Research Article

Two Blind Adaptive Mobile Receivers in Time-Hopping PAM UWB Impulse Radio System

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This paper deals with the design of blind mobile station (MS) receiver for time-hopping (TH) ultrawide-band (UWB) impulse radio (IR) system employing antipodal pulse amplitude modulation (PAM). In the presence of multipath fading channel, batch-mode minimum output energy (MOE) receiver, as well as a blind channel estimator, is first developed. To reduce the computational complexity, we propose two blind adaptive algorithms to determine the weight vector of the MS receiver. The rational of the algorithms premises on iteratively maximizing the minimum possible receiver’s output energy. The first (indirect) approach is derived by first developing an adaptive blind channel estimator, then the updated channel impulse response (IR) is used to calculate the MS receiver’s weight vector. Meanwhile the second (direct) method jointly and iteratively optimizes the weight vector and channel IR to improve system performance. Simulation results demonstrate convergence of both algorithms. Moreover, the algorithms are shown to be robust to multiuser interference (MUI) and near-far problems.

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1. INTRODUCTION

Ultrawide-band (UWB) impulse radio (IR) system has spurred great attention for the promised applications in high-speed short-range indoor wireless communication system. The attractive features of UWB IR technology include low power, low complexity, carrierless modulation, and ample multipath diversity [1–5]. The basic structure of UWB impulse radio stems from transmitting a stream of pulses of very short duration (on the order of nanosecond or less) and with very low duty cycle. When such transmissions are applied in multiple access system, the transmission model encompasses time-hopping (TH) M-ary pulse position modulation (MPPM) [5–8], TH antipodal pulse amplitude modulation (PAM) [4], and direct sequence (DS) binary phase shift keying (BPSK) [9–11] schemes.

Among the various modulation and multiple access schemes, we focus on the design of blind mobile station (MS) receiver in UWB IR multiple access communication system employing TH-PAM modulation. In TH-PAM multiple access system, separation of different users is accomplished by assigning user-specific pattern of time shifting of pulses. Though orthogonal TH codes can be chosen in downlink communication such that the pulses for each user are located in nonoverlapping time slots, however, multipath fading induced signature waveform distortion severely degrades system performance. Thereby, the above benefits vanish without accurate channel estimation. A batch-mode blind (non-data aided and only the desired user’s TH sequence is known) signal reception scheme is proposed in [12]. To make feasible application and reduce the computation load, this paper attempts to develop a blind, adaptive, joint signal extraction and channel impulse response (IR) estimation algorithm in the MS receiver.

We first propose a batch-mode MS receiver that is designed to meet the minimum output energy (MOE) criterion. Such method originated in the area of array signal processing, which is referred to as minimum power distortionless response (MPDR) [13] beamforming. It has been applied in the context of CDMA system for blind interference suppression [14]. In order to extract and estimate the UWB channel impulse response blindly, we make use of the attractive feature that the channel parameters can be determined to maximize the minimum possible mean output energy of the MOE receiver. Unfortunately, the proposed batch-mode MOE receiver and blind channel estimation algorithm
require performing an inverse of the data correlation matrix with a prohibitively large size. It is worthwhile, therefore, to explore adaptive implementation algorithms to reduce the computational complexity.

Both the gradient search and recursive least squares (RLS) [15] based methods are exploited to develop the adaptive algorithms. The indirect approach is derived by first developing an RLS-based channel IR adaptation rule. The updated channel parameters’ vector is then used to calculate the MOE receiver’s weight vector. The direct method is motivated by the concept of direct blind multichannel equalizers [16]. In this approach, the weight vector and channel IR are jointly and iteratively optimized to minimize the minimum possible output energy. Performance of the two adaptive algorithms is comprehensively evaluated.

The remainder of this paper is organized as follows. In Section 2, we formulate the transmitting and receiving signal models of the time-hopping UWB multiple access communication system using binary antipodal PAM modulation. Section 3 highlights the batch processed MOE receiver. The rationale of blind channel parameters’ estimation algorithm is also described. Section 4 describes two types of adaptive blind MOE receivers. Simulation results are presented in Section 5. Concluding remarks are finally made in Section 6.

