ACCURATE POSITIONING IN ULTRA-WIDEBAND SYSTEMS

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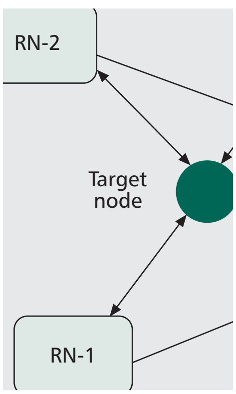

The authors study position estimation for UWB systems. After a brief introduction to UWB signals and their positioning applications, two-step positioning systems are investigated from a UWB perspective.

ABSTRACT

Accurate positioning systems can be realized via ultra-wideband signals due to their high time resolution. In this article, position estimation is studied for UWB systems. After a brief introduction to UWB signals and their positioning applications, two-step positioning systems are investigated from a UWB perspective. It is observed that time-based positioning is well suited for UWB systems. Then time-based UWB ranging is studied in detail, and the main challenges, theoretical limits, and range estimation algorithms are presented. Performance of some practical time-based ranging algorithms is investigated and compared against the maximum likelihood estimator and the theoretical limits. The trade-off between complexity and accuracy is observed.

INTRODUCTION

Ultra-wideband (UWB) signals differ from widely used narrowband and wideband signals by their very large bandwidths [1–3]. A common signaling scheme for UWB systems is known as impulse radio (IR) UWB, which consists of short duration pulses (on the order of a nanosecond) with low duty cycles, and employs different time-hopping and polarity codes [4, 5].

UWB signals have some very important properties, which make them good candidates for many applications. First, due to their large absolute bandwidths, UWB systems can employ very short duration waveforms, and hence, they can achieve high time resolution and facilitate accurate range and position estimation [2]. Large bandwidths of UWB signals also enable high-speed data transmission. In addition, since UWB signals can cover a large portion of the frequency spectrum, including low as well as high frequencies (i.e., they can have large relative bandwidths), they achieve high penetration capability through obstacles. Furthermore, UWB systems can be operated in baseband in a *carrier-free* manner, which makes it possible to design low-cost and low-power systems [2].

Due to their high time resolution, UWB signals can be employed in applications that require high positioning accuracy. Especially, the capability of performing very accurate positioning based on range estimation makes UWB signaling well suited for short-range wireless sensor networks (WSNs) [6]. UWB WSNs can be employed in many different areas. For example, they can be used for security purposes to locate an unusual activity or authorized people in high security areas. Also, after disasters such as an earthquake or avalanche, UWB WSNs can be used to locate lost people. In addition, UWB positioning systems can locate military personnel, firefighters, and police officers, and can also be used to track medical equipment or patients in a hospital. Furthermore, in daily life, UWB WSNs can be employed to locate and control home and office appliances [2].

In this study, an overview of positioning via UWB signals is presented. First, position estimation is studied, and various approaches for position estimation are evaluated from a UWB perspective. Then time-based UWB ranging, which is well suited for UWB positioning systems, is investigated in detail. The main challenges for time-based UWB ranging, theoretical limits on ranging accuracy, and range estimation algorithms are studied. Comparisons of practical algorithms and theoretical limits are also presented.

POSITION ESTIMATION

In a wireless positioning system, the position of a *target* node, such as a wireless sensor or cellular phone, is estimated based on signals traveling between that node and a number of reference (anchor) nodes. Depending on whether the position is estimated at a central unit or by the node itself, the system is called a *remote positioning* (*network-centric positioning*) or *self-positioning* system, respectively [7]. Commonly, position estimation is performed in two steps as shown in

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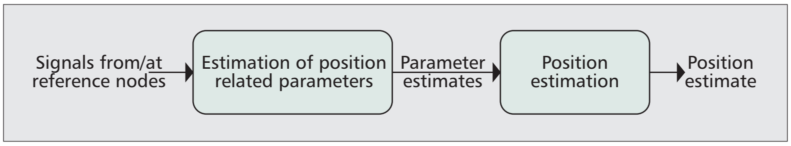

Figure 1. *Two-step positioning. In self-positioning systems, the target node first estimates position related parameters based on received signals coming from reference nodes, and then estimates its position based on those estimated parameters. In remote positioning systems, position related parameters are estimated based on the signals at the reference nodes. Then those position related parameters are sent to a central unit, which estimates the position of the target node (Fig. 2).*

