

1.0 INTRODUCTION

Ultra wideband (UWB) communication is a promising technology for short or medium-range wireless communication networks with low cost and low power implementation in an extremely large transmission bandwidth. UWB communication is operated as secondary user and coexist primary users which have exclusive right to use the spectrum. For coexistence, cognitive features enable the UWB user to sense the occupied spectrum by primary users, and adapt the opportunistic spectrum and data rate, accordingly [1], [2].

UWB consists of a variety of throughput options including very high data rates, with applications for wireless local area networks (WLAN) and wireless personal area networks (WPAN). Impulse radio based UWB (IR-UWB), known as “carrier-less short pulse”, and OFDM based UWB (OFDM-UWB) are used for UWB implementation. In cognitive IR-UWB, adaptability is performed by varying the pulse duration or waveform shape. When sensing mechanism is not perfect, cognitive IR-UWB needs to mitigate the impairments from the primary users’ interference.

In this paper, the performance of cognitive IR-UWB is investigated in the presence of different number of primary users and channel conditions. We employ Rake receiver with maximum ratio combining (MRC) to exploit multipath diversity. Channel tracking is pursued in both pilot-aided and blind estimation schemes. Pilot-aided or data-aided (DA) method periodically retransmits the training sequence, or in a decision-directed (DD) manner. On the other hand, blind estimation or non-data-aided (NDA) is helpful when new users enter the network and training sequences impede the transmitter [3].

Herein, the Cramer-Rao lower bound (CRLB) [4], [5], [6] is served as a benchmark for the ML channel estimator in both DA and NDA cases. Using errors predicted by the CRLB, unknown symbols are transmitted over a multipath channel to perform NDA estimation. Then, CRLB of the variance of the delay and gain estimates is derived. In the presence of primary users, we analyze the standard deviation of path gain and delay and compare the system performance of pilot-aided and blind estimation methods.

The rest of the paper is organized as follows. Section 2, describes the system description. Blind channel estimation is discussed in Section 3. Section 4 addresses CRLBs for ML Channel estimation. Simulation results and discussion are presented in Section 5, followed by conclusions in Section 6.

2.0 SYSTEM DESCRIPTION

One of the most significant channel models for UWB systems is the model proposed by Saleh-Valenzuela using a Rayleigh...
probability density function for fading channel coefficient [7]. Reflection, diffraction, and scattering are the main reasons for multipath occurrence in UWB channels [8]. Figure 1 represents an $L_c$-ray multipath channel with independent $L_c$ delays, $\tau_{c,l}$, and gains $\gamma_{c,l}$ of each path.

$$s_c(t) = \sum_{i=0}^{M-1} b(t - iNT_f - a_i\Delta)$$

where $s_c(t)$ is the cognitive user’s signal, and

$$b(t) = \sum_{j=0}^{N-1} g(t - jT_f - c_jT_c)$$

where $g(t)$ is the monocycle pulse with duration $T_p$, $i$ is the information bit index, $N$ is the repetition length, $T_f$ is the frame interval, $a_i \in \{0,1\}$ is the $i$-th information bit with equal a priori probabilities, $\Delta$ is the additional time shift introduced when $a_i = 1$, $c_j$ is the time-hopping code and $T_c$ is the chip time. The received signal is observed over an interval of $0 \leq t \leq T_0$, in which $T_0$ is a multiple $M$ of the symbol period $NT_f$. We also have $E_{s_c} = ME_b$, and

$$E_b = \int_0^{NT_f} b^2(t)dt.$$  

The received signal through $L_c$ paths at the output of the cognitive receiver antenna can be written as

$$r_c(t) = \sum_{l=1}^{L_c} \gamma_{c,l} s_c(t - \tau_{c,l}) + \omega_t(t)$$

where $\gamma_{c,l}$ and $\tau_{c,l}$ are attenuation, and the delay affecting its replica traveling through the $l$-th path respectively, and $\omega_t$ is thermal noise plus the interference caused by the primary users with total power spectral density $\sigma_{\omega_t}^2$, i.e.

