Indoor Geolocation Science and Technology

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ABSTRACT

This article presents an overview of the technical aspects of the existing technologies for wireless indoor location systems. The two major challenges for accurate location finding in indoor areas are the complexity of radio propagation and the ad hoc nature of the deployed infrastructure in these areas. Because of these difficulties a variety of signaling techniques, overall system architectures, and location finding algorithms are emerging for this application. This article provides a fundamental understanding of the issues related to indoor geolocation science that are needed for design and performance evaluation of emerging indoor geolocation systems.

INTRODUCTION

Recently, there is increasing interest in accurate location finding techniques and location-based applications for indoor areas. The Global Positioning System (GPS) [1] and wireless enhanced 911 (E-911) services [2] also address the issue of location finding. However, these technologies cannot provide accurate indoor geolocation, which has its own independent market and unique technical challenges. In 1997, while engaged in the Defense Advanced Research Projects Agency's (DARPA's) Small Unit Operation/Situation Awareness System (SUO/SAS) program, the lead author of this article and his research group noticed the need for fundamental research in accurate indoor geolocation [3]. The follow-up initiative of the group attracted the attention of Nokia and other Finnish organizations to the commercial importance of indoor geolocation. In recognition of this importance, an NSF grant was awarded to establish a scientific foundation in this field.

Accurate indoor geolocation is an important and novel emerging technology for commercial, public safety, and military applications [4]. In commercial applications for residential and nursing homes there is an increasing need for indoor geolocation systems to track people with special needs, the elderly, and children who are away from visual supervision, to navigate the blind, to locate in-demand portable equipment in hospitals, and to find specific items in warehouses. In public safety and military applications, indoor geolocation systems are needed to track inmates in prisons and navigating policeman, fire fighters, and soldiers to complete their missions inside buildings. These incentives have initiated interest in modeling the radio channel for indoor geolocation applications [3, 5], development of new technologies [6], and emergence of first-generation indoor geolocation products [7]. To help the growth of this emerging industry, there is a need to develop a scientific framework to lay a foundation for design and performance evaluation of such systems.

Figure 1 illustrates the functional block diagram of a wireless geolocation system. The main elements of the system are a number of location sensing devices that measure metrics related to the relative position of a mobile terminal (MT) with respect to a known reference point (RP), a positioning algorithm that processes metrics reported by location sensing elements to estimate the location coordinates of MT, and a display system that illustrates the location of the MT to users. The location metrics may indicate the approximate arrival direction of the signal or the approximate distance between the MT and RP. The angle of arrival (AOA) is the common metric used in direction-based systems. The received signal strength (RSS), carrier signal phase of arrival (POA), and time of arrival (TOA) of the received signal are the metrics used for estimation of distance. As the measurements of metrics become less reliable, the complexity of the position algorithm increases. The display system can simply show the coordinates of the MT, or it may identify the relative location of the MT in the layout of an area. This display system could be software residing in a private PC or a mobile locating unit, locally accessible software in a local area network (LAN), or a universally accessible service on the Web. Obviously, as the horizon of accessibility of the information increases, design of the display system becomes more complex.

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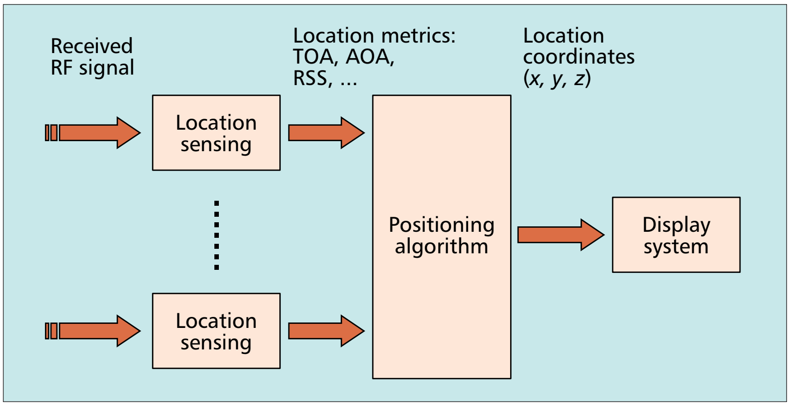
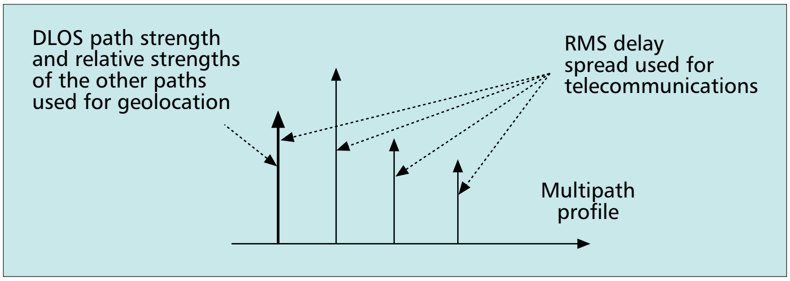
There are two basic approaches to designing a wireless geolocation system. The first approach is to develop a signaling system and a network infrastructure of location sensors focused primarily on geolocation application. The second approach is to use an existing wireless network infrastructure to locate an MT. The advantage of the first approach is that physical specification, and consequently quality of the location sensing results, is under control of the designer. The MT can be designed as a very small wearable tag or sticker, and the density of the sensor infrastructure can be adjusted to the required accuracy of the location finding application. The advantage of the second approach is that it avoids expensive and time-consuming deployment of infrastructure. These systems, however, need to use more intelligent algorithms to compensate for the low accuracy of the measured metrics. Both approaches have their own markets, and design work on both technologies has been pursued in the past few years [2, 4, 7, 8].

