ROBUST FREQUENCY-DOMAIN CHANNEL ESTIMATION AND DETECTION FOR ULTRA-WIDEBAND SIGNALS UNDER NON-GAUSSIAN NOISE

Ersen Ekrem, Mutlu Koca, and Hakan Deliç

Wireless Communications Laboratory
Department of Electrical and Electronics Engineering
Boğaziçi University
Bebek 34342 Istanbul, Turkey
E-mails:{ersen.ekrem, mutlu.koca, delic}@boun.edu.tr

ABSTRACT

In this paper, robust channel estimation and detection is considered for impulse radio ultra-wideband systems (UWB) subject to non-Gaussian noise and a frequency-domain receiver is proposed. In the proposed receiver, robust recursive least square algorithm is used for channel estimation and the least favorable density approach is employed within the detector module. A convergence analysis is presented for the robust frequency-domain estimator and an error performance analysis is provided for the robust detector. Then the bit-error rate (BER) performance of the proposed frequency domain receiver is evaluated via computer simulations. The receiver is shown to outperform the linear receiver architecture that is designed to be optimum under additive white Gaussian noise (AWGN) substantially under non-Gaussian noise without any significant additional cost in complexity. It is also shown that the frequency-domain channel estimator that is inherently robust to channel statistics performs better than its time-domain counterpart especially in non-line-of-sight channels.

1. INTRODUCTION

Impulse radio ultra-wideband (UWB) communication systems are characterized by huge bandwidths obtained through the use of very short duration pulses, usually on the order of a few nanoseconds, in time-domain (TD). This bandwidth characteristic creates new potentials for wireless applications that demand large user capacity, low cost and low power. However, because UWB communication faces severe frequency selectivity and requires high sampling rates, it introduces unique signal processing challenges in the receiver design, especially in the areas of synchronization, channel estimation and signal detection [1]. For instance, sampling rates in UWB systems are on the order of 10 GHz, which makes the number of parameters to be estimated 24 for line-of-sight (LOS) and as large as 400 for non-line-of-sight (NLOS) indoor channels [2]. In addition to the severe intersymbol interference (ISI) effect of the channels at high sampling rates, another phenomenon that must be considered in UWB system design is the noise, which is often overlooked and is simply assumed to be additive white Gaussian (AWGN). However, as reported in [3], indoor environments where the UWB devices are envisioned to be deployed are subject to noise produced by electronic devices running concurrently, which is impulsive (non-Gaussian) in nature. Therefore, UWB systems designed to be optimum under Gaussian noise face severe performance losses when the actual noise distribution deviates from the assumed nominal Gaussian model [4]. For these reasons, in this paper we consider the general channel estimation and detection problem for UWB systems under impulsive noise and present robust receiver algorithms.

The existing literature on UWB channel estimation and detection is usually limited to AWGN scenarios. For example, in [5], a two step estimation procedure is proposed where the first step consists of a time-delay search and the second step estimates the path gains. In this approach, the number of rays are assumed to be known at the receiver, which results in a performance loss otherwise. Another drawback, even in the AWGN case, is the computational load that is exponentially changing with the number of rays. This prohibitive complexity is partially simplified in [6] by assuming a resolvable channel where the paths are uncorrelated. However, this is not a fully justified assumption under realistic UWB indoor channel models such as the Saleh-Valenzuela (S-V) indoor model [7] where the multipath components arrive at the receiver in clusters with non-resolvable rays. Even with this assumption, the large number of multipath components in an UWB channel for sufficient energy capture still brings am unaffordable computational complexity to the detection and estimation. For this reason and inspired by the single-carrier frequency-domain equalization (SC-FDE) techniques proposed in [8], frequency-domain (FD) detection and estimation approaches have been proposed in [9]-[11] for UWB systems over frequency selective channels. SC-FDE is originally designed as an alternative to orthogonal frequency division multiplexing (OFDM) because of its performance improvement in frequency selective channels without any need for channel coding. FD channel estimation and detection is feasible not only because it requires only the time-delay of the first path and nothing about number of paths, but also because it is computationally less demanding depending on the channel structure. However, like their time-domain counterparts FD detection and estimation algorithms mentioned above also consider AWGN as ambient noise and are bound to suffer from a performance loss when the noise is impulsive. For this reason, in this paper a robust receiver performing both the channel estimation and detection in FD is proposed for computational saving and improved performance under non-Gaussian noise.