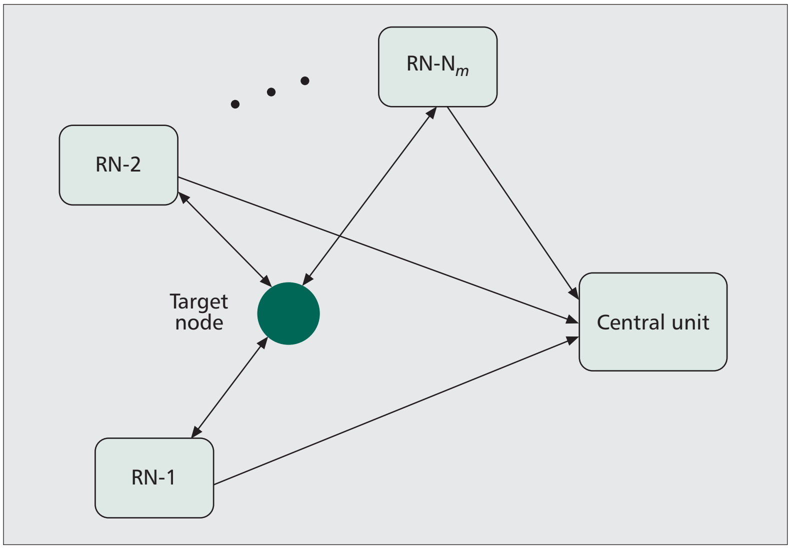

Figure 2. *Two-step position estimation in a remote positioning system. Reference nodes (RNs) estimate position related parameters based on signal exchanges with the target node, and send those parameter estimates to a central unit, which obtains the position estimate.*

Fig. 1. In the first step, position related parameters, such as time of arrival (TOA) and angle of arrival (AOA), are extracted from the signals traveling between the target and reference nodes. Then, in the second step, the position is estimated based on the position related parameters obtained in the first step. Although it is also possible to estimate the position directly from the signals traveling between the nodes, the two-step approach is commonly preferred since it can have significantly lower complexity than the direct approach, and the performance of the two approaches is usually quite close for sufficiently high signal-to-noise ratios (SNRs) and/or signal bandwidths [8, 9]. In fact, a two-step approach is a natural choice for remote positioning systems since it would be significantly more costly to send the received signals to a central unit than to send just the position related parameter estimates (Fig. 2).

In the following, a two-step positioning system as in Fig. 1 is considered, and various algorithms that can be employed in each step of the system are discussed.

Estimation of Position Related Parameters

In the first step, certain position related parameters are estimated based on signals between target and reference nodes. Those parameters are commonly related to timing, energy, and/or direction of the signals traveling between the target node and a number of reference nodes [10]. The choice of parameter type depends on the trade-off between positioning accuracy and system complexity/cost, which is investigated below from a UWB perspective.

Received Signal Strength — When a signal propagates from a transmitter to a receiver, the amount of energy collected by the receiver depends on the distance (*range*) between the transmitter and the receiver. Therefore, the received signal strength (RSS) can be considered as a parameter that carries position related information.

In wireless environments, the received signal power can vary significantly over short distances, on the order of the signal wavelength, due to constructive and destructive addition of multiple signal paths. Such small-scale effects are averaged out in order to obtain a useful relation between received power and distance. When small-scale multipath effects are averaged out, the resulting average received power on the dB scale can be 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 [11].[1] In practice, the path loss parameter (path loss exponent) and shadowing variance vary from environment to environment; hence, they can also be modeled as random variables with specific distributions in different types of environments [13].

In order to investigate the theoretical ranging accuracy that can be achieved via the RSS parameter, the Cramer-Rao lower bound (CRLB) can be considered [14]. The CRLB specifies the lower limit on the standard deviation of an unbiased estimator. For the RSS parameter, the CRLB on the standard deviation of an unbiased range estimator is specified by $(\ln 10)\, \sigma_{sh} d/(10n)$, where d is the distance (range) between the nodes, n is the path loss exponent, and σ_{sh} is the standard deviation of the shadowing [15]. Therefore, the theoretical lower bound on the ranging accuracy reduces as the standard deviation of the shadowing decreases (which reduces the random variations of the received power), and the path loss exponent increases (which makes the average power more sensitive to distance changes). Also, as the range between the nodes increases, the lower bound increases as well [10].

Commonly, the RSS parameter does not provide very accurate range estimates due to its strong dependence on the channel parameters, which is also true for UWB systems. For instance, in a non-line-of-sight (NLOS) residential environment, modeled according to the IEEE 802.15.4a UWB channel model [16], with $n = 4.58$ and $\sigma_{sh} = 3.51$, the CRLB can be calculated to be around 1.76 m. at $d = 10$ m [10].

Angle of Arrival — The AOA parameter provides information about the direction over which a target node resides. A common technique to estimate the AOA parameter is to employ multiple antennas in the form of an antenna array. Then the differences in arrival times of an

[1] *For a more accurate model of the average received power, the effects of directional antennas and the frequency dependence of path loss in UWB systems can be considered. For example, in UWB channels, the frequency dependence of the path loss is commonly modeled as being proportional to $f^{-2\kappa}$, where κ is called the frequency decaying factor. A detailed investigation of UWB channels can be found in [12, Ch. 2].*

incoming signal at different antenna elements can be used to obtain the AOA information based on the known array geometry [17]. For narrowband signals, those differences in arrival times can be represented by phase shifts of the signals. Therefore, the combinations of the phase shifted versions of received signals at antenna array elements can be tested for different angles in order to estimate the AOA [18]. However, for UWB systems, time differences cannot be represented by phase shifts; hence, time delayed versions of received signals should be considered for AOA estimation [10].

