Survey of Wireless Indoor Positioning Techniques and Systems

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***Abstract*—Wireless indoor positioning systems have become very popular in recent years. These systems have been successfully used in many applications such as asset tracking and inventory management. This paper provides an overview of the existing wireless indoor positioning solutions and attempts to classify different techniques and systems. Three typical location estimation schemes of triangulation, scene analysis, and proximity are analyzed. We also discuss location fingerprinting in detail since it is used in most current system or solutions. We then examine a set of properties by which location systems are evaluated, and apply this evaluation method to survey a number of existing systems. Comprehensive performance comparisons including accuracy, precision, complexity, scalability, robustness, and cost are presented.**

***Index Terms*—Indoor location sensing, location fingerprinting, positioning algorithm, radio frequency (RF), wireless localization.**

I. Introduction

INDOOR location sensing systems have become very popular in recent years. These systems provide a new layer of automation called automatic object location detection. Real-world applications depending on such automation are many. To name a few, one can consider the location detection of products stored in a warehouse, location detection of medical personnel or equipment in a hospital, location detection of firemen in a building on fire, detecting the location of police dogs trained to find explosives in a building, and finding tagged maintenance tools and equipment scattered all over a plant.

The primary progress in indoor location sensing systems has been made during the last ten years. Therefore, both the research and commercial products in this area are new, and many people in academia and industry are currently involved in the research and development of these systems. This survey paper aims to provide the reader with a comprehensive review of the wireless location sensing systems for indoor applications. When possible, the paper compares the related techniques and systems. The authors hope that this paper will act as a guide for researchers, users, and developers of these systems, and help them identify the potential research problems and future products in this emerging area.

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An astonishing growth of wireless systems has been witnessed in recent years. Wireless technologies have entered the realms of consumer applications, as well as medical, industrial, public safety, logistics, and transport system along with many other applications. Self-organizing sensor networks, location sensitive billing, ubiquitous computing, context-dependent information services, tracking, and guiding are some of the numerous possible application areas. Since wireless information access is now widely available, there is a high demand for accurate positioning in wireless networks, including indoor and outdoor environments [1], [2]. The process of determining a location is called location sensing, geolocation, position location, or radiolocation, if it uses wireless technologies.

Different applications may require different types of location information. The main types discussed in this paper are physical location, symbolic location, absolute location, and relative location [1]. Physical location is expressed in the form of coordinates, which identify a point on a 2-D/3-D map. The widely used coordinate systems are degree/minutes/seconds (DMS), degree decimal minutes, and universal transverse mercator (UTM) system. Symbolic location expresses a location in a natural-language way, such as in the office, in the third-floor bedroom, etc. Absolute location uses a shared reference grid for all located objects. A relative location depends on its own frame of reference. Relative location information is usually based on the proximity to known reference points or base stations.

Various wireless technologies are used for wireless indoor location. These may be classified based on: 1) the location positioning algorithm, i.e., the method of determining location, making use of various types of measurement of the signal such as Time Of Flight (TOF), angle, and signal strength; 2) the physical layer or location sensor infrastructure, i.e., the wireless technology used to communicate with the mobile devices or static devices. In general, measurement involves the transmission and reception of signals between hardware components of the system. An indoor wireless positioning system consists of at least two separate hardware components: a signal transmitter and a measuring unit. The latter usually carries the major part of the system "intelligence."

There are four different system topologies for positioning systems [3]. The first one is the remote positioning system, whose signal transmitter is mobile and several fixed measuring units receive the transmitter's signal. The results from all measuring units are collected, and the location of the transmitter is computed in a master station. The second is self-positioning in which the measuring unit is mobile. This unit receives the signals of several transmitters in known locations, and has the capability to compute its location based on the measured signals. If a wireless data link is provided in a positioning system, it is possible to send the measurement result from a self-positioning measuring unit to the remote side, and this is called indirect remote positioning, which is the third system topology. If the measurement result is sent from a remote positioning side to a mobile unit via a wireless data link, this case is named indirect self-positioning, which is the fourth system topology.

Our paper is different from the previous survey papers [1] and [2] in several ways. Comparing with the previous survey paper [1], our paper focuses on indoor application of wireless location positioning while [1] just generally describes the location systems for ubiquitous computing, without addressing different types of location algorithms, especially for wireless location methods. Also, the paper [2] presents a slight out-of-date overview of the technologies for wireless indoor location solutions, and does not offer much detail about them and performance benchmarking for indoor wireless positioning system. The publication date of this paper is 2002, and since then, several wireless indoor positioning systems or solutions have been developed. In this paper, we present the latest developed systems or solutions, and their location algorithms. Our main purpose is to provide a qualitative overview for them. When possible, we also offer a quantitive comparison of these systems or solutions.

This review paper is organized as follows. Section II shows the measuring principles for location sensing and the positioning algorithms corresponding to different measuring principles. Performance metrics for indoor positioning techniques are explained in Section III. Section IV presents current wireless indoor positioning systems and solutions, and their performance comparison. Finally, Section V concludes the paper and gives possible future directions for research on wireless positioning systems for indoor environments.

II. Measuring Principles and Positioning Algorithms

It is not easy to model the radio propagation in the indoor environment because of severe multipath, low probability for availability of line-of-sight (LOS) path, and specific site parameters such as floor layout, moving objects, and numerous reflecting surfaces. There is no good model for indoor radio multipath characteristic so far [2]. Except using traditional triangulation, positioning algorithms using scene analysis or proximity are developed to mitigate the measurement errors. Targeting different applications or services, these three algorithms have unique advantages and disadvantages. Hence, using more than one type of positioning algorithms at the same time could get better performance.

A. Triangulation

Triangulation uses the geometric properties of triangles to estimate the target location. It has two derivations: lateration and angulation. Lateration estimates the position of an object by measuring its distances from multiple reference points. So, it is also called range measurement techniques. Instead of measuring the distance directly using received signal strengths (RSS), time of arrival (TOA) or time difference of arrival (TDOA) is usually measured, and the distance is derived by computing the

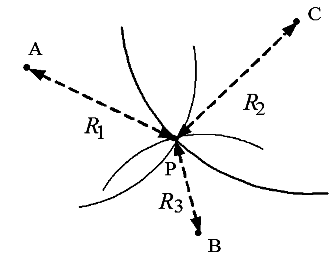

Fig. 1. Positioning based on TOA/RTOF measurements.

attenuation of the emitted signal strength or by multiplying the radio signal velocity and the travel time. Roundtrip time of flight (RTOF) or received signal phase method is also used for range estimation in some systems. Angulation locates an object by computing angles relative to multiple reference points. In this survey, we focus on the aforementioned measurements in the shorter range, low-antenna, and indoor environment.

1) Lateration Techniques:

a) TOA: The distance from the mobile target to the measuring unit is directly proportional to the propagation time. In order to enable 2-D positioning, TOA measurements must be made with respect to signals from at least three reference points, as shown in Fig. 1 [4]. For TOA-based systems, the one-way propagation time is measured, and the distance between measuring unit and signal transmitter is calculated. In general, direct TOA results in two problems. First, all transmitters and receivers in the system have to be precisely synchronized. Second, a timestamp must be labeled in the transmitting signal in order for the measuring unit to discern the distance the signal has traveled. TOA can be measured using different signaling techniques such as direct sequence spread-spectrum (DSSS) [22], [23] or ultrawide band (UWB) measurements [78].

