashed) with the Taylor-series (Dash-dot) linearization method and the CRLB (Solid). The accuracy is shown in log scale as the noise power increases [212].

by assuming correct receiver locations while they have errors as depicted in Fig. 27. A solution is then proposed that takes the receiver error into account to reduce the estimation error. It is shown that the proposed technique was able to achieve the CRLB accuracy for far-field sources It is indicated that the proposed solution is closed form, and does not possess the divergence problem of the iterative techniques.

In [215, 216] an efficient constrained WLS (CWLS) algorithm is proposed for estimating the position and velocity of a moving source by utilizing the TDOA and FDOA measurements of the signals received at a number of moving receivers as shown in Fig. 28. The proposed algorithm takes advantage of the known relation between the intermediate variable and the source location coordinates in an explicit manner. Based on Newton's method, a numerical iterative solution can be attained ensuring global convergence and permitting a real-time implementation. For the near-field source position and velocity estimations, simulation results show that the two-step WLS method departs from the CRLB at a noise power about 6 dB, while the proposed estimator gives inaccurate estimate at the noise power of about 16 dB. The threshold effect of the proposed method occurs at a noise power that is about 10 dB, which is larger than that of the two-step WLS method as

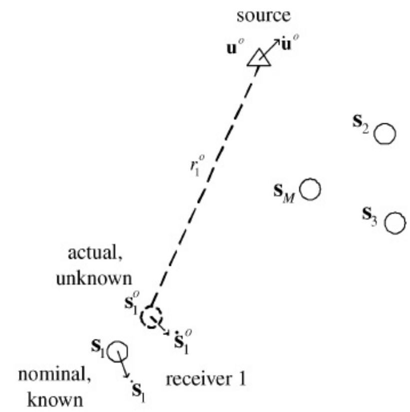

Fig. 27. Location geometry in the presence of receiver location errors [214].

the noise power increases. Also, for a far-field moving source with the same velocity, the proposed estimator is superior to the two-step WLS method in terms of estimation bias and RMSE for estimating the position and velocity of the far-field moving source. The price of the better performance for the developed approach is that its computational complexity is a bit higher than that of the two-step WLS method, but can still be implemented in a real-time system as the two-step WLS method.

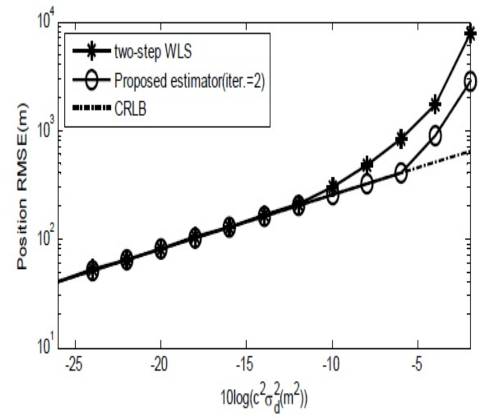

Fig. 28. Location geometry in the presence of receiver location errors [216].

A solution for locating a moving source using TDOA and FDOA measurements employing a calibration emitter, is proposed in [217]. The results show that the high sensitivity of the source localization accuracy to the error in sensor location. In this scenario, they derived the CRLB for source location estimate using a Gaussian random signal model. Then, the commonly used technique in GPS of differential calibration was analysed. It is indicated that, in most cases, the differential calibration is not capable of reaching the CRLB accuracy. They proposed a closed-form solution that employs a calibration emitter to reduce the error in sensor location. Analytically, they demonstrated that their approach reaches the CRLB for different calibration source scenarios. For the position estimate, compared with the differential calibration technique, the improvements of the proposed method are 14

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dB and 8.2 dB with the algorithm without using a calibration emitter when the sensor position error variance is 10^{-3}. The improvements are 11.5 dB and 5.7 dB, respectively, for velocity estimate.

In [218] recursive tracking of one mobile emitter using a series of TDOA and FDOA pairs of measurements collected via a pair of sensors, is considered. Each TDOA measurement establishes a region of potential emitter locations around a distinctive hyperbola. This likelihood function is approximated by a GM, which leads to a dynamic bank of KFs tracking algorithm. The FDOA measurements update relative probabilities and estimates of individual KFs. This approach shows a better result in tracking the state probability density function approximation, and the tracking result reaches the CRLB. The performance of the proposed GM approach is evaluated using a simulation study, and compared with a bank of EKF filters and the CRLB. The performance nears the theoretical optimum of the CRLB curve as shown in Fig. 29. The RMS estimation errors of 3.8m and 10.5m for the case of minimal and increased measurement errors, respectively, in this scenario (with the emitter more than 15km away).

