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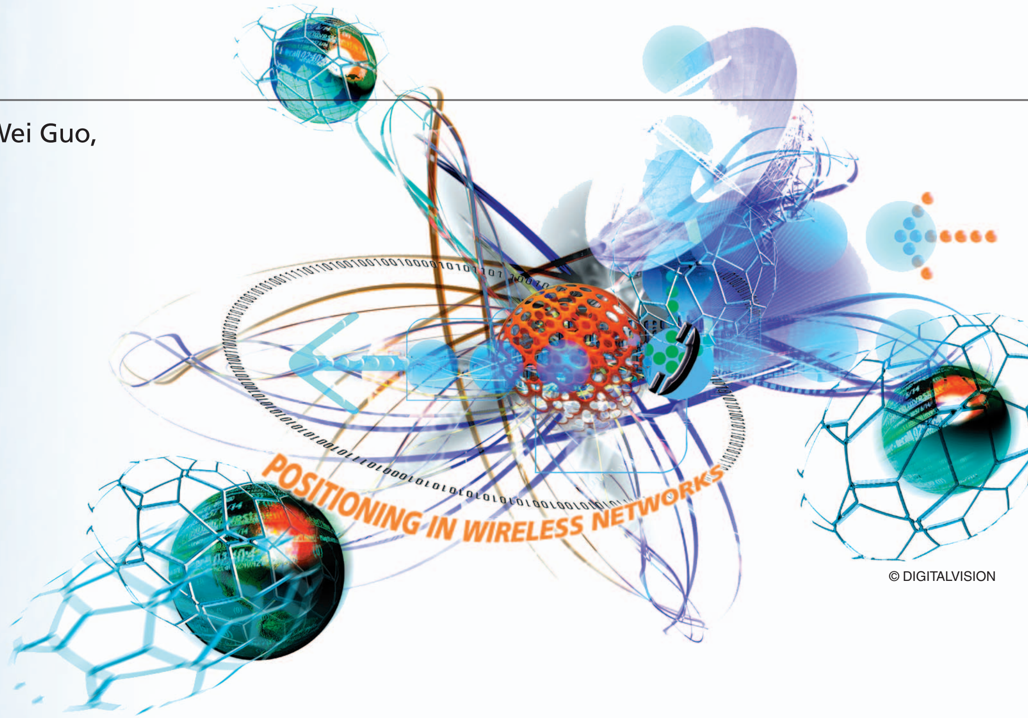


Signal Processing Techniques in Network-Aided Positioning

[A survey of state-of-the-art positioning designs]

The U.S. Federal Communications Commission (FCC) requires that the precise location of all enhanced 911 (E911) callers be automatically determined. This requirement has motivated the development of cellular-aided positioning. To facilitate emergency services, the FCC has mandated that 95% of all handsets sold be location compatible by the end of December 2005 [1]. Wireless positioning has also been found very useful for other applications besides E911 service, ranging from vehicle navigation and network optimization to resource management and automated billing. Ubiquitous computing and location-aware computing also necessitate that we develop techniques for estimating the location of mobile users in both outdoor and indoor environments. Various positioning systems have been proposed for use in ubiquitous computing [2]. As an essential prerequisite for ubiquitous computing, mobile positioning techniques, linked with wireless networks, have increasingly provided mobile users with opportunities to access personal information, corporate data, and shared resources anytime, anywhere.

Positioning systems can be grouped in many different ways, including indoor versus outdoor systems or cellular versus sensor network positioning designs, as shown in Figure 1.

- *Indoor versus outdoor systems*: Although global positioning systems (GPS) and wireless E911 services address the issue of location finding, these technologies cannot provide an

 1053-5888/05/$20.00©2005IEEE

accurate indoor geolocation because they face unique technical challenges. Indoor geolocation uses existing wireless local access network (LAN) infrastructures for positioning. An overview of indoor positioning versus outdoor positioning by satellite is shown in Table 1.

- *Cellular versus sensor network positioning designs*: Sensor networks vary significantly from traditional cellular networks, where access nodes are assumed to be small, inexpensive, homogeneous, cooperative, and often relatively autonomous. Autonomous nodes in sensor networks are equipped with sensing, computation, and wireless communication capabilities. In sensor networks, location awareness is indispensable. For many applications, like environmental sensing, it is essential to know the locations of the sensor nodes; this is known as a "localization problem" in sensor networks. A number of location-aware protocols have been proposed for "ad hoc" routing and networking [3]. Sensor networks have also been widely used for intrusion detection in battlefields as well as for monitoring wildlife.

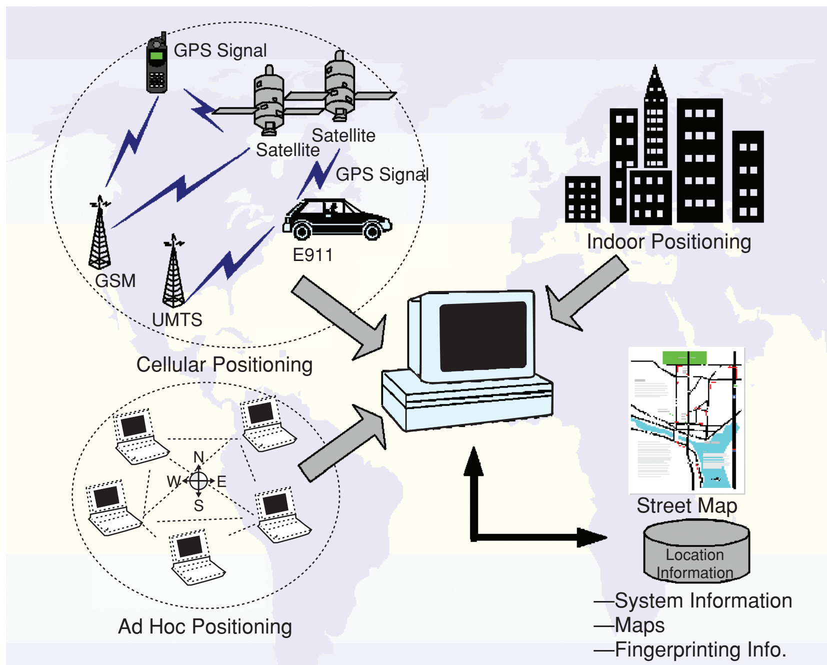
Network-aided positioning has attracted much research attention in recent years. We are facing tremendous challenges while exploring novel mobile positioning techniques to design faster, more robust, and more accurate positioning systems. Different network topologies pose various technical challenges in mobile positioning. Thus, it is not feasible to employ a universal positioning algorithm. In [59], the authors provide an overview of wireless location challenges and techniques, with special focus on network-based technologies and applications. State-of-the-art sensor network location designs and research progress in this field are discussed in [60]. In [61], the authors address challenges in ultra-wideband positioning designs and various methods for solving these problems. Possibilities and fundamental limitations associated with mobile positioning are discussed in [62]. This article surveys state-of-the-art positioning designs, focusing specifically on signal processing techniques in network-aided positioning; it serves as a tutorial for researchers and engineers interested in this rapidly growing field. It also provides new directions for future research for those who have been working in this field for many years.