In order to compare the accuracy of the AOA parameter with that of the RSS parameter, consider a uniform linear array, which has its antenna elements located along a straight line with equal spacing. The CRLB calculations in [19] indicate that the lower bound on the standard deviation of an unbiased AOA estimator is inversely proportional to the effective bandwidth [14] of the signal and the square-root of the SNR. Therefore, unlike the RSS parameter, the accuracy of the AOA parameter can be enhanced when the signal bandwidth is increased, which implies that UWB signals can facilitate accurate AOA estimation [10].

Time of Arrival — Another parameter that provides information about the range between two nodes is the TOA parameter. When the nodes are synchronized, the TOA of the signal can be used to obtain a range estimate. If the nodes are not synchronized, they can exchange timing information by certain protocols such as the *two-way ranging* protocol in order to estimate the range [20, 21].

The theoretical limits on TOA estimation and various TOA estimation algorithms are investigated for UWB systems later. At this point, in order to provide some intuition about why the TOA parameter is well suited for UWB positioning systems, consider a simple scenario in which the time-delayed version of a transmitted signal arrives at a receiver in the presence of zero mean additive white Gaussian noise (AWGN). In that case, the CRLB on the standard deviation of an unbiased TOA estimator $\hat{\tau}$ is given by

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

where β is the effective bandwidth [14, 22]. Therefore, the theoretical lower bound on TOA estimation accuracy reduces with the SNR and effective bandwidth parameters. Hence, large bandwidths of UWB signals can facilitate very accurate TOA information. For instance, for the second derivative of a Gaussian pulse [23] with a pulse width of 1 ns, the CRLB for the standard deviation of an unbiased range estimator (obtained by scaling a TOA estimator by the speed of light) is less than 1 cm at an SNR of 5 dB [10].

Time Difference of Arrival — When the reference nodes are synchronized, the time difference of arrival (TDOA) parameter can be used to obtain position related information [18]. For remote positioning, the reference nodes measure the arrival times of the signal coming from the target node, which is not synchronized with the reference nodes. Then the TDOA parameters are calculated by taking the difference between the TOA estimates, which removes the timing offset due to the asynchronism between the target node and the reference nodes. In this case, similar to the discussion for the TOA parameter, the accuracy of the TDOA parameter increases as the effective bandwidth and/or SNR increase [17].

For self-positioning, the target node measures the signals transmitted from synchronized reference nodes and calculates the TDOA values. One way to estimate the TDOA value in this case is to perform cross-correlations between the signals coming from a pair of reference nodes, and determine the time difference value corresponding to the maximum cross-correlation value [24].

Other Types of Position Related Parameters — In addition to RSS, AOA, and T(D)OA parameters or their combinations [2], two other types of position related parameters are the multipath power delay profile (PDP) and the channel impulse response (CIR) related to a received signal [25–28]. Although the PDP and CIR parameters can provide significantly more positioning information than the previously studied parameters in some cases, position estimation based on PDP/CIR information is usually more complex as it commonly requires a database consisting of previous PDP/CIR measurements at a number of known positions [10].

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Position Estimation

In the second step of the two-step positioning approach in Fig. 1, the position of a target node is estimated based on the position related parameters obtained in the first step. Two common techniques that can be employed in the second step are *statistical* and *mapping* (*fingerprinting*) techniques [17].

Statistical Techniques — The statistical techniques assume certain statistical models for the parameter estimates obtained in the first step, and try to estimate the position based on those models. Consider the following model for the parameters obtained from the first step:

$$\mathbf{z} = \mathbf{f}(\boldsymbol{l}) + \boldsymbol{\eta}, \quad (2)$$

where $\mathbf{z}$ is a vector of size N_{m} that contains the parameter estimates obtained in the first step, $\boldsymbol{\eta}$ is the noise vector that represents the estimation errors in the first step, $\boldsymbol{l}$ denotes the position of the target, and $\mathbf{f}(\boldsymbol{l})$ contains the true values of position related signal parameters. Depending on the type of position related parameter, $\mathbf{f}(\boldsymbol{l})$ can correspond to the distances between the target node and the reference nodes (for the TOA and RSS parameters), the arrival angles of the target signal at the reference nodes (for the AOA parameter), or the differences in the arrival times of the target signal at the reference nodes (for the TDOA parameter) [17]. The model in Eq. 2 can be valid also in the presence