To develop a scientific foundation, we need to examine the performance of different signaling techniques and geolocation approaches. This performance evaluation needs a suitable model for radio propagation that reflects the characteristics of the channel affecting the accuracy of location sensing and system positioning. In the next three sections we address technical issues related to channel modeling, location sensing, and positioning algorithms for indoor geolocation systems.



■ **Figure 1.** *A functional block diagram of wireless geolocation systems.*



■ **Figure 2.** *The multipath profile of an indoor radio propagation channel.*

Channel Characteristics for Indoor Geolocation

The indoor radio propagation channel is characterized as site-specific, severe multipath, and low probability for availability of a line of sight (LOS) signal propagation path between the transmitter and receiver [9]. The two major sources of errors in the measurement of location metrics in indoor environment are multipath fading and no LOS (NLOS) conditions due to shadow fading [3].

Radio propagation channel models are developed to provide a means to analyze the performance of a wireless receiver. The performance criteria for telecommunication and geolocation systems are quite different [3]. The performance criterion for telecommunication systems is the bit error rate (BER) of the received data stream, while for geolocation systems the performance measure is the estimated accuracy of location coordinates. The accuracy of location estimation is a function of the accuracy of location metrics and the complexity of positioning algorithms. Since the metrics for geolocation applications are AOA, RSS, and TOA, models for geolocation application must reflect the effects of channel behavior on the estimated value of these metrics at the receiver. The existing narrowband indoor radio channel models designed for telecommunication applications [9] can be used to analyze the RSS for geolocation applications. The AOA part of the emerging 3D channel models developed for smart antenna applications [10, 11] might be used for modeling of the AOA for indoor geolocation applications. However, the existing wideband indoor multipath channel measurements and models [9] are not suitable for analysis of the behavior of TOA for geolocation applications.

The existing statistical wideband indoor multipath models, such as the JTC model [9], represent multipath characteristics of the channel with a discrete channel profile similar to the one shown in Fig. 2. The strength and arrival time of the paths are so determined that the root mean square (RMS) delay spread and consequently BER of a telecommunication receiver obtained from the simulations using these profile represents values similar to those obtained from empirical measurements. If these models are used for performance evaluation of TOA-based geolocation systems, the statistics of distance errors do not reflect the results obtained from empirical data [3]. Besides, to confirm the modeling results of a radio channel, empirical measurement is essential to check the validity of the model. In the literature there are a number of measurements of the wideband characteristics of indoor radio channels for frequencies from 1 to 60 GHz [9]. However, none of these measurements are useful for geolocation applications because they do not have a well-calibrated estimate of the arrival time of the direct LOS (DLOS) path and a very accurate measurement of the real physical distance between the transmitter and receiver [12]. The only available short-range measurements calibrated for geolocation applications are those reported in [12], which are used in this article to analyze the performance of super-resolution techniques in the next section.