A straightforward approach uses a geometric method to compute the intersection points of the circles of TOA. The position of the target can also be computed by minimizing the sum of squares of a nonlinear cost function, i.e., least-squares algorithm [4], [5]. It assumes that the mobile terminal, located at (x_0, y_0), transmits a signal at time t_0, the N base stations located at $(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)$ receive the signal at time $t_1, t_2, \ldots, t_N$. As a performance measure, the cost function can be formed by

$$\boldsymbol{F}(\boldsymbol{x}) = \sum_{i=1}^{N} \alpha_i^2 f_i^2(\boldsymbol{x}) \tag{1}$$

where α_i can be chosen to reflect the reliability of the signal received at the measuring unit i, and $f_i(\boldsymbol{x})$ is given as follows.

$$f_i(\boldsymbol{x}) = c(t_i - t) - \sqrt{(x_i - x)^2 + (y_i - y)^2} \tag{2}$$

where c is the speed of light, and $\boldsymbol{x} = (x, y, t)^T$. This function is formed for each measuring unit, $i = 1, \ldots, N$, and $f_i(\boldsymbol{x})$ could be made zero with the proper choice of x, y, and t. The location estimate is determined by minimizing the function $\boldsymbol{F}(\boldsymbol{x})$.

There are other algorithms for TOA-based indoor location system such as closest-neighbor (CN) and residual weighting (RWGH) [5]. The CN algorithm estimates the location of the

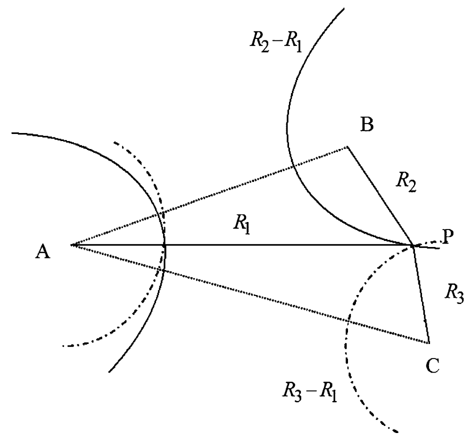

Fig. 2. Positioning based on TDOA measurements.

user as the location of the base station or reference point that is located closest to that user. The RWGH algorithm can be basically viewed as a form of weighted least-squares algorithm. It is suitable for LOS, non-LOS (NLOS) and mixed LOS/NLOS channel conditions.

b) TDOA: The idea of TDOA is to determine the relative position of the mobile transmitter by examining the difference in time at which the signal arrives at multiple measuring units, rather than the absolute arrival time of TOA. For each TDOA measurement, the transmitter must lie on a hyperboloid with a constant range difference between the two measuring units. The equation of the hyperboloid is given by

$$R_{i,j} = \sqrt{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2} - \sqrt{(x_j - x)^2 + (y_j - y)^2 + (z_j - z)^2} \quad (3)$$

where (x_i, y_i, z_i) and (x_j, y_j, z_j) represent the fixed receivers i and j; and (x, y, z) represent the coordinate of the target [3]. Except the exact solutions to the hyperbolic TDOA equation shown in (3) through nonlinear regression, an easier solution is to linearize the equations through the use of a Taylor-series expansion and create an iterative algorithm [6].

A 2-D target location can be estimated from the two intersections of two or more TDOA measurements, as shown in Fig. 2. Two hyperbolas are formed from TDOA measurements at three fixed measuring units (A, B, and C) to provide an intersection point, which locates the target P.

The conventional methods for computing TDOA estimates are to use correlation techniques. TDOA can be estimated from the cross correlation between the signals received at a pair of measuring units. Suppose that for the transmitted signal $s(t)$, the received signal at measuring unit i is $x_i(t)$. Assume that $x_i(t)$ is corrupted by the noise $n_i(t)$ and delayed by d_i, then $x_i(t) = s(t - d_i) + n_i(t)$. Similarly, the signal $x_j(t) = s(t - d_j) + n_j(t)$, which arrives at measuring unit j, is delayed by d_j and corrupted by the noise $n_j(t)$. The cross-correlation function of these signals is given by integrating the lag product of two

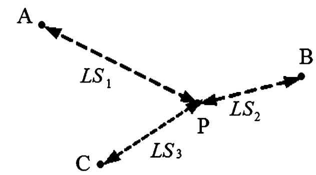

Fig. 3. Positioning based on RSS, where LS_1, LS_2, and LS_3 denote the measured path loss.

received signals over a time period T

$$\hat{R}_{x_i,x_j}(\tau) = \frac{1}{T}\int_0^T x_i(t)x_j(t-\tau)dt. \quad (4)$$

The TDOA estimate is the value τ that maximizes $R_{x_i,x_j}(\tau)$, i.e., the range differences. This approach requires that the measuring units share a precise time reference and reference signals, but does not impose any requirement on the mobile target. Frequency domain processing techniques are usually used to calculate τ. Except the previous TDOA methods, a delay measurement-based TDOA measuring method was proposed in [23] for 802. 11 wireless LANs, which eliminates the requirement of initial synchronization in the conventional methods.

c) RSS-Based (or Signal Attenuation-Based) Method: The above two schemes have some drawbacks. For indoor environments, it is difficult to find a LOS channel between the transmitter and the receiver. Radio propagation in such environments would suffer from multipath effect. The time and angle of an arrival signal would be affected by the multipath effect; thus, the accuracy of estimated location could be decreased. An alternative approach is to estimate the distance of the mobile unit from some set of measuring units, using the attenuation of emitted signal strength. Signal attenuation-based methods attempt to calculate the signal path loss due to propagation. Theoretical and empirical models are used to translate the difference between the transmitted signal strength and the received signal strength into a range estimate, as shown in Fig. 3.

Due to severe multipath fading and shadowing present in the indoor environment, path-loss models do not always hold. The parameters employed in these models are site-specific. The accuracy of this method can be improved by utilizing the premeasured RSS contours centered at the receiver [7] or multiple measurements at several base stations. A fuzzy logic algorithm shown in [8] is able to significantly improve the location accuracy using RSS measurement.

d) RTOF: This method is to measure the time-of-flight of the signal traveling from the transmitter to the measuring unit and back, called the RTOF (see Fig. 1). For RTOF, a more moderate relative clock synchronization requirement replaces the above synchronization requirement in TOA. Its range measurement mechanism is the same as that of the TOA. The measuring unit is considered as a common radar. A target transponder responds to the interrogating radar signal, and the complete roundtrip propagation time is measured by the measuring units. However, it is still difficult for the measuring unit to know the exact delay/processing time caused by the responder in this case. In long-range or medium-range systems, this delay could

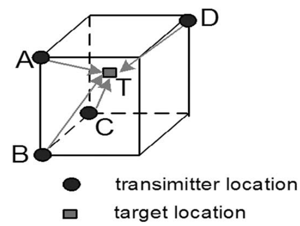

Fig. 4. Positioning based on signal phase.