2. SIGNAL MODEL

In TH UWB IR system, every information symbol (bit) is conveyed by \( N_f \) data modulated ultrashort pulses over \( N_f \) frames. There is only one pulse in each frame and the frame duration is \( T_f \). The pulse waveform, \( p(t) \), is referred to as a monocyte [1] with ultrashort duration \( T_f \) at the nanosecond scale. We assume that \( p(t) \) is normalized within \( T_f \), so that \( \int_0^{T_f} |p(t)|^2 \, dt = 1 \). Note that \( T_f \) is usually a hundred to a thousand times of chip duration, \( T_c \), which accounts for very low duty cycle. When multiple users are simultaneously transmitted and received, signal separation can be accomplished with user-specific pseudorandom TH codes, which shift the pulse position in every frame. In downlink side, all users are synchronously transmitted; we may establish the data model of the transmitted signal as

\[
 x(t) = \sum_{k=1}^{K} \sum_i d_k(i) \sum_{j=0}^{N_f-1} a_k p(t - jN_fT_f - c_k^j T_c),
 \]

where \( t \) is the clock time of the transmitter, \( K \) is the number of active users, \( a_k \) is the amplitude of the \( k \)-th user. The \( i \)-th bit transmitted by \( k \)-th user is given by \( d_k(i) \), which takes on \( \pm 1 \) with equal probability. The operation is equivalent to repeating the bit \( N_f \) times, a repetition coding with code rate \( 1/N_f \). Denoting \( T_b \) as the duration of the \( N_f \) repeated bits, then \( T_b = N_f T_f \). Suppose each frame is composed of \( N_f \) time slots each with duration \( T_c \), thus, \( T_f = N_f T_c \). User separation is accomplished by user-specific pseudorandom TH code. \( \{c_k^j\}_{j=0,1,...,N_f-1} \) accounts for the \( k \)-th user’s TH code with period \( N_f \). Thereby, \( c_k^j T_c \) is the timeshift of the pulse position imposed by the TH sequence employed for multiple access. \( c_k^j T_c \leq T_f \), or equivalently, \( 0 \leq c_k^j \leq N_c - 1 \).

In this paper, we adopt the channel models of CM4 (indoor office) and CM9 (the industrial) as described in [17], where “dense” arrivals of multipath components (MPC) were observed and each resolvable delay bin contains significant energy. In these cases, a realization of the impulse response based on a tapped delay line model with regular tap spacings is to be used. Thereby, the time-invariant channel impulse response with \((L + 1)\) resolvable paths can be written as

\[
 h(t) = \sum_{l=0}^{L} a_l \delta(t - lT_c),
 \]

where \( a_l \) denotes the attenuation coefficient of the \( l \)-th resolvable path. In writing (2), we have implicitly assumed that the maximum time dispersion is \( L T_c \). To simplify the analysis, we assume that the channel parameters vary so slowly that they are essentially constant over observation interval, and \( \sum_{l=0}^{L} |a_l|^2 = 1 \). In downlink channel, signals are subject to the same fading. Consequently, the received composite waveform at the desired mobile is made up of a weighted sum of attenuated and delayed replicas of the transmitted signal \( x(t) \), that is,

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

(3)

where \( n(t) \) is assumed to be a zero-mean, wide-sense stationary (WSS) Gaussian random process with a power density spectrum that is constant (white), \( \sigma^2 \), in a finite frequency interval. Evidently, by selecting \( c_k^j = 0 \), for all \( k \), and \( T_f > L T_c \) (or, equivalently, \( N_c > L \)), we can guarantee no intersymbol interference (ISI). Note that under multipath fading, the original pulse, \( p(t) \), has been distorted and lengthened to \( \tilde{p}(t) \) with support of \([0,LT_c]\):

\[
 \tilde{p}(t) = \sum_{l=0}^{L} a_l p(t - lT_c).
 \]

Hence, we may re-express (3) as

\[
 r(t) = \sum_{k=1}^{K} \sum_{i=0}^{N_f-1} a_k \sum_{j=0}^{N_f-1} \tilde{p}(t - jN_fT_f - c_k^j T_c) + n(t).
\]

The problem addressed in this paper is the design of MS receiver based on the observation process \( r(t) \) with unknown channel parameters and without undesired users’ TH sequences.

3. DESIGN OF BLIND MS RECEIVER

3.1. Minimum output energy (MOE) receiver

As depicted in (4), multipath fading leads to time dispersion of \( p(t) \), which adversely affects the orthogonality between
the TH codes. In what follows, MUI occurs even in down- link side employing orthogonal (nonoverlapping) TH codes. At the receiver, chip-matched filtering followed by chip-rate sampling yields a sequence of \(N_cN_f\) vectors. The samples of chip-matched filter (CMF) output during the \(l\)th symbol interval can be expressed as

\[
\mathbf{r}(i) = \sum_{k=1}^{K} \mathbf{a}_k \mathbf{d}_k(i) + \mathbf{n}(i) = \hat{\mathbf{C}} \mathbf{d}(i) + \mathbf{n}(i),
\]

