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Precise Indoor Positioning Using UWB: A Review of Methods, Algorithms and Implementations

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Abstract The demand and growth of indoor positioning has increased rapidly in the past few years for a diverse range of applications. Various innovative techniques and technologies have been introduced but precise and reliable indoor positioning still remains a challenging task due to dependence on a large number of factors and limitations of the technologies. Positioning technologies based on radio frequency (RF) have many advantages over the technologies utilizing ultrasonic, optical and infrared devices. Both narrowband and wideband RF systems have been implemented for short range indoor positioning/real-time locating systems. Ultra wideband (UWB) technology has emerged as a viable candidate for precise indoor positioning due its unique characteristics. This article presents a comparison of UWB and narrowband RF technologies in terms of modulation, throughput, transmission time, energy efficiency, multipath resolving capability and interference. Secondly, methods for measurement of the positioning parameters are discussed based on a generalized measurement model and, in addition, widely used position estimation algorithms are surveyed. Finally, the article provides practical UWB positioning systems and state-of-the-art implementations. We believe that the review presented in this article provides a structured overview and comparison of the positioning methods, algorithms and implementations in the field of precise UWB indoor positioning, and will be helpful for practitioners as well as for researchers to keep abreast of the recent developments in the field.

Keywords UWB · Positioning · RSSI · TOA · AOA

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1 Introduction

In the past few years, accuracy and reliability of indoor positioning have gained a great importance. For outdoor environments, the global positioning system (GPS) provides accurate positioning and maximum coverage; this is mainly because of an unobstructed line-of-sight (LOS) between the object and a satellite. Owing to the fact that signals of GPS cannot penetrate through buildings and that they are highly affected by indoor surroundings, GPS becomes impractical for many indoor environments. Thus alternative real-time locating systems (RTLS) are required to meet the demands of accurate indoor positioning. Position-based indoor systems find its numerous applications in factories and warehouses, hospitals, smart homes and high-security areas. Some examples of practical scenarios are finding tagged equipment in hospitals, locating lost people after a natural disaster such as earthquake and tracking of maintenance tools spread all over a plant. Moreover, Ambient Assistant Living (AAL) for elderly, location-based services at shopping malls, and context-awareness requirements of the devices are also emerging application scenarios.

For indoor positioning, accuracy requirements of different applications can vary significantly as sometimes even an accuracy of less than a foot is of interest. Depending upon varying requirements, many technologies for indoor positioning based on short range communication have been proposed and are also used in practice such as Ultrasonic ranging [1], Optical positioning [2], Infrared radiations [3], Inertial MEMS coupled with global navigational satellite system (GNSS) [4] and Radio frequency (RF) based positioning [5]. Infrared wireless devices operate in a LOS communication mode and are highly affected by the interference from fluorescent light, and are thus unsuitable for indoor environment. RF technology, on the other hand, does not incur these problems and is commonly used as it also provides large penetration power, coverage area and reduced hardware cost. RF-based positioning solutions utilizing Bluetooth, Wi-Fi, ZigBee, RFID and UWB technology are common and commercially available.

In order to implement an indoor positioning system for a specific application and environment, many aspects of these wireless technologies are taken into account for instance, the type of modulation technique it adopted for data transmission, energy efficiency of the system, throughput or channel capacity, transmission time and robustness of transmission technique to fading and interference. UWB based communication and positioning systems have become popular as UWB signals possess the capability of measuring accurate position up to centimeter level due to its high multipath resolution [6]. In addition, high speed data transmission can be achieved owing to the large bandwidth of UWB signals. In contrast, the limited channel capacity of narrowband systems leads to unreliability and poor signal quality. In 2002, the Federal Communications Commission (FCC) allowed deployment of UWB radio systems and also defined that a transmission system will be called a UWB system if it has an instantaneous spectral occupancy of 500 MHz or a fractional bandwidth of more than 20% [7, 8]. Impulse radio (IR) is a popular physical layer transmission technique that utilizes baseband UWB pulses of very short duration, typically on the order of nanoseconds [9]. A positioning system based on IR-UWB provides accuracy, low-complexity implementation and longer battery life making it a preferable and economical choice in many applications [10, 11].

In general, wireless positioning systems determine the position by employing a two-step position estimation approach. In the first step, certain parameters related to position of a target node of unknown position are determined with the help of some fixed nodes of known position. Among these position related parameters received signal strength indication (RSSI), time of arrival (TOA) and angle of arrival (AOA) are the most common ones [6, 12–14]. In the second step, certain algorithms utilize these position related parameters to provide an estimate of position of the target node. Positioning or localization of any unknown target node can be done either by a number of anchor nodes or by the target node itself. The latter technique requires a radio transceiver and a small battery or button cell along with the target node to achieve an active level of participation in the process of positioning that leads to a bulky and expensive system.

First, this article presents a comparison of indoor positioning based on UWB and narrowband technologies. The second objective of the article is to provide a review of UWB position estimation methods and algorithms that utilize different position estimation parameters. Third goal is to present state-of-the-art UWB positioning systems and successful implementations for different applications.

The rest of the article is organized as follows: Sect. 2 compares UWB technology with other wireless positioning technologies. In Sect. 3, an UWB signal model and a generalized measurement model are introduced. UWB positioning methods commonly used for parameter estimation are described in Sect. 4. Section 5 presents different algorithms for position estimation based on the estimated parameters. Practical implementations of UWB positioning systems are covered in Sect. 6. Finally, Sect. 7 presents the concluding remarks.

2 UWB for Indoor Positioning

In the following subsections, wireless positioning technologies are compared to establish the fact that UWB is a preferable technology for precise indoor positioning.

2.1 Multipath Resolution

In conventional narrow-band systems, receivers cannot resolve the multipath components (MPCs) of the signal arriving from various directions, rather it is considered as a single composite signal. In turn, all the indistinguishable multipath components on the receiver antenna result into signal fading such as Rayleigh, Rician or Nakagami-m fading [15]. Therefore, an indoor positioning system based on narrowband not only suffers from fading but also has a poor time-domain resolution. Conversely, UWB offers a realistic way of determining small time differences of the received signal, which is useful for applications that demand a high resolution. In a multipath environment, narrowband signals usually overlap while the UWB signals maintain their distinctiveness. If UWB signals are separated by atleast one pulse width duration, they will not overlap [16], as also illustrated in Fig. 1. Thus nanosecond-short UWB pulses work as multipath resistant because undesired multipath signals are drained out. In addition, the large bandwidth of a UWB system offers huge frequency diversity. The property of discontinuous transmission and frequency diversity not only make UWB signals resistant to severe multipath propagation but also protect against jamming [17].

2.2 Throughput

For a successful message delivery over any communication channel, parameters like channel capacity and coverage area are very important as limited channel capacity leads to unreliability and poor quality of signal. For a reliable communication in an AWGN

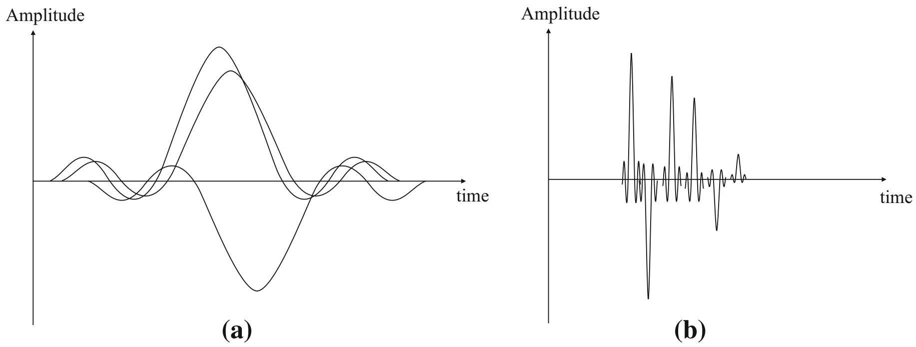

Fig. 1 An illustration of multipath resolution of **a** narrowband signal **b** UWB signal

channel, all systems are bound by the channel capacity theorem which states that the channel capacity of a continuous channel of bandwidth B Hz, perturbed by bandlimited Gaussian noise of power spectral density $N_o/2$, is given by [18],

$$C = B\log_2[1 + S/N], \tag{1}$$

where C is the channel capacity in bits/sec, B stands for bandwidth of the channel in Hz, S is the average transmitted signal power and $N = N_oB$ is the average noise power. Since the channel capacity is in a direct and logarithmic relation with bandwidth and SNR, respectively, narrow-band systems like Bluetooth and Zigbee offer very low channel capacity as compared to wide-band systems. According to Eq. 1, as the bandwidth of the system gets large for a given signal power, communication rates over a multipath fading channel approach the capacity of an infinite bandwidth additive white Gaussian channel of the same SNR without fading [22]. Moreover, the error correction techniques and packet retransmissions also require higher bandwidth for a fixed throughput, limited channel bandwidth prevents a system from implementing these techniques [19]. In contrary, UWB systems have sufficient bandwidth to accommodate essential error corrections and packet retransmissions and are thus well-suited for future high-capacity wireless systems [20].