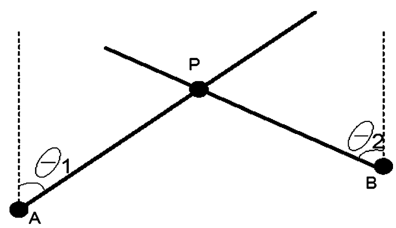

Fig. 5. Positioning based on AOA measurement.

be ignored if it is small, compared with the transmission time. However, for short-range systems, it cannot be ignored. An alternative approach is to use the concept of modulated reflection [9], which is only suited for short-range systems. An algorithm to measure RTOF of wireless LAN packets is presented in [10] with the result of a measurement error of a few meters. The positioning algorithms for TOA can be directly applicable for RTOF.

e) Received Signal Phase Method: The received signal phase method uses the carrier phase (or phase difference) to estimate the range. This method is also called phase of arrival (POA) [2]. Assuming that all transmitting stations emit pure sinusoidal signals that are of the same frequency f, with zero phase offset, in order to determine the phases of signals received at a target point, the signal transmitted from each transmitter to the receiver needs a finite transit delay. In Fig. 4, the transmitter stations A up to D are placed at particular locations within an imaginary cubic building. The delay is expressed as a fraction of the signal's wavelength, and is denoted with the symbol $\phi_i = (2\pi f D_i)/c$ in equation $S_i(t) = \sin(2\pi f t + \phi_i)$, where $i \in (A, B, C, D)$, and c is the speed of light. As long as the transmitted signal's wavelength is longer than the diagonal of the cubic building, i.e., $0 < \phi_i < 2\pi$, we can get the range estimation $D_i = (c\phi_i)/(2\pi f)$. Then, we can use the same positioning algorithms using TOA measurement. The receiver may measure phase differences between two signals transmitted by pairs of stations, and positioning systems are able to adopt the algorithms using TDOA measurement to locate the target.

For an indoor positioning system, it is possible to use the signal phase method together with TOA/TDOA or RSS method to fine-tune the location positioning. However, the received signal phase method has one problem of ambiguous carrier phase measurements to overcome. It needs an LOS signal path, otherwise it will cause more errors for the indoor environment.

2) Angulation Techniques (AOA Estimation): In AOA, the location of the desired target can be found by the intersection of several pairs of angle direction lines, each formed by the circular radius from a base station or a beacon station to the mobile target. As shown in Fig. 5, AOA methods may use at least two known reference points (A, B), and two measured angles θ_1, θ_2 to derive the 2-D location of the target P. Estimation of AOA, commonly referred to as direction finding (DF), can be accomplished either with directional antennae or with an array of antennae.

The advantages of AOA are that a position estimate may be determined with as few as three measuring units for 3-D positioning or two measuring units for 2-D positioning, and that no time synchronization between measuring units is required. The disadvantages include relatively large and complex hardware requirement(s), and location estimate degradation as the mobile target moves farther from the measuring units. For accurate positioning, the angle measurements need to be accurate, but the high accuracy measurements in wireless networks may be limited by shadowing, by multipath reflections arriving from misleading directions, or by the directivity of the measuring aperture. Some literatures also call AOA as direction of arrival (DOA). For more detailed discussions on AOA estimation algorithms and their properties, see [11]–[13].

B. Scene Analysis

RF-based scene analysis refers to the type of algorithms that first collect features (fingerprints) of a scene and then estimate the location of an object by matching online measurements with the closest *a priori* location fingerprints. RSS-based location fingerprinting is commonly used in scene analysis.

Location fingerprinting refers to techniques that match the *fingerprint* of some characteristic of a signal that is location dependent. There are two stages for location fingerprinting: offline stage and online stage (or run-time stage). During the offline stage, a site survey is performed in an environment. The location coordinates/labels and respective signal strengths from nearby base stations/measuring units are collected. During the online stage, a location positioning technique uses the currently observed signal strengths and previously collected information to figure out an estimated location. The main challenge to the techniques based on location fingerprinting is that the received signal strength could be affected by diffraction, reflection, and scattering in the propagation indoor environments.

There are at least five location fingerprinting-based positioning algorithms using pattern recognition technique so far: probabilistic methods, k-nearest-neighbor (kNN), neural networks, support vector machine (SVM), and smallest M-vertex polygon (SMP).

1) Probabilistic Methods: One method considers positioning as a classification problem. Assuming that there are n location candidates $L_1, L_2, L_3, \ldots, L_n$, and s is the observed signal strength vector during the online stage, the following *decision rule* can be obtained:

$$\text{Choose } L_i \text{ if } P(L_i|s) > P(L_j|s), \quad \text{for } i,\ j = 1, 2, 3, \ldots, n, \quad j \neq i.$$

Here, $P(L_i|s)$ denotes the probability that the mobile node is in location L_i, given that the received signal vector is s. Also assume that $P(L_i)$ is the probability that the mobile node is in location L_i. The given decision rule is based on *posteriori* probability. Using Bayes' formula, and assuming that $P(L_i) = P(L_j)$ for $i, j = 1, 2, 3, \ldots, n$ we have the following decision rule based on the likelihood that ($P(s|L_i)$ is the probability that the signal vector s is received, given that the mobile node is located in location L_i)

$$\text{Choose } L_i \text{ if } P(s|L_i) > P(s|Lj), \quad \text{for } i,\ j = 1, 2, 3, \ldots, n, \quad j \neq i.$$

In addition to the histogram approach, kernel approach is used in calculating likelihood. Assuming that the likelihood of each location candidate is a Gaussian distribution, the mean and standard deviation of each location candidate can be calculated. If the measuring units in the environment are independent, we can calculate the overall likelihood of one location candidate by directly multiplying the likelihoods of all measuring units. Therefore, the likelihood of each location candidate can be calculated from observed signal strengths during the online stage, and the estimated location is to be decided by the previous decision rule. However, this is applicable only for discrete location candidates. Mobile units could be located at any position, not just at the discrete points. The estimated 2-D location $(\hat{x}, \hat{y})$ given by (5) may interpolate the position coordinates and give more accurate results. It is a weighted average of the coordinates of all sampling locations

$$(\hat{x}, \hat{\mathrm{y}}) = \sum_{i=1}^{n} \left(\mathrm{P}(L_{\mathrm{i}}|s)(x_{L_i}, y_{L_i})\right). \tag{5}$$

Other probabilistic modeling techniques for location-aware and location-sensitive applications in wireless networks may involve pragmatically important issues like calibration, active learning, error estimation, and tracking with history. So Bayesian-network-based and/or tracking-assisted positioning has been proposed [48].

2) kNN: The kNN averaging uses the online RSS to search for k closest matches of known locations in signal space from the previously-built database according to root mean square errors principle. By averaging these k location candidates with or without adopting the distances in signal space as weights, an estimated location is obtained via weighted kNN or unweighted kNN. In this approach, k is the parameter adapted for better performance.

3) Neural Networks: During the offline stage, RSS and the corresponding location coordinates are adopted as the inputs and the targets for the training purpose. After training of neural networks, appropriate weights are obtained. Usually, a multilayer perceptron (MLP) network with one hidden layer is used for neural-networks-based positioning system. The input vector of signal strengths is multiplied by the trained input weight matrix, and then added with input layer bias if bias is chosen. The result is put into the transfer function of the hidden layer neuron. The output of this transfer function is multiplied by the trained hidden layer weight matrix, and then added to the hidden layer bias if it is chosen. The output of the system is a two-element vector or a three-elements vector, which means the 2-D or 3-D of the estimated location.