In the proposed receiver, channel estimation is done by a recursive estimator originally proposed in [12] and modified here with a different cost function. The convergence analysis of this estimator is conducted and verified via simulations. Robust FD detector is designed using the concept of least favorable density [13] rather than the least favorable pair [14] in order to alleviate the difficulties related with the latter. Moreover, theoretical bit error rate (BER) analysis of this detector is presented, which takes channel estimation errors into account. It should be noted that our all results regarding both channel estimator and detector can be generalized to the AWGN case by setting the ratio of the impulsive component in the background noise to zero.

The paper is organized as follows: Section II describes signal model, Section III explains robust FD channel estimation with its convergence analysis. Section IV presents robust FD detector. Section V presents the performance analysis of the receiver. Section VI presents numerical results and Section VII concludes the paper.

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2. SIGNAL MODEL

In an impulse radio UWB communication system, each symbol is transmitted over a duration of T_s in which N_f frames are transmitted with a duration of T_f, i.e., $T_s = N_f T_f$. In each frame, a pulse, $p(t)$, with a duration of T_p is transmitted, and the location of the pulse is controlled by time-hopping (TH) codes, according to which the pulse is hopped by amount of $c_i T_c$ where c_i is the TH code corresponding the transmitted pulse in the ith frame and T_c is the duration of the bins. The allowable range for TH codes is $[0, N_c)$ where $N_c = T_f/T_c$. The transmitted signal is given by

$$s(t) = \sum_{j=-\infty}^{\infty} b_j p_s\left(t - j(T_s + N_G T_f)\right) \tag{1}$$

where $b_j \in \{+1, -1\}$ are the pulse amplitude modulation (PAM) symbols and $p_s(t) = \sqrt{E}_s \sum_{i=-N_G}^{N_f-1} p(t - iT_f - c_i T_c)$ for which E_s denotes the symbol energy. N_G in (1) is the number of guard frames which serve as prefix for FD processing to make linear convolution of each symbol with channel look like circular convolution, which is essential for fast Fourier transform (FFT)-based signal processing techniques [8]. The channel is modeled by

$$h(t) = \sum_{l=1}^{\tilde{L}} h_l \delta(t - \tau_l)$$

where $\tilde{L}$ is the number of paths, h_l, and τ_l are the channel gain and time delay of the lth path, respectively. Throughout the paper, channel gains and the associated time delays will be treated as unknown deterministic quantities. Noise is modeled by a Gaussian mixture with a probability density function (PDF) of

$$f(x) = (1-\varepsilon)g(x; 0, \sigma^2) + \varepsilon g(x; 0, \kappa\sigma^2) \tag{2}$$

where the first term accounts for nominal noise with higher prior probability of occurence, while the second term is the impulsive part with heavier tails. κ is the impulsive part's relative variance with respect to nominal noise variance and ε is the relative frequency of outliers. The received signal is given by

$$y(t) = \left[\sum_{j=-\infty}^{\infty} b_j p_s\left(t - j(T_s + N_G T_f)\right)\right] * h(t) + w(t)$$

where $*$ denotes the linear convolution and $w(t)$ is the noise which is modeled by the two-term Gaussian mixture. After sampling, the mth sample of the jth symbol is given by circular convolution of data part of the symbol and the channel as follows.

$$y_j(mT) = b_j p_s(mT) \star h(mT) + w_j(mT),\ m = 0, 1, \ldots, N-1,$$

where $\star$ denotes circular convolution, T is the sampling period and N is the number samples taken per data part of the symbol, i.e., $N = T_s/T$. $y_j(mT)$ and $w_j(mT)$ denote the mth sample of the jth received symbol and of noise, respectively. They can also be explicitly expressed as $y_j(mT) \triangleq y\left(j(T_s + N_G T_f) + mT\right)$ and $w_j(mT) \triangleq w\left(j(T_s + N_G T_f) + mT\right)$. The FFT of the received signal is given by

$$Y_j(l) = b_j P_s(l) H(l) + W_j(l),\ l = 0, 1, \ldots, N-1,$$

where $Y_j(l), P_s(l), H(l)$ and $W_j(l)$ denote the FFT of $y_j(mT)$, $p_s(mT), h(mT)$ and $w_j(mT)$, respectively. Because $p_s(mT), h(mT)$ and $w_j(mT)$ are real-valued sequences, Hermitian symmetry results in $P_s(l) = P_s^*(N-l), H(l) = H^*(N-l)$ and $W_j(l) = W_j^*(N-l)$ where $()^*$ denotes complex conjugation. The received signal in FD can be rewritten as

