Compressed UWB signal detection with narrowband interference mitigation

Zhongmin Wang†, Gonzalo R. Arce†, Brian M. Sadler‡, Jose L. Paredes⋆, Sebastian Hoyos* and Zhuizhuan Yu*

†Department of Electrical and Computer Engineering, University of Delaware, Newark, DE, USA, 19716
‡ Army Research Laboratory, AMSRL-CI-CN Adelphi MD 20783
⋆ Electrical Engineering Department, University of Los Andes, Mérida, Venezuela 5101
* Department of Electrical and Computer Engineering, Texas A&M University, College Station, Texas 77843

***Abstract*—Operating at sub-Nyquist rate, compressed sensing (CS) has been successfully applied to the design of impulse ultra-wideband (I-UWB) receivers where Nyquist sampling is a formidable challenge. However, strong narrowband interference (NBI) can easily jam and saturate the receiver front-end and greatly degrade the system performance. In this paper, CS is applied to the design of I-UWB receivers with NBI mitigation. By exploiting the sparsity of the NBI within the pulse UWB spectrum, a compressive measurement matrix can be designed that is not only efficient at collecting signal energy, but also nulls out the NBI effectively. The performance analysis of the proposed receiver is provided. Simulation results show the effectiveness of the proposed method for UWB signal detection and NBI mitigation.**

I. Introduction

The theory of compressive sampling (CS) is applied to the design of impulse ultra-wideband (I-UWB) receivers with narrowband interference (NBI) mitigation. Since CS operates at sub-Nyquist rates, it is particularly suitable for I-UWB communications where Nyquist sampling is a formidable challenge. CS acquires the underlying signal information by projecting the received UWB signal waveform onto compressive measurements. Since the I-UWB signal is sparse on some basis Ψ, the number of measurements required is far less than that used to represent the signal at the Nyquist rate [1]. Unlike full-resolution digital receiver designs, no ultra-fast ADC is required. Compared with analog AcR receivers, wideband analog delay elements are also not required.

It has been shown that the performance of I-UWB receiver based on compressive measurements can be significantly improved if the sparsity of the UWB signal is exploited [2]. A measurement matrix that is designed with the knowledge of the sparse signal structure is more efficient at capturing the underlying signal energy. The receiver first utilizes the Basis Pursuit Denoising (BPDN) algorithm [3] to estimate the signal sparsity model from random measurements. The estimated signal model is then incorporated in constructing a measurement matrix to project the received UWB signals. Consequently, far fewer measurements are required by a generalized likelihood ratio test (GLRT) detector leading to a simplified hardware implementation that requires fewer parallel mixer-integrators for compressive measurements [2].

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This paper focus on extending the subspace detection method proposed in [2] to NBI mitigation. First, the NBI subspace is estimated from random measurements when the UWB signal is absent. When detecting the UWB symbols, a compressive measurement matrix is designed that incorporates both the UWB subspace and the null subspace of the NBI. Thus, the NBI can be effectively mitigated on the measurement stage. The proposed UWB receivers have the advantage that the NBI subspace can be estimated adaptively and the proposed method can easily null out strong NBI without introducing extra hardware.

II. Compressive subspace detection under NBI

For wideband signal detection, sampling at the Nyquist rate is generally prohibitive. The compressive detectors reduce the sampling rate by projecting the received signal onto a set of random waveforms and sampling the projected measurements [4]. Let $\mathbf{x} \in \mathcal{R}^N$ be the signal to be detected and $\mathbf{w} \sim \mathcal{N}(0, \sigma^2 \mathbf{I}_N)$ be additive white Gaussian noise. The compressive detector obtains the compressive measurements as $\mathbf{y} = \Phi\mathbf{w}$ or $\mathbf{y} = \Phi(\mathbf{x} + \mathbf{w})$, where Φ is an $M \times N$ measurement matrix with $M \leq N$.