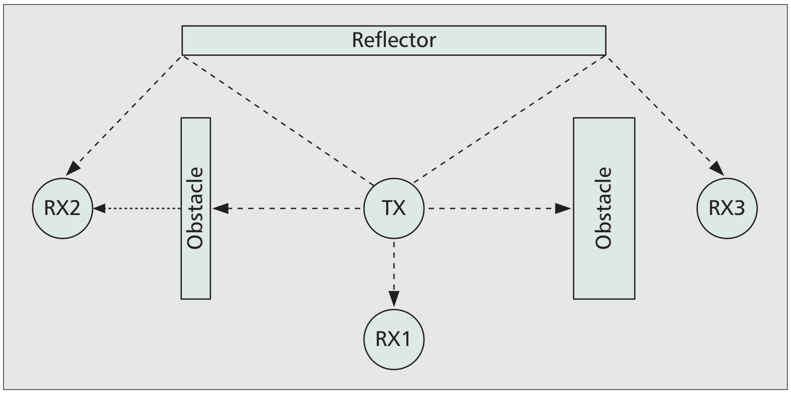

Figure 3. *Various LOS and NLOS conditions. With respect to transmitter TX, receiver RX1 is in LOS, receivers RX2 and RX3 are in NLOS. Due to different obstacle properties, the direct path is observed at RX2 after some attenuation, but it cannot be detected by RX3.*

of NLOS and multipath propagation, which mainly affect the probability distribution of the noise components [2].

Depending on the amount of information about the statistics of the noise term $\boldsymbol{\eta}$ in Eq. 2, two classes of statistical techniques can be considered.

Nonparametric Techniques — The nonparametric approach assumes no information about the form of the probability density function (PDF) of the noise, $p_n(\cdot)$. However, there is some generic information about the noise statistics [29], such as its variance and symmetry properties, which can be employed for designing nonparametric estimation rules, such as the least median of squares technique in [30], the residual weighting algorithm in [31], and the variance weighted least squares technique in [32].

Parametric Techniques — In the parametric approach, the PDF of noise $\boldsymbol{\eta}$ is known except for a set of parameters, denoted by $\boldsymbol{\lambda}$. Therefore, the unknown parameter vector in the estimation problem based on the model in Eq. 2 can be expressed as $\boldsymbol{\theta} = [\boldsymbol{l}\ \boldsymbol{\lambda}]^T$, which consists of the position of the target node $\boldsymbol{l}$, as well as the unknown parameters of the noise distribution. Depending on the availability of prior information about $\boldsymbol{\theta}$, Bayesian or maximum likelihood (ML) estimation techniques can be employed, as investigated in [10, 17, 33].

Mapping Techniques — A mapping (fingerprinting) technique uses a training data set to determine a position estimation rule (pattern matching algorithm/regression function), and then employs that rule to estimate the position of a target node for a given set of position related parameter estimates [10]. Common mapping techniques are k nearest neighbor (k-NN), support vector regression (SVR), and neural networks [28, 34–38]. For efficient utilization of mapping techniques, the training data set should provide an accurate representation of the environment. Therefore, it should be updated at certain intervals, which can be costly in dynamic environments such as outdoor positioning scenarios [10].

TIME-BASED UWB RANGING

The discussions earlier indicate that the large bandwidths of UWB signals can facilitate accurate positioning based on T(D)OA or AOA estimation. Since AOA estimation commonly requires multiple antenna elements and increases the complexity of a UWB receiver, timing related parameters, especially TOA, are usually preferred for UWB positioning systems [10]. In the following, TOA estimation for UWB signals is investigated in more detail.

MAIN CHALLENGES

For the ideal case in which the signals arrive at a receiver only over a line-of-sight (LOS) path in the absence of any interfering signals from other sources, it is possible to perform time-based UWB ranging with high accuracy using perfectly synchronized clocks. However, in a practical scenario there are various challenges [10, 39]. First of all, in most cases there is no LOS path between the transmitter and the receiver. Even if there is an LOS path, signals arrive at the receiver not only over that path but over multiple paths. Also, since UWB signals have very high time resolution, clock imperfections can cause significant errors. These challenging issues, which affect the performance of practical time-based UWB ranging, are discussed in the following.

Propagation Effects — Propagation effects on range estimation can be categorized into two groups depending on whether or not there is an LOS path between the transmitter and the receiver. In the presence of an LOS path, positioning errors can occur mainly due to multipath propagation and thermal noise. Since signals arrive at the receiver over multiple paths, it can be challenging to determine the exact TOA of the received signal. Using UWB signals can help resolve the incoming multipath components due to the very high time resolution of UWB signals. In LOS scenarios, the arrival time of the first component of the received signal corresponds to the true time delay between the transmitter and the receiver. Therefore, in order to perform time-based ranging successfully, the TOA of the first component of the received signal should be estimated accurately, which can be achieved by using *first-path detection* algorithms [20, 40–42].