4) SVM: SVM is a new and promising technique for data classification and regression. It is a tool for statistical analysis and machine learning, and it performs very well in many classification and regression applications. SVMs have been used extensively for a wide range of applications in science, medicine, and engineering with excellent empirical performance [15], [16]. The theory of SVM is found in [17] and [18]. Support vector classification (SVC) of multiple classes and support vector regression (SVR) have been used successfully in location fingerprinting [19], [20].

5) SMP: SMP uses the online RSS values to search for candidate locations in signal space with respect to each signal transmitter separately. M-vertex polygons are formed by choosing at least one candidate from each transmitter (suppose total of M transmitters). Averaging the coordinates of vertices of the smallest polygon (which has the shortest perimeter) gives the location estimate. SMP has been used in MultiLoc [74].

C. Proximity

Proximity algorithms provide symbolic relative location information. Usually, it relies upon a dense grid of antennas, each having a well-known position. When a mobile target is detected by a single antenna, it is considered to be collocated with it. When more than one antenna detects the mobile target, it is considered to be collocated with the one that receives the strongest signal. This method is relatively simple to implement. It can be implemented over different types of physical media. In particular, the systems using infrared radiation (IR) and radio frequency identification (RFID) are often based on this method. Another example is the cell identification (Cell-ID) or cell of origin (COO) method. This method relies on the fact that mobile cellular networks can identify the approximate position of a mobile handset by knowing which cell site the device is using at a given time. The main benefit of Cell-ID is that it is already in use today and can be supported by all mobile handsets.

III. Performance Metrics

It is not enough to measure the performance of a positioning technique only by observing its accuracy. Referring to [21] and considering the difference between the indoor and outdoor wireless geolocation, we provide the following performance benchmarking for indoor wireless location system: accuracy, precision, complexity, scalability, robustness, and cost. Thereafter, we make a comparison among different systems and solutions in Section IV.

A. Accuracy

Accuracy (or location error) is the most important requirement of positioning systems. Usually, mean distance error is adopted as the performance metric, which is the average Euclidean distance between the estimated location and the true location. Accuracy can be considered to be a potential bias, or systematic effect/offset of a positioning system. The higher the accuracy, the better the system; however, there is often a tradeoff between accuracy and other characteristics. Some compromise between "suitable" accuracy and other characteristics is needed.

B. Precision

Accuracy only considers the value of mean distance errors. However, location precision considers how consistently the system works, i.e., it is a measure of the robustness of the positioning technique as it reveals the variation in its performance over many trials. We also notice that some literatures define the location precision as the standard deviation in the location error or the geometric dilution of precision (GDOP), but we prefer it as the distribution of distance error between the estimated location and the true location.

Usually, the cumulative probability functions (CDF) of the distance error is used for measuring the precision of a system. When two positioning techniques are compared, if their accuracies are the same, we prefer the system with the CDF graph, which reaches high probability values faster, because its distance error is concentrated in small values. In practice, CDF is described by the percentile format. For example, one system has a location precision of 90% within 2.3 m (the CDF of distance error of 2.3 m is 0.9), and 95% within 3.5 m; another one has a precision of 50% within 2.3 m and 95% within 3.3 m. We could choose the former system because of its higher precision.

C. Complexity

Complexity of a positioning system can be attributed to hardware, software, and operation factors. In this paper, we emphasize on software complexity, i.e., computing complexity of the positioning algorithm. If the computation of the positioning algorithm is performed on a centralized server side, the positioning could be calculated quickly due to the powerful processing capability and the sufficient power supply. If it is carried out on the mobile unit side, the effects of complexity could be evident. Most of the mobile units lack strong processing power and long battery life; so, we would prefer positioning algorithms with low complexity. Usually, it is difficult to derive the analytic complexity formula of different positioning techniques; thus, the computing time is considered. Location rate is an important indicator for complexity. The dual of location rate is location lag, which is the delay between a mobile target moving to a new location and reporting the new location of that target by the system.

D. Robustness

A positioning technique with high robustness could function normally even when some signals are not available, or when some of the RSS value or angle character are never seen before. Sometimes, the signal from a transmitter unit is totally blocked, so the signal cannot be obtained from some measuring units. The only information to estimate the location is the signal from other measuring units. Sometimes, some measuring units could be out of function or damaged in a harsh environment. The positioning techniques have to use this incomplete information to compute the location.

E. Scalability

The scalability character of a system ensures the normal positioning function when the positioning scope gets large. Usually, the positioning performance degrades when the distance between the transmitter and receiver increases. A location system may need to scale on two axes: geography and density. Geographic scale means that the area or volume is covered. Density means the number of units located per unit geographic area/space per time period. As more area/space is covered or units are crowded in an area/space, wireless signal channels may become congested, more calculation may be needed to perform location positioning, or more communication infrastructure may be required. Another measure of scalability is the dimensional space of the system. The current system can locate the objects in 2-D or 3-D space. Some systems can support both 2-D and 3-D spaces.

F. Cost

The cost of a positioning system may depend on many factors. Important factors include money, time, space, weight, and energy. The time factor is related to installation and maintenance. Mobile units may have tight space and weight constraints. Measuring unit density is considered to be a space cost. Sometimes, we have to consider some sunk costs. For example, a positioning system layered over a wireless network may be considered to have no hardware cost if all the necessary units of that network have already been purchased for other purposes. Energy is an important cost factor of a system. Some mobile units (e.g., electronic article surveillance (EAS) tags and passive RFID tags, which are addressed later) are completely energy passive. These units only respond to external fields and, thus, could have an unlimited lifetime. Other mobile units (e.g., devices with rechargeable battery) have a lifetime of several hours without recharging.

IV. Survey of Systems and Solutions

Having identified the common measuring principles, the positioning algorithms and the important performance metrics of location positioning systems, we are able to discuss specific systems. 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 measuring units focused primarily on wireless location application. The second approach is to use an existing wireless network infrastructure to locate a target. The advantage of the first approach is that the designers are able to control physical specification and, consequently, the quality of the location sensing results. The tag with the target can be designed as a very small wearable tag or sticker, and the density of the sensor can be adjusted to the required positioning accuracy. The advantage of the second approach is that it avoids expensive and time-consuming deployment of infrastructure. These systems, however, may need

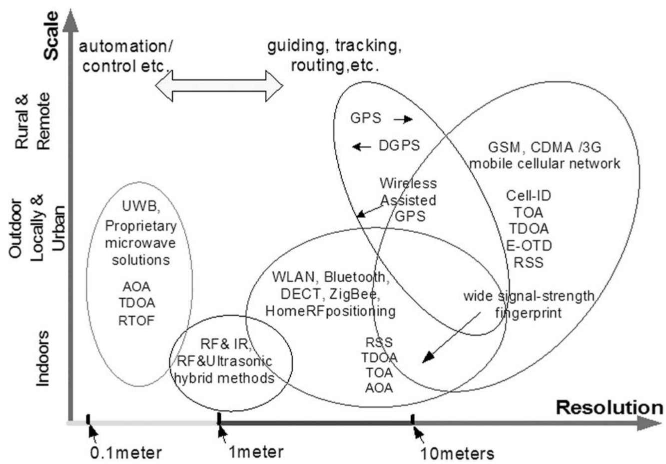

Fig. 6. Outline of current wireless-based positioning systems.

to use more intelligent algorithms to compensate for the low accuracy of the measured metrics. Several types of wireless technologies are used for indoor location. Fig. 6 depicts a rough outline of the current wireless-based positioning systems, which is a modified version of [24, Fig. 2]. It is beyond the scope of this paper to provide a complete overview of systems available till now. We focus on the wireless positioning systems primarily for indoor situations. There are some classification approaches to surveying the indoor positioning system, such as application environments (such as 2-D/3-D positioning in office, warehouse, etc.), positioning algorithms, and wireless technologies. In this paper, we adopt the wireless technologies scheme, also addressing their positioning algorithms and their application situation.