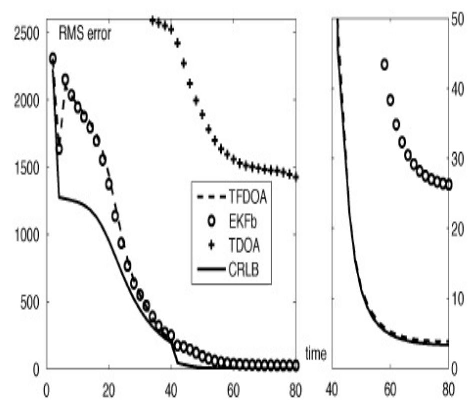

Fig. 29. Minimal measurement errorsoutput rms errors [218].

In [219] emitter tracking using a combination of TDOA measurements and other types of measurements is considered. The measurements are gained by exploiting the signal impinging from an unknown moving emitter. First, a combined set of TDOA and AOA measurements is processed using the MLE. Then, a GM filter is used to solve the tracking problem based on TDOA and FDOA measurements. Through MC simulations for the mobile emitter scenario, the superior performance of the combined methods in contrast to the single TDOA approach is shown and compared with the CRLB in Fig. 30.

In [220] the problem of locating *multiple* disjoint moving sources using TDOAs and FDOAs in the presence of sensor position and velocity errors, is considered. The authors developed an algebraic solution to this problem through nonlinearly transforming the measurements and converting them with respect to the inaccurate sensor locations. A set of pseudo-linear equations from TDOA and FDOA measurements is established with respect to the erroneous sensor locations and they are solved by the two-stage approach. The solution

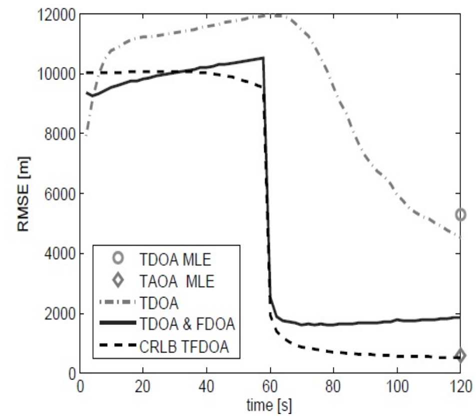

Fig. 30. RMSE for TDOA, TDOA and AOA, and TDOA and FDOA [219].

is shown analytically to achieve the CRLB performance over small noise region and does not require joint estimation with sensor locations as shown in Fig. 31. The approach used is not to obtain the source locations individually, which is possible because we have separate measurements for different sources, but rather to estimate all the source locations together simultaneously. Previous work was applied to one source only with suboptimum performance for near source, or requires joint estimation of the source and sensor locations that could be computationally demanding.

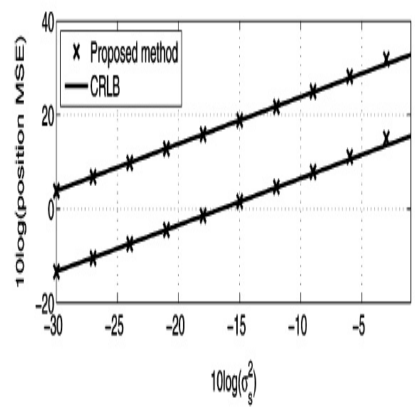

Fig. 31. Performance comparison with two sources: 1 (near) and 2 (far): The smaller MSE curve is for 1 and the other is for 2 [220].

In [221] an algorithm for tracking a moving target using the measurement signals of TDOA and the FDOA is proposed as shown in Fig. 32. The TDOA and FDOA measurement signals are employed jointly to estimate the location and the velocity of a target at discrete times pointing that the conventional target tracking using an TDOA measurement alone is not accurate enough to estimate the target location. It is mentioned that although the KF shows remarkable performance in calculation and location estimation, the estimation error can be large when the priori noise covariances are assumed with improper values. Then they suggest an adaptive EKF (AEKF) to update the noise covariance at each measurement and estimation process. The simulation results of a manoeuvring UAV as shown in Fig. 33

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show that the algorithm efficiently reduces the position error and it also greatly improves the accuracy of target tracking as shown in Fig. 34.