NETWORK-AIDED POSITIONING DESIGN

Different network topologies, physical layer characteristics, and media access control (MAC) layer characteristics require remarkably different positioning system solutions. In this section, we will provide an overview of the positioning solutions applied in cellular networks, wireless LANs, and ad hoc sensor networks. We will also compare the characteristics of various network-aided positioning solutions.

POSITIONING IN CELLULAR NETWORKS

To a large extent, the underlying cellular network determines which location techniques should be implemented. Here, we address both "standard" and "nonstandard" location designs in a typical cellular network, as shown in Table 2. Topics include the second-generation (2G), 2.5G, and third-generation (3G) positioning methods and the evolution of these mechanisms.



[FIG1] Overview of indoor versus outdoor positioning systems.

[TABLE 1] OVERVIEW OF INDOOR POSITIONING VERSUS OUTDOOR POSITIONING BY SATELLITE.

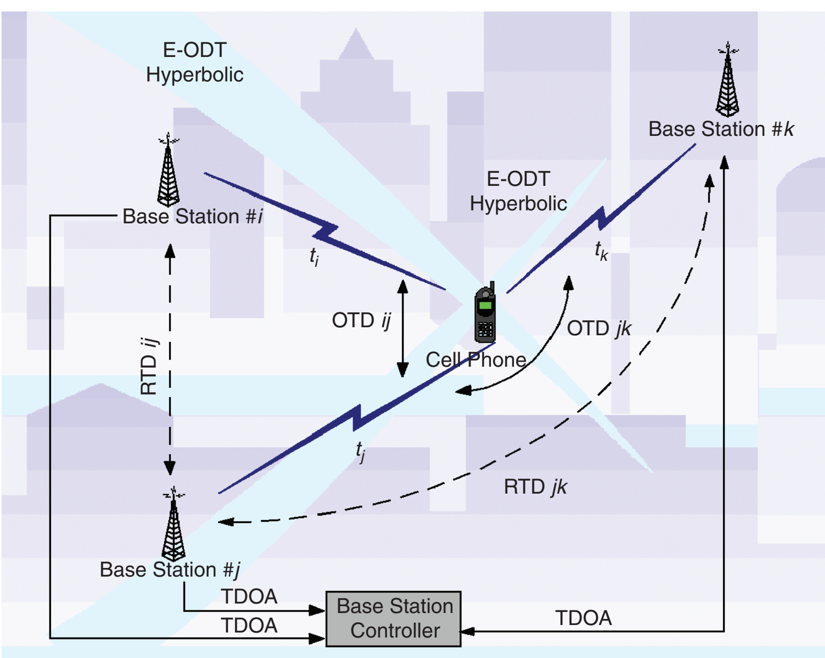
INDOOR	OUTDOOR (POSITIONING BY SATELLITE)
WLAN —CLIENT-BASED SYSTEM DESIGN —CLIENT-ASSISTED SYSTEM DESIGN SENSOR NETWORK —LOCALIZATION WITH BEACONS —LOCALIZATION WITH MOVING BEACONS —BEACON-FREE LOCALIZATION UWB —A PROMISING APPROACH FOR INDOOR GEOLOCATION —CAN ACHIEVE VERY ACCURATE SHORT DISTANCE ESTIMATION	GPS —REQUIRES MINIMAL OBSTRUCTIONS —LONG ACQUISITION TIMES (30 s–15 min) —HAS TO BE SYNCHRONOUS —HIGH POWER CONSUMPTION AND HIGH UNIT COST A-GPS —MUCH MORE ACCURATE: ACCURACY OF 10–50 m CAN BE USED EVEN FOR INDOOR POSITIONING —IMPROVES ACQUISITION TIME (< 10 s) —SYNCHRONOUS OR ASYNCHRONOUS —MORE COST EFFECTIVE THAN GPS —LITTLE/NO HARDWARE CHANGES REQUIRED IN BASE STATIONS

E-OTD for GSM

The Global System for Mobile Communication (GSM) is the most common cellular standard in Europe. E-OTD is also becoming a de facto standard for E911 Phase II implementation for GSM carriers [4]. The E-OTD location method is based on the existing observed time difference (OTD) feature of GSM systems. OTD calculates the time difference between signals traveling from two different base transceiver stations (BTSs) to a mobile station (MS), as illustrated in Figure 2. Many factors, including the relative positions of a BTS and an MS, multipath fading, and channel conditions, can impact the accuracy of the E-OTD estimation. The E-OTD method, based on time difference of arrival (TDOA) measurements, requires a "synchronous" network. A GSM network, however, is not synchronous. Location measurement unit (LMU) devices are therefore required to compute the clock differences between base stations and send this information to the corresponding BTSs. The BTSs then broadcast the synchronization information to various mobile devices. Yet, this is quite an expensive solution for operators. TDOAs can then be derived, as illustrated in Figure 2. TDOAs are combined to produce intersecting hyperbolic lines from which the location is estimated. Recent field studies implementing the E-OTD have shown two-dimensional (2-D) position estimation accuracies ranging from 50 to 500 ms. E-OTD methods offer greater positioning accuracy than OTDs but have a slower response time, typically around 5 s. In addition, they require software-modified handsets, which means that they cannot be used to provide location-specific services to existing customer bases.

[TABLE 2] OVERVIEW OF STANDARD VERSUS NONSTANDARD OUTDOOR CELLULAR NETWORK POSITIONING.