A. GPS-Based

Global positioning system (GPS), or its differential complement DGPS [25], is one of the most successful positioning systems in outdoor environments. However, poor coverage of satellite signal for indoor environments decreases its accuracy and makes it unsuitable for indoor location estimation.

SnapTrack,[1] a Qualcomm Company, pioneered wireless assisted GPS (A-GPS) to overcome the limitations of conventional GPS, and provide GPS indoors technique with an average of 5–50 m accuracy in most indoor environments. A-GPS technology uses a location server with a reference GPS receiver that can simultaneously detect the same satellites as the wireless handset (or mobile station) with a partial GPS receiver, to help the partial GPS receiver find weak GPS signals. The wireless handset collects measurements from both the GPS constellation and the wireless mobile network. These measurements are combined by the location server to produce a position estimation.

Recently, Atmel[2] and U-blox[3] announced the availability of a new GPS weak signal tracking technology, called SuperSense. With this new GPS software, GPS navigation becomes possible in building interiors and deep urban canyons because of its tracking sensitivity beyond -158 dBm[4] . Its performance is not reported so far.

Locata Corporation has invented a new positioning technology called *Locata* [26], for precision positioning both indoors and outside. Part of the "Locata technology" consists of a time-synchronized pseudolite transceiver called a LocataLite. A network of LocataLites forms a LocataNet, which transmits GPS-like signals that allow single-point positioning using carrier-phase measurements for a mobile device (a *Locata*). The Satellite Navigation And Positioning (SNAP) Group at the University of New South Wales has assisted in the development of a *Locata* and testing of the new technology. The test experiments demonstrate proof-of-concept for the "Locata technology," and show that carrier-phase point positioning (without radio modem data links) is possible with subcentimeter precision [26].

B. RFID

RFID is a means of storing and retrieving data through electromagnetic transmission to an RF compatible integrated circuit and is now being seen as a means of enhancing data handling processes [27]. An RFID system has several basic components, including a number of RFID readers, RFID tags, and the communication between them. The RFID reader is able to read the data emitted from RFID tags. RFID readers and tags use a defined RF and protocol to transmit and receive data. RFID tags are categorized as either passive or active.

Passive RFID tags operate without a battery. They are mainly used to replace the traditional barcode technology and are much lighter, smaller in volume, and less expensive than active tags. They reflect the RF signal transmitted to them from a reader and add information by modulating the reflected signal. However, their ranges are very limited. The typical reading range is 1–2 m, and the cost of the readers is relatively high. Passive RFID systems usually make use of four frequency bands: LF (125 kHz), HF (13.56 MHz), UHF (433, 868–915 MHz), and microwave frequency (2.45 GHz, 5.8 GHz).[20] Bewator[5] is a known passive RFID manufacturer.

Active RFID tags are small transceivers, which can actively transmit their ID (or other additional data) in reply to an interrogation. Frequency ranges used are similar to the passive RFID case except the low-frequency and high-frequency ranges. The advantages of active RFID are with the smaller antennae and in the much longer range (can be tens of meters). Active tags are ideally suited for the identification of high-unit-value products moving through a harsh assembly process. WaveTrend Technologies[6] is one of the famous Active RFID manufacturers. A well-known location sensing system using the RFID technology is SpotON [28]. SpotON uses an aggregation algorithm for 3-D location sensing based on radio signal strength analysis. SpotON researchers designed and built hardware that serves as object location tags. In the SpotON approach, objects are located by homogenous sensor nodes without central control, i.e., Ad Hoc manner. SpotON tags use received RSS value as

[1]SnapTrack. http://www.snaptrack. com/
[2]Atmel Corporation. http://www.atmel. com/
[3]U-blox AG. http://www.u-blox. com
[4]Atmel/U-blox. http://www.automotivedesignline.com/products/164901239
[5]Bewator Ltd. http://www.bewator.com/uk/
[6]WaveTrend Technologies Ltd. http://www.wavetrend. co.za/

a sensor measurement for estimating inter-tag distance. They exploit the density of tags and correlation of multiple measurements to improve both accuracy and precision. Another system is called LANDMARC (indoor location sensing using active RFID) [29]. Its prototype uses the RFID reader's operating frequency with 308 MHz. In order to increase accuracy without placing more readers, the system employs the idea of having extra fixed location reference tags to help location calibration. These *reference tags* serve as reference points in the system. The LANDMARC approach requires signal strength information from each tag to readers. The kNN method is adopted to calculate the location of the RFID tags. It is reported that the 50 percentile has an error distance of around 1 m while the maximum error distances are less than 2 m for LANDMARC system.

C. Cellular-Based

A number of systems have used global system of mobile/code division multiple access (GSM/CDMA) mobile cellular network to estimate the location of outdoor mobile clients. However, the accuracy of the method using cell-ID or enhanced observed time difference (E-OTD) is generally low (in the range of 50–200 m), depending on the cell size. Generally speaking, the accuracy is higher in densely covered areas (e.g, urban places) and much lower in rural environments [30].

Indoor positioning based on mobile cellular network is possible if the building is covered by several base stations or one base station with strong RSS received by indoor mobile clients. Otsasen *et al.* presented a GSM-based indoor localization system in [31]. Their key idea that makes accurate GSM-based indoor localization possible is the use of *wide signal-strength fingerprints*. The wide fingerprint includes the six strongest GSM cells and readings of up to 29 additional GSM channels, most of which are strong enough to be detected but too weak to be used for efficient communication. The higher dimensionality introduced by the additional channel dramatically increases localization accuracy. They present results for experiments conducted on signal-strength fingerprints collected from three multifloor buildings using weighted kNN technique. The results show that their indoor localization system can differentiate between floors and achieve median within-floor accuracy as low as 2.5 m. The same method could be applied in IS-95 CDMA and 3G mobile network.

