Threshold Selection for Ultra-Wideband TOA Estimation based on Neural Networks

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Abstract—Because of the good penetration into many common materials and inherent fine resolution, Ultra-Wideband (UWB) signals are widely used in remote ranging and positioning applications. On the other hand, because of the high sampling rate, coherent Time of Arrival (TOA) estimation algorithms are not practical for low cost, low complexity UWB systems. In order to improve the precision of TOA estimation, an Energy Detection (ED) based non-coherent TOA estimation algorithm using Artificial Neural Networks (ANN) is presented which is based on the skewness after energy detection. The expected values of skewness and kurtosis with respect to the Signal to Noise Ratio (SNR) are investigated. It is shown that the skewness is more suitable for TOA estimation. The best threshold values for different SNRs are investigated and the effects of integration period and channel modes are examined. Comparisons with other ED based algorithms show that in CM1 and CM2 channels, the proposed algorithm provides higher precision and robustness in both high and low SNR environments.

Index Terms—Artificial neural network (ANN), UWB, TOA estimation, Ranging, Skewness

I. INTRODUCTION

Among the potential applications, precision indoor ranging, positioning and tracking have been the most obvious for Impulse Radio (IR) Ultra-wideband (UWB) technology [1-3]. UWB technology is increasingly considered as an ideal radio system to enable accurate indoor positioning for tasks such as asset and people tracking or ambient intelligent sensing, even in dense multipath, Non-Line of Sight (NLOS) fading environments. This is because of the high time resolution (sub-nanosecond to nanosecond) available due to the high sampling rate. In addition, the wide signal bandwidth results in a very low power spectral density, which reduces interference to other RF systems, and the short pulse duration reduces or eliminates pulse distortion (fading) and spurious signal detections due to multipath propagation [4]. In addition, some frequency components may be able to penetrate obstacles to provide a line-of-sight (LOS) signal. Thus, these high resolution, wide bandwidth UWB signals are suitable for positioning applications [5].

Positioning technologies can be classified into range based [2, 3, 6, 7] and non-range based [8]. For example, Time of Arrival (TOA) [7, 9] and Time Difference of Arrival (TDOA) [10] are range based techniques, while Received Signal Strength (RSS) and Angle-of-Arrival (AOA) [8] are non-range based. Range based positioning (TOA or TDOA) is the most suitable for use with UWB technology [11], as it can take full advantage of the high time resolution available with very short UWB pulses. Accurate TOA estimation is the key to precise ranging, but this is very challenging due to the potentially hundreds of multipath components in UWB channels. TOA estimation has been extensively studied [9, 12-15]. There are two approaches applicable to UWB TOA estimation, a Matched Filter (MF) [13] (such as a RAKE or correlation receiver) with a high sampling rate and high-precision correlation, or an Energy Detector (ED) [15] with a lower sampling rate and low complex. A MF is the optimal technique for TOA estimation, where a correlator template is matched exactly to the received signal. However, a UWB receiver operating at the Nyquist sampling rate makes it very difficult to align with the multipath components of the received signal [12]. In addition, a MF requires a priori estimation of the channel, including the timing, fading coefficient, and pulse shape for each component of the impulse response [12]. Because of the high sampling rates and channel estimation, a MF may not be practical in many applications. As opposed to a more complex MF, an ED is a non-coherent approach to TOA estimation. It consists of a square-law device, followed by an integrator, sampler and a decision mechanism. The TOA estimate is made by comparing the integrator output with a threshold and choosing the first sample to exceed the threshold. This is a convenient technique that directly yields an estimate of the start of the received signal. Thus, a low
complexity, low sampling rate receiver can be employed without the need for *a priori* channel estimation.

The major challenge with ED is the selection of an appropriate threshold based on the received signal samples. In [14], a normalized threshold selection technique for TOA estimation of UWB signals was proposed which exploits the kurtosis of the received samples. In [15], an approach based on the minimum and maximum sample energy was introduced. Threshold selection for different SNR (Signal to Noise Ratio) values was investigated via simulation. These approaches have limited TOA precision, as the strongest path is not necessarily the first arriving path.