where the \(N_cN_f\)-vector \(\hat{\mathbf{C}}_k\) represents the chip-rate sampled version (during \(T_k\)) of the composite waveform \(\sum_{j=N_c}^{N_c+N_f-1} \sum_{l=0}^{L} a_l p(t - jT_f - c_l^T T_e - IT_e)\), \(\hat{\mathbf{C}} \in \mathbb{R}^{N_cN_f \times K}\), \(\hat{\mathbf{C}} := [\mathbf{c}_1 \ \mathbf{c}_2 \ \cdots \ \mathbf{c}_K]\), \(\mathbf{A} := \text{diag}[a_1 \ a_2 \ \cdots \ a_K]\), and \(\mathbf{d}(i) := [d_1(i) \ d_2(i) \ \cdots \ d_K(i)]^T\). Denoting \(\mathbf{q}_k\) as the chip-rate samples at the output of CMF (within a bit) of the received waveform coming from the \(l\)th path, then \(\int_{n=N_c}^{N_c+N_f-1} \sum_{j=0}^{N_f-1} p(t - jT_f - c_l^T T_e - IT_e)dt, n = 0, 1, \ldots, N_cN_f - 1\), thereby, each \(\mathbf{q}_{k,l}\) represents a delayed version of the original signature vector, \(\mathbf{c}_k\). It is evident that \(\hat{\mathbf{C}}_k\) can be expressed as

\[
\hat{\mathbf{c}}_k = \sum_{l=0}^{L} a_l \mathbf{q}_{k,l} = \mathbf{C}_k \mathbf{a}, \quad k = 1, 2, \ldots, K,
\]

where \(\mathbf{C}_k := [\mathbf{q}_{k,0} \ \mathbf{q}_{k,1} \ \cdots \ \mathbf{q}_{k,L}]\), \(\mathbf{a} := [a_0 \ a_1 \ \cdots \ a_L]^T\). Clearly, \(\mathbf{C}_k\) is full column rank provided that \(N_f > (L + 1)\).

From (6), we can obtain the correlation matrix of \(\mathbf{r}(i)\):

\[
\mathbf{R}_{rr} := E[\mathbf{r}(i)\mathbf{r}^H(i)] = \mathbf{C}\mathbf{A}^\ast \mathbf{C}^T + \sigma^2 \mathbf{I}_{N_cN_f}.
\]

Without loss of generality, we assume user 1 is the desired user hereafter. In order to recover the desired signal, \(\mathbf{d}_1(i)\), an \(N_cN_f\)-by-1 weight vector should be designed to effectively suppress MUI and a sign test is proceeded to determine the information bit:

\[
\hat{d}_1(i) = \text{sign}(\mathbf{w}^H\mathbf{r}(i)).
\]

Figure 1 depicts the block diagram of the MOE receiver. The choice of weight vector, \(\mathbf{w}\), for the MOE receiver [12, 14] aims to minimize the output energy, \(E[|\mathbf{w}^H\mathbf{r}(i)|^2]\), while distortionlessly passes the desired signal, yielding

\[
\arg \min_{\mathbf{w}} \mathbf{w}^H\mathbf{R}_{rr}\mathbf{w},
\]

subject to \(\mathbf{w}^H\mathbf{c}_1 = 1\).

Applying Lagrange multiplier method [18] to solve the above-constrained optimization problem, we arrive at the optimal solution of (10):

\[
\mathbf{w}_{MOE} = \eta \mathbf{R}_{rr}^{-\frac{1}{2}} \hat{\mathbf{c}}_1 = \frac{\mathbf{R}_{rr}^{-\frac{1}{2}} \mathbf{c}_1}{\mathbf{c}_1^T \mathbf{R}_{rr}^{-\frac{1}{2}} \mathbf{c}_1},
\]

where \(\eta = 1/(\hat{\mathbf{c}}_1^T\mathbf{R}_{rr}^{-\frac{1}{2}}\hat{\mathbf{c}}_1)\) stands for the minimum output energy at \(\mathbf{w}_{MOE}\). In what follows, the output of the MOE receiver and the corresponding signal-to-interference-plus-noise power ratio (SINR) can be obtained as

\[
\mathbf{z}_{MOE}(i) = \mathbf{w}_{MOE}^H\mathbf{r}(i) = a_id_1(i) + \mathbf{w}_{MOE}^H\sum_{k=2}^{K} a_k \mathbf{d}_k(i) \hat{\mathbf{c}}_k + \mathbf{w}_{MOE}^H\mathbf{n}(i),
\]

\[
\gamma_{MOE} = \frac{\alpha_l^2}{\sum_{k=2}^{K} a_k^2 \mathbf{w}_{MOE}^H \hat{\mathbf{c}}_k^2 + \sigma^2||\mathbf{w}_{MOE}||^2}.
\]