D. UWB

UWB is based on sending ultrashort pulses (typically $<$1 ns), with a low duty cycle (typically 1 : 1000). On the spectral domain, the system, thus, uses an UWB (even $>$500 MHz wide). UWB location has the following advantages [32]. Unlike conventional RFID systems, which operate on single bands of the radio spectrum, UWB transmits a signal over multiple bands of frequencies simultaneously, from 3.1 to 10.6 GHz. UWB signals are also transmitted for a much shorter duration than those used in conventional RFID. UWB tags consume less power than conventional RF tags and can operate across a broad area of the radio spectrum. UWB can be used in close proximity to other RF signals without causing or suffering from interference because of the differences in signal types and radio spectrum used. UWB short duration pulses are easy to filter in order to determine which signals are correct and which are generated from multipath. At the same time, the signal passes easily through walls, equipment and clothing. However metallic and liquid materials cause UWB signal interference. Use of more UWB readers and strategic placement of UWB readers could overcome this disadvantage. Short-pulse waveforms permit an accurate determination of the precise TOA and, namely, the precise TOF of a burst transmission from a short-pulse transmitter to a corresponding receiver [33], [32]. UWB location exploits the characteristics of time synchronization of UWB communication to achieve very high indoor location accuracy (20 cm). So it is suitable for high-precision real-time 2-D and 3-D location. 3-D location positioning can be performed by using two different measuring means: TDOA, which is measuring the time difference between a UWB pulse arriving at multiple sensors, and AOA. The advantage of using both means in conjunction is that a location can be determined from just two sensors decreasing the required sensor density over systems that just use TDOA. More UWB knowledge and products are given in[7] and their related references.

To date, several UWB precision localization systems have been fielded [34].[8,9,10] The Ubisense system[8] is a unidirectional UWB location platform with a conventional bidirectional time division multiple access (TDMA) control channel. The tags transmit UWB signals to networked receivers and are located using AOA and TDOA. Ubisense works by creating sensor cells. Each cell requires at least four sensors or readers. Throughout buildings or collections of buildings, an unlimited number of readers can be networked together in a manner similar to cellular phone networks. The readers receive data from the tags, from as far as 150 ft, and send it through the Ubisense Smart Space software platform.

Microwave frequency, covered by the UWB frequency band, is used in Siemens local position radar (LPR) [24]. Siemens LPR is an RTOF system, in which the RTOF between a transponder unit and measuring units/base stations is measured via the frequency modulated continuous wave (FMCW) radar principle. It was launched for industrial applications like crane and forklift positioning. It is applicable only for LOS environment.

E. WLAN (IEEE 802.11)

This midrange wireless local area network (WLAN) standard, operating in the 2.4-GHz Industrial, Scientific and Medical (ISM) band, has become very popular in public hotspots and enterprise locations during the last few years. With a typical gross bit rate of 11, 54, or 108 Mbps and a range of 50–100 m, IEEE 802.11 is currently the dominant local wireless networking standard. It is, therefore, appealing to use an existing WLAN infrastructure for indoor location as well, by adding a location

[7]Intel Corporation. http://www.intel.com/technology/comms/uwb/. And Ultrawideband planet: http://www.ultrawidebandplanet.com

[8]UbiSense Company. http://www.ubisense.net

[9]Aether Wire & Location, Inc. http://www.aetherwire.com

[10]Time Domain Company. http://www.timedomain.com

server. The accuracy of typical WLAN positioning systems using RSS is approximatly 3 to 30 m, with an update rate in the range of few seconds.

Bahl *et al.* [35] proposed an in-building user location and tracking system—RADAR, which adopts the nearest neighbor(s) in signal-space technique, which is the same as the kNN. The authors proposed two kinds of approaches to determine the user location. The first one depends on the empirical measurement of access point signal strength in offline phase. By these experiments, it is reported that user orientations, number of nearest neighbors used, number of data points, and number of samples in real-time phase would affect the accuracy of location determination. The second one is signal propagation modeling. Wall attenuation factor (WAF) and floor attenuation factor (FAF) propagation model is used, instead of Rayleigh fading model and Rician distribution model, which are used in outdoor situation. WAF takes into consideration the number of walls (obstructions). The accuracy of RADAR system is about 2–3 m. In their following work [36], RADAR was enhanced by a Viterbi-like algorithm. Its result is that the 50 percentile of the RADAR system is around 2.37–2.65 m and its 90 percentile is around 5.93–5.97 m.

Horus system [37], [38] offered a joint clustering technique for location estimation, which uses the probabilistic method described previously. Each candidate location coordinate is regarded as a class or category. In order to minimize the distance error, location L_i is chosen while its likelihood is the highest. The experiment results show that this technique can acquire an accuracy of more than 90% to within 2.1 m. Increasing the number of samples at each sampling location could improve its accuracy because increasing the number of samples would improve the estimation for means and standard deviations of Gaussian distribution. Roos *et al.* [39] developed a grid-based Bayesian location-sensing system over a small region of their office building, achieving localization and tracking to within 1.5 m over 50% of the time. Nibble [40], one of the first systems of this generation, used a probabilistic approach (based on Bayesian network) to estimate a device's location.

In [41], Battiti *et al.* proposed a location determination method by using neural-network-based classifier. They adopted multilayer perceptron (MLP) architecture and one-step secant (OSS) training method. They chose the three-layer architecture with three input units, eight hidden layer units, and two outputs, since this architecture could acquire the lowest training and testing error, and it is less sensitive to the "overfitting" effect. They reported that only five samples of signal strengths in different locations are sufficient to get an average distance error of 3 m. Increasing the number of training examples helps decrease the average distance error to 1.5 m. The authors in [42] compared the neural-networks-based classifier with the nearest neighbor classifier and probabilistic method. It is reported in [42] that neural networks give an error of 1 m with 72% probability.

Wireless location-sensing is actually a specialized case of a well-studied problem in mobile robotics, that of robot localization—determining the position of a mobile robot given inputs from the robot's various sensors (possibly including GPS, sonar, vision, and ultrasound sensors). Robot-based or tracking-assisting wireless localization has been studied by many researchers [43]. Ladd *et al.* [44], [45] propose a grid-based Bayesian robot localization algorithm that uses the IEEE 802.11 infrastructure. In the first step of the algorithm, a host uses a probabilistic model to compute the likelihood of its location for a number of different locations, based on the RSS from nine APs. The second step exploits the limited maximum speed of mobile users to refine the results (of the first step) and reject solutions with significant change in the location of the mobile host. Depending on whether the second step is used or not, 83% and 77% of the time, hosts can predict their location within 1.5 m. Haeberlen *et al.* [46] presented a practical robust Bayesian method for topological localization over the entirety of an 802.11 network deployed within a multistorey office building. They have shown that the use of a topological model can dramatically reduce the time required to train the localizer, while the resulting accuracy is still sufficient for many location-aware applications. Siddiqi *et al.* [47] used Monte Carlo localization technique, and obtained similar result to that of [44]. Kontkanen *et al.* also introduced a tracking-assistant positioning system [48]. This system was used to develop the Ekahau system,[11] a commercial wireless location-sensing system that combines Bayesian networks, stochastic complexity and online competitive learning, to provide positioning information through a central location server. In [49], Xiang *et al.* proposed a model-based signal propagation distribution training scheme and a tracking-assistant positioning algorithm in which a state machine is used to adaptively transfer between tracking and nontracking status to achieve more accuracy. This system is reported to achieve 2 m accuracy with 90% probability for static position determination. For a walking mobile device, 5 m accuracy with 90% probability is achieved.