2.3 Transmission Time

The transmission time is another important factor that depends on the data rate, the message size, and the distance between two nodes. The transmission time (usually in the order of microseconds) can be expressed as [21]:

$$T_{tx} = \left(N_d + (N_d/N_{mP} \times N_o)\right) \times T_b + T_{pr} \tag{2}$$

where N_d, N_{mP} and N_o are the data, maximum payload and the overhead size, respectively, whereas T_b and T_{pr} are the bit duration and signal propagation time, respectively. As the transmission time is inversely proportional to maximum data rate, transmission time for Zigbee technology is extensive in comparison to other short range wireless techniques; a comparison based on different parameters is also given in Table 1. Moreover, since Bluetooth transmission undergoes device discovery procedure, its transmission time increases due to significant raise in the latency time. Conversely, with high data rates and

Table 1 Comparison of wireless positioning technologies

	Bluetooth	Wi-Fi	ZigBee	UWB
Modulation	GFSK	BPSK, QPSK, COFDM, CCK, M-QAM	BPSK(+ASK), O-QPSK	PPM, PAM, BPSK, QPSK, OOK
Frequency band	2.4 GHz	2.4 GHz, 5 GHz	868/915 MHz, 2.4 GHz	3.1–10.6 GHz
Nominal range	10–100 m	30–100 m	10–100 m	10 m
Data rate	1 Mbps	11 Mbps	250 Kbps	110–400 Mbps
Spatial rate[a]	834	9183	203	91833
Transmission time	High	Moderate	High	Low
Energy consumption	Low	High	Very-low	Ultra-low

[a] Spatial rate is measured as bits per second per square meter, and here transmission distance is of 20 m

desirable data coding efficiency,[1] UWB systems surpass the other technologies. Moreover, an advantage of a conventional IR-UWB system is that the data rate and hence the transmission time can be reconfigured according to the desired BER [23].

2.4 Energy Efficiency

The term energy efficiency is, in fact, an umbrella term for many different aspects of a system, and it should be carefully distinguished to form actual, measurable figures of merit [24]. The figures of merit for energy efficiency may be capacity per unit cost and a long battery life support for energy efficient operation. In UWB systems, it is possible to increase the occupied bandwidth of the pulse or reduce the pulse repetition time, which in turn can increase the data rate and the transmission range. This factor is what allows UWB systems to operate at a very low average transmit power spectral density (PSD), while achieving useful data rates and transmission ranges [20]. Since UWB signals have low PSD, it has low probability of detection, which is of particular interest for certain military applications [16].

For low data rate systems, Bluetooth and ZigBee lead to longer battery lifetime owing to their low power consumption. On the other hand, Wi-Fi would be a better solution for high data rate implementations due to low normalized energy consumption of Wi-Fi [21]. Similarly, UWB systems are well-suited to fulfil the requirements of low energy consumption at low as well as sufficiently high data rates. The absence of heterodyning, tuning, and IF filtering in carrierless implementation of UWB leads toward simplified UWB transceivers with much simpler RF architectures than narrowband systems [25]. In addition to fewer components requirement, UWB low-power transmissions do not require a power amplifier [26].

2.5 Modulation Techniques

In general, higher order modulations may be employed to send more bits per symbol and thus achieve higher throughputs or better spectral efficiencies [27]. In UWB systems, data

[1] Coding efficiency is the ratio of data size to the number of bytes to transmit.

transmission may be achieved by digital pulse modulation of data bit stream instead of conventional analogue modulation techniques. In case of frequency modulated continuous wave (FMCW) system, the high resolution requirement of the system demands a large wideband linearity, which is not trivial to realize in practice [28]. The carrierless UWB baseband pulses result into a low complexity transceiver due to the absence of heterodyning, tuning, and IF filtering. Various traditional pulse modulation schemes like On-Off Keying (OOK), Binary Phase Shift Keying (BPSK), Pulse Position Modulation (PPM), Pulse Amplitude Modulation (PAM), and M-ary PAM are applicable to UWB systems. Since a higher order of modulation has a lower noise tolerance, a low order modulation such as antipodal signaling or BPPM is preferred for UWB systems.

2.6 Interference

Unlike narrow-band systems which operate on a single band of the radio spectrum, UWB signals may be transmitted simultaneously over multiple frequency bands [29]. The ultra-wide spectrum with a very low PSD makes it feasible to operate a UWB system in an environment where the spectrum is occupied by narrow-band systems. One of the technique employed for this purpose is based on detection and avoidance (DAA) method [30]. In this technique the UWB transmitter may first detect (detection is based on FFT) the presence of another active device as well as its likelihood of interference, and avoid that specific band. In case of multiple-access, UWB systems make it possible to increase the number of users for a given transmission capacity and bit error rates without increasing the transmitted power of each user [31]. For narrowband systems, coexistence mechanism is of great importance as Bluetooth, ZigBee and Wi-Fi all use the 2.4 GHz band. ZigBee technology is found to be susceptible to interference from a wide range of signal types using the same frequency which can disrupt radio communication because it operates in the unlicensed ISM bands [32, 33]. Due to noise like characteristics, UWB signal are also secure because low power and wide band reduces the chance of interception by unauthorized users. For a number of applications, the large bandwidth make it possible to simultaneously achieve both high data rates and a margin of processing gain [34].

As discussed in the above subsections, owing to its low cost, sub-meter accuracy and multipath resolving ability, UWB is a promising technology for precision indoor positioning.

3 UWB Signal and Measurement Model

For the positioning problem in wireless sensor networks, assuming a network assisted model that includes some fixed reference nodes, usually called anchor nodes (ANs) or base stations (BSs), which are used to determine the position of a target node (TN) often equipped with a transmitter. Let $s_{tx}(t)$ denotes the signal transmitted by *TN* that consists of a train of UWB pulses, i.e.,

$$s_{tx}(t) = \sum_{i=0}^{\infty} w(t - iT_f), \tag{3}$$

where $w(t)$ is waveform of UWB pulses and T_f is the pulse repetition period. The received signal in a single user scenario may be written as

$$r(t) = h(t) * s_{tx}(t) + n(t), \tag{4}$$

where $h(t) = \sum_{k=1}^{K} \beta_k \delta(t - \tau_k)$ is a model of the channel impulse response, $n(t)$ denotes noise, β_k and τ_k denote the amplitude and delay of the kth multipath component (MPC), respectively. The received signal can also be written as

$$r(t) = \sum_{i=0}^{\infty} \sum_{k=1}^{K} \beta_k w(t - \tau_k - iT_f) + n(t). \tag{5}$$

It is further assumed that the UWB signals are used by L anchor nodes (ANs) to estimate the position of the target node (TN). Mathematically, a generalized measurement model for different UWB positioning methods can be formulated. In a 2D positioning model, let (x, y) be the unknown $x-$ and $y-$coordinates of the TN and (x_l, y_l) be the known position of the lth AN, where $l = \{1, 2, \ldots, L\}$. Further, as the ANs measure certain parameters (i.e., TOA, AOA etc.) which are provided to the position estimation algorithm, let $\mathbf{r} = [r_1\, r_2 \ldots r_L]^T$ be the measurement vector obtained from the l ANs. The measurement model for different parameters can be written in a generalized form as

$$\mathbf{r} = \mathbf{f}(x, y) + \mathbf{n}, \tag{6}$$

where $\mathbf{f}(x, y) = [f_1(x, y), \ldots, f_l(x, y)]^T$ is generally a nonlinear function of the position of the target (x, y) and $\mathbf{n} = [n_1, \ldots, n_l]^T$ is an additive zero-mean noise vector. This generalized measurement model can be used by position estimation algorithms to estimate the unknown position (x, y) given $\mathbf{r}$.

4 Positioning Parameters Estimation

In practice, different methods are employed to determine the parameters required for position estimation algorithms. For UWB-based precise indoor positioning, these methods may be categorized as depicted in Fig. 2. A brief description of these methods is given in the following subsections. Moreover, effect of the propagation channel on the estimation of positioning parameters is discussed in the last subsection.

4.1 Fingerprinting Method

Location fingerprinting or scene analysis refers to techniques that match the *fingerprint* of some characteristic of a signal that are location dependent [29]. A fingerprinting method works in two modes i.e., offline and online modes. In the offline mode, on the basis of a cite survey, a database of target location coordinates and received signal strength from the nearby anchor nodes is determined. Subsequently, in the online mode, an estimated location is figured out with the help of observed and previously collected signal strength information. The main challenge to the technique for an indoor positioning environment is the signal strength degradation due to reflection, diffraction and scattering which leads to a laborious and time consuming calibration process [35]. Parameters like multipath power delay profile (PDP) and channel impulse response (CIR) can be used to determine the received signal [36–39]. Although the PDP and CIR parameters can provide sufficient positioning information, position estimation based on PDP/CIR information is usually

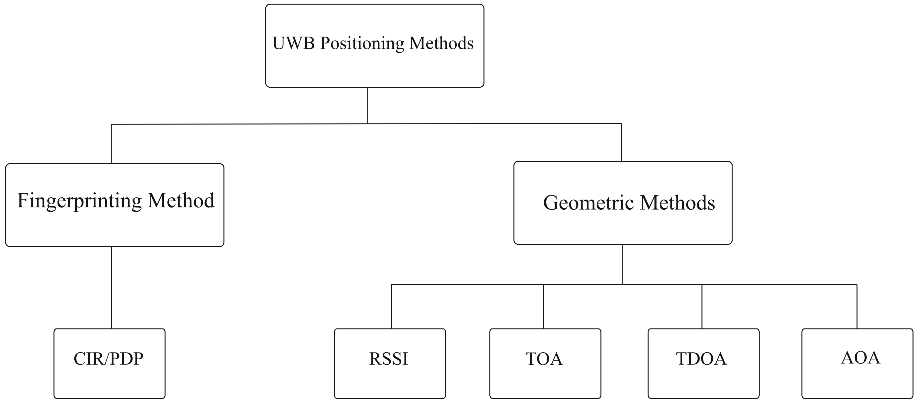

Fig. 2 Categorization of UWB positioning methods

more complex as it commonly requires a database consisting of previous PDP/CIR measurements at a number of known positions [40].