Neural networks have been used extensively in signal processing applications. The weights between the input and output layers can be adjusted to minimize the error between the input and output. Because of the complicated wireless environments, it is difficult to derive a closed-form expression to estimate the TOA. On the other hand, an ANN can provide a very flexible mapping based on the training input. Thus an ANN can be used to establish an accurate relationship between the input and output.

In this paper, we consider the relationship between the SNR and the statistics of the integrator output including skewness and kurtosis. A metric based on skewness is the delay of the *n*th path, which differs for each user to allow for multiple access communications. The Time Hopping (TH) is provided by a pseudorandom integer-valued sequence *c*/*p* which differs for each user to allow for multiple access communications. The chip time, and the pulse position modulation (PPM) time shift is *e*, with the data *a* either 0 or 1. If *a* = 1, the signal will be shifted in time, otherwise there is no PPM shift. The pulse is given by *p(t)*. For example, the second derivative Gaussian pulse is

\[ p(t) = \frac{d^2 f(t)}{dt^2} = (1 - 4\pi^2 \alpha^2) e^{-\frac{2\pi^2 \alpha^2}{\sigma^2}}, \]

where \( \alpha \) is the shape factor and \( f(t) \) is the Gaussian pulse. A smaller value of \( \alpha \) results in a shorter pulse duration and thus a larger bandwidth.

### B. Multipath Fading Channel

Because of the multipath channel between the transmitter and receiver, the received signal can be expressed as

\[ r(t) = \sum_{n=1}^{N} \alpha_n p(t - \tau_n) + n(t), \]

where \( N \) is the number of received multipath components, \( \alpha_n \) and \( \tau_n \) denote the amplitude and delay of the *n*th path, respectively, and \( n(t) \) is Additive White Gaussian Noise (AWGN) with zero mean and two-sided power spectral density \( N_0/2 \). Equation (3) can be rewritten as

\[ r(t) = s(t) * h(t) + n(t), \]

where \( s(t) \) is the transmitted signal, and \( h(t) \) is the channel impulse response given by

\[ h(t) = X \sum_{n=1}^{N} \alpha_n \delta(t - T_n - \tau_{nk}), \]

where \( X \) is a log-normal random variable representing the amplitude gain of the channel, \( N_c \) is the number of observed clusters, \( K(n) \) is the number of multipath contributions received within the *n*th path, \( \alpha_{nk} \) is the coefficient of the *k*th multipath contribution of the *n*th cluster, \( T_n \) is the time of arrival of the *n*th path and \( \tau_{nk} \) is the delay of the *k*th multipath contribution within the *n*th cluster.

### C. Energy Detector

As shown in Fig. 1, after the low noise amplifier (LNA), the received signal is squared, and then input to an integrator with integration period \( T_b \). Because of the inter-frame leakage due to multipath signals, the integration duration is set to \( 3T_b/2 \) [14], so the number of signal values for energy detection is \( N_b = (3T_b)/(2T_b) \). The integrator output can then be expressed as

PPM-TH-UWB signals are very short in time, typically a few nanoseconds, and can be expressed as

\[ s(t) = \sum_{j} p(t - (jT_f - c_jT_e - a_je)), \]

where \( j \) and \( T_f \) are the frame index and frame duration, respectively. The Time Hopping (TH) is provided by a pseudorandom integer-valued sequence \( c_j \) which differs for each user to allow for multiple access communications. The chip time, and the pulse position modulation (PPM) time shift is \( e \), with the data \( a_j \) either 0 or 1. If \( a_j = 1 \), the signal will be shifted in time, otherwise there is no PPM shift. The pulse is given by \( p(t) \). For example, the second derivative Gaussian pulse is

\[ p(t) = \frac{d^2 f(t)}{dt^2} = (1 - 4\pi^2 \alpha^2) e^{-\frac{2\pi^2 \alpha^2}{\sigma^2}}, \]

where \( \alpha \) is the shape factor and \( f(t) \) is the Gaussian pulse. A smaller value of \( \alpha \) results in a shorter pulse duration and thus a larger bandwidth.
\[ z[n] = \sum_{j=1}^{N_s} \int_{(j-1)T_T}^{(j+n)T_T} r^2(t) dt, \quad (6) \]

where \( n \in \{1, 2, ..., N_s\} \) denotes the sample index with respect to the start of the integration period and \( N_s \) is the number of pulses per symbol. Here, \( N_s \) is set to 1, so the integrator output is

\[ z[n] = \int_{(n-n-1)T_T}^{(c+n)T_T} r^2(t) dt. \quad (7) \]