In the absence of an LOS path between the transmitter and the receiver (i.e., when there is an obstacle between them), two types of challenges can be encountered in time-based ranging (Fig. 3) [39]. First, the signal component traveling over the LOS path can be attenuated or totally blocked by the obstacle in such a way that the first-path detection algorithms would identify one of the multipath components as the first path [43–45]. The second type of challenge is encountered when the transmitted signals propagate slower in the obstacle than they do in the air. Even if the transmitted signal is not attenuated significantly in the obstacle, it can be delayed so significantly that the first incoming signal at the receiver does not correspond to the true LOS delay [39].

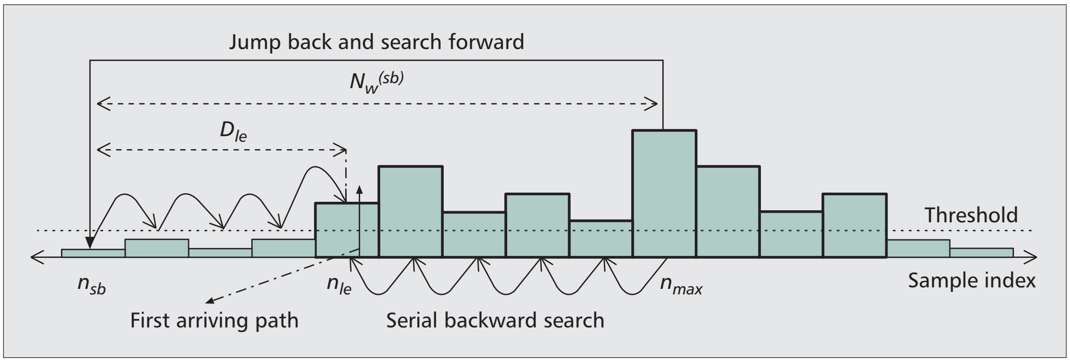

Figure 4. *Illustration of jump back and search forward (JBSF) and serial backward search (SBS) algorithms [2].* $N_w^{(sb)}$ *denotes the search-back window length in samples,* n_{max} *is the index of the strongest sample,* n_{le} *is the index of the first arriving path's sample,* n_{sb} *is the index of the first sample within the search-back window, and* D_{le} *is the delay between the index of the first sample within the search window and the first arriving path's sample [57].*

UWB signals have very large bandwidths, and hence, very high time resolution, which facilitates accurate positioning based on time based ranging. However, this high resolution property of UWB signals also presents certain challenges for time based ranging.

NLOS situations can significantly complicate the time-based ranging task [10]. First of all, it becomes important to identify a link between two nodes as an LOS or NLOS link. In some cases, it is possible to identify an NLOS link by using the measurement statistics obtained from that link [46–48]. Also, the information embedded in the multipath components of the received signal can be used to detect NLOS scenarios [49, 50]. Once two nodes are identified to be in NLOS of each other, several techniques can be employed to mitigate NLOS induced errors. One of the common ways of performing time-based ranging in NLOS scenarios is to employ a mapping technique that utilizes training data obtained from the environment in which positioning will be performed [28, 34–38]. Another way of mitigating NLOS errors is to simply ignore NLOS measurements [51]. Also, using several scattering models for an environment, the statistics of time-based parameters, such as TOA, can be obtained for that environment, and then MAP and ML estimators can be employed to perform time-based ranging in NLOS scenarios [33, 52].

Interference — There are two basic sources of interference for UWB systems; narrowband interference (NBI) and multiple access interference (MAI). Since a UWB system uses a very large portion of the frequency spectrum, there are many other narrowband systems that operate in the same frequency band as the UWB system. Therefore, the NBI coming from those systems can affect the performance of time-based UWB ranging, as investigated in [39, 53].

The second source of interference is the other UWB users in the same environment, which result in MAI. MAI can be handled by using time-division multiple access (TDMA) or frequency-division multiple access (FDMA) for the users in the same network. Still, these precautions may not be enough if there is another UWB network operating in the same environment. One approach for mitigating MAI is proposed in [54] in order to improve the ranging accuracy of noncoherent receivers via nonlinear filtering. Also, codes with good cross-correlation properties can be used to mitigate the effects of MAI [2, 21, 42]. For example, the IEEE 802.15.4a standard assigns two unique ternary codes for each frequency band [2].