Assume the signal $\mathbf{x}$ is K sparse on some basis $\Psi = [\underline{\psi}_1, \underline{\psi}_2, \ldots, \underline{\psi}_N]$. That is, $\mathbf{x}$ can be represented by a linear combination of K vectors from Ψ where $K \ll N$. The K vectors of Ψ construct a $N \times K$ matrix $\mathbf{H} = [\underline{\psi}_{n_1}, \underline{\psi}_{n_2}, \ldots, \underline{\psi}_{n_K}]$, where $n_i \in \{1, 2, \ldots, N\}$ for $i = 1, \ldots, K$. The signal $\mathbf{x}$ then can be represented as $\mathbf{x} = \mathbf{H}\underline{\theta}$, where $\underline{\theta}$ is a $K \times 1$ vector with all non-zero entries. If the signal subspace $\mathbf{H}$ is known, then instead of using a random matrix Φ where each entry is drawn from a i. i. d. random distribution, we can construct a compressive subspace measurement matrix as follows:

$$\bar{\Phi} = \mathbf{G}(\mathbf{H}^T\mathbf{H})^{-1}\mathbf{H}^T, \tag{1}$$

where $\mathbf{G}$ is an $M \times K$ i.i.d. random matrix with $M \leq K$. It has been shown that $\bar{\Phi}$ is more efficient than Φ at gathering the received signal energy, thus leading to better detection performance [2], [5]. When the signal $\mathbf{x}$ is unknown, $\mathbf{H}$ can be estimated from the compressive measurements of the pilot signals via nonlinear optimizations [2], [5].

In this paper, we extend the design of the compressive subspace measurement matrix for NBI mitigation. Let the NBI be $\mathbf{Z} = \mathbf{S}\varphi$, where $\mathbf{S} \in \mathcal{R}^{N\times J}$ is the NBI subspace, $\varphi \in \mathcal{R}^J$ and $J \ll N-K$ (narrowband interference). The original problem of sparse signal detection under NBI is to distinguish between two hypothesis $\mathcal{H}_0$ and $\mathcal{H}_1$:

$$\begin{aligned}\mathcal{H}_0 &: \quad \hat{\mathbf{y}} = \mathbf{S}\varphi + \mathbf{w},\\ \mathcal{H}_1 &: \quad \hat{\mathbf{y}} = \mathbf{H}\underline{\theta} + \mathbf{S}\varphi + \mathbf{w}.\end{aligned} \tag{2}$$

The proposed compressive detector first projects the received signal onto the NBI null space and then constructs a subspace measurement matrix $\breve{\Phi}$ to obtain compressive measurements. Let $\mathbf{P}_S^{\perp} = \mathbf{I}_{N\times N} - \mathbf{S}(\mathbf{S}^T\mathbf{S})^{-1}\mathbf{S}^T$ be the orthogonal projection matrix for the NBI null space, then the detection problem is converted to distinguish between two hypothesis:

$$\begin{aligned}\mathcal{H}_0 &: \quad \breve{\mathbf{y}} = \breve{\Phi}\mathbf{P}_S^{\perp}(S\varphi + \mathbf{w}),\\ \mathcal{H}_1 &: \quad \breve{\mathbf{y}} = \breve{\Phi}\mathbf{P}_S^{\perp}(H\underline{\theta} + S\varphi + \mathbf{w}).\end{aligned} \tag{3}$$

Note that under $\mathcal{H}_1$, $\breve{\mathbf{y}}$ reduces to: $\breve{\mathbf{y}} = \breve{\Phi}\mathbf{P}_S^{\perp}(H\underline{\theta} + \mathbf{w})$. Thus, the NBI is eliminated at the measurement stage. Let $\breve{H}$ be $\breve{H} = \mathbf{P}_S^{\perp}H$, then based on the principle of subspace measurement matrix design, the matrix $\breve{\Phi}$ is designed as follows:

$$\breve{\Phi} = \mathbf{G}(\breve{\mathbf{H}}^T\breve{\mathbf{H}})^{-1}\breve{\mathbf{H}}^T. \tag{4}$$

Let $\tilde{\Phi} = \breve{\Phi}\mathbf{P}_S^{\perp}$ be the composite measurement matrix, then the detector performance depends on the term: $t = \mathbf{x}^T\tilde{\Phi}^T(\tilde{\Phi}\tilde{\Phi}^T)^{-1}\tilde{\Phi}\mathbf{x}$, which is the signal energy the detector can collect. It can be shown that $t \approx (M/K)\mathbf{x}^T\mathbf{P}_S^{\perp}\mathbf{x}$. Compared with Nyquist sampling, there is no performance loss when $M = K$. The introduction of the random matrix $\mathbf{G}$ makes the detector robust to magnitude variations over $\underline{\theta}$. Each measurement is equally important.