### 3.2. Blind channel estimation algorithm

Intuitively, \(\eta\) is mainly determined by the desired signal's energy, \(\alpha_l\), since any signature vector, that is not exactly matched to \(\hat{\mathbf{c}}_1\), is suppressed to minimize the output energy. We may obtain from (7), \(\hat{\mathbf{c}}_1 = \mathbf{C}_1 \mathbf{a}\), that \(\hat{\mathbf{c}}_1\) is uniquely determined by \(\mathbf{a}\). Or equivalently, the estimation error of parameter \(\mathbf{a}\) may lead to the output energy degradation. Motivated by the output energy degradation that arises from estimation error, we propose to estimate \(\mathbf{a}\) such that \(\eta\) is maximized:

\[
\arg \max_{\mathbf{a}} \eta = \arg \min_{\mathbf{a}} \mathbf{c}_1^T \mathbf{R}_{rr}^{-\frac{1}{2}} \mathbf{c}_1 = \arg \min_{\mathbf{a}} \mathbf{a}^H \mathbf{Q}_1 \mathbf{a},
\]

where \(\mathbf{Q}_1 := \mathbf{C}_1^T \mathbf{R}_{rr}^{-\frac{1}{2}} \mathbf{C}_1\), and incorporating the unit-norm constraint, \(\sum_{l=0}^{L} a_l^2 = 1\), we may re-express (14) as a constrained optimization problem:

\[
\arg \min_{\mathbf{a}} \mathbf{a}^H \mathbf{Q}_1 \mathbf{a},
\]

subject to \(\mathbf{a}^H \mathbf{a} = 1\).

Since the correlation matrix \(\mathbf{R}_{rr}\) is positive definite and \(\mathbf{C}_1\) is full column rank, thus, \(\mathbf{Q}_1\) is also positive definite. From the theorem related to Rayleigh quotient or the method of Lagrange multipliers [18], the optimal solution of (15) can be derived as

\[
\hat{\mathbf{a}} = \mathbf{e}_{\text{min}},
\]

where \(\mathbf{e}_{\text{min}}\) represents the normalized eigenvector of \(\mathbf{Q}_1\) corresponding to its minimum eigenvalue. Note that, in practice, \(\mathbf{R}_{rr}\) is unknown and needs to be estimated. Under ergodic (with respect to the autocorrelation function) assumption, we may perform time average on the measurements. Hence, for an observation length (window size) of \(k\) bits, the estimate of \(\mathbf{R}_{rr}\) is given by

\[
\hat{\mathbf{R}}_{rr} = \frac{1}{k} \sum_{j=1}^{k} \mathbf{r}(j)\mathbf{r}^H(j).
\]
4. RECURSIVE IMPLEMENTATION OF THE MOE RECEIVER

As we can observe from (11) and (14), the batch-mode MOE receiver and the blind channel estimator involve the inversion of $R_{rr}$. Unfortunately, since the size of $R_{rr}$, $N_cN_f$-by-$N_cN_f$, is generally prohibitively large, hence from the computational load point of view, it is crucial to develop iterative algorithms to implement the MOE receiver. In this section, we propose two constrained adaptive optimization techniques. The indirect approach premises on recursively updating the channel parameters and then exploiting the result to derive the weight vector. While the second scheme jointly updates the channel parameters and weight vector which is referred to as direct approach.

4.1. Indirect approach

To accommodate the time-varying characteristics and compute $Q_1$ without performing $R_{rr}^{-1}$, we attempt to develop an adaptive algorithm instead of the batch constrained optimization method as described in Section 3.2. Using the method of Lagrange multipliers to solve the constraint optimization problem of (15), we can establish the cost function

$$J(\alpha) = \alpha^H Q_1 \alpha - \lambda (\alpha^H \alpha - 1),$$

where $\lambda$ is the corresponding Lagrange multiplier. The gradient of $J$ with respect to $\alpha$ is given by

$$\nabla_{\alpha} J(\alpha) = 2(Q_1 \alpha - \lambda \alpha).$$

Substituting (24) into (19), we have

$$\nabla J(k) = 2(Q_1(k)\alpha(k) - \lambda(k)\alpha(k)).$$

Employing steepest decent gradient search, we get the update equation for $\alpha$:

$$\alpha(k+1) = \alpha(k) - \mu J(k)$$

$$= \alpha(k) - \mu(Q_1(k) - \lambda(k)I_{L+1})\alpha(k),$$

where the step size $\mu$ is a positive number. To make the algorithm consistent with the unit-norm constraint of (15), we further normalize $\alpha(k+1)$ at each iteration. Then, the effective signature vector at $(k+1)$th iteration can be obtained as

$$\tilde{\alpha}(k+1) = C_1\alpha(k+1).$$

It follows from (20) to update $\lambda$ by

$$\lambda(k+1) = \alpha^H(k+1)Q_1(k)\alpha(k+1).$$

Substituting (23), (27), and (28) into (11), we obtain $w(k+1)$. In summary, we may generalize the above RLS-gradient-based adaptation algorithm as follows.