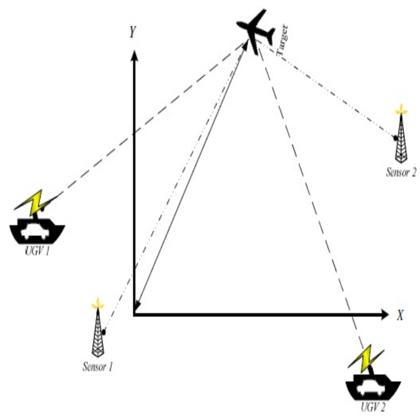

Fig. 32. Concept of target location using TDOA and FDOA measurements [221].

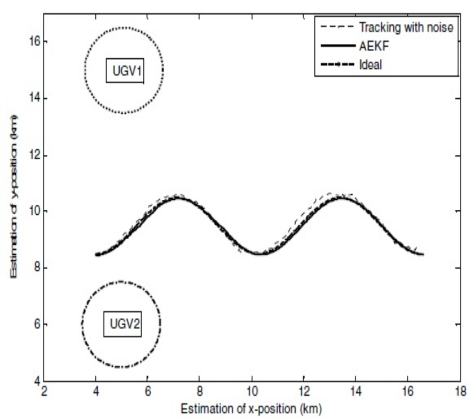

Fig. 33. Position estimation of a sinusoidal movement [221].

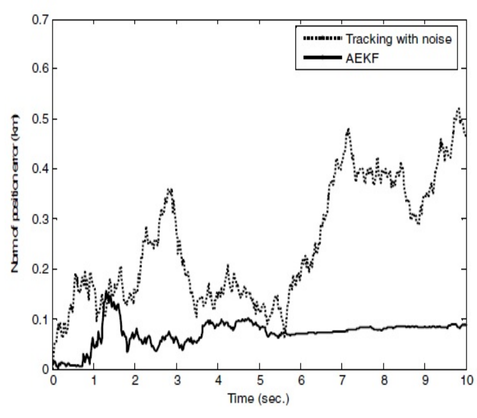

Fig. 34. Norm of position error for sinusoidal movement [221].

In [222–224] a conditional (or a signal-specific) CRB is derived, which models the signal as a deterministic unknown as opposed to classical derivation of the associated CRB that relies on a stochastic, stationary Gaussian signal-model. They explain that the assumptions in the classical derivation lead to a diagonal Fisher information matrix (FIM) with respect to the TDOA and FDOA. They stated that this diagonality implies that (under asymptotic conditions) the respective estimation errors are uncorrelated. However, for some specific (non-stationary, non-Gaussian) signals, especially chirp-like signals, these errors can be strongly correlated. On the other hand, they explain that given any particular signal, their CRB reflects the possible signal-induced correlation between the TDOA and FDOA estimates. They pointed that in addition to the theoretical value of this derived CRB, the resulting CRB can be used for *optimal weighting* of TDOA-FDOA pairs estimated over different signal-intervals, when combined for estimating the target location. Accounting for the TDOA-FDOA correlation in the weighting enables to take advantage of the diversities in chirp structures (increasing/decreasing frequencies) between intervals, so as to attain significant improvement in the localization accuracy. In their simulation examples with chirp-like signals, the use of proper weighting reduced the scatter area of the localization results by a factor of 25 under good SNR conditions.

In [225] the localization of a stationary transmitter using receivers mounted on fast moving platforms is considered. It is assumed that the transmitted radio signal is random with known statistics. They advocate a direct position determination (DPD) approach that is more computationally efficient and more precise for weak signals than the conventional two-step approach. The direct method is a single-step method that uses the same signals as the two-step approach but searches directly for the emitter position without first estimating intermediate parameters such as Doppler frequency and the time delay. They also include a secondary result which is a derivation of closed-form and compact expressions of the CRLB. Results for the simulated sensors and target locations scenario of Fig. 35 are shown in Fig. 36.