If \( z[n] \) is the integration of noise only, it has a centralized Chi-square distribution, while it has a non-centralized Chi-square distribution if a signal is present. The mean and variance of the noise and signal values are given by [14]

\[ \mu_0 = F\sigma_0^2, \quad \sigma_0^2 = 2F\sigma_d^2, \quad (8) \]
\[ \mu_n = F\sigma_d^2 + E_n, \quad \sigma_n^2 = 2F\sigma_d^4 + 4\sigma_d^2 E_n, \quad (9) \]

respectively, where \( E_n \) is the signal energy within the \( n \)th integration period and \( F \) is the number of degrees of freedom given by \( F = 2BT_s + 1 \). Here \( B \) is the signal bandwidth.

III. TOA ESTIMATION BASED ON ENERGY DETECTION

A. TOA Estimation Algorithms

There are many TOA estimation algorithms based on energy detection which can be used to determine the start of a received signal, as shown in Fig. 2. The simplest is Maximum Energy Selection (MES), which chooses the maximum energy value to be the start of the signal. The TOA is estimated as the center of the corresponding integration period

\[ \tau_{MES} = [\text{arg max}\{z[n]\} - 0.5]T_T. \quad (10) \]

However, as shown in Fig. 2, the maximum energy value is not always the first [13], especially in NLOS environments. Typically, the first energy value \( z[\hat{n}] \) is located before the maximum \( z[n_{\text{max}}] \), i.e., \( \hat{n} \leq n_{\text{max}} \). Thus, Threshold Crossing (TC) TOA estimation has been proposed where the received energy values are compared to an appropriate threshold \( \xi \). In this case, the TOA estimate is given by

\[ \tau_{TC} = [\text{arg min}\{n \mid z[n] \geq \xi\} - 0.5]T_T. \quad (11) \]

It is difficult to determine an appropriate threshold \( \xi \), so a normalized threshold \( \xi_{\text{norm}} \) is usually employed so that

\[ \xi = \xi_{\text{norm}} \left( \text{max}(z(n)) - \text{min}(z(n)) \right) + \text{min}(z(n)). \quad (12) \]

The TOA estimate is then obtained using (11). The problem in this case becomes one of how to set the threshold, i.e., how to establish the relationship between the received energy values and \( \xi_{\text{norm}} \). There are two main methods in the literature, curve fitting and fixed threshold. In [14], a normalized threshold selection technique for TOA estimation of UWB signals was proposed which uses exponential and linear curve fitting for the kurtosis of the received samples. A simpler TC algorithm is the Fixed Threshold (FT) algorithm where the threshold is set to a fixed value, for example \( \xi_{\text{norm}} = 0.4 \). If \( \xi_{\text{norm}} \) is set to 1, the algorithm is the same as MES. Here, an ANN algorithm is employed to obtain the normalized threshold based on the signal energy statistics.

B. TOA Estimation Error

In [15], the Mean Absolute Error (MAE) of TC based TOA estimation was analyzed, and closed form error expressions derived. The MAE can be used to evaluate the quality of an algorithm, and is defined as

\[ \text{MAE} = \frac{1}{N} \sum_{n=1}^{N} |t_n - \hat{t}_n|, \quad (13) \]

where \( t_n \) is the \( n \)th actual propagation time, \( \hat{t}_n \) is the \( n \)th TOA estimate, and \( N \) is the number of TOA estimates.

IV. STATISTICAL CHARACTERISTICS OF THE SIGNAL ENERGY

In this section, the skewness and kurtosis of the energy values are analyzed.