$$\omega_t(t) = I_p(t) + n(t),$$

and

$$I_p(t) = \left[ \sum_{l=1}^{L_p} \sum_{k=1}^{N_p} \gamma_{k,l,p} \delta_p(t - \tau_{k,l,p}) \right]$$

where $N_p$ is the number of primary users, $L_p$ denotes the number of primary user paths, and

$$\sigma_{\omega_t}^2 = \sigma_{I_p}^2 + \sigma_n^2$$

Assume $\delta_p(t - \tau_{k,l,p})$ is deterministic, so

$$\sigma_{I_p}^2 = \sum_{l=1}^{L_p} \sum_{k=1}^{N_p} \left[ E(\gamma_{k,l,p}^2) - E^2(\gamma_{k,l,p}) \right] E_{\delta_p}$$

Then

$$\sigma_{\omega_t}^2 = E_{\delta_p} \sum_{l=1}^{L_p} \sum_{k=1}^{N_p} \left[ E(\gamma_{k,l,p}^2) - E^2(\gamma_{k,l,p}) \right] E_{\delta_p}$$

All-RAKE (A-RAKE) receiver is an optimal design with enough number of fingers, and selective-RAKE (S-RAKE) receiver is suboptimal with the limited number of fingers which are investigated in [9]. A zero forcing (ZF) Rake receiver can be combined with ordered successive interference cancellation (OSIC) as proposed in [10].

IR-UWB serves the same spread spectrum concepts as code division multiple-access (CDMA), with DS-SS transceiver implementation. The information is modulated by pulse position modulation (PPM), in which N positions indicate the N symbols. In order to smooth the energy spikes in the spectrum, caused by periodicity of the pulse repetition, a pseudo-random sequence of delays technique, known as time hopping (TH), is applied.

TH-PPM format of the transmitted cognitive IR-UWB signal in our system is expressed as
3.0 BLIND CHANNEL ESTIMATION

In this section, we consider cognitive users, and analyze blind (NDA) channel estimation when the symbols are unknown. As indicated in [7], we can get rid of these unknown information by first computing the Likelihood function, \( \Lambda(\hat{a}, \hat{\gamma}_c, \hat{\tau}_c) \), for

\[
a = (a_0, a_1, \ldots, a_{M-1}), \gamma_c = [\gamma_{c,1}, \gamma_{c,2}, \ldots, \gamma_{c,L_c}] \quad \text{and} \quad \tau_c = [\tau_{c,1}, \tau_{c,2}, \ldots, \tau_{c,\tilde{L}_c}],
\]

and then averaging over the probability density of \( \hat{a} \). This produces the marginal Likelihood function for \((\hat{\gamma}_c, \hat{\tau}_c)\) as

\[
\Lambda(\hat{\gamma}_c, \hat{\tau}_c) = \int \Lambda(\hat{a}, \hat{\gamma}_c, \hat{\tau}_c) p(\hat{a}) d(\hat{a})
\]

from which the channel estimates are derived.

Since there is no specific knowledge of the data symbols, except for independent zero or one values with the same probability, we model \( p(\hat{a}) \) as

\[
p(\hat{a}) = \prod_{k=0}^{M-1} \frac{[\delta(\hat{a}_k) + \delta(\hat{a}_k - 1)]}{2}
\]

(9)

where \( \delta(\hat{a}) \) is the Dirac function. Therefore, (8) and (9) yield

\[
\log[\Lambda(\hat{\gamma}_c, \hat{\tau}_c)] = \sum_{k=0}^{M-1} \log[\frac{1}{2} \exp\left\{ -\frac{1}{\sigma^2} \sum_{l=1}^{L_c} \hat{\gamma}_c \hat{l}_c \hat{z}_k(\hat{\tau}_c, l, 0) \right\}]
\]

\[
+ \frac{1}{2} \exp\left\{ -\frac{1}{\sigma^2} \sum_{l=1}^{L_c} \hat{\gamma}_c \hat{l}_c \hat{z}_k(\hat{\tau}_c, l, 1) \right\} - \frac{1}{2 \sigma^2} M E_b \sum_{l=1}^{L_c} \hat{z}_k^2(\hat{\tau}_c, l, 0)
\]