In practice, both the interference subspace $\mathbf{S}$ and the signal subspace $\mathbf{H}$ are unknown. They have to be estimated before the subspace measurement matrix can be constructed.

III. Ultra-wideband communication system model

Consider a peer-to-peer I-UWB communication system where binary symbols are conveyed by a stream of ultra-short pulses $g(t)$. $g(t)$ has unit energy and time duration T_g. Binary PAM modulated pulses of $g(t)$ are repeated over consecutive N_f frames to transmit one binary symbol. The duration of a frame is T_f and a symbol period is $T_s = N_f T_f$. Each frame contains N_c chips with chip duration T_c.

Pilot symbol assisted modulation combined with direct sequence spread spectrum (DS) coding and time-hopping (TH) coding is proposed for signaling [6], [7], [8]. Each burst includes N_p pilot symbols which are not data modulated and N_s symbols which are data modulated. The total number of symbols in one burst is $N_d = N_p + N_s$. The pilot symbols are divided into three groups. The first group contains N_{p1} symbols that are used to estimate the NBI subspace; the second group contains N_{p2} symbols that are used to estimate the UWB signal subspace; the third group contains N_{p3} symbols that are used to provide side information about the channels. The transmitted waveform $x(t)$ over a burst can be represented as:

$$x(t) = \sum_{n=0}^{N_d N_f - 1} a_n b_{\lfloor n/N_f \rfloor}\sqrt{E}g(t - nT_f - c_n T_c), \tag{5}$$

where $a_n \in \{\pm 1\}$ is pseudorandom (PN) DS code; c_n is the PN TH code. The TH codeword is assumed to be uniformly distributed in $[0, N_c - 1]$. E denotes the energy of the transmitted waveforms. When transmitting the first group of the pilot symbols, no UWB pulse is transmitted, thus $b_i = 0$ for $i \in [0, N_{p1} - 1]$. It follows that $b_i = 1$ for $i \in [N_{p1}, N_p - 1]$ and $b_i \in \{\pm 1\}$ with equal probability for $i \in [N_p, N_d - 1]$. It can be shown that the proposed DS-TH signaling has the advantage that the transmitted signal spectrum is smooth, thus providing coexistence with other narrowband communications.

The signal $x(t)$ are transmitted through a multipath I-UWB channel that is modeled as:

$$h(t) = \sum_{l=0}^{L-1} \alpha_l \delta(t - \tau_l), \tag{6}$$

where L is the number of propagation paths and α_l and τ_l are the attenuation and the delay of the lth path, respectively. $\delta(t)$ denotes the delta function. The maximum excess delay of the dense multi-path channel is given by T_{med}. To avoid intersymbol interference (ISI) and intrasymbol interference, it is assumed that $T_c > T_g + T_{med}$.

It is assumed that the received UWB signal is corrupted by both narrowband interference $v(t)$ and noise $w(t)$. The NBI $v(t)$ is modeled as the sum of N_v interferences $v_i(t)$, where $i = 0, \ldots, N_v - 1$ and the spectrum of $v_i(t)$ is given by:

$$S_{v_i}(f) = \begin{cases} \frac{P_{v_i}}{2}, & f_{v_i} - \frac{B_{v_i}}{2} \le |f_{v_i}| \le f_{v_i} + \frac{B_{v_i}}{2} \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

Here, $P_{v_i}/2$ is the interference level; f_{v_i} is the interference central frequency; B_{v_i} is the interference bandwidth. The autocorrelation function of $v_i(t)$ is: $R_{v_i}(\tau) = P_{v_i}B_{v_i}\cos(2\pi f_{v_i}\tau)\text{sinc}(B_{v_i}\tau)$.