$$\mathbf{Y}_j = b_j \mathbf{G} + \mathbf{W}_j$$

where $\mathbf{Y}_j, \mathbf{G}$ and $\mathbf{W}_j$ are $N \times 1$ column vectors collecting the first half of the received samples, aggregate channel response samples, i.e. $\mathbf{G}$, and the noise samples which are explicitly given by

$$\begin{aligned}
\mathbf{Y} &= \left[\Re\left(Y_j(0)\right) \ldots \Re\left(Y_j(N/2)\right)\ \Im\left(Y_j(0)\right) \ldots \Im\left(Y_j(N/2)\right)\right]^T \\
\mathbf{G} &= \left[\Re(P_s(0)H(0)) \Re(P_s(N/2)H(N/2))\ \Im(P_s(0)H(0)) \ldots\right. \\
&\qquad \left.\ldots \Im(P_s(N/2)H(N/2))\right]^T \\
\mathbf{W}_j &= \left[\Re\left(W_j(0)\right) \ldots \Re\left(W_j(N/2)\right)\ \Im\left(W_j(0)\right) \ldots \Im\left(W_j(N/2)\right)\right]^T
\end{aligned}$$

where $\Re(x)$ and $\Im(x)$ denote real and imaginary parts of x, respectively and $()^T$ means transpose. It should be noted that $\mathbf{W}_j$ consists of independent and identically distributed (iid) noise samples which will enable us to estimate each element of $\mathbf{G}$ independently.

3. ROBUST FREQUENCY-DOMAIN CHANNEL ESTIMATION

In this section, we derive the robust FD channel estimator. The recursive channel estimation in FD can be carried out with usual methods such as recursive least squares (RLS) or least mean squares (LMS). However, both methods employ a quadratic cost function that is very sensitive to the tail behavior of the distribution (outliers). As a consequence they suffer from performance deterioration when the noise distribution is impulsive with a heavy tail. To obtain a robust estimator, the quadratic cost function should be replaced with one of the cost functions given in [**?**]. The cost function

$$\rho(x) = \begin{cases} \frac{x^2}{2\sigma^2} & \text{for } |x| < k\sigma^2, \\ \frac{k^2\sigma^2}{2} - k|x| & \text{for } |x| > k\sigma^2 \end{cases} \tag{3}$$

is used, which results in the M-estimator for the PDF in (2). In (3), k is the trimming parameter which should be adjusted according to the intensity, κ, and the relative frequency, ε, of the outliers. More detail on the calculation of k is given in Section VI. Since samples are independent, estimation of each frequency bin can be carried out separately. Using (3), the cost function can be written as

$$J(\hat{\mathbf{G}}_n(m)) = \sum_{j=1}^{n} \lambda^{n-j} \rho\left(\mathbf{Y}_j(m) - \hat{\mathbf{G}}_n(m)\right) \tag{4}$$

where $\hat{\mathbf{G}}_n$ denotes the estimate of the aggregate channel response at nth iteration, i.e., using n symbols. The recursive solution to (4) can be written as [12]

$$\begin{aligned}
\hat{\mathbf{G}}_n(m) &= \hat{\mathbf{G}}_{n-1}(m) + \frac{q\left(\mathbf{E}_n(m)\right)\mathbf{E}_n(m)}{z_n(m)} && (5) \\
z_n(m) &= \lambda z_{n-1}(m) + q\left(\mathbf{E}_n(m)\right) && (6) \\
\mathbf{E}_n(m) &= \mathbf{Y}_n(m) - \hat{\mathbf{G}}_{n-1}(m) = \Delta\hat{\mathbf{G}}_{n-1}(m) + \mathbf{W}_n(m)
\end{aligned}$$

where $\mathbf{E}_n(m)$ is the composite error, which includes the channel estimation error plus noise. The channel estimation error at the nth step is given by $\mathbf{G}(m) - \hat{\mathbf{G}}_{n-1}(m) = \Delta\hat{\mathbf{G}}_{n-1}$. The clipping function $q(x) = \psi(x)/x$ where $\psi(x)$ is the derivative of $\rho(x)$ detects whether or not the error contains an outlier. If an outlier is detected, the corresponding sample is clipped; otherwise, it is directly added to the channel estimate.

3.1 Convergence Analysis of Robust Frequency-Domain Channel Estimation

In this section, we analyze the convergence properties of robust FD channel estimation. Although such an analysis is conducted in [12], the penalty function, $\rho(\cdot)$, and the signal model in this paper differ from the former requiring a new performance analysis. Generally speaking, an exact analysis of RLS-type algorithms is tedious, but under a few reasonable assumptions, a consistent analysis can be carried out. We make the following standard assumptions.