(10)

where

\[
z_k(\hat{\tau}_c, \hat{a}_k) = \left[ r(t) \otimes b(-\tau) \right]_{t=kNT + \hat{a}_k + \hat{\tau}_c}
\]

(11)

Thus, \( \log[\Lambda(\hat{\gamma}_c, \hat{\tau}_c)] \) is maximized as a function of \( \hat{\gamma}_c, \hat{\tau}_c \).

The first step provides

\[
\hat{\gamma}_{c,l} = \frac{1}{M E_b} J(\hat{\tau}_{c,l}) \quad \text{for} \quad 1 \leq l \leq L_c
\]

(12)

when

\[
J(\hat{\tau}_c) = \sum_{k=0}^{M-1} z_k(\hat{\tau}_c, 0) + z_k(\hat{\tau}_c, 1)
\]

(13)

then, the problem reduces to looking for the location of the extrema of \( J(\hat{\tau}_c) \) and specify the value of \( \hat{\tau}_c \).

4.0 CRLB FOR ML CHANNEL ESTIMATION

In this section, we calculate the CRLB of the path delay and amplitude estimation errors as a function of the parameters of the transmitted signals. We define channel parameter vector as

\[
\theta = [\gamma_{c,1}, \gamma_{c,2}, \ldots, \gamma_{c,L_c}, \tau_{c,1}, \tau_{c,2}, \ldots, \tau_{c,\tilde{L}_c}]^T
\]

(14)

Thus, from [10], we have

\[
- E(\frac{\partial^2 \log(\Lambda(\theta))}{\partial \gamma_{c,l} \partial \gamma_{c,j}}) = \left\{ \begin{array}{ll}
- \frac{1}{\gamma_{c,l} \gamma_{c,j}} & \text{for} \quad i \neq j \\
2 M T - \frac{1}{\gamma_{c,l}} & \text{for} \quad i = j
\end{array} \right.
\]

(15a)

\[
- E(\frac{\partial^2 \log(\Lambda(\theta))}{\partial \tau_{c,i} \partial \tau_{c,j}}) = \left\{ \begin{array}{ll}
0 & \text{for} \quad i \neq j \\
\sum_{k=0}^{M-1} [\gamma_{c,i}^2, I_{ik} + H_{ik}] & \text{for} \quad i = j
\end{array} \right.
\]

(15b)

\[
- E(\frac{\partial^2 \log(\Lambda(\theta))}{\partial \gamma_{c,l} \partial \tau_{c,j}}) = -E(\frac{\partial^2 \log(\Lambda(\theta))}{\partial \tau_{c,i} \partial \gamma_{c,j}}) = 0
\]

(15c)

where \( \Gamma = E_b / (2 \sigma_{\theta}^2) \) is the signal-to-interference-pulse-noise ratio (SINR) and

\[
R_{ik} = \frac{1}{2 \pi \sigma_{\theta}} \int_{-\infty}^{+\infty} \frac{r_h(k \nu) e^{-2 k^2 \sigma_{\theta}^2}}{\nu^2 + \Gamma \nu^4} \left( R y_{c,i} \gamma_{c,j}^2 + \frac{\gamma_{c,j}^2 (a_k - RT + \gamma_{c,j}^2)}{R} \right) dx
\]

(16)

\[
G_{ik} = \frac{1}{2 \pi \sigma_{\theta}} \left[ \gamma_{c,i}^2 \left( \frac{a_k - RT}{2 \Gamma} \right)^2 + \Gamma \left( R - \gamma_{c,j}^2 \right) \gamma_{c,j}^2 dx \right]
\]