While we do not have any good models for the multipath characteristics of indoor radio channels for geolocation applications, there are three classes of recent statistical modeling approaches that can be used to develop reliable models in the future, which are wideband 2D

In indoor areas, due to obstruction by walls, ceilings, or other objects, the DLOS propagation path is not always the strongest path and even in some casess, for example, NLOS, it may not be detectable with a specific receiver implementation. In such cases, dramatically large errors occur in TOA estimation.

multipath modeling [3, 5], 3D geometrical statistical modeling [10], and 3D measurement-based statistical modeling [11]. In measurement-based 2D statistical modeling, the measurement data are used to define a multipath profile by

$$h(\tau) = \sum_{k=0}^{L_p - 1} \alpha_k \delta(\tau - \tau_k), \tag{1}$$

where L_p is the number of multipath components, and $\alpha_k = |\alpha_k| \, e^{j\phi_k}$ and τ_k are complex amplitude and propagation delay of the kth path, respectively. The strength and statistical characteristics of the first path and its relative strength with respect to other paths fit similar results obtained from empirical data. The measurement systems for this approach are the same as those used for telecommunication applications [7, 9]. However, these systems are calibrated for accurate measurement of the TOA of the DLOS, and for each measurement the physical distance between the transmitter and receiver is accurately recorded. Preliminary measurement and modeling work in this field is reported in [5, 12]; larger calibrated measurement databases and more practical multipath models need further investigation.

In 3D modeling, the mathematical model for the channels is represented by

$$h(\tau, \theta) = \sum_{k=0}^{L_p - 1} \alpha_k \delta(\tau - \tau_k, \theta - \theta_k), \tag{2}$$

where θ_k is the AOA of the kth path [11]. While in 2D modeling each path was associated with a TOA, in 3D modeling each path is associated with a TOA and an AOA. The 3D models can be developed either based on geometric analysis of the statistics of the paths arriving from different directions or out of empirical 3D channel measurement data. The 3D geometrical statistical models, developed for smart antenna applications, use an analytical approach to relate propagation parameters to the structure of scattering in the environment [10]. In this approach, a mathematical description of radio propagation based on statistical building features and a geometric optics approximation of Maxwell's equations are employed to derive relevant radio propagation models such as distributions of the TOA, AOA, and RSS. The statistics of the AOA and RSS in these models can be used directly for indoor geolocation applications. Further research in this area is needed to develop statistical models for the TOA of the DLOS path and its relation to other paths to make them useful for the analysis of positioning errors in TOA-based geolocation systems.

In 3D measurement-based statistical modeling, measured channel characteristics are used to develop models for AOA, TOA, and RSS. The major challenge of this approach is the implementation of a system to measure the 3D characteristics of the channel. Recently two techniques have been studied for this purpose. The first technique mechanically rotates a directional antenna to measure the strength of the signal arriving from different directions, and the second technique measures a set of eight channel impulse responses using an antenna array and calculates the AOA using signal processing techniques [11]. Preliminary 3D modeling of an indoor area using a limited database in a building is available in [11]. More extensive measurement and modeling in this field can result in realistic models for indoor geolocation applications.

Location Sensing Techniques

As discussed in the introduction, the location sensing elements measure RSS, AOA, and TOA as location metrics. The indoor radio channel suffers from severe multipath propagation and heavy shadow fading, so the measurements of RSS and AOA provide less accurate metrics than does TOA [4]. As a result, similar to GPS systems, independent systems designed for indoor geolocation normally employ the more accurate TOA as the location metric. Systems using existing infrastructures installed for wireless LANs or the third-generation (3G) indoor systems may use RSS, AOA, or less accurate TOA measurements to fully exploit the existing hardware implementation designed for traditional telecommunication applications [8]. In indoor areas, due to obstruction by walls, ceilings, or other objects, the DLOS propagation path is not always the strongest; in some cases (e.g., NLOS), it may not even be detectable with a specific receiver implementation [3]. In such cases, dramatically large errors occur in TOA estimation. To accurately estimate the TOA in indoor areas, we need to resort to different and more complex signaling formats, frequency of operation, and signal processing techniques that can resolve the problems. The following subsection is devoted to accurate TOA estimation techniques.

Estimation of TOA for Indoor Ranging

The TOA-based systems measure distance based on an estimate of signal propagation delay (i.e., TOA) between a transmitter and a receiver since in free space or air, radio signals travel at the constant speed of light. The TOA can be measured by either measuring the phase of received narrowband carrier signal or directly measuring the arrival time of a wideband narrow pulse. The wideband pulses for measuring TOA can be generated either directly [6] or using spread spectrum technology [7]. In the following, we present these techniques in three classes: narrowband, wideband, and ultra wideband techniques.

Narrowband Signals and Phase Measurement Systems — In the narrowband ranging technique, the phase difference between received and transmitted carrier signals is used to measure the distance between two points. The phase of a received carrier signal, ϕ, and the TOA of the signal, τ, are related by $\tau = \phi/\omega_c$, where ω_c is the carrier frequency in radian. It is well known that the differential GPS (DGPS) using measured reference carrier phase at the receiver improves the location accuracy of the traditional GPS from about 20 m to within 1m [1]. However, unlike the DGPS, where the DLOS signal path is always present, the severe multipath condition of the indoor geolocation environment causes substantial errors in phase measurements. When a narrowband carrier signal is transmitted in a multipath environment, the composite received carrier signal is the sum of a number of carriers, arriving along different paths, of the same frequency but different amplitude and phase. The frequency of the composite received signal remains unchanged, but the phase will be different from that of the DLOS signal [9]. An immediate conclusion is that phase-based distance measurement using a narrowband carrier signal cannot provide accurate estimate of distance in a heavy multipath environment.

