Abstract—In this paper we derive and propose constrained blind adaptive multiuser detection algorithm for DS-CDMA UWB multipath channel to suppress the multi access interference (MAI). Variance of the receiver output is minimized subject to appropriate constraints. Receiver does not require spreading code knowledge of all users other than that of the user of interest. Simulation results show that bit error probability performance of the proposed method is better than that of adaptive minimum mean square error (MMSE) detector and much better than RAKE receiver performance in multipath AWGN channel.

Key words: Adaptive systems, Blind detector, Constrained optimization, DS-CDMA, Multipath channel, Ultra wideband.

I. INTRODUCTION

Ultra wideband (UWB) is a new technology that has the potential to revolutionize wireless communication by delivering high data rates with very low power densities [1]. Several attempts are being made to use UWB at the physical layer for personal area networks (PAN) to meet the FCC standards [2]. FCC has released 3.1 GHz to 10.6 GHz frequency spectrum with restrictions on minimum transmission bandwidth of 500 MHz and transmit power spectral density of -41.3 dBm/MHz, which restricts the use of UWB to PAN.

Under multiple access scenario the presence of multiple signals transmitting at the same time is a typical source of interference for wireless signals. Several multiple access schemes are proposed for UWB, namely, Time Hopping (TH) [4], [3], Frequency Hopping (FH) [5] and Direct Sequence (DS) [6]. In TH, MAI can be reduced by increasing number of time hops, but this is at the cost of reduced data rate. Similarly, in FH, MAI can be reduced by increasing number of frequency hops. However the maximum frequency hops that can be achieved in FCC UWB spectrum is thirteen [7].

DS-CDMA is a well known powerful multi-access technique in the presence of strong narrowband interference and AWGN. There are many multiuser detection techniques available in literature [8] which effectively cancel the MAI under the given conditions. Some of these techniques are extended to DS-CDMA UWB. Adaptive minimum mean square error multiuser detection technique for DS-CDMA UWB wherein known training bits are required to adapt to channel conditions to cancel the MAI have been proposed in [9], [10], [11]. The major draw back of proposed techniques in [12], [13] is that the probability of error performance degrades significantly in the presence of noise.

Blind multiuser DS-CDMA detector proposed for AWGN channel [8] cannot be directly extended to multipath channel, as these systems are very sensitive to signal mismatch and interchip interference. Blind adaptive multiuser DS-CDMA detector for both AWGN and multipath channel is proposed in [14]. This technique optimizes receiver output energy with a constraint on the response of the user of interest. The major drawback of this system is that it fails to converge for lower signal to noise ratio (SNR).

Constrained optimization methods [15] have received considerable attention as a means to derive blind multiuser receivers with low complexity. In this paper we derive an expression for optimum tap weights under constraints for DS-CDMA UWB multipath receiver. The technique is extended for adaptive implementation using least mean square (LMS) and recursive least square (RLS) algorithms. In section II the signal and system model are described. In section III the proposed constraint LMS and RLS algorithm is developed. In section IV simulation results are presented for a given specification and the concluding remarks are made in section V.

II. SIGNAL AND SYSTEM MODEL

We consider K user DS-CDMA UWB system transmitting over multipath channel. Each user employs orthogonal spreading codes modulated by the second derivative of the Gaussian pulse. The transmitted signal generated by kth user is given by

\[ x_k(t) = \sum_{n=-\infty}^{\infty} b_k(n)s_k(t - nT_s) \]  

(1)

where, \( b_k(n) \) is the kth user information bearing sequence (±1) with zero mean and unit variance. The sequence of each user are independent and identically distributed (iid). \( T_s \) is symbol duration and \( s_k \) is the spreading waveform of kth user with unit energy (\( ||s_k|| = 1 \)) and is given by

\[ s_k(t) = \sum_{i=0}^{N_s-1} s_k(i)p(t - iT_c) \]
where, $N_s$ is spreading gain, $T_c$ is chip duration and $p(t)$ is the second derivative of Gaussian pulse and is given by
$$p(t) = \left[1 - 4\pi \left(\frac{t}{\tau_m}\right)\right] \exp\left[-2\pi \left(\frac{t}{\tau_m}\right)^2\right]$$ \hspace{1cm} (2)

where, $\tau_m$ is the pulse shaping parameter.