OUTDOOR CELLULAR NETWORK POSITIONING (STANDARD)	OUTDOOR CELLULAR NETWORK POSITIONING (NONSTANDARD)
GSM (WITH E-OTD) —ESTIMATION WITH 50–125 m OF ACCURACY —SLOW, ABOUT 5 s —SOFTWARE CHANGE IS NEEDED	SMART ANTENNA TECHNIQUES —NO CHANGES IN THE HANDSET —CHANGES REQUIRED IN EACH BASE STATION —ZONING IMPLICATIONS OF ANTENNA CHANGES —NOT AS ACCURATE AS A-GPS IN MOST SITUATIONS —PROVIDE MORE ACCURATE ESTIMATION
CDMA/GPRS (WITH A-GPS) —HANDSET NEEDS AN A-GPS RECEIVER —PROVIDES ENOUGH ACCURACY < 10 m	—NO CHANGE IN HANDSET, BUT SPECIAL ANTENNA AT THE BASE STATION IS REQUIRED
WCDMA (WITH IPDL, TA-IPDL, OTDOA-PE) —NOT AS ACCURATE AS A-GPS IN MOST SITUATIONS (50 m) —NEED TO BE VISIBLE TO AT LEAST THREE BASE STATIONS —REQUIRES CHANGES IN THE BASE STATION	HYBRID POSITIONING USING DATA FUSION —REDUCTION OF HANDSET HARDWARE COMPLEXITY HYBRID TOA/TDOA/AOA CAN IMPROVE ACCURACY —GPS + CDMA CAN IMPROVE ACCURACY AND COVERAGE
CELLULAR ID —NO AIR INTERFACE NEEDED —ACCURACY DEPENDS ON SECTOR SIZE —ACCURACY CAN BE IMPROVED BY HYBRIDIZATION WITH OTHER METHODS SUCH AS CELL ID + RTT —ACCURACY CAN BE IMPROVED WITH OTHER METHODS	PATTERN MATCHING FOR POSITIONING —ONLY SERVER BASE STATION REQUIRED —SOFTWARE SOLUTION WITH HARDWARE MODIFICATION



[FIG2] E-OTD positioning solution. Here $TDOA_{ij} = OTD_{ij} - RTD_{ij}$.

Assisted-GPS for Narrowband CDMA

Assisted GPS (A-GPS) uses a terrestrial cellular network to improve GPS receiver performance by providing satellite constellation information directly to the GPS receiver [5]. A-GPS consists of three parts: a location server, a mobile station with partial or full GPS receiver, and wireless communication link. The mobile station and location server transfer information to the GPS receiver. This information is called "assistance information," which is used by the A-GPS. There are two kinds of A-GPS: *MS-assisted GPS* and *MS-based GPS*.

- *MS-assisted GPS*: MSs provide assistance data to the location sever in MS-assisted GPS design. An individual MS acquires GPS satellite signals and determines the corresponding pseudoranges. These time-stamped satellite pseudoranges are sent to the location server, which then calculates the location. The function of the location sever is to monitor satellites and compute a particular user's location based on data obtained from the user. The information transferred from a mobile user to a location server includes location requests, the rough position of the user, and GPS pseudoranges with time tags. The information transferred from the location server to the user includes service satellites with which it is communicating and corresponding Doppler frequency correction. Compared to the standalone GPS solution, the benefits of A-GPS include: 1) an increase in the sensitivity of the GPS receiver by providing the receiver with auxiliary information to ensure that positioning functions accurately even in bad communication environments, 2) a reduction in the initial time to synchronize the GPS receiver with its serving satellites from more than 30 s to just a few seconds, and 3) an increased positioning accuracy.

- *MS-based GPS*: MS-based GPS is defined as a GPS implementation where the location server provides assistance data to the MS so that the MS can calculate its own location. The major drawback to this design is that cellular handsets must be equipped with a separate receiver.

DIFFERENT NETWORK TOPOLOGIES, PHYSICAL LAYER CHARACTERISTICS, AND MEDIA ACCESS CONTROL LAYER CHARACTERISTICS REQUIRE REMARKABLY DIFFERENT POSITIONING SYSTEM SOLUTIONS.

OTDOA for Wideband CDMA (WCDMA)

Observed TDOA (OTDOA), as its name indicates, is a TDOA-based approach. It is designed to operate over wideband-code division multiple access (WCDMA) networks. Similar to the E-OTD, OTDOA uses LMUs to calibrate the downlink measurements from neighbor base stations for individual mobile users. If measurements from three or more stations are available, a position can be estimated [1]. Considering the similarities between the systems, we can view OTDOA as a WCDMA version of an E-OTD. It has the same weaknesses as E-OTD: location estimation cannot be performed in areas without at least three visible base stations, a multipath can degrade the location measurements, and it is not compatible with other networks. The OTDOA has an additional inherent characteristic that results in performance inferior to that of E-OTD: the WCDMA network is based on CDMA and all base stations therefore share the same downlink frequency. Compared to the GSM design in which different frequencies can be assigned to neighboring base stations, the most significant challenge encountered by WCDMA location algorithms is in-band interference. This effect is particularly noticeable if a mobile station is near its serving site and is required to take measurements from neighbor base stations, a situation known as the "Near-Far" problem.

The OTDOA location method, on the other hand, faces other challenges, such as those posed by unsynchronized base stations in the FDD mode [4]. Attempts to solve these problems have led to the modification of OTDOA, namely the creation of idle period downlink (IPDL), synchronized IPDL (TA-IPDL), and positioning elements (OTDOA-PE) to enhance OTDOA's locational accuracy [4]. The basic idea behind IPDL design is that base stations pseudo randomly disable their downlink for a short period so that mobile stations are able to receive signals from neighboring base stations during that short period. IPDL is a solution to the near-far problem; it is difficult to observe neighboring BTSs when a mobile is near its serving BTS. In OTDOA-PE, positioning elements synchronize with adjacent base stations and are capable of inserting a short synchronization pulse along with the transmission signal. Since the positioning elements are deployed at known locations, this design enables mobile stations to use their transmitted signals as references in OTDOA to estimate their MS locations. Simulations suggest that these methods enable OTDOA to meet FCC E911 requirements. However, no large-scale field tests have yet verified this conclusion.