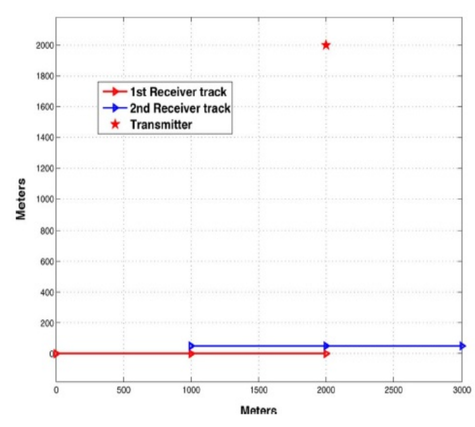

Fig. 35. Receivers track and emitter location [225].

In [226] distributed tracking in clutter environments, with particular emphasis on the situation where (at least some) sensors take non-linear measurements, is considered. The non-linearity is assumed severe enough that the measurements can not be linearised. Due to the presence of clutter and target non-detections, both true and false tracks are initialized. The false track discrimination (FTD) recognizes and confirms true tracks, and terminates false tracks, and is an essential functionality in this environment. They state that with non-linear/non-

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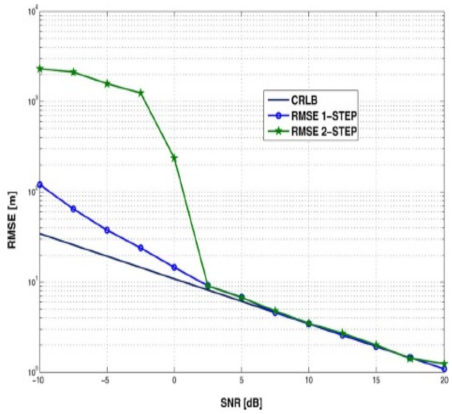

Fig. 36. RMSE of the DPD method (single step), the two-step method, and the CRLB versus SNR [225]

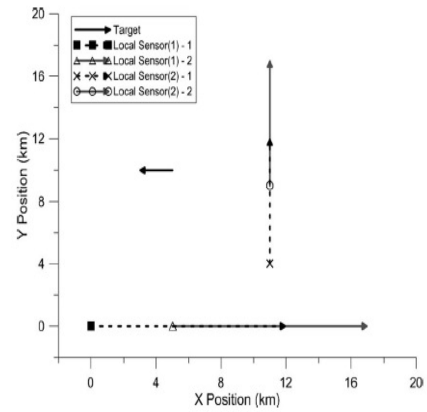

Fig. 37. Simulated surveillance scenario [226].

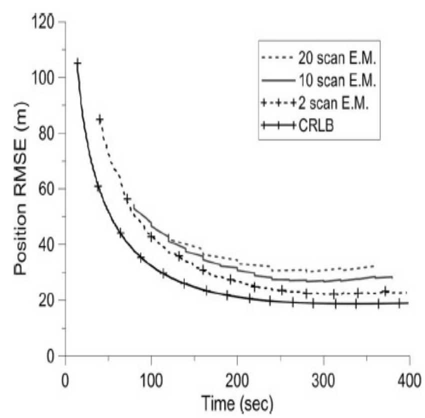

Fig. 38. Position RMS estimation errors over time [226].

observable sensors they may locally track the measurement state. They show that increasing the local measurement state derivative (partially) compensates the non-linearity of the local measurement state propagation. Given a uniform target motion, one should also track the measurement state acceleration. In addition, they also simplify the distributed fusion by avoiding the explicit track-to-track (T2T) association. The equivalent measurements (EMs) are used to both update all existing and initialize new global tracks. This approach allows distributed false track discrimination (FTD) and trajectory estimation. They apply this material to distributed tracking in clutter using the TDOA-FDOA (TFDOA) sensors. Fig. 37 depicts a sample surveillance scenario for two sensors mounted on each of the two UAV configuration used for tracking a moving target and the corresponding simulation results in Fig. 38.

The benefits and disadvantages of TDOA measurements were mentioned before. Accurate FDOA measurements can be obtained in LOS scenarios only when the relative velocity between the target and receivers is large enough so the frequency measurement error is outweighed. The receivers also need to measure the frequency with more resolution than the smallest frequency shift, otherwise the FDOA is undetectable below the noise. In addition, NLOS measurements can severely degrade the FDOA measurements due to the lack of direct path and change in doppler frequency. Due to these limitations, FDOA measurements may not be suitable for indoor areas where the devices are moving slowly and there are a lot of NLOS and multipaths.