A. Kurtosis

The kurtosis is calculated using the second and fourth order moments and is given by

\[ k = \frac{1}{(N_s - 1)\delta^4} \sum_{i=1}^{N_s} (x_i - \bar{x})^4, \quad (14) \]

where \( \bar{x} \) is the mean, and \( \delta \) is the standard deviation. The kurtosis for a standard normal distribution is three. For this reason, \( k \) is often redefined as \( K = k - 3 \) (referred to as "excess kurtosis"), so that the standard normal distribution has a kurtosis of zero. Positive kurtosis indicates a "peaked" distribution, while negative kurtosis indicates a "flat" distribution. For noise only (or for a low SNR) and sufficiently large \( F \) (degrees of freedom of the
Chi-square distribution), $z[n]$ has a Gaussian distribution and $K=0$. On the other hand, as the SNR increases, $K$ tends to increase.

In [14], the normalized threshold with respect to the kurtosis and the corresponding MAE were investigated. To model the relationship, a double exponential function was used for $T_b = 4ns$, and a linear function for $T_b = 1ns$. The resulting expressions are

$$\xi_{\text{best}}^{(4ns)} = 0.673e^{-0.37\log_2 K} + 0.154e^{-0.001 \log_2 K},$$

and

$$\xi_{\text{best}}^{(1ns)} = -0.082\log_2 K + 0.77.$$

The model coefficients were obtained using data from both the CM1 and CM2 channels. In Section 7, these expressions are used to obtain the performance results.

B. Skewness

The skewness is given by

$$S = \frac{1}{(N_x-1)\delta^2} \sum_{i=1}^{N_x} (x_i - \overline{x})^3,$$

where $\overline{x}$ is the mean, and $\delta$ is the standard deviation of the energy values. The skewness for a normal distribution is zero, in fact any symmetric data will have a skewness of zero. Negative values of skewness indicate that the data is skewed left, while positive values indicate data that is skewed right. Skewed left indicates that the left tail is long relative to the right tail, while skewed right indicates the opposite. For noise only (or very low SNRs), and sufficiently large $F$, $S=0$. As the SNR increases, $S$ tends to increase.

In [18], exponential functions were fit to the skewness results for $T_b = 1ns$ and $T_b = 4ns$, with $S$ as the $x$-coordinate and $\xi_{\text{best}}$ as the $y$-coordinate. The resulting functions are

$$\xi_{\text{best}}^{(1ns)} = 0.9028e^{0.1347S},$$

$$\xi_{\text{best}}^{(4ns)} = 0.9265e^{0.2025S}.$$

C. Characteristics of the Two Statistical Parameters

In order to examine the characteristics of the two statistical parameters (skewness and kurtosis), the CM1 (residential LOS) and CM2 (residential NLOS) channel models from the IEEE802.15.4a standard are employed. For each SNR value, 1000 channel realizations were generated and sampled at $f_c = 8GHz$. The other system parameters are $T_s = 200\text{ns}$, $T_b = 1\text{ns}$, $T_b = 4\text{ns}$ and $N_r = 1$. Each realization has a TOA uniformly distributed within $(0, T)$. The two statistical parameters were calculated, and the results obtained are shown in Fig. 3. This shows that the characteristics of the parameters with respect to the SNR are similar for the two channels. Further, Fig. 3 shows that the kurtosis and skewness increase as the SNR increases in channels CM1 and CM2, but the skewness changes more rapidly. Since the skewness changes more rapidly than the kurtosis, it better reflects changes in SNR, and so is more suitable for TOA estimation.

V. NORMALIZED THRESHOLD WITH RESPECT TO $S$

Before training the ANN, the relationship between $S$ and the normalized threshold must be established, because the former is the ANN input and the latter is the output. According to Fig. 3, the curves for channels CM1 and CM2 for a given value of $T_b$ are similar, so models are derived for $T_b=1\text{ns}$ and for $T_b=4\text{ns}$. The relationship between MAE and the normalized threshold is investigated. For each value of $S$, the normalized threshold with respect to the minimum MAE is required to establish the model. The mean of the normalized thresholds for channels CM1 and CM2 for each $S$ is selected as the optimal normalized threshold $\xi_{\text{opt}}$.