High Time Resolution and Clock Drift — UWB signals have very large bandwidths and hence very high time resolution, which facilitates accurate positioning based on time-based ranging. However, this high resolution property of UWB signals also presents certain challenges for time-based ranging. First, since the time resolution is very high, even very small timing errors can cause significant errors in time-based ranging. The main reason for such timing errors is the clock drift. In both one-way and two-way ranging protocols, the clock drift can cause significant errors in some cases [39, 55]. However, the effects of the clock drift can be mitigated by a symmetric double-sided two-way ranging protocol, which relates the drift to the difference of the processing times at two devices [21, 56]. Another problem with the high time resolution of UWB signals is that due to the very large bandwidth, it is both costly and power consuming to sample UWB signals at the Nyquist rate. Therefore, TOA estimation algorithms based on low-rate samples are desirable for UWB systems. Finally, the high time resolution of UWB signals results in a large number of possible delay values that need to be searched by a correlation based receiver for time delay estimation. Therefore, instead of an exhaustive search on the delay space, two-step approaches are commonly preferred for UWB systems [2, 41].

Theoretical Limits

In this section, theoretical limits on time-based UWB ranging are presented in terms of the CRLB and Ziv-Zakai lower bound (ZZLB). The following received signal model is considered based on a single-user scenario,

$$r(t) = \sum_{j=0}^{N_r-1} \sum_{l=1}^{L} \alpha_l \omega(t - \tau_l - jT_f) + n(t), \tag{3}$$

where $\omega(t)$ represents a UWB pulse with duration T_p, T_f is the *frame* duration ($T_f \gg T_p$), N_r is the number of frames in the received signal, and $n(t)$ is zero mean AWGN with spectral den-

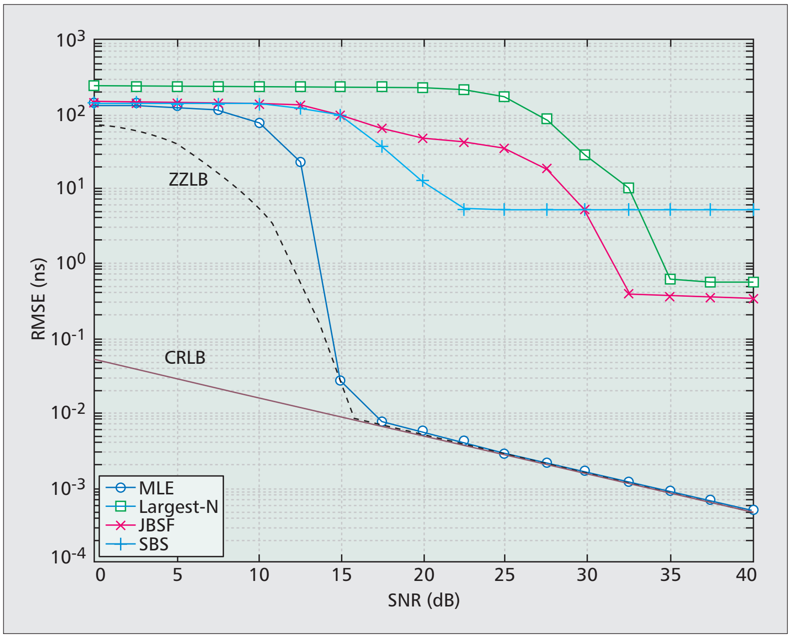

Figure 5. *Root mean-squared error (RMSE) vs. SNR for various algorithms, and the CRLB and ZZLB.*

sity $N_0/2$ [57]. In addition, a channel model with L multipath components is considered, and α_l and τ_l denote, the channel coefficient and the delay of the lth multipath component for $l = 1, \ldots, L$, respectively. Also, it is assumed that the pulses in different frames do not interfere with each other.

CRLB — For an estimation problem with multiple unknown parameters, the CRLB is determined by the inverse of the Fisher information matrix (FIM). For the received signal model in Eq. 3, there are $2L$ unknown parameters corresponding to the channel coefficients and the delays of the multipath components. For the unknown parameter vector $\boldsymbol{\theta} = [\alpha_1 \cdots \alpha_L \; \tau_1 \cdots \tau_L]$, the FIM can be formed as in [6], and then the CRLB on the variances of unbiased path delay estimators can be written as[2]

$$\mathrm{CRLB}(\tau_l) = \frac{N_0/2}{N_r \alpha_l^2 \left(E_p'' - (E_p')^2 / E_p\right)} \quad (4)$$

for $l = 1, \ldots, L$, where E_p is the energy of $\omega(t)$, $E_p' = \int_0^{T_p} \omega(t)\omega'(t)dt$, and $E_p'' = \int_0^{T_p} |\omega'(t)|^2 dt$, with $\omega'(t)$ denoting the first derivative of $\omega(t)$. From Parseval's relation, E_p'' can be expressed as $E_p'' = 4\pi^2 \int_{-\infty}^{\infty} f^2 |P(f)|^2 df$, where $P(f)$ represents the Fourier transform of $\omega(t)$. In addition, $E_p' = 0$ when the UWB pulse satisfies $\omega(0) = \omega(T_p)$. Then, Eq. 4 can also be expressed as

$$\mathrm{CRLB}(\tau_l) = \frac{1}{8\pi^2 N_r \beta^2 \mathrm{SNR}_l}, \quad (5)$$

where β is the effective bandwidth defined as $\beta^2 \triangleq (1/E_p) \int_{-\infty}^{\infty} f^2 |P(f)|^2 df$, and SNR_l denotes the SNR of the lth path, $\mathrm{SNR}_l \triangleq \alpha_l^2 E_p / N_0$. It is observed from Eq. 5 that the CRLB depends on the pulse shape, SNR, and number of pulses employed in time delay estimation. Also, a comparison of Eqs. 1 and 5 reveals that the CRLB in Eq. 5 is in the same form as that in Eq. 1 with the exception that the path SNR is employed and there is a factor of N_r since N_r pulses are employed in the estimation.