Step 1. Initialize the algorithm by setting

$$R_{rr}^{-1}(0) = \frac{1}{\sigma^2}I_{N_cN_f}, \quad \lambda(0) = \frac{1}{\alpha_1^2}, \quad \alpha(0) = e_1.$$ 

Calculate $Q_1(0)$, $\nabla J(0)$, and $\alpha(1)$, normalize $\alpha(1)$, and calculate $\tilde{\alpha}(1)$, $\lambda(1)$, and $w(1)$. For $k = 1, 2, \ldots$, do the following.

Step 2. Accept new data vector $\mathbf{r}(k)$ and use (23) to update $R_{rr}^{-1}(k)$.

Step 3. Calculate $Q_1(k)$ using (24).

Step 4. Calculate $\nabla J(k)$ using (25).

Step 5. Update $\alpha(k+1)$ using (26), then normalize $\alpha(k+1)$.

Step 6. Calculate $\tilde{\alpha}(k+1)$ using (27).

Step 7. Update $\lambda(k+1)$ using (28).

Step 8. Calculate $w(k+1)$.

Step 9. Go back to Step 2 until converge.

The above steps are displayed in Figure 2(a). Towards the above adaptation rule, the following remarks are in order.

(i) In the absence of signal, the data is full of white noise with correlation matrix $R_{rr}(0) = \sigma^2I_{N_cN_f}$, thus we set $R_{rr}^{-1}(0) = (1/\sigma^2)I_{N_cN_f}$ in Step 1. Intuitively, $\lambda = \alpha^H Q_1 \alpha$ stands for the inverse of the output energy of the MOE receiver. Hence, we set $\lambda(0) = 1/\alpha_1^2$, since the MOE receiver’s output energy is mainly determined by the desired signal’s power. To meet the constraint $\alpha^H \alpha = 1$ and ensure nontrivial solution, we set $\alpha(0) = e_1$. 

Substituting (24) into (19), we have

$$\nabla J(k) = 2(Q_1(k)\alpha(k) - \lambda(k)\alpha(k)).$$

Substituting (23), (27), and (28) into (11), we obtain $w(k+1)$.
To determine the step size $\mu$, we first assume that $Q(k), \lambda(k)$ converge asymptotically to their respective optimum values $\lim_{k \to \infty} Q(k) = Q_1$ and $\lim_{k \to \infty} \lambda(k) = \lambda$. Let the error vector at time $k$ be defined as $c(k) := a(k) - a_0$, where $a_0$ denotes the optimum channel impulse response vector. Exploiting the fact that $Q_1 a_0 = \lambda_{\min} a_0$, we may rewrite (26) in terms of the error vector

$$c(k+1) = c(k) - \mu(Q_1 - \lambda_{\max} I_{L+1})(a(k) - a_0)$$

$$= c(k) - \mu(Q_1 - \lambda_{\max} I_{L+1})c(k)$$

$$= ((1 + \mu \lambda) I_{L+1} - \mu Q_1)c(k).$$  \hspace{1cm} (30)

Using eigenvalue decomposition (EVD), we may express $Q_1$ as

$$Q_1 = \text{PAP}^H,$$  \hspace{1cm} (31)

where $P$ is a unitary matrix ($PP^H = P^HP = I_{L+1}$) with column vectors associated with the eigenvectors of $Q_1 \cdot \Lambda := \text{diag}(\lambda_1, \lambda_2, \ldots, \lambda_{L+1})$ with its diagonal elements being the eigenvalues of $Q_1$. Substituting (31) into (30), we get

$$c(k+1) = ((1 + \mu \lambda) I_{L+1} - \mu \text{PAP}^H)c(k).$$  \hspace{1cm} (32)

Premultiplying both sides of (32) by $\text{P}^H$ and defining $v(k) = \text{P}^Hc(k)$, we may reformulate (32) as

$$v(k+1) = ((1 + \mu \lambda) I_{L+1} - \mu \Lambda)v(k).$$  \hspace{1cm} (33)