Wideband Signals and Superresolution Techniques — The direct-sequence spread-spectrum (DSSS) wideband signal has been used in ranging systems for many years [1]. In such a system, a signal coded by a known pseudo-noise (PN) sequence is transmitted by a transmitter. Then a receiver cross-correlates received signal with a locally generated PN sequence using a sliding correlator or a matched filter [7, 9]. The distance between the transmitter and receiver is determined from the arrival time of the first correlation peak. Because of the processing gain of the correlation process at the receiver, the DSSS ranging systems perform much better than competing systems in suppressing interference from other radio systems operating in the same frequency band. In single-path radio propagation channels, only disturbed by additive white Gaussian noise, the Cramer-Rao lower bound is commonly used for performance assessment of cross-correlation-based TOA estimation techniques. However, due to the complexity of multipath indoor radio propagation channels, such a bound is not directly applicable to indoor geolocation systems. Instead, the resolution of TOA estimation in DSSS ranging systems is roughly determined by the base width of the PN correlation function, or equivalently the signal bandwidth [7]. For example, if a bandwidth of 200 MHz is used, the absolute distance estimation errors are less than 1.5 m if the DLOS signal is detectable.

Due to the scarcity of the available bandwidth in practice, in some indoor geolocation applications, the DSSS ranging systems cannot provide adequate accuracy. On the other hand, it is always desirable to achieve higher ranging accuracy using the same bandwidth. Inspired by high-resolution spectrum estimation techniques, a number of researchers have studied super-resolution techniques for time-domain analysis such as [13]. A frequency-domain superresolution technique can be used to determine the TOA with high resolution from frequency channel response. In practice, discrete samples of frequency channel response can be obtained by sweeping the channel at different frequencies [9], by taking advantage of an existing multicarrier (orthogonal frequency-division multiplexing, OFDM) communication system, or in a DSSS system by deconvolving received signal over the frequency band of high signal-to-noise ratio [13].

To understand the concept of frequency-domain super-resolution technique, we take the Fourier transform of Eq. 1 so that the frequency channel response is obtained as