- **A1**: The signal is ergodic [12].
- **A2**: For sufficiently large n, the channel estimation error, $\Delta\hat{\mathbf{G}}_n(m)$, is small compared to $\mathbf{W}_n(m)$ for $\forall m \in \{0,1,\ldots,N-1\}$.

The rationale behind assumption **A2** is that the composite error usually falls in the linear part of the clipping function when outliers are acting in (2).

Before starting the convergence analysis of the mean, it should be noted that for sufficiently large n, using (**A1**), $z_n(m)$ can be approximated as

$$\begin{aligned} z_n(m) &= \sum_{i=1}^{n} \lambda^{n-i} q\big(\Delta\hat{\mathbf{G}}_{n-1}(m) + \mathbf{W}_i(m)\big) \\ &\approx \Big(\sum_{i=1}^{n} \lambda^{n-i}\Big) E\big\{q\big(\mathbf{W}_i(m)\big)\big\} = \overline{\lambda}(n)\gamma \end{aligned} \tag{7}$$

where $\overline{\lambda}(n) = (1-\lambda^{n+1})/(1-\lambda)$, $\gamma = E\big\{q\big(\mathbf{W}_i(m)\big)\big\}$. In the next two sections, the convergence analysis of the robust FD channel estimator will be conducted using (7) and the assumptions (**A1**)-(**A2**).

3.1.1 Convergence of the mean

In this section, convergence of the robust FD channel estimator is investigated. The recursive relationship for the mean of aggregate channel estimate is given by

$$E\{\Delta\hat{\mathbf{G}}_n(m)\} = E\{\Delta\hat{\mathbf{G}}_{n-1}(m)\} - \frac{1}{\overline{\lambda}(n)\gamma} E\{\psi\big(\mathbf{E}_n(m)\big)\} \tag{8}$$

where the expectation is over both noise and the channel estimation error. Using (**A2**), the output of the clipping function can be written as

$$\psi(\mathbf{E}_n(m)) = \begin{cases} \frac{\mathbf{E}_n(m)}{\sigma^2} & \text{if } \mid \mathbf{W}_n(m) \mid \le k\sigma^2, \\ k\,\mathrm{sgn}(\mathbf{W}_n(m)) & \text{if } \mid \mathbf{W}_n(m) \mid > k\sigma^2. \end{cases} \tag{9}$$

Therefore, using (9), the expected value of the clipping function's output can be written as

$$E\{\psi\big(\mathbf{E}_n(m)\big) \mid \Delta\hat{\mathbf{G}}_{n-1}(m)\} = \frac{2\Delta\hat{\mathbf{G}}_{n-1}(m)\beta}{\sigma^2} \tag{10}$$

where

$$\beta = 0.5 - (1-\varepsilon)Q(k\sigma) - \varepsilon Q\left(\frac{k\sigma}{\sqrt{\kappa}}\right) \tag{11}$$

and $Q(u) = \int_u^\infty \big(1/\sqrt{2\pi}\big)\exp\big(-t^2/2\big)\,dt$. Using (10), the recursive equation for the expected value of the channel estimation error, namely (8), can be expressed as

$$E\{\Delta\hat{\mathbf{G}}_n(m)\} = \left(1 - \frac{2\beta}{\overline{\lambda}(n)\gamma}\right) E\{\Delta\hat{\mathbf{G}}_{n-1}(m)\}$$

from which the asymptotic mean of the channel estimation error is found to be

$$\lim_{n\to\infty} E\{\Delta\hat{\mathbf{G}}_n(m)\} = 0,$$

which implies that the robust FD channel estimator with the cost function defined in (3) is an asymptotically unbiased estimator.

3.1.2 Convergence of the variance

In this section, we consider the convergence of the variance of the robust FD channel estimator. The recursive equation for the second moment of the aggregate channel estimate can be written as

$$\begin{aligned} E\big\{\Delta\hat{\mathbf{G}}_n^2(m)\big\} &= E\big\{\Delta\hat{\mathbf{G}}_{n-1}^2(m)\big\} + \frac{1}{\overline{\lambda}^2(n)\gamma^2} E\big\{\psi^2\big(\mathbf{E}_n(m)\big)\big\} \\ &- \frac{2}{\overline{\lambda}(n)\gamma} E\big\{\Delta\hat{\mathbf{G}}_{n-1}(m)\psi\big(\mathbf{E}_n(m)\big)\big\} \end{aligned} \tag{12}$$

where the expectations are over both noise and channel estimation error. The conditional expected value of the cross-correlation between the channel estimation error and the output of the clipping function is evaluated next, which is given by