Cell-ID

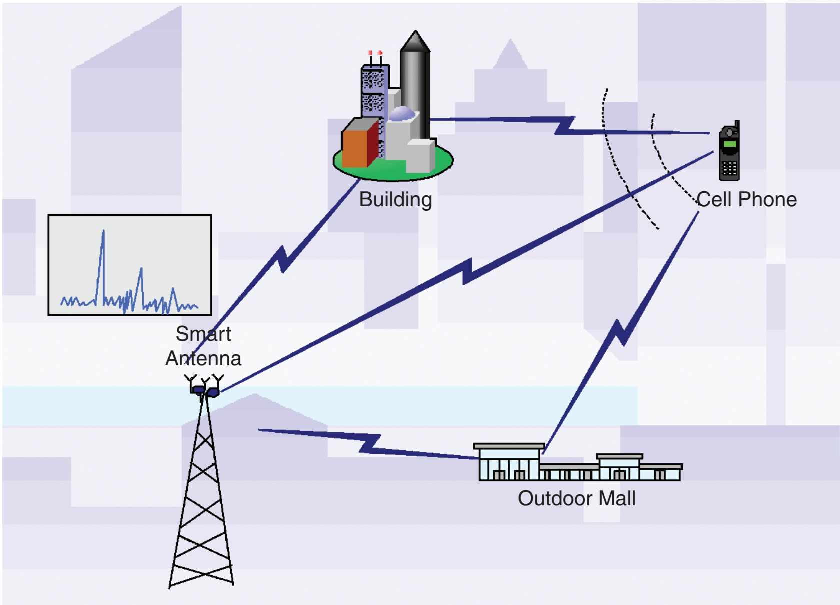
Cell-ID is a simple positioning method based on cell sector information recommended by the 3rd Generation Partnership Project (3GPP) [1]. In current cellular networks, coverage is provided by a number of distributed base stations (cells). Each cell is normally divided into three sectors. Cell size varies from 1 to 3 km in urban areas and 3–20 km in suburban/rural areas. The current sector is known only during an active voice or data call. With this method, no air interface resources are required to obtain cell sector information (if the user is active), and no modifications to handset hardware are required. The method's disadvantage is obvious: location estimation accuracy depends strictly on the size of the cell sector. To improve the method's accuracy, Cell-ID + TA (timing advance) and Cell-ID + RTT (round trip time) hybrid positioning methods are proposed in [6].

NONSTANDARD POSITIONING SOLUTIONS

Besides the previously mentioned standard-based solutions, new nonstandard approaches have been proposed to improve the performance of positioning in cellular networks.

Smart Antennas Techniques for Localization

Multilateral location is based on pseudorange measurements, while smart-antenna-based location systems use the angle of arrival (AOA) as the measurement parameter. The AOA signals at the base station are determined by electronically steering the main lobe of an adaptive phased array antenna in the direction of the arriving mobile signal [7], [8]. An adaptive antenna system consists of an array of sensor elements and a real-time adaptive signal processor. The system can automatically adjust the antenna's beam pattern, frequency response, and other parameters to enhance location performance. A receiver structure for an advanced adaptive array antenna that can increase capacity in cellular mobile radio is discussed in [9]. The position of an MS is calculated from the intersection of a minimum of two lines of bearing using smart antennas techniques, as shown in Figure 3. To combat inaccuracies introduced by multipath propagation effects, more than two base stations may be employed, along with highly directional



[FIG3] **Smart antennas techniques for localization. The system can automatically adjust the antenna's beam pattern, frequency response, and other parameters.**

antennas. In the area of using smart antenna techniques for localization, some work has been done on space-time processing with multiple transmitting and receiving antennas, the employment of coding, and the exploitation of spatial diversity for synchronous 3G CDMA networks, using blind Alamouti space-time block codes in fading channels to increase capacity [10]. AOA-based solutions have the advantage of not requiring changes in the handset. A significant drawback to AOA systems is that AOA requires specialized receivers at the base stations in addition to the construction of directional antenna arrays on the existing cell tower. Existing cell site antennas are not suitable for the AOA method. Another drawback to this method is that angular error in the antenna array can translate into a significant error in lateral distance if the cellular telephone is far from the cell site. Location finding for CDMA subscribers using a multiple-input, multiple-output (MIMO) antenna array at the base station and deploying multiple base stations has been studied in [11]. An algorithm for estimating the TOA and AOA in a multi-user CDMA system that employs interference cancellation techniques to improve accuracy has been described in [11]. The other new class of receivers uses linearly constrained interference cancellation (IC), as presented in [12]. The system operates over channels from 5 to 15 MHz. AOA does not require an accurate (sub-microsecond) timing reference at each site and also does not require system-wide synchronization (to within less than a microsecond). However, it does require calibration at each individual receiver site to compensate for receiver mismatches and temperature variations. The AOA technique is particularly suitable for future wideband spread-spectrum systems thanks to its improved immunity to multipath propagation effects.

Hybrid Positioning Using Data Fusion

Data fusion is a group of methods for merging various types of information. The idea of data fusion is derived from the basic TOA, TDOA, and AOA techniques [13] as previously discussed. Smart integration of measurements obtained from different sources, known as data fusion, helps to improve positioning accuracy. Different sources, however, are subject to different propagation errors that contribute unequally to global position estimation errors. Adaptive data fusion and hybrid localization techniques are employed to better integrate different types of position and navigation information. The work in [14] and [15] shows that combined hyperbolic-based position location systems, such as GPS and cellular networks, can achieve better performance than single-source methods. Tight integration of a GPS receiver and a CDMA handset can significantly reduce hardware complexity, memory allocation, and the computational load upon a mobile station [13]. In addition to system fusion, various types of measurement data can also be combined to achieve more robust performance. A TOA/TDOA data fusion model for increasing the accuracy of position estimates within wireless networks is presented in [13]. The accuracy with which a TOA-AOA system with a single base station in a line-of-sight scenario can determine location is analyzed in [16]. AOA and TDOA have also been combined to improve accuracy and to limit multipath effects [17]. An enhanced two-step least squared approach for TDOA/AOA wireless location is proposed in [14]. Another TOA-AOA hybrid location determination method based on a hierarchical multilayer perception neural network is described in [18].

Pattern Matching for Positioning

Both AOA and TOA/TDOA may encounter difficulties when the multipath problem is quite severe, especially in urban areas [18], [19]. To solve this problem, we can use pattern matching based positioning, which considers multipath characteristics as the "fingerprinting" of mobile phones, as shown in Figure 4. The design involves a location server with a database that includes measured and predicted signal characteristics for a specific area. When an E911 call is made, the location of the mobile phone can be computed by comparing signals received by the mobile with the signal values stored in the database. Various signal characteristics, including received signal levels and time delays, may be utilized. For GSM location, it is natural to use measured signal levels, since it is then possible to locate GSM handsets without any modifications. Wideband signals from 3G cellular networks enable accurate timing measurements to be made as well as accurate measurement of the channel multipath profile. Using a multipath delay profile to locate a mobile terminal is possible with pattern matching. This avoids many of the problems that multipath propagation poses for conventional location methods based on distance measurements.

POSITIONING IN WIRELESS LAN

The recent increase in interest in context-aware computing and location-aware services has motivated the development of wireless LAN-based indoor positioning systems, such as Bluetooth and Wi-Fi. In [20], Salazar compared typical WLAN systems in terms of markets, architectures, usage, mobility, capacities, and industrial concerns. Many customers install WLANs to reduce positioning costs. The technical challenges faced by WLANs and their performance with different frequency spectrums are discussed in [21]. WLAN-based indoor positioning solutions mostly depend on signal strength utilization.