$w(t)$ is zero-mean, white Gaussian noise with two-sided power spectral density $N_0/2$. The noisy signal goes through an ideal bandpass filter with one-sided bandwidth B and center frequency f_c. It is assumed that the desired signal and the NBI $v(t)$ pass through the filter without any distortion. The received signal at the output of the filter is:

$$\tilde{r}(t) = \int_0^t h(t-\tau)x(\tau)d\tau + v(t) + \tilde{w}(t). \tag{8}$$

$\tilde{w}(t)$ is a zero-mean Gaussian random process with autocorrelation function: $R_{\tilde{w}}(\tau) = BN_0\text{sinc}(B\tau)cos(2\pi f_c\tau)$.

The filtered signal is then projected onto a set of measurement waveforms where each waveform is matched to a row vector of a measurement matrix. The compressive measurement is implemented by M mixer-integrators where the integration interval T_{prj} satisfies $T_g + T_{med} > T_{prj} \ge T_g$.

Perfect knowledge of PN sequences a_n, c_n and ideal synchronization are assumed on the receiver. The compressive measurements of received nth frame begin at $t = c_n T_c + (n-1)T_f$. During the first group of the pilot symbols, the compressive measurement multiplied by a_n is represented as:

$$\mathbf{y}_1[n] = a_n\Phi_1\mathbf{v}[n] + a_n\Phi_1\mathbf{w}[n],\ n = 0, \ldots, N_{p1}N_f - 1. \tag{9}$$

$\mathbf{y}_1[n]$ is an $M \times 1$ measurement vector contains the outputs of the M mixer-integrators of the nth frame. $\mathbf{v}[n]$ ia an $N \times 1$ digitized NBI within the measurement interval of the nth frame. A sampling frequency F_s is implied. As in critical Nyquist sampling, the underlying sampling frequency F_s satisfies $F_s = 2 * (f_c + 0.5B)$. The data length is thus $N = T_{prj} F_s$. $\mathbf{w}[n]$ is the digitized noise within the measurement interval of the nth frame. $\mathbf{w}[n]$ is assumed to be white Gaussian noise (WGN) with variance $N_0 B$. Φ_1 is a measurement matrix of size $M \times N$ with entry drawn from a i. i. d. Bernoulli distribution. Note that no UWB signals are transmitted during this time period. Based on the compressive measurements $\mathbf{y}_1[n]$, the NBI subspace can be estimated.

During the second group of the pilot symbols, the received data are projected onto a different measurement matrix Φ_2 that exploits the information of NBI subspace. The compressive measurement multiplied by a_n during this period is represented as:

$$\mathbf{y}_2[n] = \Phi_2 \mathbf{x} + a_{n+\triangle N} \Phi_2 \mathbf{v}[n + \triangle N] + a_{n+\triangle N} \Phi_2 \mathbf{w}[n + \triangle N], n = 0, 1, \ldots, N_{p2} N_f - 1, \quad (10)$$

where $\triangle N = N_{p1} N_f$. $\mathbf{x}_{N \times 1}$ is the digitized noise-free received signal $h(t) \bigotimes w(t)$ within the measurement interval T_{prj}, where $\bigotimes$ denotes convolution. Let $\mathbf{P}_v^{\perp}$ be the projection matrix of the estimated null space of $v(t)$, then Φ_2 is given by $\Phi_2 = \Phi_1 \mathbf{P}_v^{\perp}$ and $\Phi_2 \mathbf{v}[n + \triangle N] \approx 0$. Based on the measurements $\mathbf{y}_2[n]$, the UWB signal subspace can be estimated.

For the pilot symbols in the third group and all following data modulated symbols, the received data are projected onto another measurement matrix Φ_3. As will be described in Sec.IV-B, the design of Φ_3 exploits both the NBI subspace information and UWB signal subspace information. The compressive measurement multiplied by a_n during the third group of pilot symbols is represented as:

$$\mathbf{y}_3[n] = \Phi_3 \mathbf{x} + a_{n+\tilde{\triangle} N} \Phi_3 \mathbf{v}[n + \tilde{\triangle} N] + a_{n+\tilde{\triangle} N} \Phi_3 \mathbf{w}[n + \tilde{\triangle} N], n = 0, 1, \ldots, N_{p3} N_f - 1, \quad (11)$$