4.2 Geometric Methods

Geometric methods estimate the position of the target node on the basis of parameters like signal strength, arrival time and direction of the signal traveling between the TN and a certain number of AN. The performance of these positioning parameters is often compared on the basis of Cramer-Rao lower bound (CRLB) [41–43]. CRLB, defined as the inverse of Fisher information matrix (FIM), is the theoretical lower bound of variance of the position estimations and represents the smallest possible positioning error [44]. From the UWB perspective, the choice of parameter type for positioning algorithms depends on a trade-off between complexity and accuracy. In the following, positioning parameters measured using geometric methods are presented.

4.2.1 Received Signal Strength Indication (RSSI)

When a radio signal propagates from transmitter to receiver, it undergoes some attenuation in power of the signal and this attenuation goes on increasing with the increased distance. The signal power captured by the receiver carries the signal related parameter. This technique is very susceptible to noise and interference due to multiple signal paths that constructively or destructively interfere with each other. When small-scale multipath effects are averaged out, the resulting average received power on the dB scale is modeled as a Gaussian random variable, which has a mean determined by the path loss effect and a variance that is specified by the shadowing variance [45]. Signal energy is affected by a factor called *pathloss*, which exploits the relation between the distance and signal energy i.e., $p(r) = p(r_0) - 10n\log_{10}(r/r_0)$, where n is called the pathloss exponent, $p(r)$ and $p(r_0)$ are the signal strength at distance r and r_0, respectively. For RSSI, CRLB of an unbiased range estimator is specified as [46]:

$$\sqrt{\mathrm{Var}(\hat{d})} \geq \frac{(\ln 10)\sigma_{sh} d}{(10n)}, \tag{7}$$

where $\hat{d}$ is an unbiased estimate of the distance d between two nodes, σ_{sh} is the standard deviation of the shadowing. CRLB of the RSSI parameter indicates that with the decrease in standard deviation i.e., random variations of the received signal, the accuracy of the estimation increases. However, RSSI-based positioning does not fully exploit the benefit brought by the wide bandwidth of UWB signals [6]. The mobility of the anchor nodes and unpredictable variations in the channel behavior results into the drastic changes of RSSI behavior. In some cases, in which the target node is very close to some anchor nodes, the signal strength measurements can be used in conjunction with time delay measurements of other anchor nodes [47]. This hybrid scheme can help to improve the location estimation accuracy.

4.2.2 Time-of-Arrival (TOA)

Assuming that the positions of anchor nodes are known, the TOA parameter (also sometimes called 'time-of-flight') determines the distance d between an anchor and a target node as the distance is directly proportional to the propagation time. In 2D positioning, TOA uses at least three ANs and requires three measurements of distances from one node to another in order to localize a TN.

Figure 3 shows three anchor nodes labeled AN_l where $l = 1, 2$ and 3. These nodes form circles as a locus of points at the estimated range of the target node *TN*. TOA exploits the relationship between distance and transmission time when the propagation speed is known

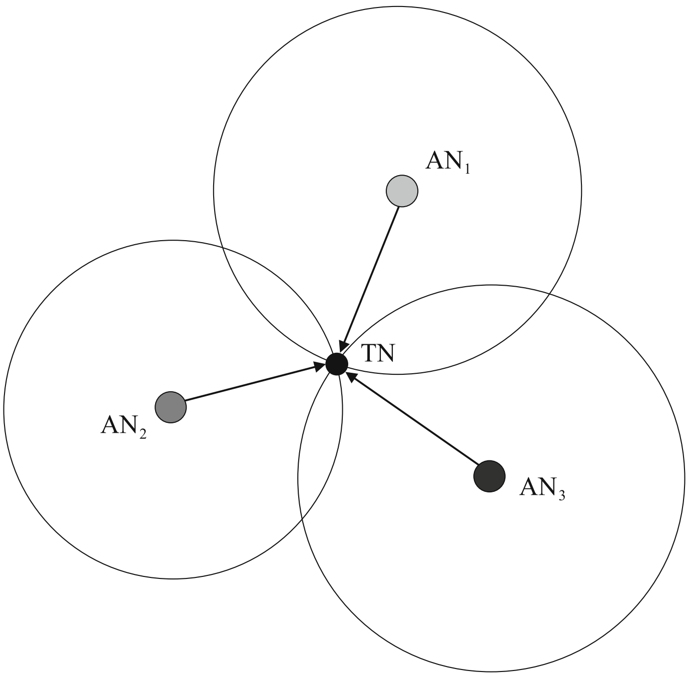

Fig. 3 TOA and RSSI based positioning

[24]. If the signal is transmitted at a time t_0 which is received at time t_l and the time that the signal takes to arrive from TN to AN_l is denoted as τ_l, then

$$\begin{aligned} t_l &= \tau_l + t_0 \\ &= \frac{d_l}{c} + t_0 \\ &= \frac{\sqrt{(x_l - x)^2 + (y_l - y)^2}}{c} + t_0, \end{aligned} \tag{8}$$

where c is the propagation speed. Hence, the nonlinear function $f_l(x, y)_{TOA}$ for lth AN from Eq. 6 would be

$$f_l(x, y)_{TOA} = \sqrt{(x_l - x)^2 + (y_l - y)^2}. \tag{9}$$

Equation 9 is the simplest case of finding the location of target node when the measurements are assumed to be noise free. Multipath phenomena in realistic Non-LOS (NLOS) scenarios, is a major source of error in TOA estimation [48, 49] since overlap of the arriving multipaths becomes a source of error in the estimation of the first-arriving signal. CRLB quantifies TOA estimator accuracy limits as [50, 51]:

$$\sqrt{\mathrm{Var}(\hat{\tau})} \geq \frac{1}{2\sqrt{2}\pi\sqrt{SNR}\beta}, \tag{10}$$

where $\hat{\tau}$ is the estimated TOA and β is the effective bandwidth. It is evident from Eq. 10 that the standard deviation of the position estimation using TOA is inversely proportional to SNR; that is intuitively reasonable since stronger signals are easier detected. The inequality also shows that the TOA accuracy increases with the bandwidth, making UWB a good candidate for time-based ranging [52].

In spite of the advantages offered by TOA, it requires clock synchronization among all the ANs and TN, which implies a higher hardware cost [53]. This problem is minimized by using two way ranging technique i.e., the time required by the signal to complete a round trip time (RTT), that determines the distance from the TN, to the measuring unit and back. Therefore, only one node is involved in time delay measurements. Here it is assumed that information related to time synchronization is not necessary, however processing time for position location is long and power consumption may also increase [54].

4.2.3 Time Difference-of-Arrival (TDOA)

For a positioning system, TDOA determines the difference of TOAs of the signal transmitted from the TN to the AN in order to reconstruct the location of target node. In 2D positioning, since the number of ANs required for TDOA is one less than TOA, therefore the location of a TN is determined by the intersection of two hyperbolas, drawn from three known AN positions, see Fig. 4. It implies that TDOA requires highly precise synchronization between the ANs but requirement of precise synchronization between the TN and an AN is relatively relaxed [55]. Assuming AN_i and AN_j be any two anchor nodes that receive signals from the TN with speed of c, and the time required by these signals to travel is denoted as t_i and t_j, respectively. Then, in case of TDOA, Eq. 8 can be written for measurement taken at two anchor nodes as

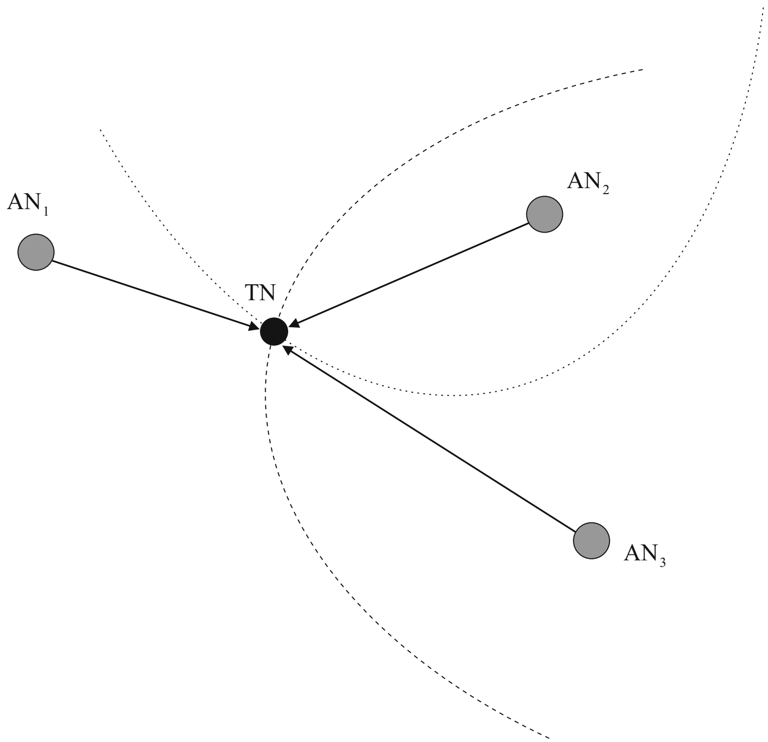

Fig. 4 TDOA based positioning

$$\begin{aligned} t_i - t_j &= \tau_i + t_0 - (\tau_j + t_0) \\ &= \tau_i - \tau_j \\ &= \frac{\sqrt{(x_i - x)^2 + (y_i - y)^2} - \sqrt{(x_j - x)^2 + (y_j - y)^2}}{c}. \end{aligned} \tag{11}$$