$$H(f) = \sum_{k=0}^{L_p-1} \alpha_k e^{-j2\pi f \tau_k}. \qquad (3)$$

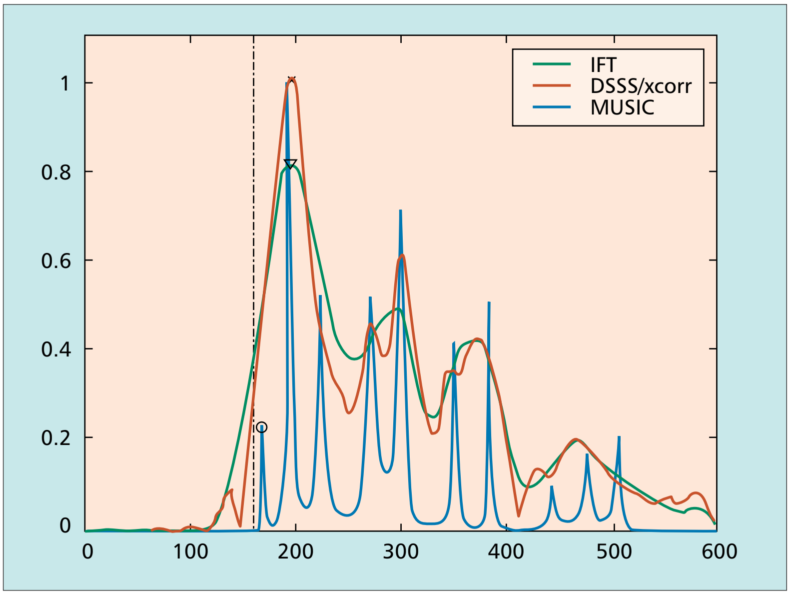
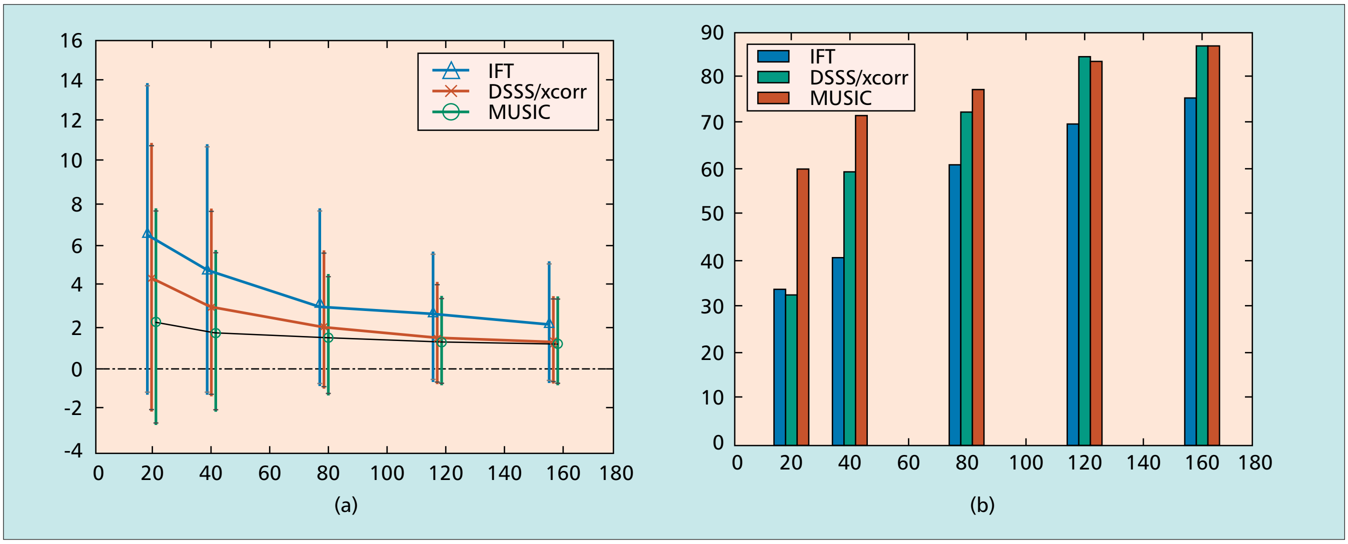


Figure 3. *Estimated TOA of the DLOS path and normalized time domain responses obtained using three different techniques. The vertical dash-dot line denotes the expected TOA. The x-axis is delay in ns.*

If we exchange the role of time and frequency variables in Eq. 3, we observe that it becomes the harmonic signal model, which is well known in the spectrum estimation literature. Therefore, all spectrum estimation techniques used for harmonic signal models can be applied to frequency domain measurement data of radio propagation channel to determine the delay of multipath signals.

In order to demonstrate the usefulness of the super-resolution technique we compare its performance based on measured indoor channel characteristics reported in [12] with two other time delay estimation techniques. The MUSIC algorithm is used as an example of super-resolution techniques. In the first of these, the frequency domain channel response is directly converted to the time domain using inverse Fourier transform (IFT) [9], and then the arrival time of the DLOS is detected. The second technique uses the traditional cross-correlation techniques with DSSS signals (DSSS/xcorr). Figure 3 shows simulation results using the three techniques over sample channel measurement data. We observe that the MUSIC algorithm shows much higher time domain resolution than the other two and accurately detects the arrival time of the DLOS path, while the other two fail. Figure 4a presents mean and standard deviation of ranging errors vs. the bandwidth of the system over channel measurement data in several different buildings reported in [12]. Figure 4b presents percentage of measurement locations where absolute ranging errors are smaller than 3 m. In general, the superresolution technique has the best performance and is preferred, especially when the signal bandwidth is small. It should be noted that while using the superresolution technique and large bandwidth improves statistical performance, it couldn't eliminate large ranging errors at some locations because of NLOS conditions between transmitter and receiver. This needs to be dealt with in the positioning process to achieve high positional accuracy, as presented



■ **Figure 4.** *Simulation results: a) mean of ranging errors in meter vs. bandwidth in MHz using three different TOA estimation techniques; the vertical line corresponds to one standard deviation; b) percentage of measurement locations where absolute ranging errors are smaller than 3 m vs. bandwidth in MHz.*

in the next section. Using the superresolution technique increases the complexity of system implementation, and there are a number of issues in practical implementation that need to be further investigated. More details of this study will be available in a separate publication.