While most systems based on WLAN are using signal strength, AeroScout (formerly BlueSoft) [50] uses 802.11-based TDOA location solution. It requires the same radio signal to be received at three or more separate points, timed very accurately (to a few nanoseconds) and processed using the TDOA algorithm to determine the location.

There are several other location systems using WLAN [7], [51]–[54]. For space limitations, we do not discuss their details here.

F. Bluetooth (IEEE 802.15)

Bluetooth operates in the 2.4-GHz ISM band. Compared to WLAN, the gross bit rate is lower (1 Mbps), and the range is shorter (typically 10–15 m). On the other hand, Bluetooth is a "lighter" standard, highly ubiquitous (embedded in most phones, personal digital assistants (PDAs), etc.) and supports several other networking services in addition to IP. Bluetooth tags are small size transceivers. As any other Bluetooth device, each tag has a unique ID. This ID can be used for locating the Bluetooth tag. [74]. The BlueTags tag is a typical Bluetooth tag.[12]

[11] Ekahau, Inc. Ekahau Positioning Engine 2.0. http://www.ekahau.com/
[12] Bluelon Company. www.bluetags. com

The **Topaz** local positioning solution[13]is based on Tadlys' Bluetooth infrastructure and accessory products. This modular positioning solution is made up of three types of elements: positioning server(s), wireless access points, and wireless tags. The system's performance makes it suitable for tracking humans and assets. This system provides roomwise accuracy (or, alternatively, 2-m spatial accuracy), with 95% reliability. The positioning delay is 15–30 s. The performance is further enhanced in their new generation **Topaz** system that integrates infrared and other transducers, with the Bluetooth positioning and communication capabilities.

Antti *et al.* present the design and implementation of a Bluetooth Local Positioning Application (BLPA) [55]. First, they convert the received signal power levels to distance estimates according to a simple propagation model, and then, they use the extended kalman filter (EKF) to compute 3-D position estimate on the basis of distance estimates. The accuracy of BLPA is reported to be 3.76 m. A similar work has been done by Hallberg *et al.* [56].

G. Others

1) Proprietary Solutions Using Ultra High Frequency (UHF): The UHF location systems operate, typically either at the 433-MHz band (medical telemetry) or at the 868-MHz and 2.4-GHz ISM band. At such frequency ranges, walls have a moderate attenuation.

Some proprietary solutions such as the 3-D-ID system from PinPoint [57] or the TDOA system from WhereNet[14] have similar performance as the WLAN systems mentioned later. However, the specially designed hardware and a protocol with longer power down periods allows for minimal power consumption in the mobile. For example, WhereNet, a real-time locating system (RTLS), uses the same 2.4 GHz band as the IEEE 802.11 and Bluetooth systems, but it uses a dedicated standard protocol (ANSI 371.1) optimized for low-power spread-spectrum location. It works by timing the signals transmitted from tags to a network of receivers. 3D-ID is a commercial location system produced by PinPoint. Pinpoint uses RTOF to do ranging. It uses an installed array of antennas at known positions to perform multilateration. When a mobile tag receives a broadcast, the tag immediately rebroadcasts it on a different frequency, modulated with the tag's identifier. A cell controller cycles through the antennas, collecting a set of ranges to the tag. Using a 40 MHz signal, this system achieves a 30-m range, 1-m precision, and 5-s location update rate.

Commercial indoor positioning systems using mesh network techniques such as MeshNetwork positioning system (MPS)[15] are also worth to mention. The MPS technology leverages the patented position location and determination methods built into MeshNetwork Quadrature Division Multiple Access (QDMA) radio technology, which uses direct sequence spread spectrum (DSSS) and operates in the ISM 2.4-GHz bands. It is reported that MPS position location information, accurate to within 10 m, is generated in less than 1 s at mobility speeds of up to 200 mi/h.

2) Positioning Using Multiple Media: Designing a location system for a single environment presents difficulties when the system is applied to other environments. To successfully bridge the differences among different types of sensors and overcome the limitations of a single type of positioning sensor, hybrid systems attempt to compensate for the shortcomings of a single technology by using multiple sensor types. HP Labs SmartLOCUS [58] uses synchronized RF and ultrasound differential time-of-flight measurements to determine the internodal range between any two nodes. HP Labs researchers developed several techniques to create relative coordinate geometries with little user intervention. To create an absolute frame of reference and tie internodal topology to building geometry, a minimum of three or four nodes (for 2-D or 3-D localizations) must be preassigned to suitable fixed locations. All the remaining nodes are free to move, and locations are continuously updated and known to the rest of the system. The well-known cricket indoor location system also uses RF and ultrasound media [59].

Infrared Radiation (IR) wireless is the use of wireless technology in devices or systems that convey data through infrared radiation. IR is used in wireless personal area network (WPAN) since it is a short-range narrow-transmission-angle beam suitable for aiming and selective reception of signals. Most of the Infrared Data Association (IrDA) wireless system is based on the LOS mode. Considering the high room accuracy of the IR location [60], and the high availability of the UHF location, it makes sense to combine the two methods into a hybrid location system. Several other companies like Radianse[16] and Versus[17] use a combination of RF and IR signals to perform location positioning. Their tags emit IR and RF signals containing a unique identifier for each person or asset being tracked. The use of RF allows coarse-grain positioning (e.g., floor) while the IR signals provide additional resolution (e.g., room). The EIRIS local positioning system[18] uses an IRFID triple technology that combines IR, RF (UHF), and LF (RF low-frequency transponder) signals. It combines the advantages of each technology, i.e., the room location of IR, the wide range of RF, and the tailored range sensitivity of LF. However, comparing to RF and IR hybrid system, it could be more costly.

3) Positioning Using Cordless Phone System: Cordless phone system is a modern wireless communication infrastructure. Schwaighofer *et al.* [61] used digital enhanced cordless telecommunications (DECT) cellular network to solve the indoor positioning problem. They used Gaussian process (GP) algorithm to calculate the phone location based on the RSS of phones in the DECT network. They showed that their Gaussian process positioning system (GPPS) can provide sufficient accuracy of 7.5 m when used within a DECT network. They also used kNN to compare with the GP method, and showed that kNN can reach an accuracy of 7 m for DECT cellular network.