V. Comparison of Different Techniques and Future Directions

We have considered and reviewed a collection of algorithms from the technical literature that deal with wireless networks deploying mobile receivers (sensors or BSs) departing from the traditional assumption of fixed infrastructure in the wireless networks.

In Table IV, we list and summarize the reported details of the subclass of algorithms from the ones reviewed in this section that are suitable to be utilized and deployed in network scenarios where the receivers are also moving and it is desired to track the location of a moving target. Thus, the overall wireless network topology may change rapidly enabling greater versatility in the network. Note that these methods are tested in outdoor environments where the distances between transmitter and receiver are in the order of kilometers. For indoor areas, the distances are shorter and hence the errors will be smaller accordingly.

The mobility of the receivers greatly enhances the performance of the geolocation and tracking system, but it also brings in certain design issues that will be briefly mentioned below:

- One of such issues is how to efficiently choose a minimum set of mobile receivers (sensors or BSs) [227], and how to do the placement and motion coordination strategies of mobile receivers [228] to achieve optimal coverage performance and tracking [229, 230]. For example, in [229], the authors combined the performance metrics of sensing quality, communication quality, and area coverage in a cost function to adjust mobile sensors' positions accordingly.
- Another interesting topic to consider is how can the system provide a reasonably low geometric delusion of precision (GDOP) when localizing the mobile target, and hence improve the positioning accuracy by directing the

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TABLE IV
SUMMARY OF ALGORITHMS' SPECIFICATIONS AND PARAMETERS

No.	Ref.	Parameter	Accuracy(m)	Distance (m)	Target Speed (m/s)	Sensor Speed (m/s)	No. Sensors	Jointly Multiple Targets	Tracking Filter
1	[189]	RSS	<500	15k x 40k	40km/h	50km/h	1 or 2	No	REKF
2	[196]	TDOA	10m @ 1ns STD 100m @ 25ns STD	8km x 10km	Stationary and moving	100m/s	2<	Yes -5	IMM-UKF
3	[199]	TDOA	150m	3.5km x 4.5km	15m/s	30m/s	2	No	GMM-ITS GMM-UKF IMM-EKF
4	[206]	AOA	2km	60km x 60km	400km/h-800km/h	900km/h	2	No	IMM-EKF IMM-UKF MM-PF
5	[207]	AOA	50m	10.5km x 10.5km	7.7m/s (max 15m/s)	2.5m/s	1	No	GMM-ITS
6	[209]	AOA	70m	10km x 10 km	9m/s	30m/s	2	No	GMM-ITS
7	[211]	TDOA-AOA	200m	120km x 120km	45km/h	360km/h	2	No	CKF
8	[219]	TDOA-AOA	500m	30km x 25km	40m/s	50m/s	2	No	MLE-Simplex
9	[212]	TDOA-FDOA	25m	2km x 2.5km x 3km	48m/s	41m/s	5	No	2-step WLS
10	[214]	TDOA-FDOA	45 m	2km x 2.5km x 3km	48m/s	41m/s	6	No	2-step WLS
11	[216]	TDOA-FDOA	25m	2km x 2.5km x 3km	48m/s	41m/s	5	No	CWLS
12	[217]	TDOA-FDOA	14m @-30dB sensor location error	2km x 2.5km x 3km	48m/s	41m/s	6	No	LMMSE & 2-step WLS
13	[218]	TDOA-FDOA	3.8m-10.5m	25km x 20km	10m/s (max. 15m/s)	100m/s	2	No	GMM-ITS-EKFb
14	[219]	TDOA-FDOA	2000m	30km x 25km	40m/s	50m/s	2	No	GM-EKF
15	[220]	TDOA-FDOA	8m 30m @0dB	1.5km x 1.5km	48m/s	41m/s	6	Yes	2-step WLS
16	[221]	TDOA-FDOA	150m 250m	70km x 30km		1.35km/s	2 or 4	No	AEKF
17	[226]	TDOA-FDOA	30m	10km x 10km	5m/s (20m/s max)	30m/s & 20m/s	2	No	GMM-ITS

receiver to certain positions.

- Moreover, due to the constraint on transmit power in cellular networks [231, 232], further design challenges may need to be re-considered at every step when moving BSs (anchors) are deployed.
- Another aspect is how the receiver should move to cover a certain area efficiently and avoid getting too far from or loosing the LOS connection of a target.
- Another critical problem is the NLOS error, which can severely degrade the performance of localization systems, and to the knowledge of the authors it has been rarely considered for roving receiver applications, while studied extensively for applications with fixed receivers.
- How the receivers should move to efficiently localize multiple targets in a cooperative manner is also another interesting topic to consider.