The Ultra Wideband Approach — As mentioned before, signal bandwidth is one of the key factors that affect TOA estimation accuracy in multipath propagation environments. The larger the bandwidth, the higher the ranging accuracy. Ultra wideband (UWB) systems, which exploit bandwidths in excess of 1 GHz, have attracted considerable attention as a means of measuring accurate TOA for indoor geolocation applications [6]. Due to the high attenuation associated with the use of a high-frequency carrier, the frequency band considered for a UWB system is typically focused on 2–3 GHz unlicensed. With results of propagation measurement in a typical modern office building, it has been shown that the UWB signal does not suffer multipath fading [14], which is desirable for accurate TOA estimation in indoor areas. The actual deployment of UWB systems in the United States is subject to FCC approval, which was due in late 2001. The main concern of the FCC authorities is the interference of UWB devices with, among other licensed services, the GPS systems that operate at approximately the 1.5 GHz frequency band. Similar to the spread spectrum signals, the UWB signal has a low, flat, and noise-like power spectrum. But given the weak satellite signals that must be processed by GPS receivers, the noise-like UWB signal is still harmful for GPS systems in close vicinity. A significant amount of research work is underway to assess the effect of UWB interference on GPS receivers.

Positioning Algorithms

As discussed earlier, the measurement accuracy of location metrics in indoor areas depends on location sensing technologies and site-specific indoor radio propagation conditions. Due to imperfect implementation of location sensing techniques, lack of bandwidth, and the complexity of the multipath indoor radio propagation channel among others, there are always varying errors associated with measurements of location metrics. To achieve high positional accuracy when the measurements of location metrics are unreliable, the errors encountered in the measurement process have to be mitigated in the positioning process. In the next two subsections we discuss the traditional positioning algorithms used with reliable measurements of location metrics and more intelligent pattern recognition techniques that can be used to improve the positioning performance when the measurements of location metrics are unreliable.

Traditional Techniques

In the indoor radio channel, it is difficult to accurately measure AOA, POA and RSS so that most of the independent indoor positioning systems mainly use TOA based techniques. With reliable TOA-based distance measurements, simple geometrical triangulation methods can be used to find the location of the MT [2, 4]. Due to estimation errors of distances at RP receivers caused by inaccurate TOA measurement, the geometrical triangulation technique can only provide a region of uncertainty, instead of a single position fix, for estimated location of the MT. To obtain an estimate of location coordinates in the presence of measurement errors of location metrics, a variety of direct and iterative statistical positioning algorithms have been developed to solve the problem by formulating it into a set of nonlinear equations [2].

In some indoor geolocation applications, the purpose of positioning systems is to provide a visualization of possible mobile locations instead of an estimate of location coordinates [7]. On the other hand, positional accuracy is not constant across the area of coverage, and poor geometry of relative position of MT and RP can lead to high geometric dilution of precision [15].

The output of statistical methods is an estimate of mobile location coordinates, and the changes of the shape of the region of uncertainty are not revealed by this method. When the region of uncertainty information as well as the estimate of location is needed, both geometric and statistical triangulation algorithms are used [15].

For traditional outdoor geolocation, intelligent techniques, such as Kalman filter-based techniques for tracking and fusion of multiple metrics, are normally used to improve positioning performance [1]. In essence, these techniques are readily applicable to indoor geolocation systems. However, the indoor application environment has some unique features, discussed in the next section, which make the traditional positioning algorithms less attractive. On the other hand, these unique features of indoor applications enable the design of intelligent positioning algorithms that can significantly improve the positioning performance in indoor areas.

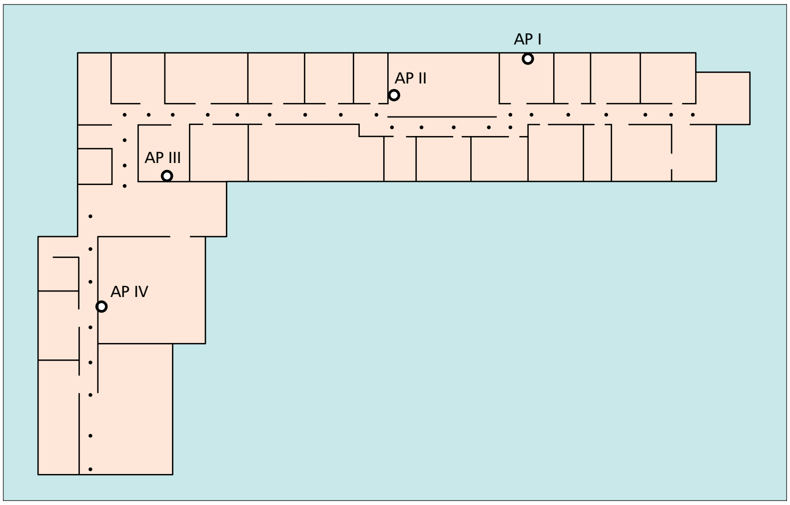


Figure 5. *Partial layout of the TLab and CWC, University of Oulu, as well as the locations of the four 802.11b APs and the measurement points.*