$$E\big\{\Delta\hat{\mathbf{G}}_{n-1}(m)\psi\big(\mathbf{E}_n(m)\big) \mid \Delta\hat{\mathbf{G}}_{n-1}\big\} = \frac{2\Delta\hat{\mathbf{G}}_{n-1}^2(m)\beta}{\sigma^2} \tag{13}$$

where we use (9), and the fact that channel estimation error at the $(n-1)$th step, $\Delta\hat{\mathbf{G}}_{n-1}(m)$, is independent of noise at the nth step, $\mathbf{W}_n(m)$. The conditional second moment of the output of the clipping function can be expressed as

$$E\big\{\psi^2\big(\mathbf{E}_n(m)\big) \mid \Delta\hat{\mathbf{G}}_{n-1}(m)\big\} = \frac{2\beta}{\sigma^4}\Delta\hat{\mathbf{G}}_{n-1}^2(m) + (\alpha_1+\alpha_2) \tag{14}$$

where α_1 and α_2 are defined to be

$$\begin{aligned} \alpha_1 &\triangleq \frac{2(1-\varepsilon)}{\sigma^2}\left[0.5 - Q(k\sigma) - \frac{k\sigma}{\sqrt{2\pi}}\exp\left(-\frac{k^2\sigma^2}{2}\right)\right] \\ &+ \frac{2\varepsilon\kappa}{\sigma^2}\left[0.5 - Q\left(\frac{k\sigma}{\sqrt{\kappa}}\right) - \frac{k\sigma}{\sqrt{2\pi\kappa}}\exp\left(-\frac{k^2\sigma^2}{2\kappa}\right)\right], \end{aligned} \tag{15}$$

$$\alpha_2 \triangleq 2k^2\left[(1-\varepsilon)Q(k\sigma) + \varepsilon Q\left(\frac{k\sigma}{\sqrt{\kappa}}\right)\right]. \tag{16}$$

In deriving (14), we again use (9), and the independence of the channel estimation error at the $(n-1)$th step, $\Delta\hat{\mathbf{G}}_{n-1}(m)$, and the noise, $\mathbf{W}_n(m)$. Using (13) and (14), the recursive relationship for the second moment of the channel estimator, (12), is given by

$$\begin{aligned} E\big\{\Delta\hat{\mathbf{G}}_n^2(m)\big\} &= E\big\{\Delta\hat{\mathbf{G}}_{n-1}^2(m)\big\}\left(1 - \frac{2\beta\big(2\overline{\lambda}(n)\gamma\sigma^2 - 1\big)}{\overline{\lambda}^2(n)\gamma^2\sigma^4}\right) \\ &+ \frac{(\alpha_1+\alpha_2)}{\overline{\lambda}^2(n)\gamma^2} \end{aligned}$$

from which the asymptotic variance of the channel estimator is found to be

$$\lim_{n\to\infty} E\big\{\Delta\hat{\mathbf{G}}_n^2(m)\big\} = \frac{\sigma^4(\alpha_1+\alpha_2)}{2\beta\left(\frac{2\gamma\sigma^2}{1-\lambda} - 1\right)} \approx \frac{\sigma^2(1-\lambda)(\alpha_1+\alpha_2)}{4\beta\gamma},$$

which is smaller than the total noise variance $(1-\varepsilon+\kappa\varepsilon)\sigma^2/2$, which is the noise floor induced by the RLS algorithm.

4. ROBUST FREQUENCY-DOMAIN DETECTION

In this section, we consider robust detection under the noise model given in (2). From now on, the subscripts in $\hat{\mathbf{G}}_n, \mathbf{Y}_n, \mathbf{W}_n$ and $\Delta\hat{\mathbf{G}}_n$ indicating the symbol number will be dropped for notational simplicity. The primary work considering robust detection is that of Huber [14], where robustness is achieved by setting up the likelihood ratio (LR) according to the least favorable pair. However, some difficulties related with this method are reported in [14]. First is that for weak-signal conditions, there may not exist such a pair.