VI. CONCLUSIONS AND FUTURE WORK

Different types of measurements and technologies that are currently deployed for localization in both indoor and outdoor scenarios have been discussed in this paper. Also a discussion regarding the current research articles related to position location systems for wireless systems deploying moving receivers (anchors or BSs) has been given, where the main challenge is in the ad-hoc nature of the network. The collection of various proposed state-of-the-art algorithms rely in their cores on variant forms of KF, EKF, UKF, or GMM for state estimation to deal with the random mobile nature of the infrastructure and/or mobile targets. The various proposed methods vary significantly in their suggested approaches for tackling this problem, however, in most cases, the achieved estimation accuracy reached the CRLB closely. Selecting an appropriate algorithm for efficient localization of the target is dependent upon the desired deployment environment and application scenario, therefore, direct comparison might not be reliable. There are several potential research directions that can be considered in the future work, e.g., the NLOS problem, receiver location uncertainty, receiver movement scheme, sensor fusion (GPS, WiFi, BLE, cellular, etc.), the receiver movement scheme to reduce the GDOP, and cooperative localization.

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VII. Glossary

2-D	Two Dimensional
3-D	Three Dimensional
2G	2nd Generation Cellular Radio System
3G	3rd Generation Cellular Radio System
3GPP	Third Generation Partnership Project
4G	4th Generation Cellular Radio System
5G	5th Generation Cellular System
AECID	Adaptive Enhanced Cell-ID
AEKF	Adaptive Extended Kalman Filter
A-GPS	Assisted Global Positioning System
A-GNSS	Network-assisted GNSS
AOA	Angle-of-Arrival
AP	Access Point
AWGN	Additive White Gaussian Noise
BTS	Base Transceiver Station
BPE	Block Phase Estimation
BS	Base Station
CDF	Cumulative Distribution Function
Cell-ID	Cell Identification
CKF	Constrained Kalman Filtering
CN	Core Network
COST	European Cooperation in Science and Technology
CRB	Cramer-Rao Lower Bound
CRLB	Cramer-Rao Lower Bound
CSI	Channel State Information
CWLS	Constrained Weighted Least Squares
DF	Data Fusion
DC	Data Center
DCM	Database Correlation Method
DL	Down Link
DOA	Direction of Arrival
DPD	Direct Position Determination
E-911	Emergency positioning requirements in the USA
E-CID	Enhanced Cell ID
EKF	Extended Kalaman Filter
EGNOS	European Geostationary Navigation Overlay Service
EMs	Equivalent Measurements
eNode B	Evolved UMTS terminology for Base Station
E-OTD	Enhanced Observed Time Difference
ES	Electronic Surveillance
E-SMLC	Evolved SMLC
E-UTRAN	Evolved UMTS Terrestrial RAN
FTD	False Track Discrimination
FCC	Federal Communication Commission
FDD	Frequency-Division Duplexing
FDOA	Frequency Difference of Arrival
FOA	Frequency of Arrival
FoV	Field of View
FIM	Fisher Information Matrix
GALE	Geometry-Assisted Location Estimation
GAGAN	GPS Aided Geo Augmented Navigation GAGAN
GCC	Generalized Cross-Correlation
GDOP	Geometric Dilution Of Precision
GERAN	GSM EDGE RAN
GMM	Gaussian Mixture Model
GMTs	Ground Moving Targets
GNSS	Global Navigation Satellite System
GPRS	General Packet Radio Service
GPS	Global Positioning System
GSM	Global System for Mobile communications
ICT	Information and Communication Technology
ILBS	Indoor Location Based Services
INS	Inertial Navigation System
IMM	Interacting Multiple Model
IoT	Internet of Things
IPDL	Idle Period DownLink
ITS	Intelligent Transportation System
ITSF	Integrated Track Splitting Filter
KF	Kalman Filter
k-NN	k-Nearest Neighbour
LCS	Location Services
LBS	Location-Based Services
LMU	Location Measurement Unite
LOB	Line-of-Bearing
LOS	Line-Of-Sight
LS	Least Squares
LTE	Long Term Evolution
MAP	Maximum a Posteriori
MC	Monte Carlo
MF	Matched Filter
MLE	Maximum Likelihood Estimation
MMSE	Minimum Mean Squared Error
MS	Mobile Station
MSAS	Multi-functional Satellite Augmentation System
MSE	Mean Square Error
MT	Mobile Terminal
MUSIC	Multiple Signal Identification
NLOS	Non-Line-Of-Sight
NLS	Non-linear Least Sqaures
Node B	UMTS terminology for Base Station
OSM	OpenStreetMap
OTD	Observed Time Difference
OTDOA	Observed Time Difference Of Arrival
OVSF	Orthogonal Variable Spreading Factor
PMI	Precoder Matrix Indices
P-CPICH	Primary Common Pilot Channel
PF	Particle Filter
PN	Pseudo-Noise
PTT	Push-to-Talk
PV	Probe Vehicle
QoS	Quality of Service
RAN	Radio Access Network
RF	Radio Frequency
RFID	Radio Frequency Identification
RIPS	Radio Interferometric Positioning System
REKF	Robust Extended Kalman Filter
RMS	Root Mean Square
RMSE	Root Mean Square Error
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
RSE	Root Square Error
RSTD	Reference Signal Time Difference