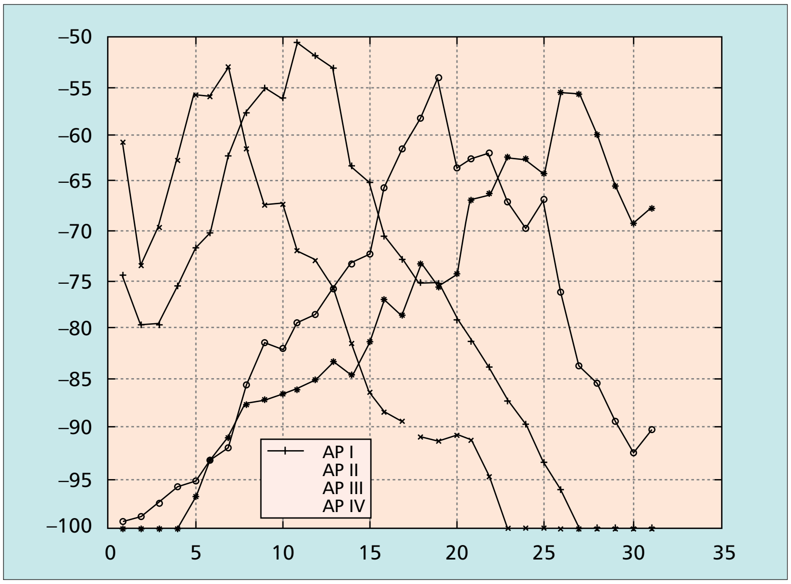
PATTERN RECOGNITION TECHNIQUES

For indoor geolocation applications, the service area is restricted to inside and the close vicinity of a building, and nowadays the building floor plan is normally accessible as an electronic document. The availability of electronic building floor plans is one of the features of indoor applications that can be exploited in positioning algorithms. For example, while tracking an MT in a building, with the aid of a building floor plan situations involving crossing walls or jumping through floors can easily be identified and eliminated. Another unique feature of indoor applications is that the size of the coverage area is much smaller than outdoor applications. This makes it possible to conduct comprehensive planning of the placement of sensors. Careful planning of a sensor network can significantly reduce measurement errors of location metrics caused by NLOS propagation. The structural information of the sensor network can also be employed in intelligent positioning algorithms similar to the use of building floor plans. The small coverage of the system also makes it possible to conveniently conduct extensive premeasurement in the areas of interest. As a result, the premeasurement-based location pattern recognition (also called *location fingerprinting*) technique is gaining increasing attention for indoor applications [8]. On the other hand, in most indoor applications, such as finding needed equipment or locating patients in critical condition, the MT is used in a quasi-stationary way. For these situations, pattern recognition work better than traditional triangulation techniques and Kalman filter-based tracking techniques.

The basic operation of pattern recognition positioning algorithms is simple. Each building has unique signal propagation characteristics; each spot in a building would have a unique signature in terms of RSS, TOA, and/or AOA, observed from different sensors in the building. A pattern recognition system determines the unique pattern features (i.e., the location signature) of the area of interest in a training process, and then this knowledge is used to develop rules for recognition. The challenge for such algorithms is to distinguish locations with similar signatures. To build the signature database, a terminal is carried through the service area transmitting signals to a monitoring site through all location sensing elements. The service area is divided into nonoverlapping zones or grids, and the algorithm analyzes the received signal patterns and compiles a unique signature for each zone.

For quasi-stationary applications, the simplest way of pattern recognition is the nearest-neighbor method. In this method the Euclidean distance measure is calculated between the measured metrics, RSS, TOA, and/or AOA, and all entities in the signature database. The location estimate is determined to be the one associated with the minimum Euclidean distance [8]. A simple experiment has been conducted to demonstrate the usefulness of this technique. Figure 5 presents a partial layout of the Telecommunications Laboratory (TLab) and the Center for Wireless Communications (CWC) at the University of Oulu, Finland. The locations of four 802.11b access points (APs) and 31 measurement locations along a long corridor, with about 2 m separation between adjacent points, are illustrated in the figure. An MT is carried along the corridor, and the RSS is measured at each location. Figure 6 shows the measured RSS at all four APs as the terminal travels from the right corner close to AP-I to the end of the vertical corridor after AP-IV. Then the nearest-neighbor pattern recognition method is applied to the measurement data. In this experiment the standard deviation of the positioning error was 2.4 m, and at about 80 percent locations the positional error was less than 3 m. Similar results in a different building are available in [8].