CLIENT-BASED SYSTEM DESIGN

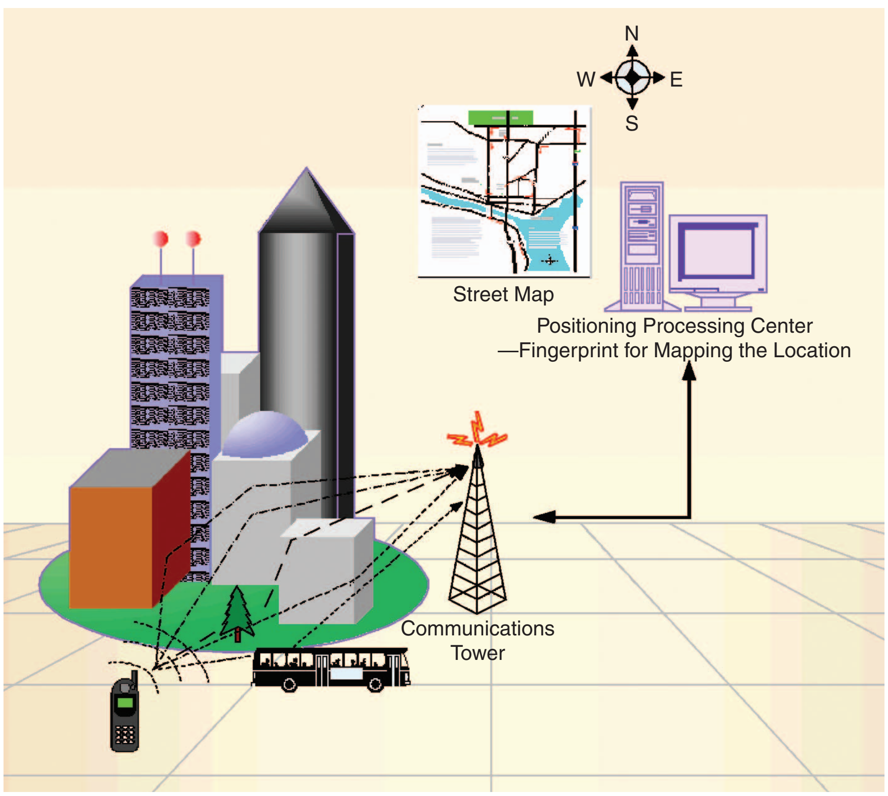
Many signal processing techniques have been proposed for location estimation for 802.11-based wireless networks [2], [22]. Location estimation is usually performed by scene analysis of RF or ultra wideband (UWB) signal strength characteristics, which works much like pattern matching in cellular location systems. Because signal strength measurement is part of the normal operating mode of wireless equipment, as in wi-fi systems, no other hardware infrastructure is required. A basic design utilizes two phases. First, in the offline phase, the system is calibrated and a model is constructed based on received signal strengths at a finite number of locations within a targeted area. Second, during online operation in the target area, mobile units report the signal strengths received from each access point (AP) and the system determines the best match between online observations and the offline model. The best matching point is then reported as the estimated position. Specific algorithms (e.g., fingerprinting) that use existing WLAN infrastructures will be addressed in the section "Positioning Algorithms."

CLIENT-ASSISTED SYSTEM DESIGN

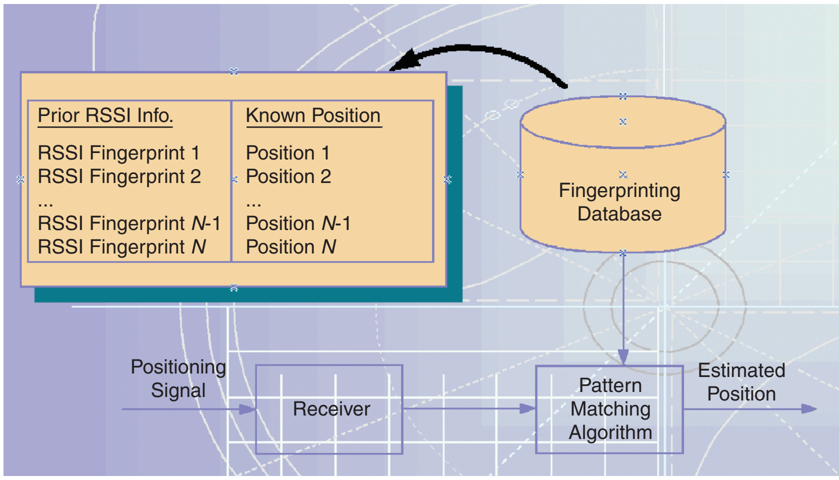
To ease the burden of system management (provisioning, security, deployment, and maintenance), many enterprises prefer client-assisted and infrastructure-based deployments in which simple sniffers monitor client activity and measure the signal strength of transmissions received from clients [23]. In client-assisted location system design, client terminals, access points, and sniffers collaborate to locate the clients in a WLAN. The sniffers operate in a passive scanning mode and sense transmissions on all channels or on predetermined channels with sniffing tools (software). They listen to communication from mobile terminals and record timestamp information. The sniffers then put together estimations from all sniffers based on a prior model. A client's received signal strength at each sniffer is compared to this model using nearest neighbor searching to estimate the client's location [24]. In terms of system deployment, sniffers can either be colocated with APs or be located at other positions and function just like the LMUs in a cellular-based location system.

POSITIONING IN AD HOC SENSOR NETWORKS

Due to the ad hoc nature of sensor networks, it is important to extract location information from data collected for location aware routing and from information dissemination protocols and query processing in a sensor network. It is especially difficult to estimate node positions in ad hoc networks without a common clock as well as in absolutely unsynchronized networks. Most localization methods in sensor networks are based on RF signals. However, UWB techniques are quite promising for indoor positioning. The UWB technique is a viable approach for future gigabit indoor communications and geolocation problems [25]. A UWB signal is a series of very short base band pulses with time durations of only a few nanoseconds that exist on all frequencies simultaneously, resembling a blast of electrical noise [25]. The fine time resolution of UWB signals makes them promising for use in high-resolution ranging. A generalized maximum-likelihood (ML) detector for multipaths in UWB propagation measurement is described in [26]. In terms of systems, the types of localization solutions can generally be classified into three categories: localization with beacons, localization with moving beacons, and beacon-free localization.



[FIG4] Pattern matching method collecting multipath characteristics as the "fingerprinting" of mobile phones.



[FIG5] Pattern matching algorithm for location estimation.