Hence for a noise free environment, nonlinear function $f_l(x, y)_{TDOA}$ can be written as:

$$f_l(x, y)_{TDOA} = \sqrt{(x_i - x)^2 + (y_i - y)^2} - \sqrt{(x_j - x)^2 + (y_j - y)^2}. \tag{12}$$

Similar to TOA, the accuracy bounds of TDOA estimation depends upon *SNR* and β. The theoretical lower bound for TDOA localization using a fixed number of anchor nodes is identical to that of TOA localization. In practice, using a Maximum Likelihood (ML) estimator, some characteristic features of the cost functions give reason to expect a superior performance for TOA compared to TDOA localization [56].

4.2.4 Angle of Arrival (AOA)

AOA measures the angle between the direction of propagation of an incident wave and some reference direction, which is known as *orientation*. Orientation, defined as a fixed direction against which the AOAs are measured, is represented in degrees in a clockwise direction from the North [57]. One common approach to obtain AOA measurements is the use of multiple antenna in the form of antenna array on each node. For angle determination, the main lobe of an antenna array is steered in the direction of the peak incoming energy of the arriving signal, this approach is called beamforming [58]. In this approach, two beamformers can uniquely decide the position of the target node by the rays from each of the two direction [59], see Fig. 5.

However, this method incurs higher cost, complexity, and power consumption [53]. Let a signal having an AOA θ_l at lth receiver, then

$$\tan(\theta_l) = \frac{y - y_l}{x - x_l} \tag{13}$$

For a noise free environment, we can determine the non linear function for AOA as

$$f_l(x, y)_{AOA} = \arctan\frac{y - y_l}{x - x_l}. \tag{14}$$

The CRLB for the variance of unbiased AOA estimate $\hat{\theta}$ using a uniform linear array (ULA) configuration with N_a elements is given as [60]:

$$\sqrt{\mathrm{Var}(\hat{\theta})} \geq \frac{\sqrt{3}c}{\sqrt{2}\pi\sqrt{SNR}\beta\sqrt{N_a(N_a^2 - 1)}\gamma\cos\theta}, \tag{15}$$

where β is the effective bandwidth and γ is the inter-element spacing. Eq. 15 employs that with the increase in SNR, effective bandwidth, inter-element spacing (upto a certain limit) and number of antenna elements, a more accurate estimation of AOA can be achieved.

4.2.5 Hybrid Techniques

In order to produce a more robust estimate of position, a combination of position related parameters can be utilized. A hybrid location estimation scheme provides heterogeneity of sensor networks, in terms of time synchronization, routing capabilities of network devices and communication range. Moreover, in short range wideband communication, hybrid techniques provide significantly lower CRLB that results into better positioning accuracy [47]. For instance, an advanced forward link trilateration (AFLT) method proposed in [16] is similar to TDOA method in which the TN measures the TOA of the transmitted signal which is sent back to the network of three ANs for position calculation. A hybrid technique based on AOA and TDOA parameters is also proposed in [61] which shows significant

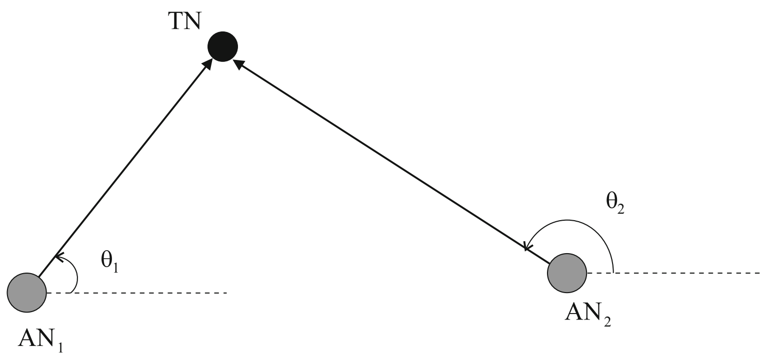

Fig. 5 AOA based positioning

improvement in location error performance and coverage area. The advantage of using this combination is that location can be determined by only two ANs, hence reducing the sensor density of a system that just work on TDOA. Similarly, [62] has presented a technique based on the combination of TDOA and RSSI which can work even in a partially synchronized wireless sensor network (WSN). A hybrid technique in which AOA parameters have been combined with TOA parameters is presented in [63]. This technique, in spite of its implementation complexity, offers many advantages in terms of power consumption and performance.

4.3 Propagation Effects on Parameter Estimation

The measurement models for different parameters discussed in the above subsections assume an ideal scenario in which there is a LOS between TN and ANs and the signal is received in the absence of any interfering signal. Under these conditions, a UWB positioning system can accurately estimate the position of the TN with highly synchronized clocks. In a more realistic and practical scenario, main sources of error are NLOS, multipath propagation and multiple access interference (MAI). The blockage of LOS between the two nodes results into extra time delays (NLOS error) that undergoes considerable changes in the Gaussian random distribution noise model [46, 64]. Therefore, accurate position estimation essentially requires information about NLOS errors. In multipath propagation, the receiver finds a mismatch between the transmitted template signal and the received one that leads to erroneous location estimation. In addition, MAI also plays a vital role in the estimation performance as the signal is degraded by the interference caused by other users. To minimize the NLOS and MAI errors, many algorithms are proposed in literature [65–68].

The performance of accurate position estimation is often assessed by channel models provided in the standard IEEE 802.15.4a [69, 70]. The standard channel model supports UWB-based communication at low-data rate with ranging capability and is valid over larger distances. The channel model is categorized (CM1-CM8) in eight environments for LOS as well as NLOS situations in office indoor, indoor residential, industrial, and outdoor environments. The main goal of the channel model was to model attenuation (shadowing and pathloss) and delay dispersion (power delay profile, small scale fading) of UWB channel in both LOS and NLOS conditions [71, 72].

In [40], the channel model 3 (CM3) of the IEEE 802.15.4a channel model for LOS of indoor office is used for TOA estimation. The performance of different TOA estimators is compared against theoretical limits and it is concluded that time-based positioning techniques are suitable for LOS propagation channels. Moreover, TOA estimation accuracy is affected by the wrong estimation of first arriving path which is often the case under NLOS conditions. Similarly, AOA-based positioning also has its limitations because it is highly affected by NLOS and multipath propagation. In [73], joint TOA and AOA estimation in multi-antenna IR-UWB systems are evaluated on CM1 channel and significant improvements in estimation accuracy are demonstrated.

5 Position Estimation Algorithms

The position estimation algorithms may be categorized in two broad classes, i.e., algorithms for fingerprinting methods and geometric methods, and are discussed in the following subsections.

5.1 Algorithms for Fingerprinting Method

Fingerprinting methods make use of training data in order to infer position estimation rules. These rules while making use of position related parameters, lead towards the position estimation of the TN. As described in the previous section, a database of target location coordinates and position related parameters such as RSSI, PDP or CIR are determined from the possible location candidates in the offline mode. During the online mode, fingerprint-based positioning uses techniques from machine learning (also called statistical learning) to find the optimal estimate of the position [74]. Mentioned below are some of the fingerprinting-based positioning algorithms. Moreover, a summary of advantages and limitations offered by these algorithms are enlisted in Table 2.

5.1.1 Probabilistic Method

This method performs decision rules based on a *posteriori* probability. During the online mode, let $\mathbf{s}$ be the observed signal strength vector for n locations $L_1, L_2, \ldots, L_n$. If $P(L_i|\mathbf{s})$ represents probability that the TN is in the location of L_i, given that $\mathbf{s}$ is the received signal strength. The decision rule is obtained as:

$$\text{if} \quad P(L_i|\mathbf{s}) > P(L_j|\mathbf{s}) \qquad \textit{for} \quad i,j = 1,2,\ldots,n \quad i \neq j \tag{16}$$

then the TN will be in the location of L_i. Using Bayes' formula, if $P(L_i) = P(L_j)$ then, based on the likelihood, the following decision rule is obtained,

$$P(\mathbf{s}|L_i) > P(\mathbf{s}|L_j), \tag{17}$$

where $P(\mathbf{s}|L_i)$ represents the probability of received signal vector $\mathbf{s}$, given that the TN is near location L_i. In order to calculate the likelihood many approaches such as histogram, Gaussian, log normal and inverse function may be used [75]. The mean and standard deviation of each location can be calculated by assuming the likelihood of locations to be Gaussian distributed. Hence, the overall likelihood of any location is the multiplication of the likelihood of all the independent measuring units.