The received signal for asynchronous multipath channel for each user is
$$y(t) = \sum_{n=-\infty}^{\infty} \sum_{k=1}^{K} b_k(n)s_k(t - nT_s - \tau_k) \otimes g_k(t) + z(t)$$ \hspace{1cm} (3)

where, $\tau_k$ is relative delay offset of the received asynchronous channel for $k$th user, $g_k$ is unknown multipath channel for user $k$, $\otimes$ is convolution and $z(t)$ is a zero mean additive white Gaussian noise (AWGN) with variance $\sigma_z^2$.

Assuming $g_k(t)$ has finite impulse response of maximum order $L << N_s$, then the chip rate sampled received signal after UWB pulse matched filtering with length $N_s + L - 1$ is given by
$$y(n) = \sum_{k=1}^{K} b_k(n)h_k + z(n)$$ \hspace{1cm} (4)

where $h_k$ is effective spreading code of $k$th user. Let us assume $k = 1$ is the user of interest at receiver. We can rewrite (4)
$$y_1(n) = b_1(n)h_1 + i_m(n) + z(n)$$ \hspace{1cm} (5)

where, $i_m(n)$ is the interference contributed by other users and is given by
$$i_m(n) = \sum_{k=2}^{K} b_k(n)h_k$$ \hspace{1cm} (6)

$h_k$ can be decomposed as
$$h_k = S_k g_k$$

where, $S_k \in R^{(N_s + L - 1) \times L}$ is code filtering matrix which is composed of delayed versions of the spreading code of user $k$, and $g_k$ is the unknown multipath parameter vector of user $k$ and is given by
$$S_k = \begin{bmatrix} s_k(0) & \ldots & 0 \\ \vdots & \ddots & \vdots \\ s_k(N_s - 1) & \ldots & 0 \end{bmatrix}$$

and $g_k = [g_{k,0} \quad g_{k,1} \ldots \quad g_{k,(L-1)}]^T$

We consider the constrained minimum variance criterion to estimate desired signal of user 1 as,
$$\hat{b}_1(n) = w^H y(n)$$ \hspace{1cm} (7)

where $w^H$ is receiver tap weight vector of same length as the data vector $y(n)$.

Output variance is given by
$$J = E\{||b_1(n)||^2\} = w^H R_y w$$ \hspace{1cm} (8)

where $R_y = E\{y(n)y^H(n)\}$

The receiver vector $w$ may be optimized by minimizing the output variance $J$ subject to
$$S^H w = g$$ \hspace{1cm} (9)

$w_{opt}$ is found by method of Lagrange multipliers $\lambda$.

$$J = w^H R_y w + X^H [S^H w - g]$$ \hspace{1cm} (10)

Taking the gradient of (10) with respect to $w$.

$$\nabla_w \cdot J = R_y w + S \lambda$$ \hspace{1cm} (11)

Scaling factor has not been considered for simplicity. For optimality, the first and second term of (11) must be orthogonal, which is achieved by setting the sum of the vector equal to 0.

$$\nabla_w \cdot J = R_y w + S \lambda = 0$$ \hspace{1cm} (12)

The optimal weight vector is then
$$w_{opt} = -R_y^{-1} S \lambda$$ \hspace{1cm} (13)

Since $w_{opt}$ must satisfy constraint (9)

$$S^H w_{opt} = g = -S^H R_y^{-1} S \lambda$$ \hspace{1cm} (14)

and the Lagrange multipliers are found to be

$$\lambda = -[S^H R_y^{-1} S]^{-1} g$$ \hspace{1cm} (15)

From (13) and (15) the optimum constrained LMS weight vector is given by
$$w_{opt} = R_y^{-1} S [S^H R_y^{-1} S]^{-1} g$$ \hspace{1cm} (16)
Substituting (16) in (7) the constrained least square estimate of output is
\[
\hat{h}_i(n) = w_{\text{opt}}^H y(n)
\]  

(17)

III. PROPOSED CONSTRAINED BLIND ADAPTIVE ALGORITHMS

A. Least mean square approach

In time varying multipath channels, the optimum filter weights must be computed periodically. Implementation of (16) requires inversion of input correlation matrix which increases computational complexity. The proposed constraint blind LMS algorithm has lower computational complexity and simple to implement.