LOCALIZATION WITH BEACONS

In sensor networks, some nodes are equipped with special positioning devices that are aware of their locations (e.g., equipped with a GPS receiver). These nodes are called *beacons*. Other nodes that do not initially know their locations are called *unknowns*. When these systems perform localization, the *unknowns* are located using ranging or connectivity (also known as proximity) based methods [27], [28]. Generally, an *unknown* can estimate its location if three or more beacons are available in its 2-D coverage. Once an *unknown* has estimated its position, it becomes a *beacon* and other *unknowns* can use it in their position estimations. The major challenge in localization with beacons is to make localization algorithms as robust as possible using as few beacons as possible. The resulting design consumes little energy and few radio resources.

LOCALIZATION WITH MOVING BEACONS

Using moving beacons in a system design can significantly reduce power consumption and cost. In this type of system, nodes determine their own locations by estimating their distance from moving beacons (also referred to as mobile observers) in a coordinated fashion by applying a transform to the range estimations to determine each node's position within a global coordinate system. The impact of predictable observer mobility upon power consumption in a sensor network is discussed in [29]. A localization system design for processing information using a single mobile beacon aware of its position is proposed in [30]. Sensor nodes receiving beacon packets infer their distance from a mobile beacon and use these measurements as constraints to construct and maintain position estimates. However, optimizing mobility is not feasible for full coverage in some areas. The relationship between mobility, navigation, and localization in the context of wireless sensor networks with mobile beacons or targets has been studied in [31]. Mobility can aid in network node localization. Also, once localized, network nodes can localize and track a mobile object (robot) and guide its navigation. Work in [31] exploits the application-specific nature of sensor networks to further optimize for localization. This work significantly builds upon prior approaches, incorporating additional constraints over time through sensor measurements of the distance to an unknown target rather than a beacon. Results indicate that mobility of targets can be used to significantly enhance position estimation accuracy, even when the number of reference nodes is small.

BEACON-FREE LOCALIZATION

In nonurban outdoor environments, localization may be achieved using several beacons equipped with GPS. However, equipping sensors with GPS does not work in indoor or urban environments. In addition, the use of beacons, even assuming that sensors are scattered randomly at the start, increases the cost of building a sensor network. In practice, a larger network may be designed to operate without beacons, which is known as *beacon-free* design. Such a design determines the position of every node via local node-to-node communication. Beacon-free positioning should be a fully *decentralized* solution: all nodes start from a random initial coordinate assignment. Then, they cooperate with each other using only local distance estimations to figure out a coordinate assignment. The resulting coordinate assignment has both translation and orientation degrees of freedom and has to be correctly scaled. A post-process is needed to convert the translation and orientation coordinate assignment to absolute position information based on reference information, such as information from GPS [32].

POSITIONING ALGORITHMS

In the previous section, we addressed different system design solutions for cellular, WLAN, and sensor network aided positioning. We will focus on presenting different positioning algorithms and comparing their characteristics in this section. Note that some algorithms are designed specifically for a single network configuration (e.g., sensor network) while others can be applied for two or more types of wireless networks. For example, the characteristics of offline training and online position estimation in fingerprinting algorithms make it possible for many statistical learning methods to be applied in mobile positioning. A novel mobile positioning method using GSM cellular phones and an artificial neural network (ANN) has been developed [33]. A hybrid vehicular location method based on pattern recognition using hidden Markov models (HMMs) and TOA measurements has also been proposed in [19]. Fingerprinting algorithms remain the most viable solution for WLAN-based indoor geolocation. Most recently developed indoor geolocation algorithms based on statistical learning theory require a substantial amount of site profiling to build their signal strength models [2], [34]. In this section, various algorithms will be compared and their advantages and disadvantages will be discussed.

POSITIONING ALGORITHMS FOR CELLULAR NETWORKS

FINGERPRINTING VERSUS TRIANGLE ALGORITHM

Fingerprinting positioning algorithms have been developed, especially for urban and indoor areas [35]. The location of a mobile phone can be calculated by comparing a multipath signal pattern received by a base station with prior known information stored in a database through pattern matching algorithms known as fingerprinting, as shown in Figure 5. In fact, fingerprinting algorithms need only one base station and several multipath copies of a signal to locate a user. Fingerprinting algorithms can therefore overcome many problems in conventional TOA, AOA, and TDOA algorithms, including errors in pseudorange measurement, multipath resolution, and NLOS propagation, without requiring handset modification. Other fingerprinting algorithms, including the K-nearest neighbor (KNN), the Kalman filter, ANN, and the support vector machine, are discussed in [34]. More robust location algorithms [36] have also been developed for indoor tracking and location problems. While probabilistic-based signal processing algorithms like the Bayesian method [37] can provide accurate estimation, they do require the knowledge of the signal propagation model in the form of a probability distribution. The main limitation of fingerprinting algorithms, however, is that they are not suitable for use in many outdoor applications because they require a more stable and secure radio environment for mapmaking in the initialization phase. The dynamic nature of the outdoor radio environment makes fingerprinting infeasible and requires the use of a triangle-based algorithm.

Based on their mathematical model characteristics, most multilateral range-based location algorithms are classified as *deterministic* and *probabilistic* models.

Deterministic Models

In a range-based deterministic model, the mobile positioning problem is usually modeled as the intersection of a set of hyperbolic curves defined by TOA/TDOA estimates. Very important contributions to the field of wireless location have been made in designing robust algorithms to compute mobile handset position using TOA/TDOA measurements. Smith and Abel have proposed a closed-form solution based on a spherical interpolation estimator in [38], but their solution is not optimal. To improve location accuracy at reasonable noise levels, the Taylor series method [39] is commonly employed. In addition, Chan's estimator for hyperbolic location is a well-known method that can be used as an approximation of the maximum likelihood (ML) estimator when the TDOA error is small [40]. In range-based location schemes, a generalized estimator is normally used for TOA in determinate models, as shown here:

$$\hat{x} = \arg_x \min \sum_{i \in S} \rho(r_i - \|x - X_i\|). \tag{1}$$

No a priori information about the distribution of the range or range difference measurements is required. In (1), $\|\cdot\|$ denotes the norm operation over a vector, $\|x - X_i\|$ represents the distance between vectors x and X_i (where S is the BSs index set), r_i is the range measurement from the MS to ith BS, $i \in S$. x is an MS position, and $\hat{x}$ is an estimate of MS position. $r_i\|x - X_i\|$ is called the ith residual for a particular x. If the residual follows the Gaussian distribution, the least square (LS) estimator can be applied to solve $\rho(\cdot)$ for the optimal solution. Actual measurements are often corrupted by some error, including errors due to loss of sight, inaccurate synchronization errors, and non-loss of sight (NLOS) errors. In practical communications, the residual most likely will follow an unknown distribution beyond the Gaussian; thus, many robust estimators have been proposed to enhance positioning accuracy [41].