where $\tilde{\triangle} N = (N_{p1} + N_{p2}) N_f$. The compressive measurement multiplied by a_n for the data modulated symbols is represented as:

$$\mathbf{y}_{d|j}[n] = b_j \Phi_3 \mathbf{x} + a_{n+\hat{\triangle} N} \Phi_3 \mathbf{v}[n + \hat{\triangle} N] + a_{n+\hat{\triangle} N} \Phi_3 \mathbf{w}[n + \hat{\triangle} N], \quad n = 0, 1, \ldots, N_f - 1, \quad (12)$$

where $\hat{\triangle} N = (N_p + j) N_f$ and $j = 0, 1, \ldots, N_s - 1$. $b_j \in \{\pm 1\}$ is the modulated data for transmission.

IV. Subspace Estimation and Symbol Detection

A. Estimation of NBI subspace

Since $v(t)$ is the sum of narrowband signals, $\mathbf{v}(n)$ can be sparsely representated in the DFT or DCT domain. However, $\mathbf{v}(n)$ is length-limited. Thus, its DFT/DCT representation is not strictly sparse and the signal DCT components show power-law decaying. We are interested in cancelling the most significant NBI components in the DCT domain. Thus, $\mathbf{y}_1[n]$ is rewrited as:

$$\mathbf{y}_1[n] = a_n \Phi_1 \mathbf{C} \zeta[n] + a_n \Phi_1 \mathbf{w}[n]. \quad (13)$$

where $\mathbf{C} = [\mathbf{c}_0, \mathbf{c}_1, \ldots, \mathbf{c}_{N-1}]$ is the inverse DCT transform matrix and $\zeta[n]$ is the representation of $\mathbf{v}[n]$ in the DCT domain. Since $a_n \Phi_1 \mathbf{w}[n]$ is colored noise, a whitening procedure is followed. The whitened measurement data is:

$$\tilde{\mathbf{y}}_1[n] = a_n \mathbf{U} \Phi_1 \mathbf{C} \zeta[n] + a_n \mathbf{U} \Phi_1 \mathbf{w}[n]. \quad (14)$$

where $\mathbf{U}$ is the whitening matrix such that $\mathbf{U}\mathbf{U}^T = (\Phi_1 \Phi_1^T)^{-1}$. Since $\mathbf{U} \Phi_1 \mathbf{w}[n]$ is white Gaussian noise, the BPDN method can be directly used to estimate $\zeta[n]$. The resultant solution $\hat{\zeta}[n]$ is then used to estimate the NBI subspace in the DCT domain.

Let $\tilde{\zeta}$ be

$$\tilde{\zeta} = \sum_{n=0}^{N_{p1} N_f - 1} |\hat{\zeta}[n]| \quad (15)$$

and let $\zeta_{max} = \max\{\tilde{\zeta}_0, \tilde{\zeta}_1, \ldots, \tilde{\zeta}_{N-1}\}$ be the entry in $\tilde{\zeta}$ with the largest magnitude. Then the NBI subspace can be approximately represented by $\mathbf{C}_v = [\mathbf{c}_{n_0}, \mathbf{c}_{n_1}, \ldots, \mathbf{c}_{n_J}]$, where $n_j \in \{i | |\zeta_i| > \mu \zeta_{max}\}$. Here μ is an adjustable threshold used to detect the most significant components of NBI. The projection matrix $\mathbf{P}_v^{\perp}$ is then designed as: $\mathbf{P}_v^{\perp} = \mathbf{I}_N - \mathbf{C}_v (\mathbf{C}_v^T \mathbf{C}_v)^{-1} \mathbf{C}_v^T$.

B. Estimation of UWB signal subspace

It has been demonstrated that the received I-UWB signal is sparse on some dictionary Ψ_c [1]. The design of the dictionary Ψ_c exploits the time sparsity of the multipath UWB channel model $h(t)$. Please refer to [1] for details on the dictionary design for I-UWB signals.