We thus can obtain the $n$th element of $v(k+1)$:

$$v_n(k+1) = ((1 + \mu \lambda) - \mu \lambda_n)v_n(k)$$

$$= (1 + \mu(\lambda - \lambda_n))v_n(0), \quad n = 1, 2, \ldots, L + 1,$$  \hspace{1cm} (34)

where $v_n(0)$ is the initial value of the $n$th mode. The stability or convergence of the steepest descent algorithm is assured provided that

$$|1 + \mu(\lambda - \lambda_n)| < 1.$$  \hspace{1cm} (35)

Since $\lambda - \lambda_n < 0$, it follows that a necessary and sufficient condition for convergence is that the $\mu$ satisfies

$$0 < \mu < \frac{2}{\lambda_{\max} - \lambda_{\min}}.$$  \hspace{1cm} (36)

where $\lambda_{\max}, \lambda_{\min}$ are the maximum and minimum eigenvalues of $Q_1$, respectively.

It is worthy to note that if $L \ll N_c N_f$, then finding the minimum eigenvector of $Q_1$ does not result in computational burden. In what follows, we may develop the RLS-EVD-based adaptation rule in steps.

**Step 1.** Set the initial parameters: $R_{zr}^{-1}(0) = (1/\sigma^2)I_{N_c N_f}$. For $k = 1, 2, \ldots$, do the following.

**Step 2.** Accept new data vector $r(k)$ and use (23) to update $R_{zr}^{-1}(k)$.

**Step 3.** Calculate $Q_1(k)$ using (24).
Step 4. Find $\alpha(k) = e_{\text{min}}(k)$, where $e_{\text{min}}(k)$ is the minimum eigenvector (normalized) of $Q_1(k)$.

Step 5. Calculate $\tilde{c}_1(k) = C_1 \alpha(k)$.

Step 6. Calculate $w(k)$
\[
 w(k) = \frac{R^{-1}_{rr}(k) \tilde{c}_1(k)}{\lambda_{\text{min}}(k)},
\] (37)
where $\lambda_{\text{min}}(k)$ is the minimum eigenvalue of $Q_1(k)$.

Step 7. Go back to Step 2 until converge.

The above steps are displayed in Figure 2(b). In order to reduce the computation load induced by EVD in Step 4, we may apply the power method [18] that recursively update the eigenvector according to
\[
e^{l+1}(k) = \frac{\tilde{Q}_1(k) e^{l}(k)}{||\tilde{Q}_1(k) e^{l}(k)||}, \quad l = 0, 1, 2, \ldots,
\] (38)
where $\tilde{Q}_1(k) := c I_{l+1} - Q_1(k)$ and $c$ is an arbitrary positive number to make all the eigenvalues of $\tilde{Q}_1(k)$ positive. In what follows, the eigenvector corresponds to the maximum eigenvalue of $\tilde{Q}_1(k)$ that is identical to the eigenvector associated with the minimum eigenvalue of $Q_1(k)$. It is evident that the vector in (38) will asymptotically converge to the maximum eigenvector of $\tilde{Q}_1(k)$.

4.2. Direct approach
Incorporating $\tilde{c}_1 = C_1 \alpha$, $\alpha^H \alpha = 1$ into the distortionless constraint of (10), we arrive at an alternative constrained optimization problem:
\[
\arg \min_w w^H R_{rr} w,
\] subject to $C_1^H w = \alpha$.

The cost function towards (39) can be explicitly written as
\[
J(w, \alpha) = w^H R_{rr} w - \beta^H (C_1^H w - \alpha) - (w^H C_1 - \alpha^H) \beta,
\] (40)
where vector $\beta$ comprises the corresponding Lagrange multipliers. The problem addressed in (40) is similar to the linearly constraint minimum power (LCMP) beamforming problem in [13] and the solution is
\[
w = R^{-1}_{rr} C_1 \beta = R^{-1}_{rr} C_1 (C_1^T R^{-1}_{rr} C_1)^{-1} \alpha = R^{-1}_{rr} C_1 Q_1^{-1} \alpha,
\] (41)
where $\beta = (C_1^T R^{-1}_{rr} C_1)^{-1} \alpha = Q_1^{-1} \alpha$. Substituting the solution of $\alpha$ as deduced in (16), we have
\[
\beta = Q_1^{-1} \alpha = \frac{1}{\lambda_{\text{min}}} e_{\text{min}}.
\] (42)