5.1.2 Weighted k-Nearest Neighbour (WKNN)

A simple *k-NN* method compares the online positioning parameters from the k closest matches in a signal space with the offline training data. This method choose k parameters

Table 2 Summary of advantages and limitations of fingerprinting methods

Methods	Advantages	Limitations
Probabilistic method	Estimates the PDF of RSSI for a given location	Complex training and requires large dataset
WKNN	Low computational complexity and ease of implementations	Does not work well for sparse training database
ANN	Robust against noise and interference	Computational cost increases to achieve higher accuracy
SVM	Better accuracy	Computationally expensive

from the training data that have the smallest Euclidian distances to the measured estimation. Further an estimated location of TN is obtained by averaging all the k location candidates. For further improvement in the algorithm, the location of TN is estimated as the weighted average of finger print locations. A performance analysis of different values of k closest matches in a signal space is found [75].

5.1.3 Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) have been proposed as a solution to the location determination problem [76–78]. ANNs are used to map the fingerprints training data into locations in the physical space. Training of ANN is carried out by the system using data collected in the offline mode for envisioned localization. In order to accomplish the positioning, different ANN models namely the Multi Layer Perceptron (MLP), Radial Basis Function (RBF) and Generalized Regression Neural Network (GRNN) may be evaluated for the implementation [79].

5.1.4 Support Vector Machine (SVM)

Support vector machines are machine learning and statistical analysis tools that map the input data on a high dimensional feature space through non-linear mapping chosen a priori [80]. Some of the data collected during the offline mode is retrieved as training data for SVM. This training data is then used for inference purpose by converting the client identity into numeric data. In online mode, the received information is compared with the training data for location estimation. This universal learning machine is widely used for classification and regression based applications. Statistical regression builds a model that has least deviation of experimentally observed responses from the predicted ones. Therefore, to achieve a generalized performance, support vector regression (SVR) attempts to minimize generalized error bounds instead of observed training error reduction.

5.2 Algorithms for Geometric Method

This class of algorithms is mainly used for geometric method which is based on geometric parameters for position determination of a TN. For a noise free environment, geometric method is preferable for position estimation, but in practice, this method does not present a systematic approach. Real environments which happens to be very noisy give rise to multiple point intersection position problem and the situation becomes even worse with the increase in number of ANs. This problem is solved by using statistical algorithms that provides a theoretical framework for position estimation based on certain statistical models. Depending upon the characteristics of noise factor in the measurement model, statistical algorithms are categorized into parametric and non-parametric algorithms.

5.2.1 Parametric Algorithms

Parametric technique is implemented if probability density function(PDF) of the noise is known but some parameters of the distribution are unknown. Let $\boldsymbol{\theta}$ be the vector of unknown parameter $\boldsymbol{\lambda}$ that includes position of the TN alongwith the unknown noise distribution parameters i.e., $\boldsymbol{\theta} = [x, y, \boldsymbol{\lambda}^T]^T$. Based on a priori information of $\boldsymbol{\theta}$, many position estimators can be employed.

Maximum likelihood (ML) estimates the parameter $\boldsymbol{\theta}$ in order to maximize the PDF $p(\mathbf{r}|\boldsymbol{\theta})$ i.e.,

$$\hat{\boldsymbol{\theta}}_{ML} = \underset{\boldsymbol{\theta}}{\operatorname{argmax}}\ p(\mathbf{r}|\boldsymbol{\theta}), \tag{18}$$

whereas the likelihood function is,

$$p(\mathbf{r}|\boldsymbol{\theta}) = p_n(\mathbf{r} - \mathbf{f}(x, y)|\boldsymbol{\theta}). \tag{19}$$

Here $p_n(\cdot|\boldsymbol{\theta})$ is the conditional pdf of noise vector. To find the maximum likelihood estimate of the distribution parameters from an incomplete data set, an algorithm known as maximum likelihood expectation-maximization (ML-EM) is used [68]. Another application of the EM algorithm is for the case when maximizing the likelihood function is analytically intractable, then the likelihood function is simplified by estimating the values of some hidden parameters [68].

Another well known technique called *Bayesian method*, probabilistically estimates the state of a dynamic system from a sequence of noisy sensor observations [81]. This algorithm is highly robust to NLOS situations [74]. In estimating any statistical situation, the target node position is estimated by predictions and corrections. In prediction mode, without taking a single measurement, a priori position is estimated on the basis of previous data collected at time $t-1$. In the second phase, correction mode compares the estimations with a set of measurements in the time interval $t-1$ to t. After processing many imprecise predictions, Bayesian method transforms these estimations into precise measurements [74].

5.2.2 Nonparametric Algorithms

Without any information of PDF of the noise, nonparametric technique is based on descriptive statistics like variance, mean and symmetry properties. Without any a priori information, accurate position can be determined by filtering out the erroneous measurements from the redundant data. In the presence of NLOS, *Least median of squares (LMedS)* provides a robust solution as compared to any other algorithm like least square [82]. The main benefit of LMedS is that it reduces the outliers when calculating the coordinates of the target node [35]. LMedS makes subsets of the available data to obtain the possible solution and select the one that minimizes the median of the residuals.

Assuming $\mathbf{z} = [x, y]^T$ be a vector representing unknown position of the TN and $\mathbf{z}_l = (x_l, y_l)$ be a vector of known position of the lth AN in Cartesian coordinates, where $l = \{1, 2, \ldots, L\}$. For TOA parameter, a least square (LS) estimator used to determine the position of the TN over L range measurements is given by,

$$\hat{\mathbf{z}} = \underset{\mathbf{z}}{\operatorname{argmin}} \sum_{l=1}^{L} (r_l - ||\mathbf{z} - \mathbf{z}_l||)^2, \tag{20}$$

where $\hat{\mathbf{z}}$ is the estimation of vector $\mathbf{z}$, r_l is the range measurement by the lth AN and $||\mathbf{z} - \mathbf{z}_l||$ is Euclidean distance between the lth AN and the TN. For TDOA based system, an idea of spherical interpolation (SI) is adopted that transforms the non-linear hyperbola equations into set of linear equations [83, 84].

In a realistic environment, least square measurements are highly contaminated by NLOS conditions and measurement errors. For the mitigation of NLOS errors, an algorithm named *Residual weighted* is adopted [67]. Without the aid of a statistical model, this technique works on the assumption that the number of range measurements should be greater than that of minimum required. Since $(r_l - ||\mathbf{z} - \mathbf{z}_l||)$ is defined as the lth residual for a particular $\mathbf{z}$, Eq. 20 may be rewritten as,

$$\hat{\mathbf{z}} = \underset{\mathbf{z}}{\operatorname{argmin}} \quad R_{es}(\mathbf{z}), \tag{21}$$

where residual $R_{es}(\mathbf{z})$ is given by the sum of residual squares of $\mathbf{z}$ for L measurements i.e.,

$$R_{es}(\mathbf{z}) = \sum_{l=1}^{L} [r_l - ||\mathbf{z} - \mathbf{z}_l||]^2. \tag{22}$$

As the NLOS conditions can vary for different measurement sets, the estimate $\hat{\mathbf{z}}$ is weighted on the basis of their respective $R_{es}(\mathbf{z})$ [67].

6 UWB-Based Indoor Positioning Implementations

In this section we present some practical implementations of UWB based positioning systems for a number of applications and scenarios. In practice, wireless positioning systems can be classified into two basic types with regard to network infrastructure and implementation approach. The first approach is to develop a positioning application specific network infrastructure. Whereas, the second approach makes use of an existing infrastructure for positioning of a target node. No doubt, first approach leads towards an expensive and time consuming deployment of a network infrastructure but it can enhance the quality of location sensing significantly. Depending upon the required accuracy of the positioning system, the density of sensors can be adjusted accordingly. As UWB practical systems are relatively new and there is lack of existing infrastructure, it requires a dedicated implementation approach. In a dedicated infrastructure, parameters like position accuracy, coverage, scalability and cost are of great importance. Based on these parameters a comparison of different UWB-based positioning systems is shown in Tables 3 and 4.

In order to provide an efficient UWB-based RTLS solution, many companies have manufactured UWB chipsets and hardware. For instance, *Time Domain* [85] has developed UWB solutions with an aim to unleash the full potential of UWB technology. Time Domain implementations rely on coherent signal processing that allows the signal energy to spread over multiple pulses providing with increased energy per bit and an improved SNR. The company develops the PulsON chipset and is built upon five generations of custom UWB silicon. PulsON 410 (P400) integrates advanced positioning and sensor communications capabilities directly into products. Although, the system takes benefit of

Table 3 Comparison of different UWB-based indoor positioning systems based on accuracy and coverage

Implementations	Method	Accuracy	Coverage
Time Domain MDS Tracking	RTT & odometry data	2 cm–1 m	Large
DecaWave DW1000	TDOA & TOA	10 cm	upto 300 m
Multispectral Solutions Ltd PAL650	TDOA	>1 ft	>200 ft
Zebra Technologies Dart UWB	TDOA	upto 30 cm	upto 200 m
BeSpoon UPosition	RTT	–	–
Ubisense Dimension4	TDOA & AOA	> 30 cm	upto 400 cm
IST EUROPCOM	TDOA	Within 10 cm	1000 m

Table 4 Comparison of different UWB-based indoor positioning systems based on cost, complexity and application area

Implementations	Cost	Complexity	Application
Time Domain MDS Tracking	High	Very High	R&D, Chipset
DecaWave DW1000	Low	Low	R&D, Chipset
Solutions Ltd PAL650	Moderate	Moderate	Industrial & Commercial
Zebra Technologies Dart UWB	High	Moderate	Military, health care, & asset tracking
BeSpoon UPosition	Very High	Moderate	Sports, Office Logistics
Ubisense Dimension4	Moderate	Low	Industrial Process
IST EUROPCOM	Moderate	Low	Rescue operations

extended operating range, this results into a complex system with an increased number of measurements, hence reducing the update rates. Recently, Georgia Tech/ Georgia Tech Research Institute (GTRI) has developed a real time anchor free node tracking system using range measurements and odometry data [86]. The system combines the range measurement (RTT) and odometry data using Multidimensional Scaling (MDS). It outperforms the traditional tracking based on Extended Kalman Filter (EKF). Many other companies like Intel Corporation, Motorola and Freescale Semiconductor are also among the chip manufacturer in the field of UWB based positioning systems.