A. MAE with Respect to the Normalized Threshold

To determine the optimal threshold $\xi_{\text{opt}}$ based on $S$, the relationship between MAE and the normalized threshold $\xi_{\text{norm}}$ was determined. 1000 CM1 and CM2 channel realizations for each of SNR=4, 5, ..., 32 dB were generated. $\xi$ is the threshold which is compared to the energy values to find the first threshold crossing, as defined in (12). When $\xi$ is larger than the maximum energy value $z_{\text{max}}$, no $r$ is found, so in this case $\xi$ is set to $z_{\text{max}}$ and $\xi_{\text{norm}}$ is set to 1.

Figures 4, 5, 6 and 7 show the MAE for $S=1,2,3,4,5,6,7,8$ for the CM1 and CM2 channels, and $T_b=1\text{ns}$ and $T_b=4\text{ns}$. The relationship is always that the MAE decreases as $S$ increases. In addition, the minimum MAE is lower as $S$ increases.

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B. Optimal Thresholds

The normalized threshold $\xi_{\text{norm}}$ with respect to the minimum MAE is called the best threshold $\xi_{\text{best}}$ for a given $S$. These best thresholds $\xi_{\text{best}}$ are shown in Figures 8 and 9. These show that the relationship between the two parameters is not affected significantly by the channel model, but is more dependent on the integration period, so the values for channels CM1 and CM2 can be combined. Therefore, the mean is selected as the optimal normalized threshold as shown in (20) and (21).

$$\xi_{\text{norm}}^{(T_b=1)}(s) = \frac{\xi_{\text{best}}^{(CM=1,T_b=1)}(s) + \xi_{\text{best}}^{(CM=2,T_b=1)}(s)}{2}, \quad (20)$$

$$\xi_{\text{norm}}^{(T_b=4)}(s) = \frac{\xi_{\text{best}}^{(CM=1,T_b=4)}(s) + \xi_{\text{best}}^{(CM=2,T_b=4)}(s)}{2}. \quad (21)$$
The value of $\tilde{\xi}_{\text{norm}}$ ranges from 0 to 1, so the logsig function is selected as the transfer function for both the input layer and hidden layer. 'Logsig' is defined as $\text{logsig}(x) = 1/(1 + \exp(-x))$, as shown in Fig. 12. 'Trainlm' is a network training function that updates the weight and bias values according to Levenberg-Marquardt optimization [19]. Although 'Trainlm' requires more memory than other algorithms, it is often the fastest backpropagation algorithm. Because there is only one input and one output element in the proposed ANN, and only 27 samples ($S=0$ to 17 for $T_b=1ns$ and $S=0$ to 8 for $T_b=4ns$), the memory requirements are modest. Thus, 'trainlm' is selected as the backpropagation network training function. The weights and biases for all layers of each ANN before training were set to random values uniformly distributed between -1 and 1.

B. ANN Training

In order to train the ANN, i.e., to determine the relationship between $S$ and the normalized threshold $\tilde{\xi}_{\text{norm}}$ 1000 CM1 and CM2 channel realizations for each value of $\text{SNR}=4$, 5, ..., 32 dB were generated for both $T_b=1ns$ and $T_b=4ns$. The optimal thresholds for all possible $S$ were calculated and the corresponding ANN outputs are shown in Figures 8 and 9. For $T_b=1ns$, the ANN inputs are values of $S$ range from 0 to 17, and for $T_b=4ns$, from 0 to 8. Thus there are 27 samples to train the ANN.

In order to get the best ANN, 100 separate train iterations were conducted for each value of $T_b$, and the one with the lowest MES was selected. After training, the lowest MSE for $T_b=1ns$ was 5.6494E-33, and the corresponding weights and bias values are as follows.