(17)

\[
H_{ik} = \frac{1}{2 \pi \Gamma} \int_{-\infty}^{+\infty} \frac{\tanh(h x) e^{-2 R \Gamma}}{R \gamma_{c,i}^2} \left( \gamma_{c,j}^2 - \frac{RT}{2 \Gamma} \right) dx
\]

(18)

\[
I_{ik} = \frac{\eta}{2 \pi \Gamma} \int_{-\infty}^{+\infty} \frac{\tanh(h x) e^{-2 R \Gamma}}{R \gamma_{c,i}^2} \left( \gamma_{c,j}^2 - \frac{RT}{2 \Gamma} \right) dx
\]

(19)
where \( \mathcal{E} = \frac{\int_0^{NT_f} b(t) b^*(t) \, dt}{E_b} \), \( \eta = \frac{\int_0^{NT_f} b^2(t) \, dt}{E_b} \), and

\[
\bar{a}_k = \text{sgn}(l - 2a_k), \quad R = \sum_{l_c=1}^{L_c} \gamma_{c,l_c}^2. \quad \text{Based on [5], the Fisher information matrix is}
\]

\[
I(\theta) = \begin{bmatrix} B & C \\ C & D \end{bmatrix}
\]

\[\text{(20)}\]

where

\[
B = \begin{bmatrix}
2M^T - \frac{1}{\gamma_{c,l_c}^2} \sum_{k=0}^{M-1} G_{ik} & \ldots & \frac{1}{\gamma_{c,l_c}^2} \sum_{k=0}^{M-1} F_{ik} & \ldots & \frac{1}{\gamma_{c,l_c}^2} \sum_{k=0}^{M-1} F_{ik} \\
\ldots & \ldots & \ldots & \ldots & \ldots \\
\frac{1}{\gamma_{c,l_c}^2} \sum_{k=0}^{M-1} F_{ik} & \ldots & \frac{1}{\gamma_{c,l_c}^2} \sum_{k=0}^{M-1} F_{ik} & \ldots & \frac{1}{\gamma_{c,l_c}^2} \sum_{k=0}^{M-1} F_{ik}
\end{bmatrix}
\]

\[\text{(21)}\]

\[
C = \text{diag}(0, \ldots, 0)
\]

\[\text{(22)}\]

\[
D = \text{diag}\left\{-\sum_{k=0}^{M-1} \left[ \Gamma \gamma_{c,l_c}^2 I_{lk} + H_{lk} \right], \ldots, -\sum_{k=0}^{M-1} \left[ \Gamma \gamma_{c,l_c}^2 I_{lk} + H_{lk} \right] \right\}
\]

\[\text{(23)}\]

The CRLB of the delay estimation and amplitude estimation for \( l \)-th path are defined as:

\[
\text{var}(\hat{\tau}_{c,l_c}) \geq \text{var}(\hat{\tau}_{c,l_c})_{\text{CRLB}} = \text{var}(\hat{\tau}_{c,l_c})_{\text{CRLB}} = (B - CD^{-1}C)^{-1}
\]

\[\text{(24)}\]

\[
\text{var}(\hat{\gamma}_{c,l_c}) \geq \text{var}(\hat{\gamma}_{c,l_c})_{\text{CRLB}} = \text{var}(\hat{\gamma}_{c,l_c})_{\text{CRLB}} = (D - CB^{-1}C)^{-1}
\]

\[\text{(25)}\]

Then, we can obtain CRLBs of estimates for \( l_c = 1, \ldots, L_c \).