ZZLB — The CRLB is widely used for performance evaluation. However, it is known that it can result in some loose limits at low SNR values. The ZZLB, on the other hand, provides tight bounds even at low SNR values. Since the ZZLB cannot be expressed in closed form in many cases, one approach to evaluating the ZZLB is to consider channel realizations that belong to a random process with a finite ensemble of realizations $\{s^{(k)}(t)\}_{k=1}^{N_{ch}}$, where N^{ch} denotes the number of realizations [39]. Then the ZZLB can be obtained as [58]

$$\mathrm{ZZLB} = \frac{1}{T_a} \int_0^{T_a} (T_a - z) z P_{\min}(z) dz, \quad (6)$$

where the time delay is assumed to be uniformly distributed in $[0, T_a)$, and $P_{\min}(z)$ is approximated by

$$P_{\min}(z) \approx \frac{1}{N_{ch}} \sum_{k=1}^{N_{ch}} Q\left(\sqrt{\frac{D_k^2(z)}{2N_0}}\right). \quad (7)$$

In Eq. 7, $Q(\cdot)$ denotes the Q-function that is defined as $Q(x) = (1/\sqrt{2\pi}) \int_x^{\infty} \exp(-t^2/2)dt$, and $D_k^2(z)$ is given by

$$D_k^2(z) = \min_i \int_{T_{obs}} \left(s^{(k)}(t-\tau) - s^{(i)}(t-\tau-z)\right)^2 dt \quad (8)$$

with T_{obs} denoting the observation interval [39].

Other approaches for evaluating the ZZLB in multipath channels are discussed [39, 58]. Although the ZZLB cannot be evaluated analytically in many cases, it provides a tighter bound than the CRLB for low-to-medium SNRs, as can be observed in Fig. 5.

TOA Estimators

In this section various TOA estimators are studied for time-based UWB ranging. First, ML-based estimators are presented under various conditions. Then some practical TOA estimators are discussed.

ML-Based Estimators — If the received waveform structure is completely known, it is possible to perform ML estimation by using a correlator with a template signal that is perfectly matched to the received waveform [6]. However, the incoming signal to the receiver consists of multipath components with different time delays, channel coefficients, and even pulse shapes in some cases. Therefore, it is not possible to know the exact waveform of the received signal in practice. Hence, the ML estimator based on a correlator with the received signal template cannot be implemented in practical systems.

In the absence of prior information, it is necessary to jointly estimate the time delays and channel coefficients of the multipath components even though the main parameter of interest is the time delay of the first component of the received signal. The ML estimates for the unknown parameters $\boldsymbol{\tau} = [\tau_1 \cdots \tau_L]$ and $\boldsymbol{\alpha} = [\alpha_1 \cdots \alpha_L]$ are given by [59]

[2] *It is assumed that there is no inter-pulse interference.*

$$\hat{\tau} = \arg\max_{\tau} \left\{ \left[\Omega^T(\tau)\mathbf{r} \right]^T \mathbf{R}_{\Omega}^{-1}(\tau) \left[\Omega^T(\tau)\mathbf{r} \right] \right\} \quad (9)$$

$$\hat{\alpha} = \mathbf{R}_{\Omega}^{-1}(\hat{\tau})\Omega^T(\hat{\tau})\mathbf{r}, \quad (10)$$

where $\mathbf{r}$ denotes the vector of received signal samples, and $\mathbf{R}_{\Omega}(\tau) = \Omega^T(\tau)\Omega(\tau)$ with $\Omega(\tau) = [\omega^{(D1)}\ \omega^{(D2)} \cdots \omega^{(DL)}]^T$ and $\omega^{(Dl)} = [\mathbf{0}_{Dl}\ \omega\ \mathbf{0}_{N_{smp}-N_{\omega}-Dl}]^T$ [2]. Note that D_l is defined as the largest integer smaller than or equal to τ_l/T_{smp} (with T_{smp} denoting the sampling interval), ω denotes a vector of size N_{ω} that consists of the samples of the UWB pulse, $\mathbf{0}_i$ is a vector of i zeros, and N_{smp} represents the number of samples.