The goal for the direct approach is to minimize $J(w, \alpha)$ with respect to $w$, while maximizing $J(w, \alpha)$ with respect to $\alpha$. The gradient of $J(w, \alpha)$ with respect to $w$ and $\alpha$ is given by
\[
\nabla_w J(w, \alpha) = 2 R_{rr} w - 2 C_1 \beta,
\]
\[
\nabla_\alpha J(w, \alpha) = 2 \beta.
\] (43)

Based on the gradient decent adaptation rule, we obtain two update equations for $w$ and $\alpha$, respectively as
\[
w(k + 1) = w(k) - \mu_1 (R_{rr}(k) w(k) - C_1 \beta),
\] (44)
\[
\alpha(k + 1) = \alpha(k) + \mu_2 \beta(k),
\] (45)
where $\mu_1$ and $\mu_2$ are the step sizes setting for $w$ and $\alpha$, respectively. To solve $\beta(k)$ of the above update equations, we exploit the constraint of (39) and enforce $C_1^H w(k+1) = \alpha(k)$ in (44), which yields
\[
C_1^H w(k+1) = \alpha(k) = C_1^H w(k) - \mu_1 C_1^H (R_{rr}(k) w(k) - C_1 \beta(k)).
\] (46)

After some manipulations, we can obtain
\[
\beta(k) = \frac{1}{\mu_1} ((C_1^H C_1)^{-1} \alpha(k) - (C_1^H C_1)^{-1} C_1^H w(k))
\]
\[
+ (C_1^H C_1)^{-1} C_1^H R_{rr}(k) w(k).
\] (47)

Substituting (47) into (44) and (45), we arrive at the update equations
\[
w(k + 1) = P_{C_1}^\perp (I_{N_N, N_f} - \mu_1 R_{rr}(k)) w(k) + C_1 (C_1^H C_1)^{-1} \alpha(k),
\] (48)
\[
\alpha(k + 1) = \left( I_{l+1} + \frac{\mu_2}{\mu_1} (C_1^H C_1)^{-1} \right) \alpha(k)
\]
\[
- \frac{\mu_2}{\mu_1} (C_1^H C_1)^{-1} C_1^H (I_{N_N, N_f} - \mu_1 R_{rr}(k)) w(k),
\] (49)

where $P_{C_1}^\perp$ denotes the orthogonal projection matrix with respect to the constraint space $C_1$
\[
P_{C_1}^\perp = I_{N_N, N_f} - C_1 (C_1^H C_1)^{-1} C_1^H.
\] (50)

From (17), we can obtain a simple update equation for the correlation matrix
\[
R_{rr}(k) = \frac{k - 1}{k} R_{rr}(k - 1) + \frac{1}{k} r(k) r^H(k).
\] (51)

The above adaptation algorithm can be summarized as follows.

Step 1. Initialize the algorithm by setting
\[
\alpha(0) = e_1, \quad R_{rr}(0) = \sigma^2 I_{N_N, N_f}, \quad w(0) = C_1 (C_1^H C_1)^{-1} \alpha(0).
\] (52)

Calculate $w(1)$, $\alpha(1)$, respectively. For $k = 1, 2, \ldots$, do the following.

Step 2. Accept new data vector $r(k)$ and use (51) to calculate $R_{rr}(k)$. 
Figure 3: Implementation of the direct blind adaptive MOE receiver.

Step 3. Substitute $\mathbf{R}_{rr}(k)$ into (49) to calculate $\mathbf{a}(k + 1)$.

Step 4. Normalize $\mathbf{a}(k + 1)$.

Step 5. Calculate $w(k + 1)$ using (48).

Step 6. Go back to Step 2 until converge.

The above steps are displayed in Figure 3. To determine the step size $\mu_1$ in (48), we first assume that $\mathbf{R}_{rr}(k)$, $\mathbf{R}_{rr}$ converge asymptotically to their respective optimum values $\lim_{k \to \infty} \mathbf{R}_{rr}(k) = \mathbf{R}_{rr}$, $\lim_{k \to \infty} \mathbf{R}_{rr} = \mathbf{R}_{rr}$. Let the error vector at time $k$ be defined as $\mathbf{d}(k) := \mathbf{w}(k) - \mathbf{w}_0$, where $\mathbf{w}_0$ denotes the optimum weight vector. It follows from (41) that $\mathbf{C}_f \mathbf{R}_{rr} = \mathbf{R}_{rr} \mathbf{w}_0$. Thus, we may rewrite (44) in terms of the error vector

$$
\mathbf{d}(k + 1) = \mathbf{d}(k) - \mu_1 (\mathbf{R}_{rr} \mathbf{a}(k) - \mathbf{R}_{rr} \mathbf{w}_0)
$$

$$
= \mathbf{d}(k) - \mu_1 (\mathbf{R}_{rr} \mathbf{d}(k))
$$

$$
= (\mathbf{I}_{N_r N_s} - \mu_1 \mathbf{R}_{rr}) \mathbf{d}(k).
$$

Following the same procedures as we derive the step size in indirect approach, we can obtain the necessary and sufficient condition for the convergence

$$
0 < \mu_1 < \frac{2}{\lambda_{\max}},
$$

where $\lambda_{\max}$ is the maximum eigenvalue of $\mathbf{R}_{rr}$.