Probabilistic Models

Interestingly, (1) can be also represented in probability form based on the maximum likelihood estimator (MLE). Without prior information, the MLE location estimate $\hat{\theta}_{\text{MLE}}$ is calculated as [42]:

$$\hat{\theta}_{\text{MLE}} = \arg\max_{\theta} f_z(z|\theta) \tag{2}$$

where $f_z(z|\theta)$ is the conditional probability density function (PDF) of the location measurements. The estimated location vector is $\hat{\theta} = (\hat{x}, \hat{y})$, which can be used to estimate a mobile terminal's coordinates. In practice, the cellular network does have some knowledge of a mobile terminal's location. Under these circumstances, the optimal estimator is the minimum mean square error (MMSE) estimator, which can be expressed as

$$\hat{\theta}_{\text{MMSE}} = E[\theta|z] = \int_S \theta f_\theta(\theta|z) d\theta \tag{3}$$

where $f_\theta(\theta|z)$ is the posterior conditional PDF of location θ given the measurement vector z and S is the region in which the mobile terminal is known to reside [42]. Another novel location algorithm based on Bayes' rule was proposed; it uses RSSI path loss and an empirical formula in the Okumura model [43]. A detailed survey of Bayesian techniques for use in location estimation is provided in [37].

NLOS VERSUS LOS ALGORITHM

Traditional triangle positioning algorithms assume LOS propagation from the reference stations to establish geometric equations for position determination. In microcellular environments, multipath propagation is usually NLOS, and individual measurements are thus biased. NLOS propagation still poses a challenge in cellular positioning design. To overcome the error inherent in NLOS location estimations, NLOS error mitigation algorithms have been developed. A residual weighting algorithm that does not require prior knowledge of NLOS error distribution has been proposed for use in a TOA location system [44]. This mechanism, however, performs poorly if a large amount of NLOS error is present when the algorithm is used for TOA measurements. To overcome this problem, another related NLOS mitigation technique based on ML detection has been developed [45]. This approach exploits redundant time measurements using a minimum number of base stations. This design is quite promising because it can select the best hypothesis, rather than averaging the results of all possible hypotheses based on the heuristic arguments used in previous approaches. Generally, NLOS range measurements vary more than LOS range measurements, especially when the MS is moving. A time-history-based hypothesis test is proposed in [46] to identify and then reconstruct the NLOS error. The drawback of this algorithm is that it can considerably delay real-time positioning. Kalman filter-based algorithms are suggested in [47] as a promising alternative to range measurement for smoothing and mitigating NLOS error. If the NLOS error is known to appear only intermittently or as outliers, tests can be performed for both outliers and normality, as discussed in [46]. The NLOS problem occurs regularly in urban and microcellular environments; developing cellular positioning techniques that work well in these areas require that we develop algorithms to handle it. However, most LOS algorithms are feasible for use in rural or suburban environments, and thus remain foundational for NLOS positioning algorithms.

POSITIONING ALGORITHMS FOR WLAN

EMPIRICAL MODEL VERSUS PROPAGATION MODEL

In a WLAN-based deployment location system, signal strength models are built by profiling the site and using measurements from visible access points based on two major models, the *empirical model* and the *propagation model*. The empirical model is constructed by placing a client at each of a number of sample reference points and measuring the received signal strength over several seconds. The measurement values are averaged and stored in a preconstructed database. When a client is to be located, it reports back measurements from visible access points, and these measurements are compared with the measurements in the database. However, there are some disadvantages associated with empirical model-based design. To track dynamic changes in environments, the database must be manually updated. Also, system performance is influenced by environmental situations. For example, errors can arise because moving objects, including people, can cause variation in the radio wave properties in an indoor environment.

The propagation model tends to be more flexible than the empirical model. The propagation model is constructed based on the fact that a radio wave traveling through a certain environment will undergo specific types of signal distortion. This loss of signal strength is modeled using known radio propagation and path-loss theories. Utilizing these theories, the distance from a wireless device to an access point can be calculated given a received signal strength loss value. Using the distances from three or more access points, a triangle algorithm can be utilized to determine the location of the device. Through this process, we also can construct a premeasurement database based on the propagation model. However, varying radio conditions at a site caused by environmental factors such as changes in humidity may alter the effectiveness of signal propagation models. It has been shown that location estimation signal strength models need to adapt, even in seemingly static environments [23].

SIGNAL-PROCESSING-BASED VERSUS PROTOCOL-BASED ALGORITHMS

Many signal processing-based location algorithms for cellular networks and WLANs generally include two stages: *parameter measuring* and *position estimation*. For example, TOA can be determined either by measuring the phase of the received narrowband carrier signal or by directly measuring the arrival time of a wideband pulse. In conventional geolocation systems, TOA estimation techniques have been widely used for GPS, radar, and sonar applications. Because the indoor multipath environment is very different from an outdoor environment, traditional TOA estimation algorithms, like the ML TOA estimation technique, have been derived for applications where the radio propagation channel can be simply modeled as a single-path AWGN channel. Traditional TOA estimation is not suitable for indoor geolocation systems with severe multipath propagation.

To improve the performance of TOA estimation for use in an indoor multipath environment, one may attempt to increase the resolution of the estimation by increasing signal bandwidth or by employing advanced signal processing algorithms. For example, diversity techniques have been considered in the practical implementation of indoor geolocation systems [8]. Although signal processing may accelerate the development of indoor geolocation methods, mobile positioning also can be achieved by exploiting timing protocols as suggested in [48]. Emerging broadband communication systems, such as 802.11a, have great potential for accurate position estimation due to their inherent timing accuracy, which provides a protocol-based solution for indoor geolocation. OFDM has also been adopted by ETSI HIPERLAN/2 and IEEE 802.11a as a physical layer standard for next-generation WLANs [47]. A novel method for measuring geolocation metrics, TOA and TDOA exploits the OFDM-based HIPERLAN/2 MAC frame structure [35]. This feature of MAC structure can be exploited in measuring geolocation metrics, TOA, and TDOA from OFDM burst signals. This has led us to consider other possible indoor positioning solutions for WLANs and sensor networks based on timing protocols.

POSITIONING ALGORITHMS FOR AD HOC SENSOR NETWORKS

The unique properties of sensor networks cause them to require somewhat different positioning algorithms than those used in cellular networks and WLANs. There are various possibilities for constructing a localization algorithm that balances computation among sensor network nodes. These algorithm designs include: the distributed (every node should be able to estimate its own location), the localized (each node gathers information from other nodes in its immediate neighborhood), the asymptotic convergence design (computation stops when a certain degree of accuracy has been achieved), the self-organizing scheme (node functioning does not depend on the global infrastructure), the robust design (the algorithm can tolerant node failures and range errors), and the cost-effective and energy-efficient approach (this algorithm requires little computation overhead).