The ML estimation of time delays and channel coefficients has very high computational complexity, especially when the number of multipath components is large. To reduce the complexity, a simpler method called generalized maximum likelihood (GML) is proposed in [20]. GML simply searches the time delay values smaller than the delay of the strongest multipath component, assuming that the strongest multipath component has already been identified.

Low Complexity Estimators — In this section some practical estimators that have lower complexity than the ML-based approaches are presented. Let $z[k]$ denote the samples of an energy detector output, or the absolute values of the samples of a correlator output for $k = 1, 2, \ldots, N_b$. It is assumed that the sampling rate is below the Nyquist rate, and the aim is to estimate the TOA as accurately as possible based on samples $z[1], \ldots, z[N_b]$.

Possibly the simplest TOA estimator is the one that estimates the TOA based on the index of the largest sample [60]. In that case, the delay of the first signal component is estimated as $\hat{\tau}_1 = T_{smp}\, k_{max} + T_{smp}/2$, where T_{smp} is the sampling interval and k_{max} is the value of $k \in \{1, \ldots, N_b\}$ that maximizes $z[k]$. Since the strongest signal sample may not correspond to the first signal component in many cases, other low-complexity algorithms have been proposed to improve the accuracy of TOA estimation [39, 61, 62]. For example, in [62] the largest N correlation peaks are considered, and the time delay corresponding to the peak with the smallest time index is selected (called the *largest-N peak detection* algorithm). Thus, if k_i represents the time index for the ith largest correlation peak, the TOA of the received signal is estimated as $\hat{\tau}_1 = T_{smp}\min\{k_1, k_2, \ldots, k_N\} + T_{smp}/2$.

Another class of TOA estimators with low complexity includes two-step TOA estimators, which can perform accurate TOA estimation based on low-rate samples. For example, the two-step estimator proposed in [41] obtains a coarse time delay estimate in the first step, and then refines this estimate using a statistical change detection algorithm in the second step.

An important class of practical estimators are threshold-based ones, which compare the samples of the received signal against a threshold in order to determine the first path component of the received signal [40, 63, 64]. The jump back and search forward (JBSF) algorithm is one of these; it determines the strongest sample in the received signal first and then jumps a number of samples back from the strongest one, as shown in Fig. 4. After that, the samples are compared against a threshold sequentially, and the first sample that exceeds the threshold is used to obtain the TOA estimate [40]. The intuition behind the JBSF algorithm is that since the first signal path commonly resides before the strongest signal sample, it can be helpful to jump backward from the strongest signal sample and search in the forward direction starting from that position. Then a threshold test can be used to distinguish the first signal path from the noise-only samples. Similar to the JBSF algorithm, the serial backward search (SBS) algorithm first determines the strongest sample. However, unlike the JBSF algorithm, it then performs a backward search starting from the strongest sample, and selects the first sample that satisfies the following: the sample value exceeds the threshold, and the next sample in the search direction does not exceed the threshold. In this way, the SBS algorithm aims to detect the first path before which a noise-only sample resides (Fig. 4).

In Fig. 5, some of the time-based ranging algorithms discussed in this section are compared, and the theoretical lower bounds are presented. An uncertainty region of 500 ns is considered for TOA estimation, 100 realizations from the channel model 3 of the IEEE 802.15.4a channel model are used [16], and the second derivative of the Gaussian pulse [2] with around 1 ns pulse width is used in the training signal (only one pulse is employed). Also, the thresholds for the JBSF and the SBS algorithms are set to 0.25 times the maximum correlation output (the window size in Fig. 4 is 50 ns), and $N = 500$ for the largest-N peak detection algorithm. The ML estimator (MLE) is presented as a benchmark, and the other three algorithms are considered due to their practicality. It is observed that the MLE has the best performance as expected, and it gets quite close to the ZZLB at almost all SNR values and to the CRLB only at high SNRs [57]. Considering the practical estimators, the JBSF algorithm has better performance than the largest-N peak detection algorithm, and it also performs better than the SBS algorithm at high SNRs. In addition, the JBSF and largest-N peak detection algorithms can provide subnanosecond accuracy.

Conclusions

In this study, position estimation has been investigated for UWB systems. First, two-step positioning systems have been studied from a UWB perspective, and it has been concluded that time-based position estimation is well suited for UWB systems due to the large bandwidths of UWB signals. Then time-based UWB ranging has been investigated in detail, and the main challenges, theoretical limits, and TOA estimation algorithms have been presented. Specifically, the trade-offs between complexity and accuracy have been observed for time-based UWB ranging algorithms. The performance of various algorithms has been compared against the theoretical limits.

An important class of practical estimators is the threshold based estimators, which compare the samples of the received signal against a threshold in order to determine the first path component of the received signal.

Considering the practical estimators, the JBSF algorithm has better performance than the largest-N peak detection algorithm, and it also performs better than the SBS algorithm at high SNRs.

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