5. PERFORMANCE EVALUATION

In this section, we conduct simulations to evaluate and compare the performance of the proposed two types of adaptive blind receiving schemes. Moreover, the performance of the batch-mode MOE receiver with perfect channel information is also provided as an optimum bound. The channel model applied for simulation is based on (2). Unless otherwise mentioned, we set the parameters $N_r = 20$, $N_f = 20$, $L = 8$, and $K = 10$, and signal-to-noise-ratio (SNR) for each user is set to be 20 dB throughout all the simulation examples.

Figure 4 measures the SINR performance with respect to the number of iterations $(k)$, where the performance of the ideal batch-mode MOE receiver is provided as an upper bound. Notice that the output SINR, after $k$th iterations, can be obtained from (13) as follows:

$$
y(k) = \frac{a_i^2 \| \mathbf{w}^H (k) \tilde{c}_i \|^2}{\sum_{i=1}^{K} a_i^2 \| \mathbf{w}^H (k) \tilde{c}_i \|^2 + \sigma^2 \| \mathbf{w}(k) \|^2}.
$$

The convergence characteristics of both direct and indirect adaptation rules are verified in Figure 4. The RLS-gradient and RLS-EVD algorithms of the indirect approach converge to almost the same level, while the direct approach is approximately 7 dB better than the indirect one. However, there is still an 8 dB loss when comparing the direct approach with the ideal case. This is mainly due to the inevitable estimation error. We then examine the convergent behavior of the proposed adaptive channel estimators. A plausible criterion to measure the estimation accuracy is root mean-squared-error (RMSE) that is defined as

$$
\text{RMSE}(k) := \sqrt{\frac{1}{N_r} \sum_{m=1}^{N_r} \| \tilde{\mathbf{a}}_m(k) - \mathbf{a} \|^2},
$$

where $N_r$ is the Monte-Carlo trial number that is set to be $N_r = 50$. Figure 5 measures the RMSE performance with respect to $k$. As depicted in Figure 5, RMSE decreases as $k$ increases for both recursive channel estimators. In the next example, we examine the convergent rate of the indirect scheme under different weight vector sizes. Figure 6 compares the SINR performance with respect to $k$ for $N_r = N_f = 20, 15, 10$, respectively, in the presence of 10 equal power (15 dB) users. As we can observe from Figure 6, though the convergence rate is approximately the same, smaller $N_r \times N_f$ achieves essentially better performance. This is mainly due to the fact that larger $N_r \times N_f$ is more sensitive to estimation error.

In the following simulation examples, we fix the number of iterations, $k = 5000$, and examine the performance under...
Figure 5: RMSE performance with respect to the number of iterations.

Figure 6: SINR performance with respect to $k$ for $N_c = N_f = 20, 15, 10$, respectively.

Figure 7: SINR performance with respect to the number of active users ($K$).

Figure 8: The SINR performance with respect to NFR.

6. CONCLUSION

Without exploiting the undesired users' TH sequences, we developed two blind adaptive MS receivers for UWB IR system employing antipodal PAM modulation. Both algorithms are deduced to minimize the MOE receiver's output energy subject to appropriate constraints, which are chosen to maximize the minimal possible output energy. We can infer from the simulation results that the system performance for both receivers is sequentially optimized. Specifically, the direct scheme generally outperforms the indirect one under various scenarios. Compared to the batch-mode MOE receiver, the computation load of both algorithms is extensively reduced. Moreover, simulations confirm reliable convergent rate and the performance is comparable to the ideal case that the channel parameters are well known.
NOTATION

The boldface lower-case and upper-case letters:

\([\cdot]^T, [\cdot]^H]\): Transpose and complex transpose of a matrix or vector, respectively.

\(E\{\cdot\}\): Expectation (ensemble average).

\(\hat{\cdot}\): The convolution operation.

\(1\): A vector with all elements being 1.

\(\delta(\cdot)\): The Dirac delta function.

\(\hat{x}\): The estimate of parameter \(x\).

\(e\): A vector with all entries zero except for the \(i\)th entry, which is one.

REFERENCES