Second is that when detection is based on an observation vector rather than a single observation, for each sample of the observed vector, the pair of the PDFs should be found independently, possibly bringing about a computational load. Therefore, to overcome these difficulties, the method proposed in [14] will be followed, which mainly allows the two PDF families under each hypothesis to overlap and assumes that they differ only in their means resolving the difficulties related with [13]. To that end, the PDF family

$$\mathscr{H} = \left\{ h(x) = (1-\varepsilon)g(x;0,\sigma^2) + \varepsilon v(x); v(x) \text{ is a symmetric PDF} \right\}$$

is considered, to which (2) belongs. The least favorable PDF in this family is given by

$$f_{LF}(x) = \begin{cases} \frac{1-\varepsilon}{\sqrt{2\pi}\sigma} \exp(-\frac{x^2}{2\sigma^2}) & \text{for } |x| \le k\sigma^2 \\ \frac{1-\varepsilon}{\sqrt{2\pi}\sigma} \exp(\frac{k^2\sigma^2}{2} - k|x|) & \text{for } |x| > k\sigma^2 \end{cases} \tag{17}$$

which obeys a Gaussian PDF at its center, then decays exponentially, and k, ε, σ are related through

$$\frac{\phi(k\sigma)}{k\sigma} - Q(k\sigma) = \frac{\varepsilon}{2(1-\varepsilon)} \tag{18}$$

where $\phi(x) = \left(1/\sqrt{2\pi}\right)\exp\left(-x^2/2\right)$. Therefore, using (17) and defining the hypothesis H_1 (resp. H_0) as $b_j = +1$ (resp. $b_j = -1$), the robust test is

$$\sum_{m=0}^{N-1} T_{FD}(m) = \sum_{m=0}^{N-1} \log\left(\frac{f_{LF}\left(\mathbf{Y}(m) - \hat{\mathbf{G}}(m)\right)}{f_{LF}\left(\mathbf{Y}(m) + \hat{\mathbf{G}}(m)\right)} \right) \underset{H_0}{\overset{H_1}{\gtrless}} 0$$

where the decision statistic behaves in a similar way as the clipping function given in (3).

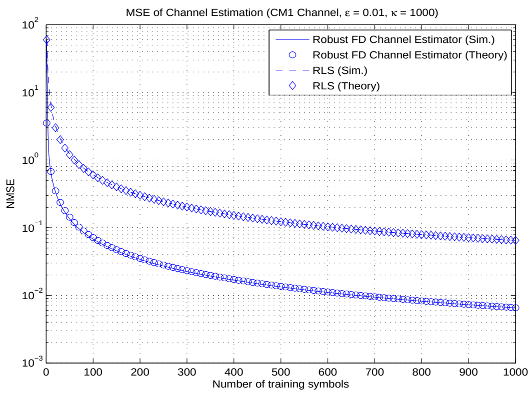

Figure 1: NMSE of FD channel estimation under CM1 channel when $\varepsilon = 0.01, \kappa = 1000$ and SNR is 10 dB.

5. PERFORMANCE ANALYSIS

In this section, we will derive the probability of error of the FD robust detector incorporating channel estimation errors. Hypothesis H_1 is assumed to be correct. Therefore, using (**A2**) stated in Section 3.1, $T_{FD}(m)$ can be expressed as

$$T_{fd}(m) = \begin{cases} \frac{2\left(\mathbf{G}(m)+\mathbf{W}(n)\right)\left(\mathbf{G}(m)-\Delta\hat{\mathbf{G}}(m)\right)}{\sigma^2} & \text{if } \mid \mathbf{W}(m) \mid \le k\sigma^2, \\ 2k\left(\mathbf{G}(m) - \Delta\hat{\mathbf{G}}(m)\right)\text{sgn}\left(\mathbf{W}(m)\right) & \text{if } \mid \mathbf{W}(m) \mid > k\sigma^2, \end{cases}$$

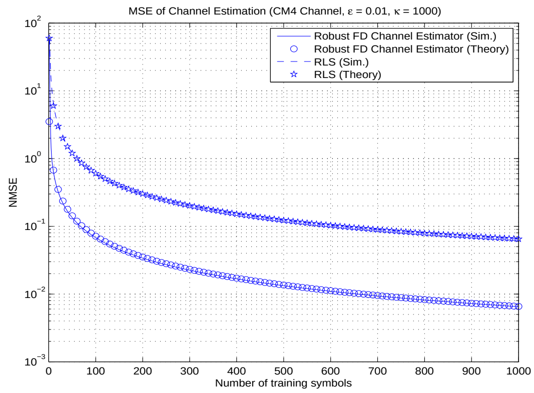

Figure 2: NMSE of FD channel estimation under CM4 Channel when $\varepsilon = 0.01, \kappa = 1000$ and SNR is 10 dB.