The CRLB for estimation of \( \gamma_{c,l_c} \) is \( \left[ \Gamma^{-1}(\theta) \right]_{l_c,l_c} \), which is the \( l_c \)-th diagonal element of the inverse matrix \( \Gamma^{-1}(\theta) \), and the CRLB for estimation of \( \tau_{c,l_c} \) is

\[
-1/\sum_{k=0}^{M-1} \text{var}(\hat{\gamma}_{c,l_c}^2 I_{lk} + H_{lk}) \quad \text{It is obvious that the CRLBs for estimations depend on} \quad a_k \quad (k = 0, 1, \ldots, M-1), \quad \gamma_{l_c} \quad (l_c = 1, 2, \ldots, L_c), \quad \text{SNR, and the sample size.}
\]

### 5.0 SIMULATION RESULTS AND DISCUSSION

The following pulse wave form is adopted in these simulations:

\[
g(t) = \left[1 - 16\pi(\frac{2}{T_p})^2 \right] \exp[-\pi(\frac{2}{T_p})^2] \quad \text{(26)}
\]

Parameters of (1), and (2) are substituted as \( \Delta = T_p \), \( T_f = 40 T_p \), and \( T_c = T_f / 20 \). The \( N_b \) is 20 and random symbols are in the interval of \([0,1, \ldots, 19]\). \( N_p \) asynchronous primary users are considered, the number of paths \( L_c = 3 \), \( R = 1.1 \), and the path delay of all users are \( 5 l T_p \). The path gains are, \( \gamma_1 = 0.73 \), \( \gamma_2 = 0.67 \), and \( \gamma_3 = 0.35 \), while the other gains vary from user to user with the Rayleigh distribution and their expectations are proportional to \( \exp(-l/4) \). Observation length of 100 symbols (\( M = 100 \)) and SNR of 0 dB to 60 dB (\( \text{SNR} = E_b / 2\sigma_n^2 \)) are assumed.

Figure 3 shows the CRLBs of blind and pilot-aided methods for \( (\gamma_1, \tau_1) \) as the number of primary users varies at different values of SNR, with \( L_c = 3 \). In this figure, \( L \) is the effective number of the paths that has been used for the processing. It has been shown that blind estimator is poorer than pilot-aided method for both gain and delay.

In Figure 4 the value of SNR is equal to 10 dB and it compares the derived CRLBs for blind and pilot-aided of the standard deviations as the number of primary users varies for \( L \)-th path of total paths, \( L_c = 3 \). Figure 5 shows obvious gaps between blind and pilot-aided curves in the derived CRLBs at \( \text{SNR}=10 \) dB, which increases with large number of primary users. Figure 6 and Figure 7 are the CRLBs of blind and pilot-aided methods for \( \gamma_1 \) and \( \tau_1 \) as the number of primary users varies at different numbers of \( L_c = [3, 5, 7] \) which the path gains are \( \gamma_1 = 0.73 \), \( \gamma_2 = 0.67 \), \( \gamma_3 = 0.35 \), \( \gamma_4 = 0.23 \), \( \gamma_5 = 0.12 \), \( \gamma_6 = 0.1 \), and \( \gamma_7 = 0.05 \).

These figures show that the CRLBs increases with increasing of the number of paths. In the previous work, [4], the standard deviation curves of gain and delay are derived only for data-aided method. Besides, the authors did not compare the pilot-aided and blind methods while their input is a non-cognitive UWB.
Figure 3 The CRLBs of NDA and DA methods for \((\gamma_1, \tau_1)\) at different values of SNR, with \(L_c = 3\)

Figure 4 The square root of CRLBs for ML estimation of \(\tau_1, \tau_2,\) and \(\tau_3\) for \(L\)-th path, when \(L_c = 3\) and SNR=10 dB

Figure 5 The gap between CRLBs of NDA and DA methods for \((\gamma_1, \tau_1)\) at SNR=10 dB

6.0 CONCLUSION

In this article, CRLBs of pilot-aided and blind ML channel identification are provided for cognitive IR-UWB communication. Numerical investigation has verified that non-data-aided method is poorer than data-aided method, and there exist obvious gaps between NDA and DA curves in the derived CRLBs. The curves illustrate that the CRLBs increase with the total number of primary users and paths. As a future work, the imperfect sensing errors can be investigated for CM1-CM4 standard of UWB channel models.

References