Another genuinely disruptive IR-UWB technology is developed by *DecaWave* [88]. This technology uses low power and is functionally, economically viable to deploy even in difficult-to-access locations. Decawave has introduced DW1000 chip that is based on IEEE802.15.4-2011 standard. This chip gives a precision of 10 cm indoors in locating the objects on real time basis. With the help of coherent receiver techniques the chip allows an excellent communication range of up to 300m. Moreover, the chip supports both two way ranging and one way ranging methods based on TOA and TDOA [89].

Recently, several companies have deployed short-pulse UWB RTLS to provide a cost effective and a precise positioning system with fast update rates. *MultiSpectral Solutions Inc.* [7] has also developed and fielded many systems representing a variety of short-pulse electromagnetic applications. The company has introduced many precision asset location systems (PALS). *PAL650* [90] is the first commercial UWB system in hospitals and industrials facilities. The system uses TDOA positioning method with 4 ANs, operational center frequency of 6.2 GHz and a battery life of more than 3.8 years. With short pulse RF waveforms, this system provides an absolute tag position accuracy of more than one foot. PAL650 consists of two separate receivers connected in a daisy-chained arrangement, however, it is replaced with hub-spoke configuration to avoid a single point of power failure in serial communication. This system is referred as *over-determined* which can calculate more than one valid position. Many optimization algorithms like Davidon-Fletcher-Powell (DFP) and quasi Newton are proposed to address this problem but these methods are demanding in terms of CPU requirements.

Zebra Technologies [91] has developed Dart Ultra-Wideband solutions for accurate tracking of equipment and personnel for both indoor and outside. Zebra's UWB based applications provide the lowest cost-of-ownership in the industry by improving installation ease, visibility, scalability, performance, asset tracking and tag management. For instance, Dart UWB for RTLS enables asset and personnel visibility solutions. The system uses Dart Hub that maximises the coverage area with minimum sensor count and hence, shows exceptional performance in highly multipath environment. Dart sensors are placed throughout the area of interest and are connected in daisy chain arrangement. The system offers a long tag battery life of upto 7 years with a blink rate of 1 Hz. The system is working in Washington Hospital Center in order to ensure emergency care goals. This solution has enabled asset location granularity down to items within one to two feet of each other, hence, reducing the purchase cost of medical equipment [92]. Moreover, in order to prevent accidents and improve worker safety, Voestalpine, an industry leader in customized high quality and high-tech steel products and solutions, has deployed Zebra's RTLS system. The system actively supports the prevention of incidents and accidents around dangerous blast furnaces with a highly accelerated search and rescue time [93]. Recently, Zebra technologies have acquired MultiSpectral Solutions for identification, asset management and tracking solutions.

Another system developed by *BeSpoon* [94] RTLS, has provided a high precision indoor positioning solution. The system uses two way ranging method. BeSpoon 3D solutions are acceptable for both software and hardware perspective. The company has manufactured UPosition module which can be easily integrated into existing hardware. Moreover, the SpoonPhones equipped with state-of-the-art sensors, locates the tag easily.

Ubisense is another successful real time positioning system based on UWB technology for building Smart Space applications [95]. The system is scalable and allows for an arbitrary number of users for arbitrary range and application. The system takes advantage of TDOA and AOA techniques in order to provide flexible capability of location sensing. The system works in sensor cells, where each cell consists of at least four sensors and have a master cell that coordinates a TDMA network using conventional RF channel. The system ensures higher accuracy of 15 cm, a sensing rate of upto 20 times per second and a long life battery of 1 year. The selection of desired frequency of user positioning is of great importance as it strongly effects the battery life of Ubitags. However, the discrete cell architecture increases installation cost and adds to complexity of post installation tuning [96]. According to the company, Ubisense has successfully completed the implementation of a new Tool Assistance System (TAS) at BMWs production facility in Regensburg [97, 98] under Dimension4 system. As the name implies, TAS is based on the Location Identification System, which is designed to locate and identify production assets.

EUROPCOM [99, 100], by Information Society Technologies (IST), is a positioning and communicating system designed especially for searching and rescue of emergency personnel within the disaster zone. The most distinguish feature of the system is a self calibrating location aware ad-hoc network of nodes. The system consists of base units (BU) that coordinates with GPS as it is deployed outside the building on any emergency service vehicle. A set of four or five mobile units (MU) working inside the building uses TDOA method to compute their position. To increase the network density, while moving deeper inside the building, the system comprises of additional dropped units (DU). These coordinates are then sent to the control unit (CU) with the support of a high speed network (HSN). The system provides absolute position accuracy of 1m or less under NLOS conditions.

7 Concluding Remarks

The state-of-the-art wireless positioning technologies such as Bluetooth, ZigBee, Wi-Fi and UWB are compared in terms of multipath resolution, throughput, transmission time, energy efficiency, interference and modulation schemes. For precise indoor positioning applications, UWB provides substantial advantage because of its large bandwidth, low power and high time resolution capability. The comparison of UWB positioning methods based on fingerprinting and geometric techniques shows that the fingerprinting methods are rigid towards the dynamic environments because of its offline stage inference model. As far as performance of RSSI, TOA, TDOA and AOA positioning parameters is concerned, the time-based approaches seem to fully exploit the advantage of high time resolution capability of UWB signal. In addition, the hybrid techniques utilizing a combination of these parameters are found to be a practical and robust approach towards position estimation. The hybrid techniques have also proved to be helpful in improving location error performance, coverage area, sensor density and power consumption. In order to handle the practical implementation issues, non-parametric algorithms can be used with both deterministic and random NLOS models. From the state-of-the-art description of UWB based systems it is found that many of the precise indoor positioning systems are practical and operational, and possess distinguishing features like high accuracy and scalability. It is also concluded that UWB-based location aware ad-hoc cooperative networks can significantly improve the quality of location sensing. Finally, it is observed that the measurement of UWB positioning parameters in the presence of NLOS conditions plays a key role and, in particular, accurate measurement of the time of first arriving signal at the receiver side can significantly improve positioning accuracy.

References

1. Xiao, J., Liu, Z., Yang, Y., Liu, D., & Han, X. (2011). Comparison and analysis of indoor wireless positioning techniques. In *2011 International conference on computer science and service system (CSSS)* (pp. 293–296). IEEE.
2. Mautz, R., & Tilch, S. (2011). Survey of optical indoor positioning systems. In *IPIN* (pp. 1–7).
3. Want, R., Hopper, A., Falcao, V., & Gibbons, J. (1992). The active badge location system. *ACM Transactions on Information Systems (TOIS)*, *10*(1), 91–102.
4. Challamel, R., Tom, P., Harmer, D., & Beauregard, S. (2008). Performance assessment of indoor location technologies. In *2008 IEEE/ION position, location and navigation symposium* (pp. 624–632). IEEE.
5. Mitilineos, S. A., Kyriazanos, D. M., Segou, O. E., Goufas, J. N., & Thomopoulos, S. C. (2010). Indoor localisation with wireless sensor networks. *Progress in Electromagnetics Research*, *109*, 441–474.
6. Gezici, S., Tian, Z., Giannakis, G. B., Kobayashi, H., Molisch, A. F., Poor, H. V., et al. (2005). Localization via ultra-wideband radios: a look at positioning aspects for future sensor networks. *IEEE Signal Processing Magazine*, *22*(4), 70–84.
7. Fontana, R. J. (2004). Recent system applications of short-pulse ultra-wideband (UWB) technology. *IEEE Transactions on Microwave Theory Techniques*, *52*(9), 2087–2104.
8. Molisch, A. F., Balakrishnan, K., Cassioli, D., Chong, C. C., Emami, S., Fort, A., & Siwiak, K. (2005). A comprehensive model for ultrawideband propagation channels. In *2005. GLOBECOM'05. IEEE global telecommunications conference* (Vol. 6, p. 6-pp). IEEE.
9. Win, M. Z., & Scholtz, R. A. (1998). Impulse radio: How it works. *IEEE communications Letters*, *2*(2), 36–38.
10. Ingram, S. J., Harmer, D., & Quinlan, M. (2004). Ultrawideband indoor positioning systems and their use in emergencies. In *2004. PLANS 2004 position location and navigation symposium* (pp. 706–715). IEEE.
11. Guvenc, I., Gezici, S., & Sahinoglu, Z. (2008). Ultra-wideband range estimation: Theoretical limits and practical algorithms. In *2008. ICUWB 2008. IEEE international conference on ultra-wideband* (Vol. 3, pp. 93–96). IEEE.
12. Caffery, J. J, Jr. (2006). *Wireless location in CDMA cellular radio systems* (Vol. 535). Berlin: Springer.