BEACON-BASED VERSUS BEACON-FREE ALGORITHMS

Beacon-based algorithms assume that a certain minimum number of nodes know their own positions through manual configuration or GPS. Individual nodes' location could then be determined by referring to a beacon's position. A detailed survey of various beacon-based localization algorithms has been provided in [28]. All beacon-based positioning algorithms, however, have their limitations because they need another positioning scheme to bootstrap the beacon node positions, and they cannot be easily employed in environments where other location systems are unavailable; thus, they are unsuitable for use indoors. It turns out, in practice, that a large number of beacon nodes are required to achieve an acceptable level of position error [28]. In contrast, beacon-free algorithms use local distance information to attempt to determine each node's relative coordinates without relying on beacons that are aware of their positions. Of course, any algorithm that does not use beacon nodes can be easily converted to one that uses a small number of beacon nodes by adding a final step in the procedure, in which all node coordinates are transformed using three (in 2-D positioning) or four (in 3-D positioning) beacon nodes. For example, multidimensional scaling (MDS) has been investigated for use in solving the localization problem in sensor networks [49], [50]. Without using beacons, all MDS-based localization algorithms are able to produce maps that represent the relative positions of nodes. With three or more beacons, the absolute coordinates of all the nodes can be determined at the same time. Another fully distributed and beacon-free localization algorithm, proposed in [51], operates in two stages. In the first stage, a heuristic is employed to create a well-spread, fold-free graph layout that resembles the desired layout. The second stage uses a mass-spring model analog. The optimized localization estimates analog can be found to be the minimum energy stage of the mass-spring model.

WE ARE FACING TREMENDOUS CHALLENGES WHILE EXPLORING NOVEL MOBILE POSITIONING TECHNIQUES TO DESIGN FASTER, MORE ROBUST, AND MORE ACCURATE POSITIONING SYSTEMS.

INCREMENTAL VERSUS CONCURRENT ALGORITHMS

Incremental algorithms begin with only three or four core nodes being aware of their own coordinates. They then recursively add appropriate nodes to this set by calculating each node's coordinates using measured relative distances from nodes with previously known coordinates. These coordinate calculations are based on either simple triangle algorithms or on local optimization schemes [52]. However, incremental algorithms have limitations because they can propagate measurement error, resulting in poor overall network localization. Some incremental algorithms can thus be applied in later stages of global optimization to reduce propagation error. Escaping from local minima and reaching global minima in the incremental stage continues to be a major challenge. In concurrent algorithms, all nodes calculate and then refine their coordinates in parallel using local information. Some of these algorithms use iterative optimization schemes that reduce the differences between measured distances and calculated distances based on current coordinate estimates [51]. Concurrent optimization algorithms have a better chance of avoiding local minima than incremental schemes. They can also avoid error propagation by continuously reducing global errors.

RANGE-BASED VERSUS RANGE-FREE ALGORITHMS

Many localization algorithms rely on the distances between nodes: this is known as range-based localization. This type of distance estimation is usually implemented using signal strength decay, TOA, or TDOA for internode range estimation [53]. While range-based algorithms require absolute point-to-point distance estimation (range) or angle estimation for positioning, range-free algorithms do not require this information. In addition to measuring range information, range-free localization algorithms achieve position estimation by solving a convex optimization problem using a connectivity matrix of sensor nodes [54]. However, due to the unique ad hoc character of wireless sensor networks, many distributed solutions are more attractive than centralized designs. Sensors locate themselves at the centroid of the locations of beacons they can detect [55]. Other algorithms have assumed node-to-node communication can be used to convey the locations of all the beacons to all the sensors [27], [32]. Using hop-count as an estimate of Euclidian distance (by computing the average distance between sensors in [27] or by analytically deriving it in [32]), a sensor can estimate its position via triangulation. Another novel "range-free" algorithm determines whether a node lies inside or outside of the triangles formed by all possible sets of three beacons (called the APIT test) [56].

SINGLE-HOP VERSUS MULTIPLE-HOP ALGORITHMS

In multihop positioning systems, nodes typically do not receive beacon nodes' signals directly. Given the influence of single-hop positioning systems such as cellular networks and WLANs, it is not surprising that the first multihop localization algorithms tried to adapt single-hop technologies. TDOA, RSSI, and/or AOA information is collected, and the position of each node is then computed using triangulation [27]. A number of connectivity-based solutions have been proposed for multihop localization. One of the simplest and earliest is DV-hop [27]. In this system, each node determines its own position based on how many hops away it is from a beacon node. A method similar to APS was suggested in [32]. It first determines the hop distance (called gradient) to the beacons (called seeds) and, as a function of the average node density, calculates the actual average hop distance to a beacon.

CONCLUSION AND FUTURE DIRECTIONS

Wireless positioning is becoming increasingly important. In this article, a state-of-the-art positioning system and the algorithm it uses have been presented. However, some important problems still remain unsolved; there continues to be a need for seamless positioning, fault-tolerance, privacy, and security

[57]. Although many positioning devices and services are currently available, it is necessary to develop an integrated and seamless positioning platform to provide a *uniform* solution for different network configurations. Directions for future research in this area can be summarized as follows:

1) *Fusion techniques*: Fusion techniques include system fusion and measurement data fusion. For outdoor geolocation, a combination of GPS and cellular networks can provide greater location accuracy. Data fusion combines different positioning techniques to improve accuracy and coverage. In addition, data fusion techniques have been designed to utilize ad hoc sensor networks to save energy, but little work has been done on the localization problem to date.

2) *Direct localization*: Conventional two-step localization processes that include parameter measurement and position estimation have been studied extensively. In these methods, computational complexity is low in the position estimation stage. However, these methods have the disadvantage of making a premature decision on an intermediate TDOA in their first step, discarding useful information. A better approach is direct localization*,* which uses the least commitment principle; these algorithms preserve and propagate all intermediate information until the end of the process and make an informed decision as a very last step [58]. Little progress has so far been made in developing RF-based network-aided positioning.

3) *Smart antennas*: Smart antennas will be available for 3G wireless networks and beyond. The application of antenna arrays in ad hoc networks to improve communication capacities has been investigated. Though promising, these techniques pose new challenges in data fusion and AOA resource allocation.

4) *Network topology*: Because different positioning techniques and algorithms work in various ways with different topology structures, we can conclude that network topology has a significant impact on network-aided positioning, especially for ad hoc networks with random topologies. To the best of our knowledge, no work has been done on this topic.

5) *System interoperation*: Nowadays, researchers are building ubiquitous communication and computing platforms. Positioning systems can be included by integrating localization systems within various networks. Much work remains to be done in this area.

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