When the area of coverage becomes large and a large number of sensors are involved, the size of the location signature database increases dramatically, which makes the use of simple nearest-neighbor pattern recognition computationally cumbersome. More complex algorithms, including fuzzy logic, neural network, subspace techniques, and hidden Markov model-based techniques among others, are being investigated to reduce overall computational complexity and improve performance. When the 3G systems using spread spectrum signals and RAKE receivers are employed for indoor geolocation, it is possible to



■ **Figure 6.** *Measured RSS in dBm at the four APs.*

use the measured time and signal strength of all fingers in place of RSS to improve the positioning performance.

CONCLUSIONS

Indoor geolocation is an emerging technology that needs a scientific foundation. To provide such a foundation we need to characterize the radio propagation features that impact the performance of the indoor geolocation systems. Two classes of indoor geolocation systems are emerging. The first class has its own infrastructure, uses reliable TOA measurement using wideband, superresolution, or UWB location sensing approaches, and employs triangulation techniques for positioning. The second class uses the existing infrastructure of a wireless system (a wireless LAN or cellular system), more unreliable metrics, premeasurement data, and pattern recognition algorithms. The challenge for TOA-based systems is to develop a signaling system and infrastructure that is inexpensive to design and deploy, complies with frequency regulations, and provides a comprehensive coverage for accurate ranging. Even though building and updating the signature database are much easier in indoor environments than in wide urban areas, the major drawback of pattern recognition techniques still lies in substantial efforts needed in generation and maintenance of the signature database in view of the fact that the working environment changes constantly. In general, both techniques demonstrate promising positioning performance for the emerging indoor geolocation applications.

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REFERENCES

[1] E. D. Kaplan, *Understanding GPS: Principles and Applications*, Artech House, 1996.
[2] J. Caffery and G. Stuber, "Subscriber Location in CDMA Cellular Networks," *IEEE Trans. VT*, vol. 47, no. 2, May 1998, pp. 406–16.
[3] K. Pahlavan, P. Krishnamurthy, and J. Beneat, "Wideband Radio Channel Modeling for Indoor Geolocation Applications," *IEEE Commun. Mag.*, vol. 36, no. 4, Apr. 1998, pp. 60–65.
[4] K. Pahlavan and P. Krishnamurthy, *Principles of Wireless Networks — A Unified Approach*, Prentice Hall, 2002.
[5] P. Krishnamurthy, "Analysis and Modeling of the Wideband Radio Channel for Indoor Geolocation Applications," Ph.D. dissertation, Worcester Polytechnic Inst., 1999.
[6] R. Fontana, "Advances in Ultra Wideband Indoor Geolocation Systems," *3rd IEEE Wksp. WLAN*, Boston, MA, Sept. 2001.
[7] J. Werb and C. Lanzl, "Designing a Positioning System for Finding Things and People Indoors," *IEEE Spec.*, vol. 35, no. 9, Sept. 98, pp. 71–78.
[8] P. Bahl and V. Padmanabhan, "RADAR: An In-Building RF-Based User Location and Tracking System," *IEEE INFOCOM*, Israel, Mar. 2000.
[9] K. Pahlavan and A. Levesque, *Wireless Information Networks*, John Wiley & Sons, 1995.
[10] M. Hassan-Ali and K. Pahlavan, "A New Statistical Model for Site-Specific Indoor Radio Propagation Prediction Based on Geometric Optics and Geometric Probability," *IEEE JSAC Wireless*, Jan. 2002.
[11] R. Tingley and K. Pahlavan, "Time-space Measurement of Indoor Radio Propagation," *IEEE Trans. Inst. Measurements*, vol. 50, no. 1, Feb. 2001, pp. 22–31.
[12] J. Beneat, K. Pahlavan, and P. Krishnamurthy, "Radio Channel Characterization for Indoor and Urban Geolocation at Different Frequencies," *IEEE PIMRC*, Osaka, Japan, Sept. 1999.
[13] M. Pallas and G. Jourdain, "Active High Resolution Time Delay Estimation for Large BT Signals," *IEEE Trans. SP*, vol. 39, no. 4, Apr. 1991, pp. 781–88.
[14] M. Win and R. Scholtz, "On the Performance of Ultra-Wide Bandwidth Signals in Dense Multipath Environment," *IEEE Commun. Letters*, vol. 2, no. 2, Feb. 1998, pp. 51–53.
[15] S. Tekinay, E. Chao, and R. Richton, "Performance Benchmarking for Wireless Location Systems," *IEEE Commun. Mag.*, vol. 36, no. 4, Apr. 1998, pp. 72–76.

BIOGRAPHY

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