13. Farid, Z., Nordin, R., & Ismail, M. (2013). Recent advances in wireless indoor localization techniques and system. *Journal of Computer Networks and Communications, 2013*, 1–12.
14. Zhang, D., Xia, F., Yang, Z., Yao, L., & Zhao, W. (2010). Localization technologies for indoor human tracking. In *2010 5th International conference on future information technology (FutureTech)* (pp. 1–6). IEEE.
15. Sklar, B. (1997). Rayleigh fading channels in mobile digital communication systems. I. Characterization. *IEEE Communications Magazine*, *35*(9), 136–146.
16. Ghavami, M., Michael, L. B., & Kohno, R. (2004). *Front matter*. Hoboken: Wiley.
17. Di Benedetto, M. G. (2006). *UWB communication systems: A comprehensive overview* (Vol. 5). Cairo: Hindawi Publishing Corporation.
18. Cover, T. M., & Thomas, J. A. (2012). *Elements of information theory*. Hoboken: Wiley.
19. Park, C., & Rappaport, T. S. (2007). Short-range wireless communications for next-generation networks: UWB, 60 GHz millimeter-wave WPAN, and ZigBee. *IEEE wireless communications*, *14*(4), 70–78.
20. Foerster, J., Green, E., Somayazulu, S., Leeper, D., Intel Architecture Labs, Intel Architecture Labs, Intel Corp., & Intel Corp. (2001). Ultra-wideband technology for short-or medium-range wireless communications. *Intel Technology Journal*, *2*, 2001.
21. Lee, J. S., Su, Y. W., & Shen, C. C. (2007). A comparative study of wireless protocols: Bluetooth, UWB, ZigBee, and Wi-Fi. In *2007. IECON 2007. 33rd annual conference of the IEEE industrial electronics society* (pp. 46–51). IEEE.
22. Telatar, I. E., & Tse, D. N. (2000). Capacity and mutual information of wideband multipath fading channels. *IEEE Transactions on Information Theory*, *46*(4), 1384–1400.
23. Ren, Q., & Liang, Q. (2008). Throughput and energy-efficiency-aware protocol for ultrawideband communication in wireless sensor networks: A cross-layer approach. *IEEE transactions on mobile computing*, *7*(6), 805–816.
24. Karl, H., & Willig, A. (2007). *Protocols and architectures for wireless sensor networks*. Hoboken: Wiley.
25. Barras, D., Ellinger, F., & Jckel, H. (2002). A comparison between ultrawideband and narrowband transceivers. *Proceedings TRLabs/IEEE Wireless*, *2002*, 211–214.
26. Sheng, H., Orlik, P., Haimovich, A. M., Cimini Jr, L. J., & Zhang, J. (2003). On the spectral and power requirements for ultra-wideband transmission. In *2003. ICC'03. IEEE international conference on communications* (Vol. 1, pp. 738–742). IEEE.
27. Masood, R. F. (2013). *Adaptive Modulation*. (QPSK, QAM).
28. Zhang, C., Kuhn, M., Merkl, B., Fathy, A. E., & Mahfouz, M. (2006). Accurate UWB indoor localization system utilizing time difference of arrival approach. In *2006 IEEE radio and wireless symposium*.
29. Liu, H., Darabi, H., Banerjee, P., & Liu, J. (2007). Survey of wireless indoor positioning techniques and systems. *IEEE Transactions on Systems Man, and Cybernetics, Part C: Applications and Reviews*, *37*(6), 1067–1080.
30. Du, K. L., & Swamy, M. N. (2010). *Wireless communication systems: From RF subsystems to 4G enabling technologies*. Cambridge: Cambridge University Press.
31. Ramirez-Mireles, F., & Scholtz, R. A. (1998). Multiple-access with time hopping and block waveform PPM modulation. In *1998. ICC 98. Conference record. 1998 IEEE international conference on communications* (Vol. 2, pp. 775–779). IEEE.
32. Neelakanta, P. S., & Dighe, H. (2003, November). Robust factory wireless communications: A performance appraisal of the Bluetooth and the ZigBee colocated on an industrial floor. In *2003. IECON'03. The 29th annual conference of the IEEE industrial electronics society* (Vol. 3, pp. 2381–2386). IEEE.
33. Sikora, A., & Groza, V. F. (2005). Coexistence of IEEE802. 15.4 with other Systems in the 2.4 GHz-ISM-Band. In *2005. IMTC 2005. Proceedings of the IEEE instrumentation and measurement technology conference* (Vol. 3, pp. 1786–1791). IEEE.
34. Miller, L. E. (2003). Why UWB? A review of ultrawideband technology. National Institute of Standards and Technology. *DARPA*, 1–72
35. Al Nuaimi, K., & Kamel, H. (2011). A survey of indoor positioning systems and algorithms. In *2011 International conference on innovations in information technology (IIT)* (pp. 185–190). IEEE.
36. Althaus, F., Troesch, F., & Wittneben, A. (2005). UWB geo-regioning in rich multipath environment. In *IEEE vehicular technology conference* (Vol. 62, No. 2, p. 1001). IEEE; 1999.
37. Nerguizian, C., Despins, C., & Affes, S. (2001). A framework for indoor geolocation using an intelligent system. In *3rd IEEE Workshop on WLANs* (pp. 1–38).

38. Nerguizian, C., Despins, C., & Affs, S. (2006). Geolocation in mines with an impulse response fingerprinting technique and neural networks. *IEEE Transactions on Wireless Communications*, *5*(3), 603–611.
39. Triki, M., Slock, D., Rigal, V., & Franois, P. (2006). Mobile terminal positioning via power delay profile fingerprinting: Reproducible validation simulations. In *2006. VTC-2006 Fall. 2006 IEEE 64th vehicular technology conference* (pp. 1–5). IEEE.
40. Gezici, S., & Poor, H. V. (2009). Position estimation via ultra-wide-band signals. *Proceedings of the IEEE*, *97*(2), 386–403.
41. Xu, J., Ma, M., & Law, C. L. (2008). Position estimation using ultra-wideband time difference of arrival measurements. *IET Science, Measurement and Technology*, *2*(1), 53–58.
42. Chang, C., & Sahai, A. (2004). Estimation bounds for localization. In *2004. IEEE SECON 2004. 2004 first annual IEEE communications society conference on sensor and ad hoc communications and Networks* (pp. 415–424). IEEE.
43. Qi, Y., & Kobayashi, H. (2002). Cramer-Rao lower bound for geolocation in non-line-of-sight environment. In *2002 IEEE international conference on acoustics, speech, and signal processing (ICASSP)* (Vol. 3, pp. III–2473). IEEE.
44. Sengijpta, S. K. (1995). Fundamentals of statistical signal processing: Estimation theory. *Technometrics*, *37*(4), 465–466.
45. Goldsmith, A. (2005). *Wireless communications*. Cambridge: Cambridge University Press.
46. Qi, Y. (2003).*Wireless geolocation in a non-line-of-sight environment* (Doctoral dissertation, Ph. D. dissertation, Princeton University, Princeton, NJ).
47. Sahinoglu, Z., & Catovic, A. (2004). A hybrid location estimation scheme (H-LES) for partially synchronized wireless sensor networks. In *2004 IEEE international conference on communications* (Vol. 7, pp. 3797–3801). IEEE.
48. Patwari, N., Ash, J. N., Kyperountas, S., Hero, A. O, III., Moses, R. L., & Correal, N. S. (2005). Locating the nodes: Cooperative localization in wireless sensor networks. *IEEE Signal Processing Magazine*, *22*(4), 54–69.
49. Pahlavan, K., Li, X., & Mkel, J. P. (2002). Indoor geolocation science and technology. *IEEE Communications Magazine*, *40*(2), 112–118.
50. Soganci, H., Gezici, S., & Poor, H. V. (2011). Accurate positioning in ultra-wideband systems. *IEEE Wireless Communications*, *18*(2), 19–27.
51. Mailaender, L. (2007). Comparing geo-location bounds for TOA, TDOA, and round-trip TOA. In *2007. PIMRC 2007. IEEE 18th international symposium on personal, indoor and mobile radio communications* (pp. 1–5). IEEE.
52. Xu, J., Ma, M., & Law, C. L. (2011). Performance of time-difference-of-arrival ultra wideband indoor localisation. *IET Science, Measurement and Technology*, *5*(2), 46–53.
53. Zekavat, R., & Buehrer, R. M. (2011). *Handbook of position location: Theory, practice and advances* (Vol. 27). Hoboken: Wiley.
54. Kang, D., Namgoong, Y., Yang, S., Choi, S., & Shin, Y. (2006, February). A simple asynchronous UWB position location algorithm based on single round-trip transmission. In *2006. ICACT 2006. The 8th international conference advanced communication technology* (Vol. 3, p. 4-pp). IEEE.
55. Guven, I., & Chong, C. C. (2009). A survey on TOA based wireless localization and NLOS mitigation techniques. *IEEE Communications Surveys and Tutorials*, *11*(3), 107–124.
56. Kaune, R. (2012). Accuracy studies for TDOA and TOA localization. In *2012 15th International conference on information fusion (FUSION)* (pp. 408–415). IEEE.
57. Peng, R., & Sichitiu, M. L. (2006). Angle of arrival localization for wireless sensor networks. In *2006. SECON'06. 2006 3rd Annual IEEE communications cociety on sensor and ad hoc communications and networks* (Vol. 1, pp. 374–382). IEEE.
58. Laoufi, M., Heddebaut, M., Cuvelier, M., Rioult, J., & Rouvaen, J. M. (2000). Positioning emergency calls along roads and motorways using a GSM dedicated cellular radio network. In *2000. IEEE-VTS Fall VTC 2000. 52nd vehicular technology conference* (Vol. 5, pp. 2039–2046). IEEE.
59. Kaiser, T., & Zheng, F. (2010). *Ultra wideband systems with MIMO*. Hoboken: Wiley.
60. Mallat, A., Louveaux, J., & Vandendorpe, L. (2007). UWB based positioning in multipath channels: CRBs for AOA and for hybrid TOA-AOA based methods. In *2007. ICC'07. IEEE international conference on communications* (pp. 5775–5780). IEEE.
61. Thomas, N. J., Cruickshank, D. G. M., & Laurenson, D. I. (2001). Performance of a TDOA-AOA hybrid mobile location system. In *2001. Second international conference on 3G mobile communication technologies* (Conf. Publ. No. 477) (pp. 216–220). IET.
62. Catovic, A., & Sahinoglu, Z. (2004). Hybrid TOA/RSS and TDOA/RSS location estimation schemes for short-range wireless networks. *Bechtel Telecommunication Technical Journal (BTTJ)*, *2*(2), 77–84.