In constrained gradient descent optimization the tap weight vector is moved in negative direction to minimize the cost function \( J \) with step size \( \mu_w \). After the \( n \)th iteration the next weight vector is
\[
w(n+1) = w(n) - \mu_w \nabla w \cdot J
\]  

(18)

The Lagrange multipliers are chosen by requiring \( w(n+1) \) to satisfy constraint (9)
\[
g(n) = S^H w(n+1) = S^H w(n) - \mu_w S^H R_y w(n)
\]
\[
- \mu_w S^H S \lambda(n)
\]  

(19)

Solving for \( \lambda(n) \) results in
\[
\lambda(n) = \frac{1}{\mu_w} [S^H S]^{-1} [S^H w(n) - \mu_w S^H R_y w(n) - g(n)]
\]  

(20)

Substituting (20) into (18) results in
\[
w(n+1) = w(n) + \mu_w [I - S[S^H S]^{-1} S^H] R_y w(n)
\]
\[
+ S [S^H S]^{-1} [g(n) - S^H w(n)]
\]  

(21)

Defining \( F \triangleq I - S[S^H S]^{-1} S^H \), (21) is rewritten as
\[
w(n+1) = F [w(n) - \mu_w R_y w(n)] + S [S^H S]^{-1} g(n)
\]  

(22)

where, \( g(n) \) is the unknown multipath channel vector and has to be updated at each iteration. To update \( g \) we will impose one more constraint \( ||g|| = 1 \) along with \( S^H w = g \). Hence cost function (10) is rewritten as
\[
J = w^H R_y w + \chi^H [S^H w - g] + \nu [g^H g - 1]
\]  

(23)

where, \( \nu \) is Lagrange multiplier.
The update equation for \( g \) is given by
\[
g(n+1) = g(n) + \mu_g \nabla g \cdot J
\]  

(24)

\( g(n) \) can be calculated by projecting \( \nabla g \cdot J \) onto the space orthogonal to \( g(n) \) to find the next set of coefficients
\[
g(n+1) = g(n) + \mu_g \left[ I - \frac{g(n) g^H(n)}{g^H(n) g(n)} \right] \lambda(n)
\]  

(25)

Solving (25) results in
\[
g(n+1) = g(n) + \frac{\mu_g}{\mu_w} \left[ I - \frac{g(n) g^H(n)}{g^H(n) g(n)} \right] [S^H S]^{-1} \cdot [\mu_w S^H R_y w(n) + g(n) - S^H w(n)]
\]  

(27)

B. Recursive least square (RLS) approach

LMS gives slow convergence when channel experiences fast frequency selective fading. RLS exhibits faster convergence rate and good tracking of channel characteristics for fast fading frequency selective channels. Here, we will derive RLS algorithm with the same constraint used in LMS algorithm.

For optimal solution of receiver tap weight vector \( w \) with constraint (9) we need to compute \( R_y^{-1} \) recursively and find eigen value of matrix \( [S^H R_y^{-1} S] \) corresponding to its minimum eigen value. Hence optimum weight vector is given by
\[
w(n) = \alpha_{\text{min}} P(n) S g_{\text{min}}(n)
\]  

(28)

where \( g_{\text{min}}(n) \) is the eigen vector corresponding to its minimum eigen value \( \alpha_{\text{min}} \). \( P \) can be updated using Kalman RLS recursions [16].
\[
k(n) = \frac{\rho^{-1} P(n-1) y(n)}{1 + \rho^{-1} y^H(n) P(n-1) y(n)}
\]  

(29)
Fig. 3. BER vs. $E_b/N_0$ performance for $K=5$ in CM1

$$P(n) = \rho^{-1}P(n - 1) - \rho^{-1}k(n)y^H(n)P(n - 1)$$  (30)

where $0 < \rho \leq 1$ is the forgetting factor.

IV. SIMULATION RESULTS

Simulations were carried out to evaluate and compare the bit error probability performance of the proposed constrained blind adaptive multiuser DS-CDMA UWB detectors with adaptive MMSE and RAKE equal gain combiner (EGC) in multipath channels. The system for simulations considered in this paper is, synchronous DS-CDMA UWB with the following specifications. All users have equal power with Gold sequence of spreading gain 31 as spreading code. Binary phase shift keying with sampling frequency of 50 GHz, chip time of 0.5 nsec and second derivative of Gaussian pulse of width 0.5 nsec used. Random binary data is generated for each user, the data is spread with the respective spreading code followed by modulation with second derivative of the Gaussian pulse. Each user undergoes a different UWB channel. Channel models CM1 and CM2 from IEEE P802.15 are used [17]. Channel model parameters are listed in table I. AWGN environment is considered and it is assumed that receiver knows spreading code of the user of interest.