The compressive measurements over all the second group of the pilot symbols are averaged to reduce the noise effect. The averaged measurement is given by:

$$\bar{\mathbf{y}}_2 = \frac{1}{N_{p2} N_f} \sum_{n=0}^{N_{p2} N_f - 1} \mathbf{y}_2[n]. \quad (16)$$

Since NBI mitigation has been explicitly performed, we can model the residual NBI $\Phi_2 \mathbf{v}[n + \triangle N]$ as zero-mean Gaussian noise with covariance matrix $\Phi_2 \mathbf{R}_v \Phi_2^T$, where $\mathbf{R}_v(i, j) = \sum_{k=0}^{N_v - 1} R_{v_k}(|i - j|/F_x)$. $\bar{\mathbf{y}}_2$ is then whitened using whitening matrix $\tilde{U}$ with $\tilde{U}\tilde{U}^T = N_{p2} N_f [\Phi_2 (\mathbf{R}_v + N_0 B \mathbf{I}) \Phi_2^T]^{-1}$.

Let Ψ_u be the sampled version of the dictionary Ψ_c with sampling frequency F_s. The signal structure is assumed to be $\mathbf{x} = \mathbf{H}_u \underline{\theta}_u$, where the $N \times K$ matrix $\mathbf{H}_u$ is constructed by K vectors of Ψ_u. Given Φ_2, Ψ_u and the whitened measurements $\bar{\mathbf{y}}_2$, the BPDN algorithm is employed to estimate K and the K relevant vectors of $\mathbf{x}$ from Ψ_u. Let $\hat{\mathbf{H}}_u$ be the estimation of $\mathbf{H}_u$ by the BPDN algorithm and $\tilde{\mathbf{H}}_u = \mathbf{P}_v^{\perp} \hat{\mathbf{H}}_u$, then the $M \times N$ measurement matrix Φ_3 is constructed by:

$$\Phi_3 = \mathbf{G} (\tilde{\mathbf{H}}_u^T \tilde{\mathbf{H}}_u)^{-1} \tilde{\mathbf{H}}_u^T, \quad (17)$$

where $\mathbf{G}$ is an $M \times K$ i.i.d. random matrix.

C. GLRT detector

Assume the data bits $\{1, -1\}$ are sent with equal probability. Without loss of generality, the compressed detection of the

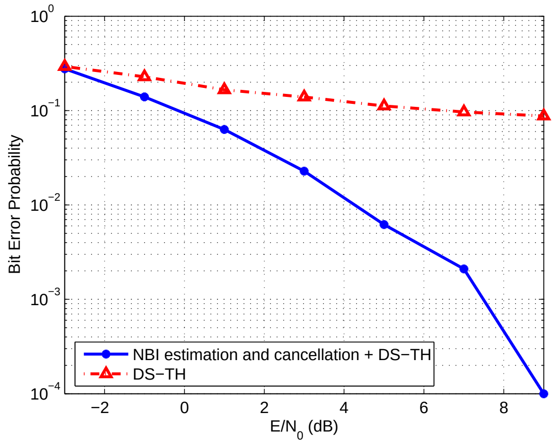

Fig. 1. Performance of subspace UWB detector with NBI mitigation.

jth symbol b_j is discussed. Depending on the compressive measurements, two hypothesis must be distinguished:

$$\begin{aligned}\mathcal{H}_0 \quad &: \quad \mathbf{y}_{d|j}[n] = -\Phi_3\mathbf{x} + a_{n+\hat{\triangle}N}\Phi_3\mathbf{v}[n+\hat{\triangle}N] \\ &\qquad +a_{n+\tilde{\triangle}N}\Phi_3\mathbf{w}[n+\tilde{\triangle}N],\ (b_j=-1), \\ \mathcal{H}_1 \quad &: \quad \mathbf{y}_{d|j}[n] = \quad \Phi_3\mathbf{x} + a_{n+\hat{\triangle}N}\Phi_3\mathbf{v}[n+\hat{\triangle}N] \\ &\qquad +a_{n+\tilde{\triangle}N}\Phi_3\mathbf{w}[n+\tilde{\triangle}N],\ (b_j=1),\end{aligned}$$

with $n = 0, 1, \ldots, N_f - 1$. Note that $\Phi_3\mathbf{x}$ can be estimated from compressive measurements of the third group of the pilot symbols within the same burst. Since the residual NBI can be approximated as Gaussian noise, it can be shown that a sufficient test statistic of the GLRT detector is:

$$T(\mathbf{y}_{d|j}) = (\Phi_3\mathbf{x}+\Phi_3\xi_p)^T(N_0B\Phi_3\Phi_3^T)^{-1}(b_j\Phi_3\mathbf{x}+\Phi_3\xi_d), \tag{18}$$

where $\xi_p = \frac{1}{N_{p3}N_f}\sum_{n=0}^{N_{p3}N_f-1}\mathbf{w}[n+\tilde{\triangle}N]+\mathbf{v}[n+\tilde{\triangle}N]$ and $\xi_d = \frac{1}{N_f}\sum_{n=0}^{N_f-1}\mathbf{w}[n+\hat{\triangle}N]+\mathbf{v}[n+\hat{\triangle}N]$. If $T(\mathbf{y}_{d|j}) > 0$, the estimation of b_j is 1; else, it is -1. An approximate expression for the bit error probability of the detector conditioned on $h(t)$ and $\mathbf{G}$, $P_e|_{G,h}$, can be derived based on Gaussian approximations. It can be shown that [9]:

$$P_e|_{G,h} = Q\left[\left((\frac{N_{p3}+1}{N_{p3}N_f})\frac{1}{|\mathbf{z}|^2}+\frac{M}{N_{p3}N_f^2|\mathbf{z}|^4}\right)^{-\frac{1}{2}}\right]. \tag{19}$$

$\mathbf{z}$ is given by $\mathbf{z} = \mathbf{V}\Phi_3\mathbf{x}$, where $\mathbf{V}$ is designed such that $\mathbf{V}^T\mathbf{V} = [\Phi_3(N_0B\mathbf{I}_N+\mathbf{R}_v)\Phi_3^T]^{-1}$.

V. Simulation Result

In our simulation, the proposed compressive detector with NBI mitigation is evaluated for I-UWB signal detection under strong narrow band interference. The UWB channel model used for simulation is IEEE 802.15.4a C-1 for residential line of sight (LOS) environment [10]. The mean root-mean-square (RMS) delay spread of C-1 is 17 ns. Unit energy of the channel model is assumed. The transmitted pulse is the second derivative of Gaussian with the central frequency $f_c = 3$ GHz and pulse width $T_g \approx 0.35$ ns. For the front-end bandpass filter, the noise bandwidth B is 8 GHz. The virtual sampling frequency F_s for the random digital sequence is 16 GHz. The I-UWB singling parameters are set as follows: $N_{p1} = 5$, $N_{p2} = 30$, $N_{p3} = 10$, $N_f = 5$, $T_c = 32$ ns, $T_f = 800$ ns and $T_{prj} = 32$ ns for objective data rate of 250 kb/s. The maximal PN TH codeword is $N_c = 25$. For subspace compressive detection, the number of compressive measurements M is only 64, compared with $N = 512$, the length of the digitized signal. The NBI is modeled as the sum of two NBI interferences. One NBI is centered at $f_1 = 1.6$ GHz with bandwidth $B_1 = 20$ MHz. The other NBI is centered at $f_2 = 1.6$ GHz with bandwidth $B_2 = 10$ MHz. QPSK modulation for both NBI signals is assumed. The signal to interference power ratio (SIR) is -20 dB.

The performance of the proposed UWB receiver is evaluated under different E/N_0 ratio and the simulation results are shown in Fig. 1. For comparison purposes, the simulation results of subspace UWB signal detection is also shown, where there is no NBI subspace estimation and cancellation, but only DS-TH coding is used for NBI mitigation ($N_{p1} = 0$ and $N_{p2} = 35$). The proposed UWB detector with NBI subspace estimation and cancellation substantially outperforms the compressive subspace detector which does not exploit the NBI signal structure.

VI. Conclusion

In this paper, CS based UWB receiver operating at sub-Nyquist rate is proposed for UWB signal detection and NBI mitigation. By exploiting the signal and NBI subspace, the proposed receiver is not only efficient at gathering signal energy, but also effective at NBI mitigation. Furthermore, NBI subspace detection and cancellation do not require extra hardware. In the future, the proposed UWB receiver design will be extended to multiuser UWB signal detection.

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