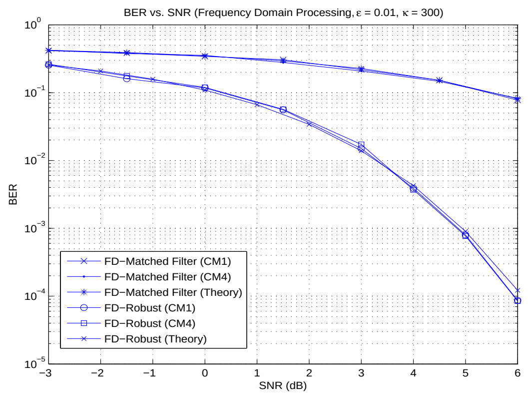

Figure 3: BER performance of FD processing when $\varepsilon = 0.01, \kappa = 300$.

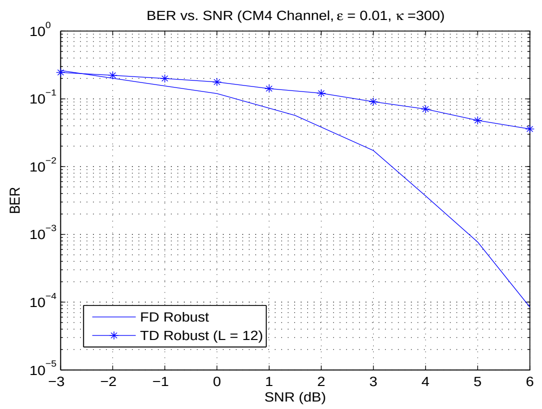

Figure 4: Comparison of BER performances of FD and TD processing when $\varepsilon = 0.01, \kappa = 300$ and the channel is CM4.

using which, the mean of $T_{FD}(m)$ under H_1 is given by

$$\mu_{FD,r}(m) \triangleq E\{T_{FD}(m)|H_1\} = \frac{4\mathbf{G}^2(m)\beta}{\sigma^2}$$

where β is given in (11). The second moment of $T_{FD}(m)$ under H_1 is

$$E\{T_{FD}^2(m)|H_1\} = 4\left(\mathbf{G}^2(m) + E\left\{\Delta\hat{\mathbf{G}}^2(m)\right\}\right)\left[\frac{2\mathbf{G}^2(m)}{\sigma^4}\beta + (\alpha_1+\alpha_2)\right]$$

where $\beta, \alpha_1, \alpha_2$ are given in (11), (15), (16), respectively. Defining the variance of $T_{FD}(m)$ as

$$\nu_{FD,r}^2(m) = E\left\{T_{FD}^2(m)\right\} - E^2\{T_{FD}(m)\} \tag{19}$$

and using the central limit theorem and the symmetry between the two hypotheses, the probability of error is given by

$$P_{e,FD}^r = Q\left(\frac{\sum_{m=0}^{N-1}\mu_{FD,r}(m)}{\sqrt{\sum_{m=0}^{N-1}\nu_{FD,r}^2(m)}}\right) \tag{20}$$

for which the effect of noise on the test statistic is governed by β, α_1 and α_2, contrary to FD matched filtering, for which this effect is governed directly by $E\{w^2\}$.

6. SIMULATION RESULTS

In this section, we test the performances of channel estimation and detection. The pulse is selected as the second derivative of the Gaussian function with duration $T_p = 1$ ns. The frame duration is selected to be 20 ns. Each symbol consists of $N_f = 15$ frames resulting in $T_s = 300$ ns. $N_G = 5$ guard frames are employed for FD processing. The chip duration is chosen as $T_c = 1$ ns and the TH codes are randomly generated from a uniformly distributed set of $\{0,1,\ldots,N_f-1\}$. The number of samples taken per data part of the symbol is given by $N = 2400$ which corresponds to the Nyquist rate. In all graphs, the signal-to-noise-ratio (SNR) value is calculated as $E_s/2\left((1-\varepsilon)\sigma^2+\varepsilon\kappa\sigma^2\right)$. Moreover, in all simulations, the forgetting factor, λ, is set to 0.999 and the threshold parameter, k, of (3) is adjusted according to (18). All theoretical results concerning the the linear estimator and detector are calculated by setting $k \to \infty$.

For channel estimation, the normalized mean square error (NMSE) is used as performance measure. In Fig. 1 and Fig. 2, learning curves of the robust FD channel estimator and RLS algorithm are plotted. In both cases, RLS converges to the total SNR whereas for the robust FD channel estimation algorithm, NMSE converges to the nominal SNR value due to the elimination of the outlier components by the nonlinearity given in (3).