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RTD	Real Time Difference
RTLS	Real Time Location System
RTT	Round Trip Time
SBAS	Satellite-based Augmentation Systems
SDP	Semi-Definite Programming
SDR	Semi-Definite Relaxation
SFN	System Frame Number
SMLC	Serving Mobile Location Center
SNR	Signal-to-Noise Ratio
SRS	Sounding Reference Signals
SUAV	Small Unmanned Aerial Vehicles
SUMO	Simulation of Urban Mobility
SVM	Support Vector Machine
T2T	Track-to-Track
TA	Timing Advance
TACS	Traffic Alert and Collision Avoidance Systems
TDOA	Time Difference Of Arrival
TFDOA	Time/Frequency Difference of Arrival
TIS	Traffic Information System
TOA	Time Of Arrival
TTFF	Time-To-First-Fix
UAV	Unmanned Airial Vehicle
UE	User Equipment
UGV	Unmanned Ground Vehicle
UKF	Unscented Kalman Filter
UL	Up Link
ULA	Uniform Linear Array
UMTS	Universal Mobile Telecommunications System
U-TDOA	Uplink Time Difference of Arrival
UTM	Universal Transverse Mercator
UTRAN	UMTS Terrestrial RAN
WAAS	Wide Area Augmentation System
WCDMA	Wide-band Code Division Multiple Access
WGS84	World Geodetic Standard 1984
WiFi	Wireless Fidelity
WLAN	Wireless Local Area Network
WLPS	Wireless Local Positioning Systems
WLS	Weighted Least Squares
WPAN	Wireless Personal Area Network
WSN	Wireless Sensor Network

Achraf Tahat received the Ph.D. degree in Electrical Engineering (EE) with a focus in Communications and Signal Processing from the Illinois Institute of Technology (IIT), in Chicago, IL, USA in 2002. He also received the BSc and MSc degrees in EE from IIT with emphasis on electronics and circuits. Before coming to the electrical engineering department at the École de Technologie Supérieure (ETS), Montreal, as an R&D Engineer working on wireless cellular network geolocalisation, he worked as an R&D scientist at the software engineering and IT department at ETS to develop a network security tool based on machine-learning and data-mining theory and principles. From 2012 to 2013, Dr. Tahat was a Visiting Research Professor/Scholar at McGill University, Montreal, QC, in the Telecommunications and Signal Processing Lab. of the ECE department. From 2005 to 2012, Dr. Tahat was an Assistant Professor and then an Associate Professor and Head of the Communications Eng. department at PSUT (Princess Sumaya University for Tech.) in Amman, Jordan, where he also performed consultation for local industrial partners. From 2002 to 2003, Dr. Tahat was an Adjunct Professor and a Post doctoral researcher at IIT, Chicago, USA. Before completing his doctoral studies, Dr. Tahat worked at Lucent Technologies Inc. (Alcatel-Lucent) on first generation ADSL modem prototypes. He was also a Software Engineer at 3Com Corporation in Illinois, USA at the voice-band modem R&D group of the Personal Communications Division. Dr. Tahat is a Senior Member of IEEE, Eta Kappa Nu, and a member of Tau Beta Pi honor societies.

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