Bit error probability is averaged over 500 realizations for each user with 2000 bits/channel. We have considered multipath gains that are lognormal distributed with total multipath gain=1, and are resolvable at chip rate. Initial value of $w = [0, 0, 0, 0]$T, $g = [1, 0, 0, 0]$T and $P(0) = 1000I$. The step size $\mu_w = 0.0035$ and $\mu_g = 0.014$, and forgetting factor $\rho = 0.9998$ are considered for simulation.

To verify and investigate receiver performance in CM1 and CM2 bit error probability vs. $E_b/N_0$ plotted for $K = 5$. Adaptive MMSE is realized using conventional LMS having a filter of length $N_s$, step size $\mu = 0.001$, and 500 bits are used as training bits. Rake receiver implemented is a L

Fig. 4. BER vs. $E_b/N_0$ performance for $K=5$ in CM2

Fig. 5. BER vs. Number of users performance for $E_b/N_0=20$ dB in CM1

Fig. 6. BER vs. Number of users performance for $E_b/N_0=20$ dB in CM2
TABLE I
IEEE UWB CHANNEL PARAMETERS.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>CM1</th>
<th>CM2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cluster arrival rate, λ(1/μs)</td>
<td>0.0233</td>
<td>0.4</td>
</tr>
<tr>
<td>Ray arrival rate, x(1/μs)</td>
<td>2.5</td>
<td>0.5</td>
</tr>
<tr>
<td>Cluster decay factor, γ</td>
<td>7.1</td>
<td>5.5</td>
</tr>
<tr>
<td>Ray decay factor, γ</td>
<td>4.3</td>
<td>6.7</td>
</tr>
<tr>
<td>Std. dev. of cluster, σ_c(dB)</td>
<td>3.3941</td>
<td>3.3941</td>
</tr>
<tr>
<td>Std. dev. of ray, σ_r(dB)</td>
<td>3.3941</td>
<td>3.3941</td>
</tr>
<tr>
<td>Std. dev. of total MP, σ_d(dB)</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

TABLE II
NUMBER OF USERS SUPPORTED IN CM1 WITH E_b/N_0 = 20 dB

<table>
<thead>
<tr>
<th>BER</th>
<th>RAKE (EGC)</th>
<th>Adaptive MMSE</th>
<th>CB-LMS</th>
<th>CB-RLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>10^-7</td>
<td>3</td>
<td>7</td>
<td>10</td>
<td>14</td>
</tr>
<tr>
<td>10^-3</td>
<td>3</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>10^-4</td>
<td>0</td>
<td>1</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td>10^-5</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>4</td>
</tr>
</tbody>
</table>

TABLE III
NUMBER OF USERS SUPPORTED IN CM2 WITH E_b/N_0 = 20 dB

<table>
<thead>
<tr>
<th>BER</th>
<th>RAKE (EGC)</th>
<th>Adaptive MMSE</th>
<th>CB-LMS</th>
<th>CB-RLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>10^-7</td>
<td>3</td>
<td>7</td>
<td>11</td>
<td></td>
</tr>
<tr>
<td>10^-3</td>
<td>0</td>
<td>1</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>10^-4</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td></td>
</tr>
</tbody>
</table>

V. CONCLUSION

In this paper we have derived and proposed constrained blind adaptive DS-CDMA UWB LMS and RLS detectors for multipath channel. It is observed that the BER performance of the proposed detectors is much better in comparison with RAKE (EGC) and adaptive MMSE detector. Further, it offers significant improvement in MAI cancellation in multipath channels with AWGN.

Proposed detectors do not require information about spreading codes of all users other than that of the user of interest. Also, note that the proposed approach does not require training sequence knowledge to adapt to varying channel conditions.

Simulation results show that constrained blind LMS algorithm BER performance is better than the adaptive MMSE receiver giving an improvement of 2 dB at BER=10^-2 in both CM1 and CM2 channels.

BER performance of constrained blind RLS algorithm in comparison with constrained blind LMS gives an improvement of 2 dB for BER of 10^-3 and substantial improvement for BER < 10^-4 in CM2.

REFERENCES