Next, we test the robust channel estimator and the detector together. For channel estimation, each packet is sent with a training sequence of 100 symbols which are all +1s. In Fig. 3, we plot the BER performances of the robust FD receiver and the FD matched filter when $\varepsilon = 0.01, \kappa = 300$. As depicted by Fig. 3, the robust receiver substantially outperforms the matched filter. Moreover, as in robust FD channel estimation, robust FD receivers have the same performance both in CM1 and in CM4 channels, despite their totally different characteristics, which indicates robustness to channel parameters, as well. As in channel estimation alone, theoretical results are in good agreement with simulations.

Lastly, we compare the FD robust receiver presented here to its TD counterpart which tries to estimate first L paths of the channel and combines them. To compare the FD and TD receivers, L is selected as $L \approx 12$ because of the fact that complexities of FD and TD processing are $\mathcal{O}(N\log N)$ and $\mathcal{O}(NL)$, respectively [10]. The resulting plot is given in Fig. 4 from which it can be concluded that robust FD processing outperforms its TD counterpart in the NLOS CM4 channel. Though not presented here, for line-sight-of channels, both have approximately the same performance and complexity.

7. CONCLUSION

In this paper, a FD receiver is presented which performs both channel estimation and detection robustly. Theoretical and numerical performance evaluations demonstrate the substantial performance gains obtained via robust design. The inherent robustness of FD techniques to channel statistics is witnessed, and the superior performance of FD processing for NLOS channels is presented.

REFERENCES

[1] L. Yang and G. B. Giannakis, “Ultra Wideband communications: An idea whose time has come,” *IEEE Signal Process. Mag.*, Vol. 21, no. 6, pp. 26-54, Nov. 2004.

[2] J. R. Foerster, “Channel modeling sub-committee report (final),” Tech. Rep. P802.15-02 / 368r5-SG3a, IEEE P802.15 Working Group for Wireless Personal Area Networks (WPANs), Dec. 2002.

[3] K. L. Blackard, T. S. Rappaport, and C. W. Bostian, “Measurements and models of radio frequency impulsive noise for indoor wireless communications,” *IEEE J. Select. Areas Commun.*, vol. 11, pp. 991-1001, Sep. 1993.

[4] N. Guney, H. Deli, and M. Koca, ”Robust detection of ultra-wideband signals in non-Gaussian noise,” *IEEE Trans. Microwave Theory and Techn.*, vol. 54, no.4, pp:1724-30, Apr. 2006.

[5] M. Z. Win and R. A. Scholtz, “Characterization of ultra-wide bandwidth wireless indoor channels: a communication theoretic view”, *IEEE J. Select. Area. Commun.*, vol. 20, no. 9, pp. 1613-1627, 2002.

[6] V. Lottici, A. D’Andrea, and U. Mengali, “Channel estimation for ultra-wideband communications”, *IEEE J. Select. Area. Commun.*, vol. 20, no. 9, pp. 1638-1645, 2002.

[7] A. A. M. Saleh and R. Valenzuela, “A statistical model for indoor multipath propagation,” *IEEE J. Select. Areas Commun.*, vol. SAC-5, no. 2, pp. 128-137, Feb. 1987.

[8] D. Falconer, S. L. Ariyavisitakul, A. Benyamin-Seeyar, and B. Eidson, “Frequency-domain equalization for single-carrier broadband wireless systems” *IEEE Commun. Mag.*, vol. 40, no. 6, pp. 58-66, 2002.

[9] Y. Wang and X. Dong, “Frequency domain channel estimation for SC-FDE in UWB communications”, *Proc. of GLOBECOM*, vol. 6, pp. 3654-3658, 2005.

[10] H. Sato and T. Ohtsuki, “Performance evaluation of frequency domain equalization and channel estimation for direct sequence-ultra wideband (DS-UWB) system”, *Proc. VHT*, vol. 1, pp. 481- 485, 2005.

[11] A. M. Tonello and R. Rinaldo, “A time-frequency domain approach to synchronization, channel estimation, and detection for DS-CDMA impulse-radio systems”, *IEEE Trans. Wireless Commun.*, vol. 4, no. 6, pp. 3005-3017, 2005.

[12] S. C. Chan and Y. X. Zou, “A recursive least M-estimate algorithm for robust adaptive filtering in impulsive noise: fast algorithm and convergence analysis,” *IEEE Trans. Signal Process.*, vol. 52, No. 4, pp. 975-991, Apr. 2004.

[13] A. H. El-Sawy and V. D. Vandelinde, “Robust detection of known signals,” *IEEE Trans. Inform. Theory*, Vol. IT-23, no. 6, pp. 722-727, Nov. 1977.

[14] P. J. Huber, “A Robust version of the probability ratio test, ”*Ann. Math. Stat.*, vol. 36, pp. 1753-1758, 1965.