[13]Topaz local positioning solution. http://www.tadlys.com
[14]WhereNet Company. http://www.wherenet.com/
[15]MPS. http://mesh.nowwireless.com/index.htm
[16]Radianse, Inc. Radianse Indoor Positioning. http://www.radianse.com
[17]Versus Technology. http://www.versustech.com
[18]EIRIS System. http://www.elcomel.com.ar/english/eiris.htm

TABLE I
WIRELESS-BASED INDOOR POSITIONING SYSTEM AND SOLUTION

System/ Solution	Wireless technologies	Positioning algorithm	Accuracy	Precision	Complexity	Scalability/ Space dimension	Robust-ness	Cost
Microsoft RADAR [35, 36]	WLAN, Received Signal Strength (RSS)	*K* NN, Viterbi-like algorithm	3~5m	50%within around 2.5 m and 90% within around 5.9 m	Moderate	Good /2D,3D	Good	Low
Horus [37,38]	WLAN RSS	Probabilistic method	2m	90% within 2.1m	Moderate	Good/2D	Good	Low
DIT [41, 19]	WLAN RSS	MLP, SVM, etc.	3m	90% within 5.12m for SVM; 90% within 5.40m for MLP	Moderate	Good/2D,3D	Good	Low
Ekahau[11]	WALN RSSI	Probabilistic method (Tracking-assistant)	1m	50% within 2m	Moderate	Good/2D	Good	Low
SnapTrack[1]	Assisted GPS, TDOA		5m-50m	50% within 25m	High	Good/2D,3D	Poor	Medium
WhereNet[14]	UHF TDOA	Least Square/ RWGH	2-3m	50% within 3m	Moderate	Very good / 2D,3D	Good	Low
Ubisense[8]	unidirectional UWB TDOA+ AOA	Least Square	15cm	99% within 0.3m	Real time response (1Hz – 10 Hz)	2-4 sensors per cell (100-1000m); 1 UbiTag per object /2D,3D	Poor	Medium to High
Sappire Dart[19]	unidirectional UWB TDOA	Least Square	<0.3m	50% within 0.3m	response frequency (0.1Hz – 1Hz)	Good/2D, 3D	Poor	Medium to High
SmartLOCUS [58]	WLAN(RSS) + Ultrasound(RTOF)	N/A	2-15cm	50% within 15cm	Medium	Good/2D	Good	Medium to High
EIRIS[18]	IR + UHF (RSS) + LF	Based on PD	<1m	50% within 1m	Medium to High	Good/2D	Poor	Medium to High
SpotON [28]	Active RFID RSS	Ad-Hoc lateration	Depends on cluster size	N/A	Medium	Cluster at least 2 Tags/2D	Good	Low
LANDMARC [29]	Active RFID RSS	KNN	<2m	50% within 1m	Medium	Nodes placed densely	Poor	Low
TOPAZ [13]	Bluetooth (RSS) + IR	Based on PD	2m	95% within 2m	positioning delay 15-30s	Nodes placed every 2-15 m	Poor	Medium
MPS[15]	QDMA	Ad-Hoc lateration	10m	50% within 10m	1s	Excellent/2D,3D	Good	Medium
GPPS[61]	DECT cellular system	Gaussian process (GP), *k*NN	7.5 m for GP; 7 m for *k*NN	50% within 7.3m	Medium	Good/2D	Good	Medium
Robot-based[44, 46, 49]	WLAN (RSS)	Bayesian approach	1.5 m	Over 50% within 1.5m	Medium	Good/2D	Good	Medium
MultiLoc [74]	WLAN (RSS)	SMP	2.7 m	50% within 2.7m	Low	Good/2D	Good	Medium
TIX [75]	WLAN (RSS)	TIX	5.4 m	50% within 5.4m	Low	Good/2D	Good	Medium
PinPoint 3D-ID [57]	UHF (40MHz) (RTOF)	Bayesian approach	1 m	50% within 1m	5s	Good/2D,3D	Good	Low
GSM fingerprinting[31]	GSM cellular network (RSS)	Weighted *k*NN	5 m	80% within 10m	Medium	Excellent / 2D,3D	Good	Medium

The Locus system uses RSS and scene analysis to locate specific personal handyphone system (PHS) wireless devices [62]. Locus is overlaid on the basic PHS cellular service. To refine location beyond cell proximity, Locus uses a signal propagation model to account for some multipath effects. They report a mean error of 40–50 m.

4) Positioning Using Wireless Sensor Network Techniques: Dramatic advances in RF and microelectromechanical (MEMS) IC design have made possible the use of large networks of wireless sensors for a variety of new monitoring and control applications [63], [64]. Accurate and low-cost sensor localization is a critical requirement for the deployment of wireless sensor networks in a wide variety of applications, including indoor location positioning [65]. Such systems using wireless sensor network have been described as "cooperative," "relative," "multi-hop," "GPS-free," or "network" localization; "ad-hoc" or "sensor" positioning; and "self-localization" in various papers. Communication and measurements between many pairs of sensors are required to achieve localization for all sensors. We refer the readers to [14] for more details about cooperative localization. Up to now, two major sensor network standards are the IEEE 802.15.4 physical (PHY) layer and medium access control (MAC) layer standard for low-rate wireless personal-area networks (LR-WPANs), and the ZigBee networking and application layer standard [67]. These standards allow for localization information to be measured between pairs of sensors. In particular, RSS can be measured in the 802.15.4 PHY standard via the link quality indication (LQI), which reports the signal strength associated with a received packet to higher layers. Most of the sensor-network-based location estimations use RSS measurement [68], [69]. Some systems also use TOA measurement [68], [70]. Others take AOA measurement such as ad hoc positioning system (APS) [71].

Table I briefly compares the current systems and solutions. The systems solutions shown in this table are mainly the ones whose specifications have been reported by their developers. We have excluded the cases in which little or no information on them has been made available.

V. Conclusion and Future Trends

This paper surveys the current indoor positioning techniques and systems. Different performance measurement criteria are discussed and several tradeoffs among them are observed. For example, the one between complexity and accuracy/precision needs careful consideration when we choose positioning systems and techniques for different applications environments such as warehousing, robotics, or emergency. Usually, location fingerprinting scheme is better for open areas while Active RFID is suitable for dense environments. In terms of scalability and availability, these positioning techniques and systems have their own important characteristics when applied in real environments. The choice of technique and technology significantly affects the granularity and accuracy of the location information.

Future trends of wireless indoor positioning systems are as follows.

1) New or hybrid position algorithms are needed. A few of the works have already been started supporting such algorithms. For example, a calibration-free location algorithm based on triangulation, triangular interpolation and extrapolation (TIX), is introduced in [75]. A hybrid algorithm is presented in [76] for indoor positioning using WLAN that aims to combine the benefits of the RF propagation loss model and fingerprinting method. The same work has been done in [77]. The selective fusion location estimation (SELFLOC) [72] algorithm infers the user location by selectively fusing location information from multiple wireless technologies and/or multiple classical location algorithms in a theoretically optimal manner.
2) Internetworking of different wireless positioning systems is a research and practical topic in order to extend the positioning range.
3) Wireless combined with other technologies such as optical (e.g., IR), inertial, dc electromagnetic and ultrasonic for indoor location is another trend. How to combine these technologies into a practical system is a topic of sensor fusion.
4) How to deploy sensors to improve the positioning accuracy, how to finish deploying wireless positioning system in a short time, especially for emergency responder application is also worth considering [73].
5) Wireless indoor location using UWB (from 3.1 to 10.6 GHz) techniques[19] and indoor positioning using mobile cellular network are other promising research topics [31].
6) How to integrate indoor and outdoor positioning system is another area of research.[20] This integration may help in developing more efficient and robust detection systems for positioning of mobile computing nodes. In this case, a mobile node will be tracked indoor or outdoor using the same detection system.

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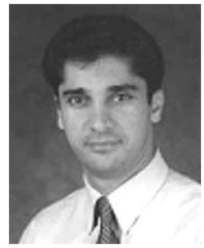

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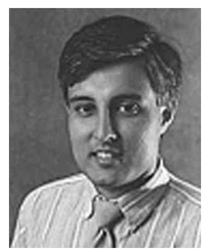

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