- Weights from the input layer to layer 1 (hidden layer): {-5.8259; -5.4336; -5.8416; -5.8918; -5.1482; -5.4236; 6.0383; 4.4864; 5.201; -3.9504; 5.974; 4.9826; -5.4379; -6.1604; 6.3402; 6.2972};
- Weights from layer 1 to the output layer: [4.3203; -3.231; -6.478; -7.4261; -6.2472; -5.4379; -6.1604; 6.3402; 6.2972];
- Weights from layer 1 to the output layer: [-1.627 -1.1462 -4.8564 5.3581 0.85273 0.030496 1.4567 0.14144 -1.574];
- Bias to layer 1: [-50.6169; 44.5631; 37.8585; 43.2072; 25.227; 19.1618; 12.6549; -6.2572; 1.636];
- Bias to layer 2: [2.1924].

After training, $S$ (from 0 to 17) for $T_b=1ns$ and $S$ (from 0 to 8) for $T_b=4ns$ are input into the ANN to get the estimated normalized thresholds. The resulting values of $\tilde{\xi}_{\text{norm}}$ are given in Figures 8 and 9. These values show that the trained ANN output fits well with the optimal normalized thresholds for $T_b=1ns$ and $T_b=4ns$.

VII. PERFORMANCE RESULTS AND DISCUSSION

In this section, the MAE is examined for different ED based TOA estimation algorithms in the IEEE 802.15.4a CM1 and CM2 channels. As before, 1000 channel realizations were generated for each case. A second derivative Gaussian pulse with a 1 ns pulse width was employed, and the received signal sampled at $F_s=8$Ghz. The other system parameters are $T_b=200$ns, $T_f=4$ns and $N_s=1$. Each realization has a TOA uniformly distributed within $(0, T_f)$.

Fig. 13 presents the TOA estimation MAE based on the ANN for $\text{SNR}$ values from 4dB to 32dB in LOS (CM1) and NLOS (CM2) channels with $T_b=1ns$ and 4ns. This shows that the ANN algorithm performs well at high SNRs. The performance in CM1 is better than in CM2 by at most 13.8 ns. When SNR>24dB, the MAE for CM1 is
less than 5.4 ns while that for CM2 is less than 11.4 ns. In most cases, the performance with $T_b=1$ ns is the same as $T_b=4$ ns, regardless of the channel.

Figures 14 and 15 present the MAE for four TOA algorithms in channels CM1 and CM2, respectively. Here “ANN” refers to the proposed algorithm, “MES” to the Maximum Energy Selection algorithm, and the normalized threshold for the Fixed Threshold algorithm is set to 0.4. As expected based on the results in Section 4, the MAE with the proposed algorithm is lower than with the other algorithms, particularly at low to moderate SNR values. The proposed algorithm is better than the Kurtosis algorithm except when the SNR is greater than 26 dB for $T_b=1$ ns and 21 dB for $T_b=4$ ns. For these large SNR values, the Kurtosis algorithm is slightly better. For example, when SNR > 27 dB, the MAE of the proposed ANN algorithm is 3 ns greater, at most, than that of the Kurtosis algorithm.

The performance of the proposed algorithm is more robust than the other algorithms, as the difference between $T_b=1$ ns and 4 ns is very small compared to the difference with the Kurtosis algorithm. For almost all SNR values, the proposed algorithm is the best. Conversely, the performance of the Kurtosis algorithm varies greatly with respect to the other algorithms, and is very poor for low to moderate SNR values.

VIII. CONCLUSIONS

Low complexity, energy-based TOA estimation algorithms have been examined for UWB ranging, positioning, and tracking applications. Two statistical parameters were investigated, and from the results obtained, the metric based on skewness was developed for Threshold Crossing (TC) TOA estimation. The optimal normalized threshold was determined using performance results for the CM1 and CM2 channels. The effects of the integration period and channel model were investigated. It was determined that the proposed threshold selection technique is largely independent of the channel model. The performance of the proposed algorithm was shown to be better than several known algorithms. In addition, the proposed algorithm is more robust to changes in the SNR and integration period.

ACKNOWLEDGMENT

This work was supported by the Nature Science Foundation of China under grant No. 60902005, the Outstanding Youth Foundation of Shandong Province under grant No. JQ200821, and the Program for New Century Excellent Talents of the Ministry of Education under grant No. NCET-08-0504.

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