63. Taponecco, L., D'Amico, A. A., & Mengali, U. (2011). Joint TOA and AOA estimation for UWB localization applications. *IEEE Transactions on Wireless Communications*, *10*(7), 2207–2217.
64. Schroeder, J., Galler, S., Kyamakya, K., & Jobmann, K. (2007). NLOS detection algorithms for ultra-wideband localization. In *2007. WPNC'07. 4th workshop on positioning, navigation and communication* (pp. 159–166). IEEE.
65. Wang, X., Wang, Z., & O Dea, B. (2003). A TOA-based location algorithm reducing the errors due to non-line-of-sight (NLOS) propagation. *IEEE Transactions on Vehicular Technology*, *52*(1), 112–116.
66. Cong, L., & Zhuang, W. (2005). Nonline-of-sight error mitigation in mobile location. *IEEE Transactions on Wireless Communications*, *4*(2), 560–573.
67. Chen, P. C. (1999). A non-line-of-sight error mitigation algorithm in location estimation. In *1999. WCNC. 1999 IEEE wireless communications and networking conference* (pp. 316–320). IEEE.
68. Al-Jazzar, S., & Caffery Jr, J. (2002). ML and Bayesian TOA location estimators for NLOS environments. In *2002. Proceedings. VTC 2002-Fall. 2002 IEEE 56th vehicular technology conference* (Vol. 2, pp. 1178–1181). IEEE.
69. Molisch, A. F., Balakrishnan, K., Chong, C-C, Emami, S, Fort, A, Karedal, J, Kunisch, J, Schantz, H, Schuster, U, & Siwiak, K (2004). IEEE 802.15. 4a channel model-final report, *IEEE P802* (Vol. 15, pp 0662). IEEE.
70. Molisch, A. F (2009). Ultra-wide-band propagation channels. In *Proceedings of the IEEE*, (Vol. 97, pp. 353–371). IEEE.
71. Karedal, J., Wyne, S., Almers, P., Tufvesson, F., Molisch, A.F. (2007). A measurement-based statistical model for industrial ultra-wideband channels. In *IEEE transactions on wireless communications*, (Vol. 6). IEEE.
72. Kannan, B and others (2004). UWB channel characterization in office environments, *Document IEEE 802.15-04-0439-00-004a*.
73. Shang, F. (2013). Parameter estimation algorithms for impulse radio UWB localization systems. Dissertations McGill University, 2013
74. Seco, F., Jimenez, A., Prieto, C., Roa, J., & Koutsou, K. (2009). A survey of mathematical methods for indoor localization. *2009. WISP 2009. IEEE international symposium on in intelligent signal processing* (pp. 9–14). IEEE.
75. Honkavirta, V., Perl, T., Ali-Lytty, S., & Pich, R. (2009, March). A comparative survey of WLAN location fingerprinting methods. In *2009. WPNC 2009. 6th workshop on positioning, navigation and communication* (pp. 243–251). IEEE.
76. Saha, S., Chaudhuri, K., Sanghi, D., & Bhagwat, P. (2003). Location determination of a mobile device using IEEE 802.11 b access point signals. In *2003. WCNC 2003. 2003 IEEE wireless communications and networking* (Vol. 3, pp. 1987–1992). IEEE.
77. Shareef, A., Zhu, Y., & Musavi, M. (2008). Localization using neural networks in wireless sensor networks. In *Proceedings of the 1st international conference on MOBILe Wireless MiddleWARE, Operating Systems, and Applications* (p. 4). ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering).
78. Battiti, R., Le, N. T., & Villani, A. (2002). Location-aware computing: a neural network model for determining location in wireless LANs.
79. Laoudias, C., Eliades, D. G., Kemppi, P., Panayiotou, C. G., & Polycarpou, M. M. (2009). Indoor localization using neural networks with location fingerprints. In *Artificial neural Networks ICANN 2009 (pp. 954–963)*. Springer Berlin Heidelberg.
80. Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, *20*(3), 273–297.
81. Fox, D., Hightower, J., Liao, L., Schulz, D., & Borriello, G. (2003). Bayesian filtering for location estimation. *IEEE Pervasive Computing*, *3*, 24–33.
82. Casas, R., & Cuartielles, D. (2007). Hidden issues in deploying an indoor location system. *IEEE Pervasive Computing*, *2*, 62–69.
83. Smith, J. O., & Abel, J. S. (1987). Closed-form least-squares source location estimation from range-difference measurements. *IEEE Transactions on Acoustics, Speech and Signal Processing*, *35*(12), 1661–1669.
84. Chan, Y. T., & Ho, K. C. (1994). A simple and efficient estimator for hyperbolic location. *IEEE Transactions on Signal Processing*, *42*(8), 1905–1915.
85. Time Domain. http://www.timedomain.com. Accessed 15 Nov 2014
86. Beck, B., Baxley, R., & Kim, J. (2014). Real-time, anchor-free node tracking using ultrawideband range and odometry data. *2014 IEEE international conference on ultra-wideband (ICUWB)*, pp. 286–291.

87. Dewberry, B., & Petroff, A. (2015). Precision navigation with ad-hoc autosurvey using ultraWideBand two-way ranging network. *12 Workshop on positioning, navigation and communication (WPNC15)*, pp. 1–4.
88. DecaWave. http://www.decawave.com/technology. Accessed 15 Jan 2016
89. DecaWave product information: DW1000. http://www.decawave.com/sites/default/files/product-pdf/dw1000-product-brief.pdf. Accessed 15 Jan 2016
90. Fontana, R. J., Richley, E., & Barney, J. (2003). Commercialization of an ultra wideband precision asset location system. In *2003 IEEE conference on ultra wideband systems and technologies* (pp. 369–373). IEEE.
91. Zebra Technologies. http://www.zebra.com. Accessed 24 Nov 2014
92. http://www.zebra.com/us/en/solutions/research-and-learn/success-stories/washington-hospital-center.html Accessed 7 Dec 2014
93. http://www.zebra.com/us/en/solutions/research-and-learn/success-stories/voestapline.html. Accessed 10 Dec 2014
94. BeSpoon. http://www.Bespoon.com. Accessed 30 Nov 2014.
95. Steggles, P., & Gschwind, S. (2005). *The Ubisense smart space platform* (pp. 73–76).
96. Gu, Y., Lo, A., & Niemegeers, I. (2009). A survey of indoor positioning systems for wireless personal networks. *IEEE Communications Surveys and Tutorials*, *11*(1), 13–32.
97. Shang, J., Yu, S., & Zhu, L. (2009, January). Location-aware systems for short-range wireless networks. In textit2009. CNMT 2009. International symposium on computer network and multimedia technology (pp. 1–5). IEEE.
98. https://ubisense.net/en/information/resources/smart-factory-resources/automotive-rework Accessed on 11 May 2017.
99. Harmer, D., Russell, M., Frazer, E., Bauge, T., Ingram, S., Schmidt, N., & Dizdarevi, V. (2008, September). EUROPCOM: emergency ultrawideband radio for positioning and communications. In *2008. ICUWB 2008. IEEE international conference on ultra-wideband* (Vol. 3, pp. 85–88). IEEE.
100. Lo, A., Xia, L., Niemegeers, I., Bauge, T., Russell, M., & Harmer, D. (2008). Europcom-An ultra-wideband (UWB)-based ad hoc network for emergency applications. In *2008. VTC spring 2008. IEEE vehicular technology conference* (pp. 6–10). IEEE.

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